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ASYMMETRIC EFFECTS OF INFLATIONARY SHOCKS ON INFLATION UNCERTAINTY IN IRAN

This paper investigates the relationship between inflationary shocks and inflation uncertainty using monthly Iranian data for the period of 1990–2011 by applying TGARCH and EGARCH models. The results show that negative inflationary shocks have less effect on inflation uncertainty as compared with the positive ones. Our results are robust to the choice of the distribution of the error term and the form in which the time varying variance enters the specification of the mean. Moreover, this paper presents a new statistical explanation for Iranian economic asymmetry.

Keywords: *inflation uncertainty; inflationary shocks; GARCH; asymmetry; Iran.*
JEL Classification: E30, E31.

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АСИМЕТРИЧНИЙ ВПЛИВ ІНФЛЯЦІЙНИХ ШОКІВ НА КОЛИВАННЯ ІНФЛЯЦІЇ: ЗА ДАНИМИ ІРАНУ

У статті досліджено взаємозв'язок між інфляційними шоками та коливаннями інфляції по щомісячних даних щодо іранської економіки з 1990 по 2011 рік. Для аналізу даних застосовано моделі GARCH та EGARCH. Результати моделювання демонструють, що негативні інфляційні шоки мають набагато менший вплив на коливання інфляції, ніж позитивні. Результати моделювання стійкі до погрішностей. Крім того, надано нове статистичне пояснення явищу асиметрії в іранській економіці.

Ключові слова: *коливання інфляції; інфляційні шоки; GARCH; асиметрія; Іран.*
Табл. 11. Рис. 4. Форм. 11. Літ. 36.

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АСИММЕТРИЧЕСКОЕ ВЛИЯНИЕ ИНФЛЯЦИОННЫХ ШОКОВ НА КОЛЕБАНИЯ ИНФЛЯЦИИ: ПО ДАННЫМ ИРАНА

В статье исследованы взаимоотношения между инфляционными шоками и колебаниями инфляции по ежемесячным данным по иранской экономике с 1990 по 2011 год. Для анализа данных применены модели GARCH и EGARCH. Результаты моделирования показывают, что отрицательные инфляционные шоки имеют гораздо меньше влияния на колебания инфляции, чем положительные. Результаты устойчивы к погрешности. Кроме того, представлено новое статистическое объяснение явления асимметрии в иранской экономике.

Ключевые слова: *колебания инфляции; инфляционные шоки; GARCH; асимметрия; Иран.*

1. Introduction

The effect of inflation on economic performance is an important topic, because if systematic inflation has real effects, policy makers can influence economic performance through monetary policy. A part from the effect of inflation, its uncertainty may also impact the economic performance. A well constructed empirical research for the real effects of inflation should consider both inflation, and its uncertainty, and the potential correlation between these two factors.

The relationship between inflation and its uncertainty, according to Friedman (1977), has been an important issue in research. The plausible harmful effect of high

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inflation rates invoking higher variability would be considered as the decreased output, the subsequently low growth rates, the more risk in longterm contracting, and a positively sloped Phillips curve (see, e.g., Hwang, 2001 and 2007 among others). There are lots of studies which consider these issues (Baillie et al., 1996; Grier, Perry, 1990, 1998, 2000; Davis, Kanago, 2000; Perry, Nas, 2000; Fountas, 2001; Fountas et al., 2001; Bhar, Hamori, 2004; Kontonikas, 2004; Berument, Nargez Dincer, 2005; Conrad, Karanasos, 2005; Vale, 2005; Caporale, Kontonikas, 2006; Grier, Grier, 2006; Thornton, 2007; Heidari, Bashiri, 2010). With Iranian data Heidari and Montakab (2008), Heidari and Bashiri (2009), and Samimi and Motameni (2009), and Heidari and Bashiri (2010) study the relationship between inflation and inflation uncertainty.

According to our best knowledge, nobody considers the relationship between inflationary shocks and inflation uncertainty with Iranian data, though there are some research studies on the US data. Friedman and Schwartz (1963) in their work on the US monetary history emphasize that dis-inflationary monetary shocks have greater effect on output than equivalently sized positive shocks. Romer and Romer (1989) show that a recession followed each period the Federal Reserve stated a desire to lower inflation. Moreover, Cover (1992) shows that negative money supply shocks significantly reduce output, while positive shocks have no measurable effect. Recently, Caporale and Caporale (2002), by using a TARCH model, show that negative inflationary shocks make greater inflation uncertainty than positive shocks, and so inflation uncertainty leads to lower output growth.

