*Paper presented at **EconAnadolu 2009**: Anadolu International Conference in Economics*
*June 17-19, 2009, Eskişehir, Turkey.*

# Does Inflation Increase With Inflation Uncertainty In Iran? An Application Of M-GARCH-M Model With FIML Method Of Estimation

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## Abstract

This paper investigates the relationship between inflation and inflation uncertainty for the period of 1979-2007 by using monthly data and applying M-GARCH-M models in the Iranian economy. The results of a two-step procedure such as Granger causality test which uses generated variables from the first stage as regressors in the second stage, suggests a positive relation between the mean and the variance of inflation. However, Pagan (1984) criticizes this two-step procedure for its misspecifications due to the use of generated variables from the first stage as regressors in the second stage. This paper uses the Full Information Maximum Likelihood (FIML) method to address this issue. The estimates we gathered with the new set of specifications suggest that inflation Granger-causes inflation uncertainty, supporting the Friedman–Ball hypothesis, that high inflation is associated with more variable inflation.

***Keywords***: Inflation Uncertainty, FIML, M-GARCH-M Models, Iran.

***JEL Classification*:** C22; E31.

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## 1. Introduction:

The relationship between inflation and inflation uncertainty has been the matter of interest among economists in recent decades. As the impact of inflation and inflation uncertainty on growth and welfare are significant, determining the direction of the causality between inflation and inflation uncertainty can help the policy makers to make appropriate decisions. Friedman (1977) points out the potential of increased inflation to crate nominal uncertainty, which lowers welfare and output growth. Ball (1992) formalizes and supports Friedman's hypothesis in a game theoretical framework. Cukierman and Meltzer (1986) and Cukierman (1992), on the other hand, argue that increases in inflation uncertainty raise the optimal inflation rate by increasing the incentive for the policy maker to create inflation surprises in a game theoretical framework.

On the empirical side of the inflation uncertainty literature, the results are mixed (see e.g. Baillie et al., 1996; Grier and Perry, 1990, 1998, 2000; Davis and Kanago, 2000; Perry and Nas, 2000; Fountas, 2001; Fountas, et. al. 2001; Bhar and Hamori, 2004; Kontonikas, 2004; Berument and Nargez Dincer, 2005; Conrad and Karanasos, 2005; Vale, 2005; Caporale and Kontonikas, 2006; Grier and Grier, 2006; Thornton, 2007; Heidari and Montakhab, 2008).

Although most of the empirical studies use the GARCH type of specifications as their common method to assess the relationship between inflation and inflation uncertainty, some studies make use of a two-step procedure. For example, Grier and Perry (1998) estimate the conditional variance of inflation by GARCH and Component GARCH methods, and then perform the Granger causality tests between these generated conditional variance measures and inflation series. However, Pagan (1984) criticises two-step procedure for its misspecifications due to the use of generated variables from the first stage as regressors in the second stage. Pagan and Ullah (1988) suggest using the Full Information Maximum Likelihood (FIML) method to address this issue.

This paper examines the relationship between inflation and inflation uncertainty in Iran for the period of 1979 to 2007 and FIML method of estimation. We use FIML method to estimate M-GARCH-M models to investigate the results of Granger causality tests. The estimates with the new set of specification confirm our results from Granger causality tests, supporting the Friedman-Ball hypothesis.

The paper is organized as follows: In section 2 we introduce GARCH models and the use of conditional residual variances as parametric measures of uncertainty. Section 3 discusses the data. In section 4, the estimation results are presented and the conclusions are given in section 5.

## 2. The Model

Since the seminal of Engle (1982), traditional time series tools such as autoregressive moving average (ARMA) models (Box and Jenkins, 1970) for the mean have been extended to essentially analogous models for the variance. Autoregressive Conditional Heteroskedasticity (ARCH) models are now commonly used to describe and forecast changes in the volatility of financial and macroeconomic time series.

Letting $y_t$ be the depended variable, $X_t$ be a vector of explanatory variables included in $\psi_{t-1}$, while the conditional error variance, $\sigma_t^2$, is a function of lagged values of the squared forecast errors, the $p^{th}$ order linear ARCH model can be formulated as follow:

$$y_t \mid \psi_{t-1} \sim N(\mathrm{X}_t\theta, \sigma_{\varepsilon t}^2) \tag{1}$$

$$\sigma^2{}_{\varepsilon t} = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_p \varepsilon_{t-1}^2$$

$$\varepsilon_t = y_t - \mathrm{X}_t\theta$$

$$\alpha_0 \succ 0, \alpha_i \geq 0 \qquad\qquad i = 1,2,\ldots, p$$

Where the vector $\theta$ and the $\alpha$ 's are parameters which should be estimated (Engle, 1983).

