The Dynamic Interaction between Inflation and Inflation Uncertainty: Evidence from Jordan

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Abstract

Objective: This paper investigates the dynamic interaction between inflation and inflation uncertainty in Jordan using quarterly data from 1976: Q1 to 2023: Q1. This is important because achieving price stability and managing inflation expectations are crucial issues in modern monetary policy analysis. It assumes that central banks should consider the interaction between inflation and inflation expectations in designing an appropriate objective function and/or reaction function.

Method: Three types of time series models are used to investigate the dynamic interaction between inflation and inflation uncertainty: Autoregressive Moving Average (ARMA), Autoregressive Conditional Heteroskedasticity (ARCH), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH).

Results: The results of the mean equation show that past inflation has a significant effect on current inflation. Conversely, the results of the variance equation indicate a high degree of uncertainty persistence in response to inflationary shocks. The Wald VAR Granger causality test provides evidence showing bidirectional causality from inflation-to-inflation uncertainty and from inflation uncertainty to inflation, supporting the "Friedman-Ball Hypothesis" and the "Cukierman-Meltzer Hypothesis".

Conclusions: The price stabilization commitment of monetary policy has not reduced the impact of current inflation on future inflation uncertainty, nor has it lessened the feedback effect from future inflation uncertainty to current inflation. This suggests that the private sector in Jordan may need more trust in the efficacy of the monetary policy's stabilization approach. Therefore, the study suggests that the Central Bank of Jordan should enhance the credibility of monetary policy and attempt to control inflation and inflation uncertainty through restrictive, proactive, and robust disinflationary measures.

Keywords: Inflation. Inflation uncertainty. ARMA. GARCH. VAR. Monetary Policy. Jordan.

التفاعل الديناميكي بين التضخم وعدم اليقين بشأن التضخم: أدلة من الأردن عمر الزعبي $^{\square 2}$ ، سعيد الخطيب 2

1 باحث اقتصادي، الأردن 2 أستاذ، قسم اقتصاديات الأعمال، الجامعة الأردنية

ملخص

الأهداف: تبحث هذه الورقة في العلاقة الديناميكية بين التضخم وعدم اليقين الذي يصاحب توقعات التضخم في الأردن وذلك باستخدام البيانات الرُّعية التي تبدأ من الربع الأول من عام 1976 إلى الربع الأول من عام 2023. وتأتي أهمية ذلك في ضوء أنّ تحقيق هدف استقرار الأسعار وإدارة توقعات التضخم اصبحت قضايا حيوية للبنوك المركزية عند تحليل الآثار التي يمكن أن تُحدثها السياسة النقدية على أساسيات الاقتصاد الكلي، والتي باتت تفترض حديثاً أنّ البنوك المركزية يجب أن تأخذ في الاعتبار التفاعل بين التضخم وتوقعات التضخم من القطاع الخاص عند تصميم دالة أهدافها و/أو دالة استجاباتها للتغيرات في الاقتصاد المحلى أو الاقتصاد العالمي.

المنهجية: هناك ثلاثة أنواع من نماذج السلاسل الزمنية المستخدمة في دراسة التفاعل الديناميكي بين التضخم وعدم اليقين في توقعات التضخم مثل نموذج الانحدار الذاتي المشروط بعدم تجانس التباين (ARCH) ، والنموذج العام للانحدار الذاتي المشروط بعدم تجانس التباين (GARCH) إلى جانب الانحدار الذاتي المتزامن مع المتوسط المتحرك (ARMA).

النتائج: تُظهر نتائجُ معادلة المتوسط المقاسة بنموذج (ARMA)أنَّ التضخم السابق له تأثير ملموس على التضخم الحالي. ومن ناحية أخرى ، تظهر نتائج معادلات (ARCH) و (GARCH)أنَّ فترة عدم اليقين في توقعات التضخم تطول إذا ما حدثت صدمات تضخمية. وفي موازاة ذلك، يُظهر اختبار السبيية القائم على اختبار Wald VAR أنَّ السببية قد جاءت في الاتجاهين وذلك من التضخم الى عدم اليقين في توقعات التضخم ومن عدم اليقين في توقعات التضخم، مما يدعم كلاً من "فرضية فريدمان بول - Friedman-Ball Hypothesis" و"فرضية كوكيرمان-ميلتزر- Whypothesis المهودية المه

الخلاصة: تستنتج الدراسة أنّ التزام السياسة النقدية باستقرار الأسعار لم يقلل من تأثير التضخم الحالي على عدم اليقين بشأن توقعات التضخم، كما أنه لم يقلل من تأثير التغذية الراجعة من عدم اليقين بشأن توقعات التضخم إلى التضخم الحالي. وقد يشير ذلك إلى أنّ القطاع الخاص في الأردن يحتاج إلى مزيد من الثقة والإيمان بفعالية نهج استقرار الأسعار الذي تنتهجه السياسة النقدية. لذلك، تقترح الدراسة ضرورة قيام البنك المركزي الأردني بتعزيز مصداقية السياسة النقدية ومحاولة السيطرة على التضخم وعدم اليقين بشأن توقعات التضخم من خلال اتخاذ تداير تقييدية أشدّ، وبنفس الوقت أن تكون هذه التداير استباقية.

الكلمات الدالة: التضخم. عدم تأكد توقعات التضخم. :ARMA GARCH.VARالسياسة النقدية. الأردن.

1.INTRODUCTION

Investigating the relationship between monetary policy and macroeconomic fundamentals requires, among other things, a deep understanding of the dynamic interaction between inflation and inflation expectations. In this context, inflation expectations among the private sector are associated with uncertainty surrounding future inflation. Demonstrating such interactions is crucial not only for formulating monetary policy regarding interest rates and monetary variables but also for guiding decision-making in the private sector.