Our paper attempts to fill a gap in the literature in a number of ways: first, we employ monthly CPI inflation on Iran, a country that has experienced high and significant variability in inflation over the last 20 years. Second, we use 3 alternative GARCH models to measure the variability of inflation: Bollerslev's (1986) GARCH, Glosten et al. (1993) and Zakoian's (1994) threshold GARCH (TGARCH) and Nelson's (1991) exponential GARCH (EGARCH) models. Third, following Fountas et al. (2004), and Heidari and Bashiri (2010), we allow for 3 different specifications of risk premium: the conditional variance, the conditional standard deviation, and the natural lag of the conditional variance.

Utilizing TGARCH and EGARCH models, we test whether inflationary shocks have asymmetric effects on inflation uncertainty. The results show that negative inflationary shocks have less effect on inflation uncertainty as compared with the positive ones.

The rest of the paper unfolds as follows: Section 2 introduces 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 paper of Engle (1982), traditional time series models such as autoregressive moving average (ARMA) models 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 ψ_{t-1}, while the conditional error variance σ_t^2, is the function of lagged values of the squared forecast errors, the P^{th} order linear ARCH model can be formulated as follow:

$$y_t \mid \psi_{t-1} \sim N(X_t\theta, \sigma^2_{\varepsilon t}) \quad (1)$$

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

$$\varepsilon_t = y_t - X_t\theta$$

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

Where the vector θ and the α's are the parameters to be estimated (Engle, 1983).

2.1. GARCH (1,1) model. GARCH specification, generally used for inflation and time-varying residual variance as a measure of inflation uncertainty, is as follows:

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

$$\sigma^2{}_{\varepsilon t} = \alpha_0 + \alpha_1\varepsilon^2_{t-1} + \alpha_2\sigma^2_{\varepsilon t-1} \quad (3)$$

Where π_t is inflation, ε_t is the residual of equation (2), $\sigma_{\varepsilon t}{}^2$ is the conditional variance of the residual term taken as inflation uncertainty at time t, and n is the lag length. Equation (2) is the autoregressive representation of inflation. Equation (3) is a GARCH (1,1) representation of conditional variance.

As Bollerslev (1990) shows the BHHH estimate of the asymptotic covariance matrix of coefficients will be consistent, we evaluate this model using the Berndt et al. (1974) numerical optimization algorithm (BHHH) to obtain the maximum likelihood estimates of the parameters.

2.2. TGARCH model. Threshold GARCH (TGARCH) models were introduced independently by Glosten et al. (1993) and Zakoian (1994). The generalized specification for the conditional variance is given by:

$$\sigma^2_{\varepsilon t} = \omega + \sum_{i=1}^{p}\alpha_i\varepsilon^2_{t-i} + \sum_{k=1}^{r}\gamma_k\varepsilon^2_{t-k}\overline{I_{t-k}} + \sum_{j=1}^{q}\beta_j\sigma^2_{\varepsilon t-j}, \quad (4)$$

where r is the threshold order. $I_t = 1$ if $\varepsilon_t < 0$ and 0 – otherwise.

In the inflation context, we define good news as $\varepsilon_{t-1} > 0$ and bad news as $\varepsilon_{t-j} < 0$ having different effects on conditional variance. Good news has an impact of $\alpha + \gamma > 0$ while bad news has an impact of α. If $\gamma > 0$ good news increases volatility, and we say there is a leverage effect for the i-th order. If $\gamma = 0$ the news impact is asymmetric.

2.3. EGARCH model. As illustrated in Equation (3), the conditional variance of inflation estimated by the GARCH model is a function only of the magnitudes of inflation shocks ($\varepsilon_{t-i}{}^2$), not also the signs of such shocks, and thus construction is blind as to whether inflation is rising or falling. It follows then that GARCH model does not yield a time-varying measure of inflation uncertainty capable of providing a reliable assessment of the response of inflation uncertainty to inflation surprises.

