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Investigating the Asymmetry in Volatility for the Iranian Stock Market

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Abstract

This paper investigates the asymmetry in volatility of returns for the Iranian stock market using the daily closing values of the Tehran exchange price index (TEPIX) covering the period from March 25, 2001 to July 25, 2012, with a total of 2743 observations. To this end, two sets of tests have been employed: the first set is based on the residuals derived from a symmetric GARCH (1,1) model. The second set is based on the asymmetric GARCH models, including EGARCH (1,1), GJR-GARCH(1,1), and APARCH(1,1) models. To capture the stylized fact that the returns series are fat-tailed distributed, in addition to classic Gaussian assumption, the innovations are also assumed to have t-student distribution and GED (Generalized Error Distribution). The results indicate that there is no evidence of the leverage effects in the Iranian stock market, meaning that negative and positive shocks of the same magnitude have the same impacts on the future volatility level. This result is in contrast with the results of most empirical studies, where an asymmetry in volatility of stock returns has been found. This seems to be the result of the governmental or quasi-governmental nature of many companies listed on the Tehran Stock Exchange.

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1. Introduction

Over the last few years, modeling and forecasting of volatility of financial time series has become one of the most important issues that has held the attention of many academic researchers and experts in the field of financial markets. This is because of the importance of volatility in risk management, portfolio optimization, asset pricing, security valuation, and monetary policy making. Volatility refers to the spread of all likely outcomes of an uncertain variable. It is related to, but not the same as, risk. Risk is associated with undesirable outcome, whereas volatility as a measure of strictly for uncertainty could be due to a positive outcome (Poon, 2005).Typically, in finance, the focus is on the spread of asset returns/price. Theory suggests that the price of an asset is a function of the volatility, or risk, of the asset. Consequently, an understanding of how volatility evolves over time is central to the decision making process (Olan Henry, 1998). A special feature of the volatility is that it is not directly observable and can only be derived in the context of a model. A good volatility model must be able to capture and reflect the characteristics of volatility in stock markets. In the past, modeling and forecasting of volatility was based on the assumption that the volatility is constant over time. But, in recent decades, financial econometricians have developed a variety of time-varying volatility models that capture most common stylized facts about stock returns such as volatility clustering, leptokurtosis and asymmetry.

Volatility clustering is a pervasive feature of equity markets. That refers to the phenomenon that there are periods of high and low variances. That means large changes of variance tend to be followed by large changes, and small changes by small changes (Li & Mizrach, 2010). Leptokurtosis means the tendency for financial asset returns to have distributions that exhibit fat tails and excess peakedness at the mean.(Brooks, 2008) Many proposed volatility models impose the assumption that the conditional volatility of the asset is affected symmetrically by positive and negative innovations (Engle & Patton, 2001). In other words, asymmetry implies that a negative shock to financial time series is to cause volatility to rise by more than a positive shock of the same magnitude (see, e.g., Black, 1976; Christie, 1982, Pagan & Schwert, 1990; Nelson, 1991; Sentena, 1992; Campbell & Hentschel, 1992; Engle & Ng, 1993). This asymmetry is sometimes ascribed to a leverage effect and sometimes to a risk premium effect.

Some of the proposed models cannot reproduce some of the assumptions and stylized facts about volatility. So, in order to select a more accurate volatility model, it is necessary to test the assumptions about volatility.

The main purpose of this paper is to test the existence of asymmetric impacts of the negative and positive shocks with the same magnitude on volatility (asymmetry or leverage effect) in the Iranian stock market. To this end, the tests based on the residuals derived from a symmetric GARCH (1,1) model and the tests based on the estimated asymmetry parameters of GARCH models including EGARCH (1,1), GJR-GARCH (1,1), and APARCH (1,1) models are employed. To capture the stylized fact that the returns series are fat-tailed distributed, in addition to classic Gaussian assumption, in what follows the innovations are also assumed to be distributed as a t-student or a GED distribution.