### 2.1 The GARCH(1,1) Model:

The GARCH specification, which is generally used for inflation and time-varying residual variance as a measure of inflation uncertainty, is as follows:

$$\pi_t = \beta_0 + \sum_{i=1}^{n} \beta_i \pi_{t-i} + \varepsilon_t \tag{2}$$

$$\sigma^2{}_{\varepsilon t} = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \sigma_{\varepsilon t-1}^2 \tag{3}$$

Where $\pi_t$ is the inflation, $\varepsilon_t$ is the residual of equation (2), $\sigma^2{}_{\varepsilon t}$ is the conditional variance of the residual term taken as inflation uncertainty at time t, and n is the lag length. Eq. (2) is an autoregressive representation of inflation. equation (3) is a GARCH (1,1) representation of conditional variance.

### 2.2 The GARCH-M Model:

If the inflation uncertainty affects the inflation, $\sigma^2{}_{\varepsilon t}$ , in the mean equation represents inflation uncertainty. If we introduce variance (or standard deviation) into the mean equation, we get the GARCH-in-Mean (GARCH-M) model (Engle, Lilien and Robins 1987). So the mean equation in a GARCH-M model can be formulated as:

$$\pi_t = \beta_0 + \sum_{i=1}^{n} \beta_i \pi_{t-i} + \lambda\, \sigma^2{}_{\varepsilon t} + \varepsilon_t \tag{4}$$

$$\sigma^2{}_{\varepsilon t} = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{\varepsilon t-1}^2 \tag{5}$$

Engle, Lilien and Robins (1987) extend the Engle's ARCH model to allow the conditional variance to be a determinant of the process. Although the GARCH-M model was firstly used for asset market, some studies about inflation uncertainty, have used GARCH-M model to examine the effect of inflation uncertainty on the level of inflation (see e.g. Grier and Perry, 2000; Berument and Yuksel, 2002).

### 2.3 Distributional Assumption:

To complete the model specification, we need an assumption about the conditional distribution of the error term $\varepsilon_t$. There are three assumptions commonly employed when working with ARCH models: normal (Gaussian) distribution, Student’s t-distribution, and the Generalized Error Distribution (GED). Given a distributional assumption, ARCH models are typically estimated by the method of maximum likelihood.

However, in practice, high frequency data, often exhibit fatter tailes than the standard normal, or Gaussian distribution. For capturing this effect, we can change our distributional assumption from normal to the Student’s t-distribution or the GED.

For the Student’s t-distribution, the log-likelihood contributions are of the form:

$$l_t = -\frac{1}{2}\log\left[\frac{\pi(v-2)\Gamma(v/2)^2}{\Gamma((v+1)/2)^2}\right] - \frac{1}{2}\log\delta_t^2 - \frac{(v+1)}{2}\log\left[1 + \frac{(Y_t - X_t\theta)^2}{\delta_t^2(v-2)}\right] \tag{6}$$

Where the degree of freedom $v > 2$ controls the tail behavior. The t-distribution approaches the normal as $v \rightarrow \infty$.

For the GED, we have:

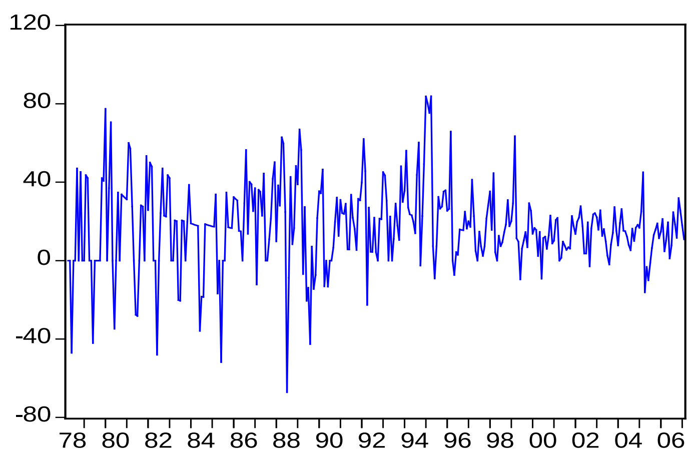
$$l_t = -\frac{1}{2}\log\left[\frac{\Gamma(1/r)^3}{\Gamma(3/r)(r/2)^2}\right] - \frac{1}{2}\log\delta_t^2 - \left[\frac{\Gamma(3/r)(Y_t - X_t\theta)^2}{\delta_t^2\,\Gamma(1/r)}\right]^{r/2} \tag{7}$$

Where the tail parameter $r > 0$. The GED is a normal distribution if $r = 2$, and fat-tailed if $r < 2$.