Achieving price stability and managing inflation expectations play an increasingly significant role in modern monetary theory. Central banks are assumed to consider the interaction between inflation and its expectations when designing appropriate objective and reaction functions. The traditional objective function of monetary policy has dual goals: stimulating economic growth and achieving price stability. The traditional reaction function aims to respond to future economic growth and inflation expectations (Fountas et al., 2006; Grier and Grier, 2006).

Moreover, it is widely argued that unpredictable inflation distorts consumption and investment choices of households and investors, leading to inefficient allocation of resources and output loss (Fatas and Mihov, 2001; Elder, 2004; Friedman, 1977). Additionally, unpredictable inflation involves high-risk premiums on private choices (Dotsey and Ireland, 1996; Lucas, 2003; Chowdhury, 2014; Almajali and Almubidin, 2022).

The impact of the interaction between inflation and inflation uncertainty on macroeconomic fundamentals has historically received substantial attention in economic literature. Various approaches have been proposed to address high and unpredictable inflation. One such approach is adopting independent monetary policy with the primary objective of stabilizing prices (Rogoff, 1985). Another approach involves inflation targeting (Bernanke & Mishkin, 1997; Svensson, 1997). A third approach, suggested by Taylor (1993, 2000) and McCallum (1997), uses pre-set monetary policy rules in response to future economic growth and inflation expectations. Enhancing the credibility of central banks is a common objective across these approaches (Al-Zoubi, 2004).

Reviewing the literature on the dynamic relationship between inflation and inflation uncertainty reveals that the use of single ARMA-ARCH and ARMA-GARCH models has received little attention in Jordan. This research attempts to fill this gap. There is also significant motivation for this research: constructing an appropriate ARMA model fit for the inflation series in Jordan and examining whether modeling inflation uncertainty with ARCH-type models improves the appropriate objective and reaction functions of monetary policy over short and medium horizons. Another objective of this research is to apply Generalized Impulse Response Functions (GIRF) of the VAR model to analyze causality between inflation and its expectations in the Jordanian context.

The remainder of the paper is organized as follows: Section 2 presents the causality debate on the interaction between inflation and inflation uncertainty. Section 3 provides a review of theoretical and empirical literature. Section 4 describes the methodology used to examine the dynamic relationship between inflation and inflation uncertainty. Empirical results are presented and discussed in Section 5. The final section concludes the study.

2.THE CAUSALITY DEBATE

There has been considerable debate in the literature regarding alternative hypotheses to understand the dynamic interaction between inflation and inflation uncertainty. Okun (1971) initially observed a positive association between inflation and its standard deviation based on data from 17 OECD countries. According to Okun, this positive relationship arises because monetary policy becomes unpredictable during periods of high inflation.

Friedman (1977) further argued that higher inflation increases uncertainty about future inflation, thereby adversely affecting economic growth. He contended that political pressures often compel central banks to address inflation but reluctance to implement contractionary monetary policies leads to greater unpredictability in monetary policy behavior during inflationary periods. Consequently, higher average inflation results in increased uncertainty about future inflation. Ball (1992) developed a formal economic model supporting Friedman's argument, proposing an asymmetric game-theoretic model between central banks and the private sector. This positive relationship between inflation and inflation uncertainty is known as the Friedman-Ball Hypothesis.

In contrast, Cukierman and Meltzer (1986) posited that causality runs from inflation uncertainty to inflation. They argued that central banks operate with discretionary objectives, preferring to stimulate economic growth or accommodate inflation through monetary policy instruments. During periods of heightened uncertainty, discretionary monetary policy tends to increase incentives for economic stimulation by expanding the money supply, leading to higher-than-expected inflation rates. This analysis suggests that increased inflation uncertainty contributes to higher inflation, termed the Cukierman-Meltzer Hypothesis.

Another perspective is based on the stabilization motive of central banks, known as the Stabilizing Fed Hypothesis proposed by Holland (1995). According to Holland, an increase in inflation prompts the private sector to revise expectations upwards about future inflation. Subsequently, central banks react to inflation expectations through commitments to price stabilization, implementing disinflationary policies by reducing money supply growth. Thus, higher uncertainty decreases average inflation rates, known as the "Holland Hypothesis".

Pourgerami and Maskus (1987) contribute to the understanding of the dynamic interaction between inflation and inflation uncertainty by proposing a negative relationship. They argue that higher inflation motivates economic agents in the private sector to invest more in accurate inflation predictions, thereby reducing inflation uncertainty. Describing the mechanism from higher inflation rates to lower inflation uncertainty is referred to as the "Pourgerami and Maskus Hypothesis".

3.THE LITERATURE REVIEW

Despite the extensive empirical work conducted on competing hypotheses regarding the relationship between inflation and inflation uncertainty, controversy among economists about the direction of causality remains active. This section thoroughly reviews the most relevant studies on the dynamic relationships between inflation and inflation uncertainty, focusing specifically on the methodologies used and the empirical results obtained across different historical periods and countries.

Kontonikas (2004) examined the impact of inflation uncertainty on inflation targeting using annual British data from 1972 to 2002. In this study, uncertainty was proxied using estimated conditional volatility from ARMA-GARCH inflation models. The results provide empirical evidence supporting a positive relationship between past inflation and current uncertainty.

Thornton (2008) conducted unit root tests using Argentinean data from 1810 to 2005. The results suggest that inflation is a stationary series when structural breaks coinciding with bouts of hyperinflation are taken into account. Additionally, using a GARCH (1,1) model of annual inflation, a positive short-run relation between the mean and variance of inflation was found, supporting Friedman's hypothesis that high inflation is associated with greater variability in inflation.