The reset of the paper is organized as follows. The section2 presents a literature review on the volatility and leverage effects in the stock markets. The data and descriptive statistics are discussed in section 3. The methodology and empirical results are presented in section 4 and the last section concludes the paper.

2. Literature Review

Modeling of financial market volatility has been one of the most active areas of research in empirical finance and time series econometrics over the past two decades (Bollerslev et al., 2009).Volatility refers to the ups and downs in the stock prices (Mittal & Goyal, 2012). Volatility means the conditional standard deviation of the underlying asset return (Ruey, 2005). Too much volatility is considered as a symptom of an inefficient stock market. The higher the volatility, the higher the risk. Low volatility is preferred as it reduces unnecessary risk borne by investors (Mittal & Goyal, 2012).

The measure of asset's volatility is a measure of its total risk. Risk is one of the features usually analyzed by investors in the process of determining their optimal efficient portfolio. Estimating and forecasting financial market volatility is very important to investors as well as to policy makers. It helps in investment decisions, security valuation, risk management, and in selecting and choosing appropriate hedging instruments (Anderson et al. 2000). In addition, understanding, measuring and pricing risk is important for allocative efficiency, which has a great impact on the economy as a whole (Rousan & Al-Khouri, 2005). "A volatility model must be able to forecast volatility; this is the central requirement in almost all financial applications" (Engle & Patton, 2001, p. 237).

Although volatility is not directly observable, it has some characteristics that are commonly seen in asset returns. First, there exist volatility clusters (i.e., volatility may be high for certain time periods and low for other periods). Second, volatility evolves over time in a continuous manner, that is, volatility jumps are rare. Third, volatility does not diverge to infinity--that is, volatility varies within some fixed range. Statistically speaking, this means that volatility is often stationary. Fourth, volatility seems to react differently to a big price increase or a big price drop, referred to as the "leverage effect". These properties play an important role in the development of volatility models. Some volatility models were proposed specifically to correct the weaknesses of the existing ones for their inability to capture the characteristics mentioned earlier (Tsay, 2005).

Among the features mentioned above, this study focuses on the leverage effect. The leverage effect refers to the observed tendency of an asset's volatility to be negatively correlated with the asset's returns. Typically, rising asset prices are accompanied by declining volatility, and vice versa (Aït-Sahalia et al., 2013).

In the literature, two popular theories attempt to explain this phenomenon. Influential studies by Black (1976) and Christie (1982) attributed the asymmetric return–volatility relationship to changes in financial leverage, or debt-to-equity ratios. They provide a possible economic interpretation for the leverage effect: as asset prices decline, companies become mechanically more leveraged since the relative value of their debt rises relative to that of their equity. As a result, it is natural to expect that their stock becomes riskier, hence more volatile (Aït-Sahalia et al., 2013). In other words, the leverage hypothesis states that when the value of a firm's stock falls, the value of its equity becomes a smaller percentage of the total firm's value. Since the equity of the firm bears the entire risk of the firm, the volatility of equity should subsequently increase.

An alternative hypothesis, often called the ‘‘volatility feedback effect’’or ‘‘time-varying risk premium’’ proposed by Pindyck (1984), Poterba & Summers (1986), French, Schwerdt, & Stambaugh (1987), and Campbell & Hentschel (1992), where asymmetric nature of the volatility response to returns shocks could simply reflect the existence of time-varying risk premiums: If volatility is priced, an anticipated increase in volatility raises the required return on the underlying asset, leading to an immediate asset price decline. Financial leverage and volatility feedback are considered as alternative explanations of the same phenomena, but in fact the former explains why a negative returns causes an increase in the future volatility, while the latter explains why an increase in the volatility lead to negative returns.

Furthermore, Hibbert et al., (2008), take the behavioral approaches of representativeness, affect, and the extrapolation bias to explain why a negative asymmetric return-volatility relation can exist, even for short intraday periods.