## 3. Data

This paper uses the monthly consumer price index (CPI) as price measure. The monthly CPI data for Iranian economy has been taken from the Central Bank of Iran for the period of 1979–2007. Inflation is the annualized monthly difference of the log of the CPI $\pi_t = (\ln cpi_t - \ln cpi_{t-1}) \times 1200$ (see, e.g. Asteriou, 2006). Figure (1) shows the inflation rate in the Iranian economy during 1988-2006.

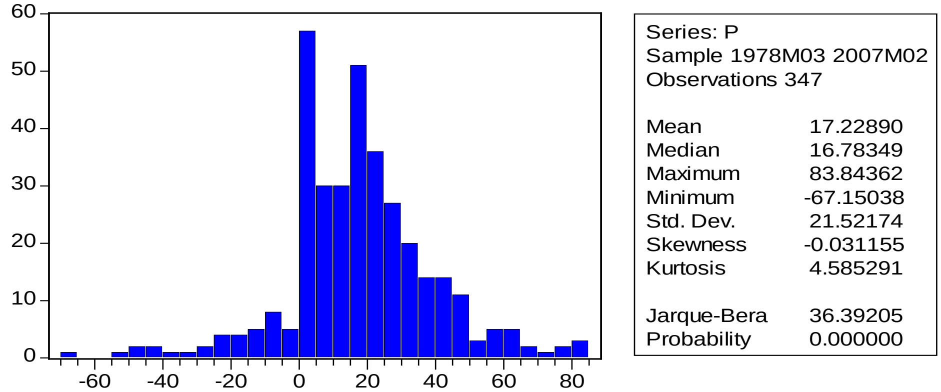
**Figure (1): Inflation Rate in the Iranian Economy**




As Figure 1 shows the Iranian economy has experienced high and volatile inflation rate during past decades.

The summary statistics for the data is given in Table (1). The large value of the Jargue-Bera statistic implies a deviation from normality.

**Table (1)**




## 3-1 Unit Root Test:

In order to investigate the stationary of the data, the paper uses the Augmented Dickey-Fuller (ADF), Philips-Perron (PP) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests. Table (2) shows the ADF, PP and KPSS tests results for the data.

**Table (2): ADF test, PP test and KPSS test result for the data**

| | Include in test equation | Statistic | Critical values 10% level | Criticalvalues 5% level | Critical values 1% level |
|---|---|---|---|---|---|
| **ADF** | Intercepet | -2.805173* | -2.571321 | -2.869952 | -3.449679 |
| | trend and intercepet | -2.828723 | -3.134591 | -3.423296 | -3.985690 |
| | none | -1.049060 | -1.616066 | -1.941773 | -2.571883 |
| **PP** | Intercepet | -12.121930* | -2.571174 | -2.869677 | -3.449053 |
| | trend and intercepet | -12.09822*** | -3.134337 | -3.422865 | -3.984804 |
| | none | -9.320797*** | -1.616086 | -1.941742 | -2.571663 |
| **KPSS** | Intercepet | 0.168512*** | 0.347000 | 0.463000 | 0.739000 |
| | trend and intercepet | 0.168056* | 0.119000 | 0.146000 | 0.216000 |

**Note: * denotes significance at the 10 % level,**

**** denotes significance at the 10%, 5 % level**

***** denotes significance at the 10%, 5%, 1 % level.**

As can be seen from Table (2), the inflation rate is stationary.

## 3-2 Test of Structural Breaks in the Mean of Iranian Inflation:

To carry out a test of no structural break against an unknown number of breaks in the Iranian inflation, this paper uses the endogenously determined multiple break test developed by

Bai and Perrron (1998)[1]. This method tests for the presence of breaks when neither the number nor the timing of breaks is known aprior. This approach allows us to test for the presence of $m$ breaks in the mean of inflation rate at unknown times using the following model:

$$\Delta p = \mu_j + \eta_t \qquad t = T_{j-1} + 1, \ldots, T_j \qquad (8)$$

$$j = 1, 2, \ldots, (m+1)$$

where $\Delta p$ is the inflation, $\mu_j$ is the regime-specific mean inflation rate, and $\eta_t$ is an error term, and $T_0 = 0$ and $T_{m+1} = T$ .