Karahan (2012) studied the relationship between inflation and inflation uncertainty in Turkey from 2002 to 2011 using a two-step procedure. In the first step, the ARMA-GARCH model of monthly inflation data was estimated, and the conditional variance derived from these estimates served as the monthly inflation uncertainty series. In the second step, Granger causality tests were conducted between inflation and the generated inflation uncertainty series following Granger (1969, 1986). The empirical results strongly support the Friedman-Ball hypothesis, indicating that periods of high inflation lead to increased inflation uncertainty.

Ananzeh (2015) examined the relationship between inflation and inflation uncertainty in Jordan from 1976 to 2013. He utilized generalized autoregressive conditional heteroscedasticity (GARCH) models and Granger causality techniques. The GARCH model results supported Friedman and Ball's hypothesis, showing a robust positive relationship between the inflation rate and its uncertainty. The Granger causality tests also supported Cukierman and Meltzer's hypothesis (1986), indicating bidirectional causality between inflation and inflation uncertainty.

Khatir et al. (2020) investigated the relationship between monthly inflation and inflation uncertainty in the Turkish economy from January 2005 to May 2020, employing the ARMA-GARCH model. While some empirical studies support the Friedman-Ball hypothesis, suggesting a positive effect of inflation on inflation volatility, others support Cukierman and Meltzer's hypothesis that inflation uncertainty contributes to higher inflation. Finally, the results also align with Holland's hypothesis, indicating that uncertainty triggers a decrease in potential inflation.

Munir and Riaz (2020) analyzed the dynamics of inflation and inflation uncertainty in Pakistan, disaggregating inflation into food and non-food components from July 1998 to March 2018. They used a two-step procedure: first employing an ARMA-GARCH model to measure inflation uncertainty through generalized conditional variance, then conducting Granger causality tests to examine relationships between variables. The findings indicate a unidirectional causality from inflation to inflation uncertainty, supporting the Friedman-Ball hypothesis. These results suggest that monetary authorities should prioritize price stability as the primary objective and target core inflation rather than headline inflation.

Grier and Perry (1998) examined the relationship between inflation and inflation uncertainty across G7 countries from 1948 to 1993. They used GARCH models to measure inflation uncertainty and Granger methods to test causality between average inflation and inflation uncertainty. The study found that inflation significantly increases inflation uncertainty in all G7 countries, consistent with predictions by Friedman and Ball. There is weaker evidence that inflation uncertainty Granger-causes inflation. Specifically, increased inflation uncertainty is associated with lower inflation in the USA, UK, and Germany, while it is linked with higher inflation in Japan and France.

Conrad and Karanasos (2005) applied long memory time series analysis to investigate the relationship between inflation and inflation uncertainty using monthly data from the USA, Japan, and the UK spanning 1962 to 2001. In all countries, inflation is shown to significantly increase inflation uncertainty, in line with Friedman and Ball's predictions. Furthermore, increased nominal uncertainty affects inflation differently in Japan and the UK. The results from Japan support the Cukierman–Meltzer hypothesis.

Wilson (2006) employed a bivariate EGARCH-M model to investigate the links between inflation, inflation uncertainty, and output growth using post-war Japanese data. The results indicate that increased inflation uncertainty is associated with higher average inflation and lower average growth in Japan. Additionally, Wilson found that increased growth uncertainty was linked to higher average inflation but was unrelated to average growth. Furthermore, inflation and growth display significant asymmetry in their respective conditional variances: negative surprises raise both inflation uncertainty and growth uncertainty more than positive surprises.

Fountas et al. (2006) used a bivariate generalized autoregressive conditional heteroskedastic (GARCH) model of inflation and output growth to examine the causal relationship among nominal uncertainty, real uncertainty, and macroeconomic performance measured by inflation and output growth rates. Applying the constant conditional correlation GARCH(1,1) model led to several interesting conclusions. Firstly, inflation causes negative welfare effects both directly and indirectly, through the inflation uncertainty channel. Secondly, in some countries, higher inflation uncertainty incentivizes central banks to surprise the public by raising inflation unexpectedly. Thirdly, contrary to the assumptions of some macroeconomic models, business cycle variability and the economic growth rate are related, with more variability in the business cycle leading to higher output growth.

Dong-Hyeon and Shu-Chin (2012) examined the link through a system of simultaneous equations that addresses reverse causality issues. They employed the identification through the heteroskedasticity approach as an identification strategy, using a panel of 105 countries from 1960 to 2007. They found a two-way interaction between inflation and its variability. Specifically, higher inflation increases inflation volatility, consistent with the Friedman-Ball Hypothesis. Moreover, greater inflation volatility fuels inflation, consistent with the arguments of Cukierman and Meltzer. The evidence is robust across alternative model specifications, periods, and country characteristics.

Živkov et al. (2014) explored the bidirectional linkage between inflation and inflation uncertainty using monthly data from 11 Eastern European countries (EEC). Their methodological approach comprised two steps. First, they created an inflation uncertainty series using an optimal GARCH model. Second, they analyzed inflation and inflation uncertainty together using two models to examine whether Friedman's and Cukierman–Meltzer hypotheses held for selected Eastern European countries. Due to heterogeneous behavior in some series of inflation and inflation uncertainty, they applied the unconditional quantile regression estimation technique for its robustness to non-normal characteristics and outliers in empirical data. The findings confirmed both the Friedman-Ball and Cukierman–Meltzer hypotheses for the largest EEC countries with flexible exchange rates. However, these theories were refuted in smaller, open economies with fixed exchange rate regimes.