Formal econometric models have been developed by researchers to capture asymmetric volatility and currently two main classes of time series models allow for asymmetric volatility. The first class is based on continuous-time stochastic volatility. These models constrain the negative correlation between the instantaneous stock return and volatility to be a constant (Bates, 2000; Bakshi et al., 1997).The second class of models extends the autoregressive conditional heteroskedasticity (ARCH) models. Among the most widespread are the exponential GARCH (EGARCH) model by Nelson (1991), the threshold GARCH (TGARCH) model by Glosten et al. (1993) and Zakoian (1994), which is also known as the GJR model, the (asymmetric) power GARCH (APARCH) model by Ding et al. (1993), and the component GARCH (CGARCH) model by Engle & Lee (1999).

Over the past three decades, many empirical studies have been conducted on the asymmetry in the relationship between stock market returns and volatility. These studies have produced conflicting results. Most of which indicate that innovations to stock returns are negatively correlated to volatility, with some studies illustrating that negative shocks are associated with a larger increase in volatility than positive shocks of the same magnitude. These studies support the existence of (asymmetric) leverage effects in the different stock markets, confirming either the financial effect hypothesis or the volatility feedback hypothesis(see for example, Black, 1976; Christie, 1982; Schwert, 1990; Nelson, 1991; Glosten et al., 1993; Koutmos & Saidi, 1995; Bekaert & Harvey, 1997; Koutmos, 1999; Figlewski and Wang, 2000; Bekaert & Wu, 2000; Andersen et al., 2001; Chiang and Doong, 2001; Blasco et al., 2002; Li et al., 2005;Bollerslev et al., 2006; Karmakar, 2007; Hung, 2009; Jegajeevan, 2010; Tan & Khan, 2010; Charles, 2010; Goudarzi & Ramanarayanan, 2011; Daouck & Ng, 2011; Abdalla & Winker, 2012)
Although asymmetric volatility phenomenon is well documented in the empirical literature, there is some evidence indicating lack of asymmetric behavior particularly in emerging stocks (See for example, Chan et al., 1992; Harrison & Zhang, 1999; Brooks, 2007; Bahadur, 2008; Alagidede & Panagiotidis, 2009; Jayasuriya, 2009; Charlse, 2010; Cheng et al., 2010).

3. Data and Descriptive Statistics

Our empirical investigations are based on the daily closing values of the Iran stock market weighted index (TEPIX) covering the period from March 25, 2001 to July 25, 2012, with a total of 2743 observations (excluding public holidays). In this paper, volatility is defined as the variance of stock returns, so the daily closing prices have been transformed into the daily stock returns using logarithmic transformation:

$$r_t = Ln\left(\frac{P_t}{P_{t-1}}\right)$$

Where $r_t$is the stock returns at time t. P_t and P_{t-1} denote the stock price index at times t and $t-1$, respectively. The stock price index and the stock returns series for the period under review are presented in

Figure 1 and Figure 2.