To remedy this shortcoming, we use exponential GARCH (EGARCH) model, which explicitly allows its measure of uncertainty to respond to the positivity or negativity of shocks. In so doing, this model permits a straightforward assessment of the response of inflation uncertainty to inflation "surprises".

$$\log(\sigma^2_{\varepsilon t}) = \omega + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} - E(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}) \right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} + \sum_{j=1}^{q} \beta_j \log(\sigma^2_{\varepsilon t-j}), \quad (5)$$

where E is the expectation. Like the GARCH model of inflation, the EGARCH model yields a time-varying measure of inflation uncertainty that responds to magnitudes of inflation shocks. For example, in equation (5) if $\alpha_i > 0$, then a deviation of $|\varepsilon_{t-i}/\sigma_{t-j}|$ from its expected value causes inflation uncertainty ($log(\sigma_t^2)$) to rise. Unlike the GARCH model, EGARCH allows this effect to be asymmetric, thus permitting its measure of uncertainty to respond also to the signs of inflation shocks. The parameter in equation (5) that allows for such asymmetry is γ_k. If $\gamma_k > 0$, then the inflation uncertainty will rise more in response to positive inflation shocks ($\varepsilon_{t-i} > 0$) than to negative shocks ($\varepsilon_{t-i} < 0$). If $\gamma_k > 0$, then it will rise more in response to negative inflation shocks than to positive shocks. And finally if $\gamma_k = 0$,, then a positive shock to inflation has the same effect on uncertainty as a negative shock of the same magnitude. In this case, the direction of change in inflation does not influence the path of inflation uncertainty.

2.4. Distributional assumption. To complete the model specification, we need an assumption about the conditional distribution of the error term ε_t. There are 3 assumptions commonly employed when working with GARCH models: normal (Gaussian) distribution, Student's t-distribution, and the generalized error distribution (GED). Given a distributional assumption, GARCH models are typically estimated by the method of maximum likelihood.

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

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

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

For the GED, we have:

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

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

3. Data

The paper uses the monthly consumer price index ( ) as a price measure. The monthly CPI data for Iranian economy has been taken from the Central Bank of Iran for the period of 1990—2011. Inflation is the annualized monthly difference of the log of the CPI $\pi_t = (\ln cpi_t - \ln cpi_{t-1}) * 1200$ (Asteriou, 2006). Figure 1 shows the inflation rate in Iranian economy during 1990—2011.

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

The summary statistics for the data is given in Figure 2. The large value of the Jargue-Bera statistics implies a deviation from normality.

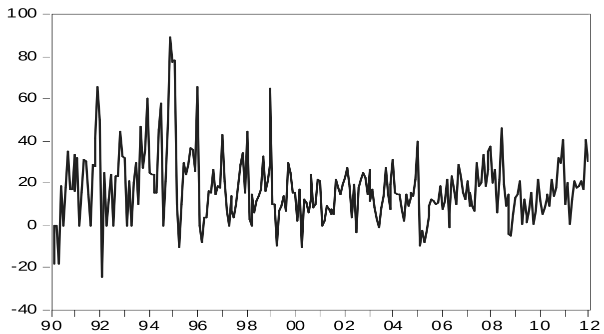

Figure 1. **Inflation rate in Iranian economy**

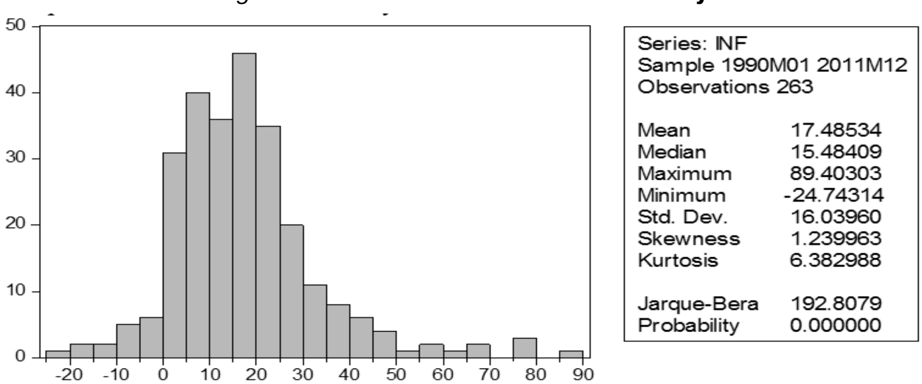

Figure 2. **Summary statistics for Iranian inflation**

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 1 shows the ADF, PP and KPSS tests results for the data.