Sharaf (2015) examined the causal relationship between inflation and inflation uncertainty in Egypt using monthly time series data from January 1974 to April 2015, employing the GARCH model. The analysis rigorously controlled for the effect of the Economic Reform and Structural Adjustment Program (ERSAP) undertaken by the Egyptian government in the early 1990s, which significantly influenced the inflation rate and its associated volatility. The results demonstrate a high degree of inflation-volatility persistence in response to inflationary shocks. Both the Granger causality test and symmetric/asymmetric GARCH models indicate a statistically significant bidirectional positive relationship between inflation and inflation uncertainty, thereby supporting both the Friedman–Ball and Cukierman–Meltzer hypotheses.

Jiranyakul (2020) employed the AR(p)-EGARCH model and quantile regression to examine the linkages between inflation and inflation uncertainty in nine Asian countries using monthly data from January 1979 to December 2019. The results reveal that inflation positively influences inflation uncertainty across all economies, regardless of whether they employ inflation targeting policies or not, thereby supporting the Friedman-Ball hypothesis. Additionally, inflation uncertainty positively influences inflation in most economies, suggesting support for the Cukierman-Meltzer hypothesis.

Chowdhury (2014) analyzed the relationship between inflation and inflation uncertainty in India using the GARCH model and Granger Causality test. The unit root test provided evidence supporting the stationarity of the inflation series. Maximum likelihood estimates from the GARCH model strongly supported the existence of a positive relationship between inflation levels and uncertainty. Granger causality results indicated a feedback relationship between inflation and uncertainty.

It is important to note that the varied outcomes observed in empirical research regarding the causal relationship between inflation and inflation uncertainty may be attributed to disparities in challenges faced by different countries and specific

monetary approaches employed by their central banks to address these challenges. Thus, the relationship between inflation and inflation uncertainty is likely to be country-specific in practice, underscoring the importance of examining this relationship in the context of Jordan.

4.THE ECONOMETRICS METHODOLOGY

This research examines the dynamic relationships between inflation and inflation uncertainty using a sample of Jordanian quarterly data spanning from 1976.Q1 to 2023.Q1, employing a two-step methodology. The first step involves estimating an Autoregressive Conditional Heteroskedasticity (ARCH) model (Engle, 1982). An ARCH model is suitable for series exhibiting periods of increased or decreased variance, such as residuals after fitting an Autoregressive Moving Average (ARMA) model to the data. It is assumed that lagged values of inflation and current as well as lagged values of shocks may contain useful information on inflation dynamics. The inflation mean equation can be expressed as a general ARMA (p, q) model for inflation rate (y_t) as:

$$y_{t} = c + \delta_{1} y_{t-1} + \dots + \delta_{p} y_{t-p} + \beta_{1} \varepsilon_{t-1} + \dots + \beta_{q} \varepsilon_{t-q} + \varepsilon_{t}$$
(1)

Where c is a constant, δ_i are the parameters of the autoregressive components of order p, β_i are the parameters of the moving average components of order q, and ε_t is the error term at time t. Identification of an AR order is often best determined with partial autocorrelation function (PACF). For an AR (p) model, the theoretical PACF shuts off past the older model. On the other hand, for an MA (q) model, the autocorrelation function (ACF) will have non-zero autocorrelation at lags involved in the model.

The extension to modeling the time-varying conditional variance (σ^2) of inflation with the application of ARCH-type models is meant to capture the uncertainty around inflation. In the ARCH model of Engle (1982), the σ^2 depends on q past squared values of ARMA error terms, while in the GARCH (p, q) model of Bollerslev (1986), it extends the ARCH model to that of σ^2 depends on its own lags as well as on lags of ARMA squared error.

Two time-varying volatility models have been developed based on the ARMA model: the ARCH (Autoregressive Conditional heteroskedasticity) and the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model. An ARCH model is often used to describe situations in which there may be a short period of increased variation.

$$y_t = c + \varepsilon_t \tag{2}$$

$$\varepsilon_t = z_t \sigma_t$$
 (3)

Where c is a constant value, ε_t is residual, z_t is the standardized residual with independently and identically distributed with mean equal to zero and variance equal to one, and σ_t is the square root of the conditional variance with non-negative process. The ARCH(q) model can be expressed as:

$$\sigma_t^2 = \eta + \sum_{j=1}^q \alpha_j \, \varepsilon_{t-j}^2 \tag{4}$$

The constraints on parameters are $\eta > 0$ and $\alpha_j \ge 0$ (j = 1, ... q), which to ensure the conditional variance, σ_t^2 is non-negative. The main problem that may arise with using ARCH is that there might be a need for a large value of the lag q, hence a large number of parameters to be estimated. This may result in difficulties in estimating parameters.

The extension to modeling the time-varying conditional variance (σ^2) of inflation with the application of ARCH-type models is meant to capture the uncertainty around inflation. In the ARCH model of Engle (1982), the σ^2 depends on q past squared values of ARMA error terms. An extension from the ARCH model was developed by Bollerslev (1986), namely GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model uses values of the past squared observations and past variances to model the variance at time t. The variance equation can be expressed as a general GARCH(p,q) model can be written as follows:

$$\sigma_t^2 = \eta + \sum_{i=1}^p \alpha_i \sigma_{t-i}^2 + \sum_{j=1}^q \beta_j \varepsilon_{t-j}^2$$
 (5)

Where $\eta > 0$ is the long-run volatility, $\alpha_i \ge 0$; i = 1,..., p and $\beta_j \ge 0$; j = 1,..., q. If $\alpha_i + \beta_j < 1$, then the GARCH(p,q) model is covariance stationary. The unconditional variance of the error terms

model is covariance stationary. The unconditional variance of the error terms
$$\operatorname{Var}(\varepsilon_t) = \frac{\eta}{1-\alpha-\beta} \tag{6}$$

From the general form of GARCH(p, q) model, the GARCH(1,1) model can be defined as

$$\sigma_t^2 = \eta + \alpha_i \sigma_{t-1}^2 + \beta_j \varepsilon_{t-1}^2 \tag{7}$$

The appropriate ARMA-GARCH model can be selected based on the minimum values of Akaike Information Criteria (AIC) (1974), Schwarz Criteria (SC) (1978), and Hannan-Quinn Information Criteria (HQC) (1979) computed as

$$AIC = -2\ln(L) + 2k \tag{9}$$

$$SC = -2\ln(L) + \ln(N)k \tag{10}$$

$$HQC = -2\ln(L) + 2(\ln(N))k$$
 (11)

Where *L* is the value of the likelihood function evaluated at the parameter estimates, *N* is the number of observations, and *k* is the number of estimated parameters.