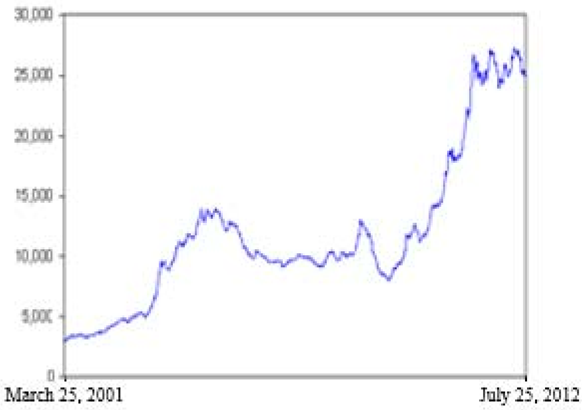

Figure 1: Stock Price Index

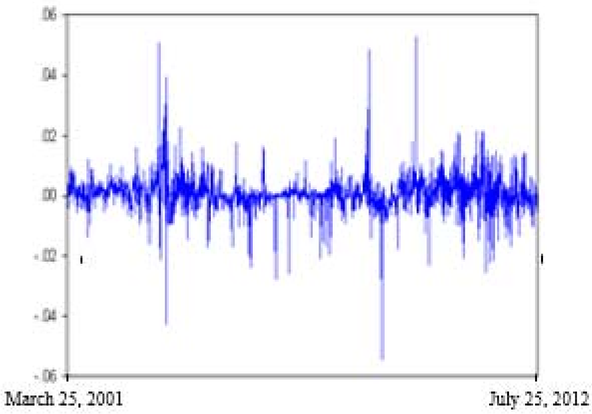

Figure 2: Stock Returns

Various descriptive statistics of the daily returns of Iranian Stock Market are summarized in Table (1).

Table 1: Descriptive statistics of Iran stock returns

Statistics	Value	Statistics	Value
Mean	0.000777	Std.Dev	0.005757
Median	0.0005	Skewness	0.34363
Maximum	0.052608	Kurtosis	16.38781

Minimum	-0.054502	Jarque-Bera (JB)	20531.38*
ADF test statistic			
With intercept	With intercept and trend	Without intercept and trend	
-10.44475*	-10.4669*	-10.12604*	

Note: * denotes statistical significance at the 1% significance level.

These descriptive statistics include skewness, kurtosis, Jarque-Bera statistic for normality test, and ADF statistic for stationary test. According to the table, the distribution of stock returns has the positive skewness implying that the distribution has a long right tail. The kurtosis is significantly greater than the normal value of 3 meaning that returns distribution is peaked relative to normal. The Jarque-Bera (JB) statistic also clearly confirms that the null hypothesis of normality is rejected at the 1% significance level. In short, these results show that the returns series has a non-normal and fat-tailed distribution. Furthermore, according to ADF-test, the null hypothesis of unit root is rejected at the 1%significance level, implying that returns series is stationary.

4. Methodology and Empirical Results

4.1. ARMA(p,q) Specification of Returns Series

In this section, we specify the conditional mean equation in the returns series by estimating ARMA(p, q) models. A stationary time series$\{X\}$ can be modeled as an ARMA(p,q) process, as follows:

$$X_t = \mu + \sum_{i=1}^{p} \delta_i X_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad (1)$$

Where p and q represent the order of autoregressive and moving average, respectively. The ε_t is assumed to be white noise error term. In this paper, the Box-Jenkins methodology has been applied to identify an appropriate ARMA(p, q) model of stock returns series (r).

Once an ARMA(p, q) model is specified, its parameters can be estimated by either the conditional or exact likelihood method. In addition, the Ljung–Box statistics of the residuals can be used to check the adequacy of a fitted model. If the model is correctly specified, then $Q(m)$ follows asymptotically a chi-squared distribution with $m - g$ degrees of freedom, where g denotes the number of parameters used in the model. In practice, the selection of m may affect the performance of the $Q(m)$statistic. Several values of m are often used. Simulation studies suggest that the choice of $m \approx Ln(T)$ provides better power performance (Tsay, 2005). Where T represents the number of time periods.

On the basis of this methodology, it seems that ARMA (2, 1) specification is the best suited model for Iranian stock returns series, such as:

$$r_t = \mu + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \theta_1 \varepsilon_{t-1} + \varepsilon_t \tag{2}$$

The parameters of this model have been estimated using maximum likelihood (ML) method. The results are reported in Table (2).

Table 2: The estimation results of ARMA (2, 1) model

Variable	Coefficient	t-statistics	p-value
Intercept	0.000743	2.074115	0.0382
AR(1)	1.257187	41.41124	0.0000
AR(2)	-0.284026	-11.71044	0.0000
MA(1)	-0.903054	-41.24956	0.0000
Q(8)=4.0558		p-value=0.3985	
F-statistic=0.00	Log Likelihood= 10538	AIC=-7.689	SBC=-7.681

Note: AIC and SIC denote Akaike Information Criteria and Schwarz Information Criteria, respectively.