Table 1. **ADF, PP and KPSS tests results for the data**

	Include in test equation	Statistics	Critical values 1% level	Critical values 5% level	Critical values 10% level
ADF	Intercept	-10.38342***	-3.455096	-2.872328	-2.572592
	trend and intercept	-10.56870***	-3.993335	-3.427004	-3.136780
	None	-0.548415	-2.574171	-1.942089	-1.615859
PP	Intercept	-10.42266***	-3.455096	-2.872328	-2.572592
	trend and intercept	-10.51609***	-3.993335	-3.427004	-3.136780
	None	-6.026827***	-2.573784	-1.942035	-1.615894
KPSS	Intercept	0.453492**	0.739000	0.463000	0.347000
	trend and intercept	0.147669*	0.216000	0.146000	0.119000

Note: * denotes significance at the 10% level; ** denotes significance at the 10%, 5% levels; *** denotes significance at the 10%, 5%, 1% levels.

As can be seen in Table 1, the inflation rate is stationary.

4. Estimation

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

$$\pi_t = \beta_0 + \beta_1 \pi_{t-1} + \beta_{11}\pi_{t-11} + \beta_{12}\pi_{t-12} + \varepsilon_t \qquad (8)$$

$$\pi_t = 5.323987 + 0.335547\pi_{t-1} + 0.147830\pi_{t-11} + 0.230435\pi_{t-12} + \varepsilon_t \qquad (9)$$

$$(3.41) \qquad (5.94) \qquad (2.51) \qquad (3.81)$$

In order to find out whether the residuals are serially correlated, we use Breush-Godfrey serial correlation Lagrange multiplier (LM) Test.

Table 2. **Breush-Godfrey serial correlation LM test**

LM test	0.803957	Probability	0.6690

Table 2 shows that the test does not reject the hypothesis of no serial correlation and so indicate that the residuals are not serially correlated.

Also the CUSUM test shows that the cumulative sum of the recessive residuals is within the 5% significance lines, suggesting of coefficient stability.

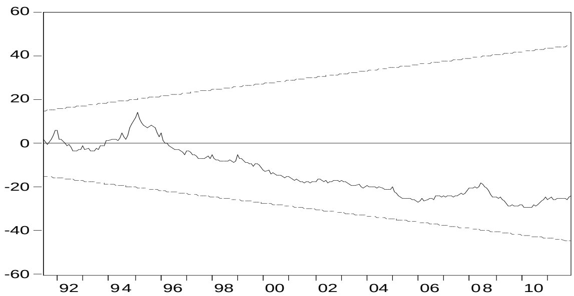

Figure 3.

Moreover, to test whether there are any remaining ARCH effects in the residuals, we use the LM test for ARCH in the residuals (Engle, 1982). The results of the ARCH-LM test in Table 3 express that the hypothesis of no remaining ARCH effects in the residuals can not be rejected. Thus, there is ARCH effect in the residuals.

Table 3. **ARCH LM test**

LM test	21.05308	Probability	0.0000

The Breush-Godfrey serial correlation LM test rejects first through 12 order serial correlation at all standard significance levels. However, the LM tests for ARCH reject the null of no first or eight order conditional heteroskedasticity at the 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 results are reported in Table 4.

Table 4. **GARCH (1,1) model estimation results**

Mean equation				
	Coefficient	Std. Error	z-Statistics	Prob.
β_0	5.968539	1.514903	3.939882	0.0001
β_1	0.264619	0.059633	4.437463	0.0000
β_{11}	0.082105	0.036775	2.232642	0.0256
β_{12}	0.275202	0.037382	7.361795	0.0000
Variance equation				
α_0	40.26737	15.76693	2.553913	0.0107
α_1	0.358582	0.099709	3.596292	0.0003
α_2	0.420277	0.138980	3.024008	0.0025

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

To test for normality assumption in prexous estimation we use QQ (Quantile-Ouantile) test. If the residuals are normally distributed, the points in QQ-plots should lie alongside a straight line. The plot indicates that the residuals are not normal distributed.

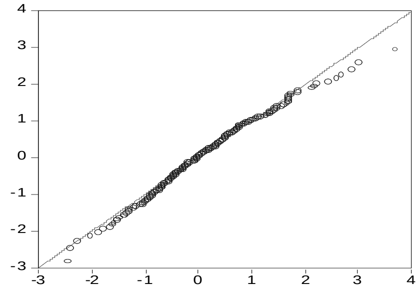

Figure 4. **Normal quintile**

Now we suppose that the residuals are distributed with GED distribution and estimate the model. Table 5 shows the results of the mean and variance equation followed by the results for GED distribution parameter.