Whereas the Durbin-Watson test is restricted to detecting first-order autoregression, the Breusch-Godfrey (BG) test will be used to detect the autocorrelation up to any predesignated order p. For an ARMA(p,q), the BG can be carried out by estimating the equation

$$\varepsilon_t = c + \delta_1 y_{t-1} + \dots + \delta_p y_{t-p} + \rho_1 \varepsilon_{t-1} + \dots + \rho_q \varepsilon_{t-n} + e_t$$
 (12)

Where ε_t is obtained from estimating Eq.(1). The next step can be carried out by testing the null hypothesis: $\rho_1 = \rho_2 = \dots = \rho_q = 0$

Based on the null hypothesis, if the sample size (n) is relatively sufficient, then the (LM) Lagrange Multiplier statistic can be approximated to the Chi-square statistic with p degrees of freedom (Asteriou & Hall, 2011) as

$$LM = nR^2 \sim \chi^2(p) \tag{13}$$

Where R^2 is the coefficient of determination computed from estimating Eq. (12). Asteriou & Hall (2011) suggested a modified version of the LM that can be approximated to F-distribution with q, and n - q - p - 1 degrees of freedom according to the formula:

$$LM^* = \frac{n - q - p - 1}{q} * \frac{R^2}{1 - R^2} \sim F_{q, n - q - p - 1}$$
(14)

4. RESULTS AND DISCUSSIONS

The inflation series $y_t = \log\left(\frac{CPl_t}{CPl_{t-1}}\right)$ used in this research is based on quarterly data of the Consumer Price Index (CPI) (2018 = 100) for the period 1976:Q1 to 2023:Q1. The first step in the analysis involves checking the stationarity of the inflation series to ensure accurate estimation and to avoid misleading results. It is evident that the inflation rate is highly volatile, and the extent of this volatility varies from one period to another. To formally test for stationarity, the results of the Augmented Dickey-Fuller (1981) and Phillips-Perron (1988) tests are presented in Table 1. Both tests reject the null hypothesis of a unit root in the inflation series at the 1% significance level.

Table (1): Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) Tests for Unit Root: Inflation Rate (π_t) (intercept included).

Variable	ADF Test Equation		PP Test Equation	
	Coefficient	Prob.	Coefficient	Prob.
C	0.006**	0.007	0.012**	0.000
π_{t-1}	-0.584**	0.000	-1.059**	0.000
π_{t-2}	-0.441**	0.001		
π_{t-3}	-0.480**	0.000		
π_{t-4}	0.527**	0.000		
$\frac{\pi_{t-4}}{R^2}$	0.732		0.531	
AIC	-4.660		-4.047	
SC	-4.573		-4.012	
Test Stat	-4.315**	0.001	-14.447**	0.000
	1 10/ 1 1			

^{**} Significant at the 1% level.

Having determined the stationarity of the inflation rate, the next step is to examine the Autocorrelation AC and Partial Autocorrelation PAC coefficients. Based on the information in Table 2, the pattern of AC and PAC does not look very similar to the theoretical pattern of a pure autoregressive (AR) model or a pure moving average (MA) model. The significant spikes of (AC) and (PAC) may point as a first approximation to inflation series as an ARMA(p, q) model. Certainly, no definitive specification can be made regarding the ordering of the ARMA model based solely on AC and PAC coefficients.

Table 2: The AC and PAC Coefficients of the Inflation (π_{t-1}) Series.

Lag	AC	PAC	Q-Stat ^a	Prob.
1	-0.050	-0.050	0.662	0.416
2	-0.200	-0.020	8.343	0.015
3	-0.100	-0.130	10.398	0.015
4	0.539	0.510	66.871	0.000
5	-0.110	-0.130	69.265	0.000
6	-0.160	-0.01	74.284	0.000
7	-0.010	0.090	74.310	0.000
8	0.423	0.154	109.82	0.000
9	-0.160	-0.090	115.06	0.000

a Ljung-Box Statistic $Q = \frac{n(n+2)\sum p_k^2}{n-k}$, where p_k is the autocorrelation at Lag k

However, following standard econometric techniques to identify the order of the ARMA model for the inflation series, the Akaike Information Criterion (AIC) and Schwarz Criterion (SC) select an ARMA(3,2) model. Thus, our empirical research specifies and models inflation in the mean equation as an AR(3) and MA(2) process, i.e., an ARMA(3,2) model. The OLS estimation of the ARMA(3,2) model for inflation is presented in Table 3. Moreover, the stationarity conditions associated with the ARMA(3,2) model are satisfied, as shown in Table 3.

Table (3): An Estimation of the ARMA(3,2) Model of Inflation

Variable	Coefficient	Prob.
c	0.012	0.000
AR(1)	-0.634	0.000
AR(2)	-0.831	0.000
AR(3)	-0.377	0.000
MA(1)	0.608	0.000
MA(2)	0.812	0.000
Statistics		
R^2	0.414	
F	25.327	
AIC	-4.551	
SC	-4.447	
HQC	-4.509	
DW	1.789	

The AR and MA components of the estimated parameters are significant. Additionally, as reported in Table 4, the serial correlation LM test of the Breusch-Godfrey test supports the null hypothesis of no serial correlation for ARMA(3,2) across two, four, and eight autocorrelation orders at a 5% significance level.