According to the table, all of the coefficients are statistically significant at the 1% and 5% significance levels. Moreover, the Ljung–Box statistics of the residuals show Q(8) = 4.0558 with p-value 0.3985, based on chi-squared distributions with 4 degree of freedom (where $Ln(2743) \cong 8$ and the number of parameters used in the model is equal to4). So, the null hypothesis of no autocorrelation in residuals is not rejected at the 1% and 5% significance levels. As a result, the model appears to be adequate.

4.2. Testing for ARCH Effect

Before applying the GARCH-class Models, it is import to first examine residuals for evidence of the autoregressive conditional heteroskedasticity (ARCH) effect. To this end, Engle's (1982, 1984) Lagrange Multiplier (LM) procedure is applied to test the null hypothesis of no ARCH effect in the residuals of mean equation (2). The test procedure is to regress the squared residuals on a constant and q lagged values of the squared residuals as in the following equation:

$$\hat{\varepsilon}_t^2 = \alpha + \sum_{i=1}^{q} \beta_i \hat{\varepsilon}_{t-i}^2 + \epsilon_t \tag{3}$$

Then, the null hypothesis, $\beta_1 = \beta_2 = \cdots = \beta_q = 0$ is tested against the alternative that at least one$\beta_i \neq 0$. The number of observations times the R-squared,TR^2, an asymptotically chi-square distributed variable with q degrees of freedom, is used as a test statistic. The results of the ARCH-LM test are represented in Table (3).

Table 3: ARCH effects test

q	1	2	3	4	5
χ^2 statistic	159.094	214.904	243.439	247.006	247.509
p-value	0.0000	0.0000	0.0000	0.0000	0.0000
AIC	-15.3386	-15.3529	-15.3698	**-15.3701**	-15.3693
SBC	-15.3343	-15.3571	**-15.3611**	-15.3593	-15.3563

Note: AIC and SBC denote Akaike and Schwarz Information Criteria, respectively. Term q represents the number of lag length in the equation (3). The number of optimal lags selected based on AIC and SBC criteria are 4 and 3, respectively.

According to the p-values related to the LM test (smaller than 0.01), the results provide strong evidence for rejecting the null hypothesis of no ARCH effect for all lags included at the 1% significance level, implying the presence of heteroskedasticity effect in the residuals of mean equation of stock returns series.

4.3. The Asymmetry Tests

4.3.1. The Asymmetry Tests based on the Residuals Derived from Symmetric GARCH (1,1) model

The residuals derived from the symmetric GARCH models can be helpful in identifying the asymmetric effect on volatility. In this section, first, a GARCH(1,1) model is estimated, under different distributional assumptions. Then, the tests proposed by Engle and Ng (1993) and Enders (2004) are employed to detect the possible asymmetry in volatility. These tests are conducted using the residuals of the estimated GARCH (1,1) model. The GARCH model was developed by Bollerslev (1986). According to this model, the conditional variance is represented as a linear function of its own lags as well as the lagged values of squared residuals. The conditional mean and conditional variance equations related to the GARCH (1,1) model can be specified as follows:

Conditional mean equation: $r_t = \mu + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \theta_1 \varepsilon_{t-1} + \varepsilon_t$
Distributional assumptions:

$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t)$, $\varepsilon_t \mid \Omega_{t-1} \sim t(0, v, \sigma_t)$, $\varepsilon_t \mid \Omega_{t-1} \sim GED(0, v, \sigma_t)$
Where $\Omega_{t-1}$the information available at time t-1.