Bai and Perron (1998) introduced two tests of the null hypothesis of no structural break against an unknown number of breaks given some upper bound (for most empirical applications this bound is 5, see, e.g., Bai and Perron, 2003). These tests are called Double Maximum tests ( $D\max$ ). The first is an equal weighted (we set all weights equal to unity) labeled by $UD\max$ . The second test, $WD\max$ , applies weights to the individual tests such that the marginal $p-$values are equal across the values of breaks. In both of these tests, break points are estimated by using the global minimization of the sum of squared residuals (for more details see, Bai and Perron, 1998 and 2003).

Table (3) presents results of $D\max$ tests. These tests show that we have no break in the mean of the Iranian inflation. These results are strongly supported by the $SupF_T(m)$ test introduced by Andrews (1993).

Table (3). $D\max$ Tests

| Tests | $UD\max$ | $WD\max$ |
|---|---|---|
| Values | 4.9009 | 4.9009 |

## 4. Estimation

[1] A GAUSS algorithm to carry out these tests can be downloaded freely from Pierre Perron’s homepage at http://econ.bu.edu/perron.

We find that the best fitting time series model for the Iranian inflation includes 1, 10, 11, 12 of  its lages. The results from estimation of this model are as follow: (t-statistics are in paranthesses)

$$\pi_t = \beta_0 + \beta_1 \pi_{t-1} + \beta_{10} \pi_{t-10} + \beta_{11} \pi_{t-11} + \beta_{12} \pi_{t-12} + \varepsilon_t \tag{9}$$

$$\pi_t = 3.645868 + 0.256114 \pi_{t-1} + 0.117343 \pi_{t-10} + 0.137606 \pi_{t-11} + 0.283162 \pi_{t-12} + \varepsilon_t \tag{10}$$

(2.35) (5.20) (2.42) (2.65) (5.61)

In order to find out whether the residuals are serialy correlated, we use Breush-Godfrey Serial Correlation Lagrange Multiplier (LM) Test.

**Table (4): Breush-Godfrey Serial Correlation LM Test**

| | | | |
|---|---|---|---|
| LM test | 0.466473 | Probability | 0.791966 |

The Table (4) shows that the test does not reject the hypothesis of no serial correlation and so indicate that the residuals are not serialy correlated.

Also to test whether there are any remaining ARCH effects in the residuals, we use the LM test for ARCH in the residuals (see, e.g. Engle 1982). The results of the ARCH-LM test in Table (5) expreses that the hypothesis of no remaining ARCH effects in the residuals can not be rejected. Thus, there is ARCH effect in the residuals.

**Table (5): ARCH LM Test**

| | | | |
|---|---|---|---|
| LM test | 22.63525 | Probability | 0.000012 |

The Breush-Godfrey Serial Correlation LM Test rejects first through 12 order serial correlation at all standard significantce levels. However, the LM tests for ARCH reject the null of no first or eight order conditional heteroskedasticity of the 0.1 level of significant. Since higher order ARCH indicates persistence in the conditional variance, the model is estimated as a GARCH(1,1) process. This resultes are reported in Table (6).

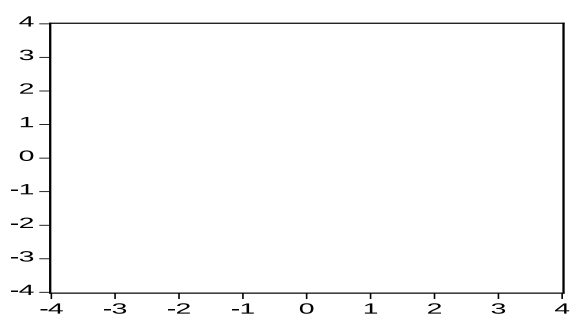
**Table (6): GARCH(1,1) model estimation results**