Table 4: Breusch-Godfrey Serial Correlation LM Test

Autocorrelation order (P)	F-Statistics $F_{p,n-p-k-1}$	Chi-square
2	$F_{2,176} = 1.437$ (0.241)	$\chi^2_{(2)}$ =2.972 (0.226)
4	$F_{4,172} = 1.921$ (0.109)	$\chi_{(4)}^2$ =7.866 (0.097)
8	F _{8,168} 1.421 (0.191)	$\chi_{(8)}^2$ =11.655 (0.167)

Having estimated the variance of the residuals from the ARMA(3,2) model using equation (4), which will be used as a measure of inflation uncertainty, an ARCH test was conducted. The results demonstrate strong evidence of heteroscedastic behavior in the residuals. Specifically, as reported in Table 5, the residuals fail to satisfy the null hypothesis of no ARCH effect at two, four, and eight autocorrelation orders, indicating the presence of an ARCH effect.

Table 5: Heteroskedasticity Test: ARCH

Autoregressive Order	F-Statistics $F_{p,n-p-k-1}$	Chi-square $\chi^2_{(p)}$
2	$F_{2,179} = 5.693^{**}$ (0.004)	$ \chi_{(2)}^2 = 10.885^{**} $ (0.004)
4	$F_{4,175} = 6.577^{**} $ (0.000)	$\chi_{(4)}^2 = 23.524^{**}$ (0.000)
8	$F_{9,167} = 4.456^{**}$ (0.000)	$\chi^2_{(8)} = 30.962^{**}$ (0.000)

^{**} Significant at the 1% level.

Engle (1982) has shown that ARCH modeling can improve the mean and variance estimates. Within the ARCH-type models, the heteroscedasticity of the inflation series is a time-variant that needs to be modeled. As we previously mentioned, in the basic ARCH model, the σ 2 depends on q past squared values of ARMA error terms, while in the GARCH(p, q) model, it extends the ARCH model to that of σ 2 depends on its own lags as well as on lags of ARMA squared error.

Our empirical research investigated the modeling problem for the time-varying conditional variance just as we did for the mean ARMA models. To determine the order of the actual GARCH model, we estimated sixteen different GARCH (p=0,1,2,3, and q = 0,1,2,3). We found that GARCH(1,1) is an appropriate fit. The GARCH(1,1) model implies that the conditional error variance of inflation depends on one past squared error from the inflation equation and one past conditional variance. As shown in Table 6, the ARMA (3,2)-GARCH (1,1) models are estimated jointly.

Table 6: ARMA(3,2)-GARCH(1,1) Estimates

Variable	Coefficient	Z-Statistic	Probability
С	0.007**	8.383	0.000
AR(1)	-0.541**	-5.136	0.000
AR(2)	-0.887**	-14.405	0.000
AR(3)	-0.245**	-3.010	0.003
MA(1)	0.588**	15.655	0.000
MA(2)	0.866^{**}	22.051	0.000
С	0.000^{**}	2.447	0.014
RESID ²	0.361**	3.797	0.000
GARCH((1,1)	0.647**	10.509	0.000
Statistics			
R^2	0.244		
AIC	-4.983		
SC	-4.828		
D-W	2.035		

^{*}Significant at the 1% level.

Upon examining the model statistics, it can be suggested that ARMA(3,2)-GARCH(1,1) effectively captures the fundamental inflation dynamics. The model demonstrates robust explanatory power, with statistical significance at the 1 percent level. Furthermore, as depicted in Table 7, the residuals exhibit no serial correlation or ARCH effects across various lag lengths, respectively.

Table 7: Breusch-Godfrey Serial Correlation LM and ARCH Heteroskedasticity Test.

The state of the s	F-Statistics	Chi-square
Test	$F_{p,n-p-k-1}$	$\chi^2_{(p)}$
Breusch-Godfrey Serial Correlation Test	$F_{1,180} = 1.313$ (0.252)	$\chi_{(1)}^2 = 2.710$ (0.233)
Breusch-Godfrey Serial Correlation Test	$F_{4,177} = 1.843$ (0.121)	$\chi_{(4)}^2 = 7.002$ (0.103)
Heteroskedasticity Test: ARCH	$F_{2,183} = 1.504$ (0.225)	$\chi_{(2)}^2 = 3.001$ (0.222)
Heteroskedasticity Test: ARCH	$F_{4,179} = 1.510$ (0.201)	$\chi_{(4)}^2 = 6.006$ (0.199)

Figures in parentheses are probabilities.

The results of the mean equation indicate that past inflation significantly influences current inflation. Conversely, the results of the variance equation reveal a high persistence in inflation, as evidenced by the sum of the coefficients of the ARCH and GARCH terms approaching one, indicating a high degree of volatility persistence.

We now turn to carry out the Granger causality test within the bivariate vector autoregression (VAR) model. Therefore, a bivariate (VAR) is used to test whether inflation Granger causes inflation uncertainty or inflation uncertainty Granger causes inflation. As pioneered by Sims (1980), the VAR(P) represents each variable as a linear function of (P) of its lagged values and (P) lagged values of the other endogenous variable. The lags included in the formulation of the endogenous variables make the VAR a better tool for analyzing the causality between inflation and inflation uncertainty.