Conditional variance equation:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (4)$$

Where constraints $\omega > 0$, $\alpha \geq 0$, and $\beta \geq 0$are needed to ensure that conditional variance is strictly positive. The estimation results of GARCH(1,1) model under the three distributional assumptions are summarized in Table (4). The residuals derived from these estimated models are used to conduct the asymmetry tests, in next steps.

Table 4: The estimation results of the ARMA(2,1)-GARCH(1,1) based on Normal, t-student, and GED distributions

	Normal	t-student	GED
$\boldsymbol{\omega}$	4.27E-06	1.92E-06	2.79E-06
	(0.0000)	(0.0000)	(0.0000)

$\boldsymbol{\alpha}$	0.347097 (0.0000)	0.634946 (0.0000)	0.467629 (0.0000)
$\boldsymbol{\beta}$	0.528844 (0.0000)	0.586867 (0.0000)	0.528024 (0.0000)
Log Likelihood	10189.66	10580.77	10519.39
LM-test statistic	0.009984 (0.9204)	0.278876 (0.5974)	0.274813 (0.6001)

Note: The values reported in parentheses are p-value.

4.3.1.1. Sign and Size Bias Tests

Engle and Ng (1993) have proposed a set of diagnostic tests to detect asymmetry in volatility. These tests investigate the size and sign bias based on the residuals obtained from a symmetric GARCH (1,1) model as follows:

Sign bias test: $\hat{v}_t^2 = \emptyset_0 + \emptyset_1 I_{t-1}^{-} + e_t$ (5)

Negative size bias test: $\hat{v}_t^2 = \emptyset_0 + \emptyset_1 I_{t-1}^{-}\hat{\varepsilon}_{t-1} + e_t$ (6)

Positive size bias test: $\hat{v}_t^2 = \emptyset_0 + \emptyset_1 I_{t-1}^{+}\hat{\varepsilon}_{t-1} + e_t$ (7)

Joint test: $\hat{v}_t^2 = \emptyset_0 + \emptyset_1 I_{t-1}^{-} + \emptyset_2 I_{t-1}^{-}\hat{\varepsilon}_{t-1} + \emptyset_3 I_{t-1}^{+}\hat{\varepsilon}_{t-1} + e_t$ (8)

Where$\hat{\varepsilon}_t$ and $\hat{v}_t(\frac{\hat{\varepsilon}_t}{\hat{\sigma}_t})$ denote the ordinary and standardized residuals derived from estimating a GARCH (1,1) model, respectively. I_{t-1}^{-} is an indicator (dummy) variable that takes a value of 1 if $\hat{\varepsilon}_{t-1} < 0$ (bad news) and 0 otherwise, and $I_{t-1}^{+} = 1 - I_{t-1}^{-}$ that that takes a value of 1 if $\hat{\varepsilon}_{t-1} > 0$ (good news) and 0 otherwise. e_t is a normally distributed error variable with zero mean and constant variance.These tests examine whether we can predict the squared standardized residual by some variables observed in the past which are not included in the volatility model being used. If these variables can predict the squared normalized residual, then the variance model is misspecified. The statistical significance of $\emptyset_1$ in sign bias test indicates that negative and positive return shocks of the same magnitude have asymmetric effects on volatility, which are not explained by the volatility model under consideration. The statistical significance of $\emptyset_1$ in the negative (positive) size bias test implies that the response of volatility to large and small negative (positive) return shocks is different, which is not predicted by the volatility model. The statistic related to each of these tests is defined as the t-ratio of the coefficient $\emptyset_1$ in regression equations (5), (6), and (7). The joint test is the LM test for adding the three variables in the variance equation under the maintained specification. The LM test statistic is equal to T times the R-squared from regression equation (8), TR^2, which is chi-square distributed with three degrees of freedom. The rejection of null hypothesis of the joint test, $H_0: \emptyset_1 = \emptyset_2 = \emptyset_3 = 0$, refers to symmetric effects on volatility, meaning that the symmetric GARCH model under consideration has been correctly specified. The results of the sign and bias tests are reported in Table (5). According to this table, the null hypothesis cannot be rejected for all four sign-size tests at the 1%significance level, under different distributional assumptions. These findings indicate that the GARCH(1,1) model has been correctly specified, implying that the negative and positive shocks of the same magnitude have the similar (symmetric) impacts on volatility level.