Table 5. **GARCH (1,1) with GED parameter**

		Mean equation		
	Coefficient	Std. Error	z-Statistics	Prob.
β_0	6.133223	1.391457	4.407769	0.0000
β_1	0.259132	0.061126	4.239335	0.0000
β_{11}	0.073205	0.040468	1.808942	0.0705
β_{12}	0.273965	0.039946	6.858315	0.0000
		Variance equation		
α_0	43.33832	19.29215	2.246423	0.0247
α_1	0.362528	0.125275	2.893856	0.0038
α_2	0.395562	0.168589	2.346309	0.0190
R	1.562919	0.216209	7.228754	0.0000

Our estimate for the GED parameter is less than two ($r = 1.56$). In order to test that the GED parameter is equal to 2, we use the Wald test. The result of this test in Table 6 shows that we can strongly reject the null hypothesis that the GED parameter is equal to 2.

Table 6. **Wald test**

F-statistics	Probability
4.086739	0.0443

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

To test whether there are remaining ARCH effects in the residuals, we use the ARCH LM test. The results reported in Table 7 show little evidence of ARCH effects.

Table 7. **ARCH LM test**

LM test	Probability
0.002158	0.9629

4.1. TGARCH Model. Now we are going to investigate whether the magnitude of the effect of positive and negative inflation innovations on uncertainty is the same. To do this, we apply a TGARCH model. If we introduce variance (or standard deviation) into the mean equation, we get the GARCH-in-Mean (GARCH-M) model (Engle et al., 1987). Some studies on inflation uncertainty have used GARCH-M model to examine the effect of inflation uncertainty on the level of inflation (Grier, Perry, 2000; Berument, Yuksel, 2002). Considering the role of asymmetry we can define our TGARCH-M model as follows:

$$\pi_t = \beta_0 + \beta_1 \pi_{t-1} + \beta_{11} \pi_{t-11} + \beta_{12} \pi_{t-12} + \lambda g(\sigma_t^2) + \varepsilon_t \qquad (10)$$

$$\sigma^2{}_{\varepsilon t} = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 D + \beta \sigma_{\varepsilon t-1}^2$$

In this model good news ($\varepsilon_{t-1} > 0$) and bad news ($\varepsilon_{t-1} < 0$) have different effects on the conditional variance. This model allows negative inflation shocks ($\varepsilon_{t-i} < 0$) to have a different effect on inflation uncertainty than positive ones. Negative shocks have impact $\alpha + \gamma$ whereas positive shocks have an effect equal to α. If γ is statistically different from zero, these shocks have an asymmetric effect on inflation uncertainty.

To carry out this operation, we need to choose the form in which the time-varying variance enters the specification of the mean to determine the risk premium. This is a matter of empirical evidence. Caporale and Mckiernan (1996) found that the logarithm of the conditional variance worked better in their estimation of the time-varying risk premia. However, as noted by Pagan and Hong (1991), the use of $ln\ \sigma_t^2$ is possibly unsatisfactory for some reasons. First, for $\sigma_t^2 < 1$, $g(\sigma_t^2) < 0$, which leads to a negative sign for the risk premium. Second, as $\sigma_t^2 \to 0$, conditional volatility in logs becomes very large and, therefore, the implicit relationship between conditional volatility and y_t is overstated. On the other hand, Henry and Olekalns (2002) used the conditional standard deviation as a regressor in the conditional mean. In the empirical results therefore form of the risk premium. In other words, we use alternatively $g(\sigma_t^2) = \sigma_t^2$, $g(\sigma_t^2) = \sigma_t$, or $g(\sigma_t^2) = ln\ \sigma_t^2$.

However, λ in the mean equation could be positive or negative. A positive λ means that inflation uncertainty has a positive effect on the level of inflation, but a negative λ means that inflation uncertainty has a negative impact on the level of inflation which can be explained by the stabilization motive of policy makers. The estimation result of the above T-GARCH-M model is presented in Table 8.

Table 8. **T-GARCH (1,1)**

		σ_t^2	σ_t	$ln\sigma_t^2$
λ	_	0.019907 (0.0357)	0.674928 (0.0055)	4 274647 (0.0003)
ω	15.72436 (0.0050)	8.085707 (0.0303)	8.454784 (0.0246)	12.98816 (0.0061)
α	0.316675 (0.0016)	0.230440 (0.0025)	0.240643 (0.0042)	0 354738 (0.0024)
β	0.761158 (0.0000)	0.881770 (0.0000)	0.884735 (0.0000)	0 827211 (0.0000)
γ	-0.389884 (0.0002)	-0.324958 (0.0001)	-0 348019 (0.0001)	-0.490675 (0 0001)

In the mean and variance equations, all coefficients are highly significant. However, the coefficient of conditional variance in the mean equation is positive and highly significant, which means that inflation uncertainty affects the level of inflation.