| Mean equation | | | | |
|---|---|---|---|---|
| | **Coefficient** | **Std.Error** | **z-Statistic** | **Prob.** |
| $\beta_0$ | 3.134056 | 1.465349 | 2.138777 | 0.0325 |
| $\pi_{t-1}$ | 0.209376 | 0.052090 | 4.019476 | 0.0001 |
| $\pi_{t-10}$ | 0.104256 | 0.040888 | 2.549781 | 0.0108 |
| $\pi_{t-11}$ | 0.113187 | 0.039487 | 2.866410 | 0.0042 |
| $\pi_{t-12}$ | 0.333505 | 0.038716 | 8.614101 | 0.0000 |
| **Variance equation** | | | | |
| $\omega$ | 12.67417 | 4.912405 | 2.580034 | 0.0099 |
| $\varepsilon^2_{t-1}$ | 0.207157 | 0.049547 | 4.181016 | 0.0000 |
| $\delta^2_{t-1}$ | 0.766851 | 0.047584 | 16.11583 | 0.0000 |

Our results show that In the mean and variance equation, all coefficients are highly significant

If the residuals are normally distributed, the points in the QQ[1]-plots shoud lie alongside a straight line. The plot indicates that it is primarily large shocks that are driving the departure from normality.

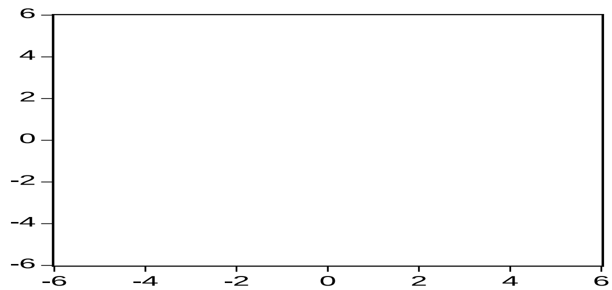
**Figure (2) Normal Quantil**




[1] Quantile-Ouantile

If we plot the residuals against the quantiles of the t-distribution, the plot indicates that the points in the QQ-plots shoud lie alongside a straight lie thus the residuals are t-student distributed.

**Figure (3) t-distribution**




When we estimate a GARCH(1,1) model, the standardized residual show evidence of excess kurtosis. To model the thick tail in the residuals, we assume that the errors follow a Student's t-distribution. Table (7) presents the results for the mean and the variance equations, followed by the results for t-student distributional parameter.

**Table (7). GARCH (1,1) model estimation with t-student distributional parameter**

| **Mean equation** | | | | |
|---|---|---|---|---|
| | Coefficient | Std.Error | z-Statistic | Prob. |
| $\beta_0$ | 4.506706 | 1.323213 | 3.405881 | 0.0007 |
| $\pi_{t-1}$ | 0.222557 | 0.047630 | 4.672634 | 0.0000 |
| $\pi_{t-10}$ | 0.083179 | 0.041464 | 2.006040 | 0.0449 |
| $\pi_{t-11}$ | 0.120016 | 0.044536 | 2.694783 | 0.0070 |
| $\pi_{t-12}$ | 0.291869 | 0.041669 | 7.004528 | 0.0000 |
| **Variance equation** | | | | |
| $\omega$ | 4.960831 | 3.787029 | 1.309953 | 0.1902 |
| $\varepsilon^2_{t-1}$ | 0.143971 | 0.050096 | 2.873896 | 0.0041 |
| $\delta^2_{t-1}$ | 0.851519 | 0.044062 | 19.32557 | 0.0000 |
| **parameter t** | | | | |
| V | 5.935673 | 2.429264 | 2.443404 | 0.0145 |

In the mean equation, all coefficients are highly significant. While, in the variance equation, all coefficients are highly significant, except the Constant term.

To test whether there are remaining ARCH effects in the residuals, we use ARCH LM Test. Results reported in Table (8) show that there is little evidence of ARCH effect.

**Test LM Table (8). ARCH**

| LM test | Probability |
|---|---|
| 1.675241 | 0.195558 |

Table (9) shows the results of the mean and variance equation followed by the results for GED distribution parameter.