The VAR model in compact form can be written as:

$$y_{t} = \mu + \alpha_{1} y_{t-1} + \alpha_{2} y_{t-2} + \alpha_{p} y_{t-p} + \epsilon_{t}$$
(15)

where y_t is a 2×1 vector of the endogenous variables of inflation

 (π_t) , and inflation uncertainty (u_t) , μ is a 2x1 vector of constants, α_i are 2×2 matrices of lag coefficients of y, up to some lag length P, and ε is 2×1 vector of shocks.

An estimate of VAR model (eq. 15) is presented in Table (8). The choice of (8) lags is supported by AIC and H-Q Criterion but not by SC. Finally, the LM test provides empirical evidence supporting no serial correlation at lag lengths 1, 2, and 3.

Table 8: Estimates of The VAR Model (Eq. 15)

	u_t	π_t
С	0.000	14.323*
	(0.246)	(2.454)
u_{t-1}	0.792**	14.323*
, -	(10.440)	(2.454)
u_{t-2}	0.079	3.191
	(0.839)	(0.440)
u_{t-3}	-0.115	-0.651
	(-1.232)	(-0.091)

$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		u_t	π_t
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	11.+ 4		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\omega_{\ell-4}$		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	21		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	w _{t-5}		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	11.		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	wt-6		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	u_{t-7}		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	<i>U</i> +_0	-0.147**	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	1-6		(1.061)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	π_{t-1}		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	ι-1		(0.288)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	π_{t-2}		
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	1-2	(0.998)	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	π_{t-3}		-0.253*
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$, ,	(-0.588)	(-2.724)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	π_{t-4}	0.004**	0.285**
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$. 4	(3.096)	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	π_{t-5}	-0.003*	-0.101
$\begin{array}{c ccccc} & (-1.045) & (-1.117) \\ \hline \pi_{t-7} & 0.001 & -0.081 \\ & (1.040) & (-0.978) \\ \hline \pi_{t-8} & -0.003^* & 0.258^{**} \\ & (-2.501) & (3.224) \\ \hline \begin{array}{c} Regression Statistics \\ \hline R^2 & 0.917 & 0.497 \\ \hline \bar{R}^2 & 0.909 & 0.448 \\ \hline F & 112.235^{**} & 10.082^{**} \\ \hline AIC & -13.488^a & -4.800^a \\ \hline SC & -13.186 & -4.990 \\ \hline HQC & -12.753^a & -5.654^a \\ \hline Breusch-Godfrey Serial Correlation LM \\ \hline \\ Lags & LM-Stat & Probability \\ \hline 1 & 7.297 & 0.121 \\ \hline 2 & 4.731 & 0.316 \\ \hline 3 & 6.161 & 0.271 \\ \hline \end{array}$		(-2.744)	(-1.189)_
$\begin{array}{c ccccc} & (-1.045) & (-1.117) \\ \hline \pi_{t-7} & 0.001 & -0.081 \\ (1.040) & (-0.978) \\ \hline \pi_{t-8} & -0.003^* & 0.258^{**} \\ (-2.501) & (3.224) \\ \hline \begin{array}{c ccccccccccccccccccccccccccccccccccc$	π_{t-6}	-0.001	-0.094
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(-1.045)	(-1.117)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	π_{t-7}	0.001	-0.081
$\begin{array}{c ccccc} & & & & & & & & & & \\ Regression Statistics & & & & & & \\ \hline R^2 & & & & & & & \\ \hline R^2 & & & & & & & \\ \hline R^2 & & & & & & & \\ \hline R^2 & & & & & & & \\ \hline R^2 & & & & & & & \\ \hline $O.909$ & & & & & & \\ \hline $O.448$ & & & & & \\ \hline $I12.235** & & & & & \\ \hline $I0.082** & & & & \\ \hline AIC & & & & & & & \\ \hline AIC & & & & & & & \\ \hline AIC & & & & & & & \\ \hline SC & & & & & & \\ \hline $I3.186$ & & & & & & \\ \hline $A.990$ & & & & \\ \hline HQC & & & & & & \\ \hline $I2.753^a$ & & & & & \\ \hline $S.654^a$ & & \\ \hline \hline $Breusch-Godfrey Serial Correlation LM$ & \\ \hline $Lags$ & & & & & & \\ \hline $LM-Stat$ & & & & & \\ \hline I & $			(-0.978)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	π_{t-8}		
$\begin{array}{c ccccc} R^2 & 0.917 & 0.497 \\ \hline R^2 & 0.909 & 0.448 \\ F & 112.235** & 10.082** \\ AIC & -13.488^a & -4.800^a \\ SC & -13.186 & -4.990 \\ HQC & -12.753^a & -5.654^a \\ \hline Breusch-Godfrey Serial Correlation LM \\ \hline Lags & LM-Stat & Probability \\ 1 & 7.297 & 0.121 \\ 2 & 4.731 & 0.316 \\ 3 & 6.161 & 0.271 \\ \hline \end{array}$		(-2.501)	(3.224)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			
F 112.235** 10.082** AIC -13.488 ^a -4.800 ^a SC -13.186 -4.990 HQC -12.753 ^a -5.654 ^a Breusch-Godfrey Serial Correlation LM Lags LM-Stat Probability 1 7.297 0.121 2 4.731 0.316 3 6.161 0.271			
AIC			
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HQC -12.753a -5.654a Breusch-Godfrey Serial Correlation LM Lags LM-Stat Probability 1 7.297 0.121 2 4.731 0.316 3 6.161 0.271	_		
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1 7.297 0.121 2 4.731 0.316 3 6.161 0.271	Breusch-Godfr	ey Serial Cor	
2 4.731 0.316 3 6.161 0.271	Lags	LM-Stat	Probability
3 6.161 0.271	1	7.297	0.121
	2	4.731	0.316
4 11.584 0.021	3	6.161	0.271
	4	11.584	0.021

^{**} and * Significant at the 1% and 5% levels, respectively.