Table 5: Sign and size bias tests for asymmetry (Engle and Ng (1993))

	GARCH(1,1)-Normal	GARCH(1,1)-t-student	GARCH(1,1)-GED
Sign bias test statistic	-0.93414 (0.3503)	-1.35467 (0.1756)	0.50506 (0.6136)
Negative size bias test statistic	0.34362 (0.7312)	1.46825 (0.1422)	0.84445 (0.3985)
Positive size bias test statistic	0.18123 (0.8562)	-1.11756 (0.2639)	-1.03817 (0.2993)
Joint test statistic	0.97538 (0.8072)	6.02219 (0.1105)	2.54388 (0.4674)

Note: The values reported in parentheses are p-value.

4.3.1.2. Enders (2004) Method

In order to detect asymmetry in volatility, Enders (2004) has proposed a simple method based on standardized residuals obtained from symmetric GARCH model. The test procedure is to regress the squared standardized residuals on a constant and q lagged values of the standardized residuals in level as in the following equation:

$$\hat{v}_t^2 = \gamma_0 + \gamma_1 \hat{v}_{t-1} + \gamma_2 \hat{v}_{t-2} + \cdots + \gamma_q \hat{v}_{t-q} + u_t \quad (9)$$

Where $\hat{v}_t(\frac{\hat{\varepsilon}_t}{\hat{\sigma}_t})$ is standardized residuals derived from estimating a GARCH model. If there is no asymmetric effect, there will be no correlation between the squared residuals and lagged values of the residuals in level. So, after estimating the regression equation (9) using least squares approach, the null hypothesis of no asymmetric effect on the conditional volatility, namely $\gamma_1 = \cdots = \gamma_q = 0$, is tested against the alternative that at least one $\gamma_i \neq 0$.This test is conducted on residuals derived from a GARCH (1,1) model estimated under different distributional assumptions for the innovations. The Table (6) shows the results. The null hypothesis of no asymmetric effect cannot be rejected at the 1%significance level, for the three models with each number of lag lengths used in the equation (9).

Table 6: Asymmetry test (Enders, 2004)

Model	q	Statistics (t-student and F)	p-value	AIC	SBC
GARCH(1,1)-Normal	1	0.218684	0.8269	**5.202481**	**5.206800**
	2	0.063961	0.9380	5.203545	5.210026
	3	0.207922	0.8910	5.204434	5.213078
GARCH(1,1)-t-student	1	0.148783	0.8817	**5.436535**	**5.440854**
	2	0.011678	0.9884	5.437628	5.444109
	3	0.042497	0.9883	5.438666	5.447310
GARCH(1,1)-GED	1	0.054280	0.9567	**5.606447**	**5.610767**
	2	0.011241	0.9888	5.607535	5.614016
	3	0.119467	0.9487	5.608485	5.617129

Note: Term q represents the number of lag light used in equation (9).The test statistic is t-student if q=1 and F otherwise.

4.3.2. The Asymmetry Test Based on the Asymmetric GARCH Models

The presence of the asymmetric effects in volatility can also be investigated using the asymmetric GARCH models. In these models, the conditional variance allowed to be differently affected by the negative and positive shocks of the same magnitude. So, the statistical significance of the asymmetric parameter (λ) in the asymmetric GARCH models reveals the evidence of the different impacts of shocks on volatility. For this purpose, we have employed the three most popular asymmetric GARCH models, including EGARCH (1,1), GJR-GARCH(1,1), and APARCH(1,1).The conditional mean and the conditional variance equations related to these models can be specified as follows:

Conditional mean equation:$r_t = \mu + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \theta_1 \varepsilon_{t-1} + \varepsilon_t$
Distributional assumptions:
$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t)$,$\varepsilon_t \mid \Omega_{t-1} \sim t(0, v, \sigma_t)$, $\varepsilon_t \mid \Omega_{t-1} \sim GED(0, v, \sigma_t)$
Where $\Omega_{t-1}$the information available at time t-1.