**Table (9). GARCH(1,1) wih GED parameter**

| | | | | |
|---|---|---|---|---|
| **Mean equation** | | | | |
| | Coefficient | Std.Error | z-Statistic | Prob. |
| $\beta_0$ | 4.773536 | 1.318692 | 3.619903 | 0.0003 |
| $\pi_{t-1}$ | 0.217059 | 0.047655 | 4.554778 | 0.0000 |
| $\pi_{t-10}$ | 0.77982 | 0.041045 | 1.899906 | 0.0574 |
| $\pi_{t-11}$ | 0.1124 | 0.042625 | 2.636946 | 0.0084 |
| $\pi_{t-12}$ | 0.289202 | 0.040901 | 7.070855 | 0.0000 |
| **Variance equation** | | | | |
| $\omega$ | 8.84797 | 5.041049 | 1.603792 | 0.1088 |
| $\varepsilon^2_{t-1}$ | 0.157050 | 0.053640 | 2.927826 | 0.0034 |
| $\delta^2_{t-1}$ | 0.824907 | 0.052424 | 15.73534 | 0.0000 |
| **parameter GED** | | | | |
| R | 1.358906 | 0.159530 | 8.518192 | 0.0000 |

Our estimate for the GED parameter is less than two (r=1.35). In order to test that the GED parameter is equal to two, we use Wald test. The result of this test in Table (10) shows that we can strongly reject the null hypothesis that the GED parameter is equal to two.

**Table (10). Walt Test**

| F-statistic | Probability |
|---|---|
| 16.14948 | 0.0001 |

With this result in hand, we can say that our conditional error distribution is fat-tailed.

## 4.1 Granger Causality Tests:

Table (11) reports the results of Granger causality tests between inflation and inflation uncertainty.

**Table (11). Granger Causality Tests**

| Null Hypothesis | F-Statistic | Probability |
|---|---|---|
| Inflation does not Granger Cause inflation uncertainty | 13.8197 | 1.7E-06 |
| Inflation uncertainty does not Granger Cause inflation | 0.82582 | 0.43878 |

These results suggest that inflation Granger-causes inflation uncertainty, supporting the Friedman–Ball hypothesis, that high inflation is associated with more variable inflation.

## 4.2 M-GARCH-M[1] Model:

To carry out the results of the Granger causality tests in section 4-1, we use a two-step procedure. However, Pagan (1984) criticises two-step procedure for its misspecifications due to the use of generated variables from the first stage as regressors in the second stage. Pagan and Ullah (1988) suggest using the FIML method of estimation to address this issue. If the inflation affects the inflation uncertainty, then the inflation variable should be included in the GARCH specification in the first step. Similarly, if the inflation uncertainty affects the inflation, then the inflation uncertainty measure must be present in the first step of the inflation specification. Thus, the inflation and inflation uncertainty specifications should be estimated jointly as a one-step procedure rather than a two-step procedure. In order to do this, we specify a M-GARCH-M model as follows:

[1] Mean in GARCH and GARCH in Mean.

$$\pi_t = \beta_0 + \lambda\sigma_{\varepsilon t}^2 + \beta_1\pi_{t-1} + \beta_{10}\pi_{t-10} + \beta_{11}\pi_{t-11} + \beta_{12}\pi_{t-12} + \varepsilon_t \tag{11}$$

$$\sigma^2{}_{\varepsilon t} = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\sigma_{\varepsilon t-1}^2 + \rho\pi_{t-6} \tag{12}$$

If the value of $\rho > 0$ in the equation (12) shows that inflation uncertainty increases as inflation rises. A positive and significant $\rho$ can be considered as confirmation of Friedman-Ball hypothesis and also means that inflation uncertainty is a cost of inflation. However, $\lambda$ in the equation (11) could be positive or negative. A positive $\lambda$ means that inflation uncertainty has a positive effect on the level of inflation, but a negative $\lambda$ means that inflation uncertainty has a negative impact on the level of inflation which can be explained by the stabilization motive of policy makers. Nonetheless, it should be noted that although this approach provides some information about the impact of inflation on inflation uncertainty and vice versa, it can not be considered as the causality test between these two variables.

The estimation result of the above M-GARCH-M model is presented in Table (12):