As can be seen in the estimated model, γ is negative and significant which means that the news impact is asymmetric and there is a leverage effect. Based on the above estimation results, the impact of good news is equal to 0.316675, while the impact of bad news is equal to 0.073. So in our model good news increases inflation uncertainty, while bad news does not seen to have any significant impact on inflation uncertainty.

In order to examine the significance of these impacts, we test the null hypothesis that the impact of bad news is equal to zero ($H_0: \alpha + \gamma = 0$). The Wald test result in Table 9 shows that the null hypothesis can not be rejected and so the bad news does not increase inflation uncertainty.

Table 9. **Wald test result**

F-statistics	Probability
4.729289	0.0306

Moreover, as α is significantly greater than zero, it can be said that good news has a significant positive impact on inflation uncertainty.

We can test the asymmetry in the news impact by testing the null hypothesis that is equal to zero ($H_0: \gamma = 0$) against the alternative hypothesis that it is different from zero ($H_1: \gamma = 0$). Rejection of the null hypothesis means that the news impact is asymmetric.

Table 10. **Wald Test result for the asymmetry in the news impact**

F-statisticss	Probability
13.85913	0.0002

With this result in hand, we can reject the null and so the news impact is asymmetric.

4.2. EGARH model. As mentioned in section 2, GARCH models include lags of the conditional variance to estimate the conditional variance of the model. Nelson (1991) proposes an extended version of such models – EGARCH. The EGARCH method is more advantageous than both ARCH and GARCH to model inflation uncertainty for the following reasons. First, it allows for the asymmetry in the responsiveness of inflation uncertainty to the sign of inflation shocks. Second, unlike GARCH specification, the EGARCH model, specified in logarithms, does not impose the non-negativity constraints on parameters. And finally, modelling the inflation and its uncertainty in logarithms hampers the effects of outliers on the estimation results. Considering our all diagnostic tests, our EGARCH model can be written as follows:

$$\pi_t = \beta_0 + \beta_1 \pi_{t-1} + \beta_{11}\pi_{t-11} + \beta_{12}\pi_{t-12} + \lambda g(\sigma_t^2) + \varepsilon_t \quad (11)$$

$$\log(\sigma_t^2) = \omega + \alpha\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta\log(\sigma_{t-1}^2)$$

Table 11 presents the estimation results of (11).

Table 11. **EGARCH (1,1)**

		σ_t^2	σ_t	$\ln\sigma_t^2$
λ	–	0.012872 (0.0000)	0.527955 (0.0000)	2.606199 (0.0000)
ω	0.484923 (0.0000)	0.386462 (0.0000)	0.415889 (0.0000)	0.414558 (0.0000)
α	-0.166569 (0.0004)	-0.208122 (0.0000)	-0.249942 (0.0000)	-0.258657 (0.0000)
γ	0.245096 (0.0000)	0.201047 (0.0000)	0.244264 (0.0000)	0.165243 (0.0000)
β	0.925761 (0.0000)	0.956047 (0.0000)	0.956118 (0.0000)	0.960469 (0.0000)

In the mean equation, all coefficients are highly significant and a positive λ means that inflation uncertainty has a positive effect on the inflation level. While, in the variance equation, all coefficients are highly significant.

$\alpha_i < 0$ means that a deviation of $|\varepsilon_{t-i} / \sigma_{t-j}|$ from its expected value causes inflation uncertainty ($log(\sigma_t^2)$) to decrease. $\gamma_k > 0$ means that the $log(\sigma_t^2)$ will rise more in response to positive inflation shocks ($\varepsilon_{t-i} > 0$) than to negative shocks ($\varepsilon_{t-i} < 0$).

5. Conclusion

This paper investigates the effects of inflation shocks on inflation uncertainty for the period 1990—2011 by using the monthly data on Iranian economy and applying TGARCH and EGARCH models. The results show that negative inflationary shocks have less effect on inflation uncertainty as compared with the positive ones. Moreover, this paper presents a new statistical explanation for the asymmetry.

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Стаття надійшла до редакції 09.06.2013.