The stability of the VAR system is assessed by examining the roots of the system described in Equation (15). As indicated in Table 9, stability in a VAR model is characterized by roots that are less than zero, and by the modulus of any complex eigenvalue being strictly less than 1, fulfilling the VAR stability criterion.

^a Determines the optimal lag length selection.

sund 1/10 duties of the characteristic 1 of normal End			
Root	Modulus		
-0.942	0.942		
0.023 - 0.939	0.940		
0.023 + 0.939	0.940		
-0.770 - 0.411	0.873		
0.770 + 0.411	0.873		
0.837 - 0.068	0.8840		
0.816	0.816		
0.564 - 0.573	0.804		
0.564 + 0.573	0.804		
-0.222 - 0.762	0.793		
-0.222 + 0.762	0.793		
0.461 - 0.607	0.762		
0.461 + 0.607	0.762		
-0.423 - 0.382	0.570		
-0.423 + 0.382	0.570		

Table (9): Roots and Modules of the Characteristic Polynomial Endogenous Variables.

The Wald VAR Granger causality test is a statistical method used to ascertain whether one variable Granger-causes another in a VAR model. The results, presented in Table 10, indicate that, using both standard F and χ^2 tests, the coefficients of lagged inflation in the inflation uncertainty equation, and lagged inflation uncertainty in the inflation equation, respectively, are statistically significant. Specifically, the Granger causality test rejects the null hypothesis that inflation does not Granger-cause inflation uncertainty across all lag lengths at the one percent significance level. Similarly, the null hypothesis that inflation uncertainty does not Granger-cause inflation is also rejected for all lag lengths at the one percent significance level. These findings suggest the existence of bidirectional causality from inflation to inflation uncertainty and from inflation uncertainty to inflation in Jordan, supporting both the Friedman–Ball hypothesis and the Cukierman–Meltzer hypotheses.

Table (10): The Wald VAR Granger Causality Test.

Null Hypothesis	F-Statistics	Chi-square
	$F_{p,n-p-k-1}$	$\chi^2_{(p)}$
H ₀ : Inflation does not Granger- cause inflation uncertainty	$F_{8,163=12.520} $ (0.000	$\chi^2_{(8)} = 100.160$ (0.000)
H ₀ : Inflation uncertainty does not Granger- cause inflation	$F_{8,163=5.034}$ (0.000	$\chi^2_{(8)}$ =40.275 (0.000)

These results lead to the conclusion that inflation poses a challenge not only through its recognized impacts on household and investor decision-making but also through increased uncertainty surrounding inflation. It is evident that the monetary policy's commitment to price stabilization has not mitigated the influence of current inflation on future inflation uncertainty, nor has it reduced the feedback effect from future inflation uncertainty to current inflation. This indicates a potential lack of confidence in Jordan's private sector regarding the effectiveness of the monetary policy's stabilization efforts. Therefore, the study recommends that the Central Bank of Jordan (CBJ) should strengthen the credibility of monetary policy by implementing stringent, proactive measures aimed at controlling both inflation and inflation uncertainty.

5. CONCLUSIONS

In this paper, we modeled the relationship between inflation and inflation uncertainty in Jordan over the period from 1976: Q1 to 2023: Q1. Generally, there are four hypotheses regarding this relationship. The first is the Friedman-Ball Hypothesis, which posits that higher inflation increases uncertainty about future inflation. In contrast, the Pourgerami-Maskus Hypothesis suggests that an increase in inflation may be associated with lower average uncertainty. The Cukierman-Meltzer Hypothesis asserts that higher inflation uncertainty leads to an increase in the inflation rate. Lastly, the Holland

Hypothesis argues that due to the costs associated with inflation uncertainty, monetary policy responds by reducing money growth, thereby decreasing the inflation rate.

Our research follows a two-step approach. In the first step, we estimate an ARMA(3,2)-GARCH(1,1) inflation model, where the generated conditional variance measures inflation uncertainty. In the second step, we perform a Granger causality test within a VAR(15) model to determine the direction of causality between inflation and the measured inflation uncertainty. The results of the mean equation indicate that past inflation significantly affects current inflation. On the other hand, the variance equation reveals a high degree of volatility persistence in response to inflationary shocks.

The Wald VAR Granger causality test examines the causal relationship between these variables. The findings support bidirectional causality between inflation and inflation uncertainty in Jordan, which aligns with both the Friedman–Ball hypothesis and the Cukierman–Meltzer hypothesis.

Based on these results, we can conclude that inflation presents a challenge not only through its well-known impacts on the decision-making of households and investors but also through increased uncertainty about future inflation. It is evident that the monetary policy's commitment to price stabilization has not mitigated the current inflation's influence on future inflation uncertainty, nor has it reduced the feedback effect from future inflation uncertainty to current inflation. This suggests a potential lack of trust in the efficacy of Jordan's private sector regarding the monetary policy's stabilization approach.

Regarding policy implications, the study recommends that the Central Bank of Jordan (CBJ) should enhance the credibility of monetary policy and strive to control both inflation and inflation uncertainty through stringent, proactive, and robust anti-inflation measures.

Furthermore, future research could explore the relationship between inflation and inflation expectations in Jordan by applying other asymmetric ARCH-type models. This approach would investigate whether interactions exhibit asymmetric behavior and explore potential differences in dynamics and policy implications. Additionally, studying the relationship between inflation and inflation expectations alongside other intermediate monetary variables could further enrich understanding.

A significant limitation of standard ARCH-GARCH models is their focus on stochastic volatility in return time series, which may not adequately capture other components like trends or moving averages. This limitation could be critical when observing asymmetric effects or different forms of instability.

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