**Table (12). The estimation result of the M-GARCH-M (1,1) model**

| | | | | |
|---|---|---|---|---|
| **Mean equation** | | | | |
| | **Coefficient** | **Std.Error** | **z-Statistic** | **Prob.** |
| $\beta_0$ | 5.271607 | 1.297657 | 4.062404 | 0.0000 |
| $\delta_t^2$ | -0.002572 | 0.003372 | -0.762707 | 0.4456 |
| $\pi_{t-1}$ | 0.229883 | 0.051140 | 4.495127 | 0.0000 |
| $\pi_{t-10}$ | 0.093811 | 0.035345 | 2.654135 | 0.0080 |
| $\pi_{t-11}$ | 0.084347 | 0.039160 | 2.153907 | 0.0312 |
| $\pi_{t-12}$ | 0.276364 | 0.035547 | 7.774592 | 0.0000 |
| **Variance equation** | | | | |
| $\omega$ | 44.27812 | 17.61080 | 2.514259 | 0.0119 |
| $\varepsilon_{t-1}^2$ | 0.478532 | 0.158077 | 3.027212 | 0.0025 |
| $\delta_{t-1}^2$ | 0.378673 | 0.094503 | 4.006979 | 0.0001 |
| $\pi_{t-6}$ | 2.237170 | 0.613592 | 3.646022 | 0.0003 |
| **parameter t** | | | | |
| V | 5.504295 | 2.512449 | 2.190809 | 0.0285 |

Our results show that in the mean and variance equations, all coefficients are highly significant.

The results of Table (12) express that show the coefficient of lagged inflation in the variance equation is positive and significant. This confirms the Friedman-Ball hypothesis. However, the coefficient of conditional variance in the mean equation is negative but highly insignificant, which means that inflation uncertainty does not affect the level of inflation.

To test whether there are remaining ARCH effects in the residuals, we use ARCH LM Test.

**Table (13). LM Test ARCH**

| LM test | Probability |
|---|---|
| 1.442918 | 0.229668 |

The results of LM test in Table (13) shows that there is little evidence of remaining ARCH effect.

Table (14) shows the results of the mean and variance equation followed by the results for GED distribution parameter.

**Table (14). M-GARCH-M (1,1) with GED parameter**

| | | | | |
|---|---|---|---|---|
| **Mean equation** | | | | |
| | Coefficient | Std.Error | z-Statistic | Prob. |
| $\beta_0$ | 3.925094 | 1.695396 | 2.315148 | 0.0206 |
| $\delta_t^2$ | -0.001178 | 0.005017 | -0.234815 | 0.8144 |
| $\pi_{t-1}$ | 0.226664 | 0.049754 | 4.555698 | 0.0000 |
| $\pi_{t-10}$ | 0.110253 | 0.034532 | 3.193755 | 0.0014 |
| $\pi_{t-11}$ | 0.120643 | 0.037842 | 3.188071 | 0.0014 |
| $\pi_{t-12}$ | 0.285255 | 0.034657 | 8.230728 | 0.0000 |
| **Variance equation** | | | | |
| $\omega$ | 83.21741 | 28.91771 | 2.877731 | 0.0040 |
| $\varepsilon_{t-1}^2$ | 0.420280 | 0.143701 | 2.924684 | 0.0034 |
| $\delta_{t-1}^2$ | 0.246277 | 0.108755 | 2.264510 | 0.0235 |
| $\pi_{t-6}$ | 2.388611 | 0.431332 | 5.537758 | 0.0000 |
| **parameter GED** | | | | |
| r | 1.345681 | 0.166014 | 8.105813 | 0.0000 |

Estimation of equations with GED distribution show that the GED parameter is less than two (r=1.54). In order to test that the GED parameter is equal to two, we use Wald test. The result of this test in Table (15) shows that we can strongly reject the null hypothesis that the GED parameter is equal to two.

**Table (15). Wald Test**

| F-statistic | Probability |
|---|---|
| 15.53419 | 0.0001 |

With this result in hand, we can say that our conditional error distribution is fat-tailed.

## 5. Conclusion:

This paper investigates the relationship between inflation and inflation uncertainty for the period of 1979-2007 by using monthly data and applying M-GARCH-M models in the Iranian economy. The results of a two-step procedure such as Granger causality test which uses generated variables from the first stage as regressors in the second stage, suggests a positive relation between the mean and the variance of inflation. However, Pagan (1984) criticizes this two-step procedure for its misspecifications due to the use of generated variables from the first stage as regressors in the second stage. This paper uses the Full Information Maximum Likelihood (FIML) method to address this issue. If the inflation affects the inflation uncertainty, then the inflation variable should be included in the GARCH specification in the first step. Similarly, if the inflation uncertainty affects the inflation, then the inflation uncertainty measure must be present in the first step of the inflation specification. Thus, the inflation and inflation uncertainty specifications should be estimated jointly as a one-step procedure rather than a two-step procedure. The estimates we gathered with the new set of specifications suggest that inflation Granger-causes inflation uncertainty, supporting the Friedman–Ball hypothesis, that high inflation is associated with more variable inflation.

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