Conditional variance equation:
EGARCH (1,1) model [Nelson (1991)]:

$$Ln(\sigma_t^2) = \omega + \alpha \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \lambda \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta Ln\sigma_{t-1}^2 \tag{10}$$

Note that the left-hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative. The λ signifies asymmetric effects of shocks (news) on volatility. The presence of asymmetric effects can be tested by the hypothesis that $\lambda = 0$. The effect is symmetric if the null hypothesis of $\lambda = 0$ cannot be statistically rejected, meaning the positive and negative shocks of the same magnitude have the same effects on volatility of stock returns. The impact is asymmetric if$\lambda \neq 0$.If $\lambda < 0$, then negative shocks tend to produce higher volatility than positive ones (leverage effects hypothesis). The opposite is true if $\lambda > 0$.

GJR-GARCH (1,1) model [Glosten et al., 1993; Zakoïan, 1994]:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \lambda I_{t-1}^- \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{11}$$

Where I_{t-1}^- is a dummy variable that takes a value of 1 if $\hat{\varepsilon}_{t-1} < 0$ (bad news) and 0 otherwise (good news). In this model, good news has an impact of $\alpha \varepsilon_{t-1}^2$ on conditional variance, while bad news has an impact

of $(\alpha + \lambda)\varepsilon_{t-1}^2$. The null hypothesis of $\lambda = 0$ implies that the news impact is symmetric: the good and bad news of the same magnitude have the same effects on volatility of stock returns. If $\lambda \neq 0$, the impact of news on volatility is asymmetric; hence, good and bad news of the same magnitude have different impacts on the volatility level, with bad (good) news having a greater effect on volatility if $\lambda > 0$ ($\lambda < 0$). Moreover, the hypothesis of$\lambda > 0$implies that there is a leverage effect.
APARCH (1,1) model [Ding et al., 1993]:

$$\sigma_t^\delta = \omega + \alpha(|\varepsilon_{t-1}| - \lambda\varepsilon_{t-1})^\delta + \beta\sigma_{t-1}^\delta \qquad (12)$$

Where, $-1 \leq \lambda \leq 1$ captures the asymmetric effect and $\delta > 0$ is the power parameter. The asymmetric model sets $\lambda = 0$. As in the previous models, the asymmetric effects are present if$\lambda \neq 0$, with bad (good) news having a greater effect on volatility if $\lambda > 0$ ($\lambda < 0$).

Thus, in all three models, If the null hypothesis of $\lambda = 0$ cannot be rejected at a statistically significant level, it means that the negative and positive shocks (bad and good news) of the same magnitude have symmetric effects on conditional variance (volatility) and asymmetric effects otherwise. The asymmetric GARCH models are estimated using Maximum Likelihood estimators under different distributional assumptions (normal, t-student, and GED).

The maximum likelihood estimates for the EGARCH (1,1), GJR-ARCH(1,1) and APARCH(1,1) models are presented in Tables (7), (8), and (9), respectively. According to the tables, the p-values related to the λ coefficient are larger than 0.05, under different distributional assumptions. So, the null hypothesis of $\lambda = 0$ cannot be statistically rejected at the 5% significance level, meaning that there is no evidence of the asymmetric impacts in volatility of Iranian stock market.

The results of diagnostic test (test for ARCH effects) are reported in the last row of the tables. The LM test statistic for all GARCH models do not exhibit any additional ARCH effect remaining in the residuals of the models. This shows that the variance equations are well specified for the stock returns.

Table 7: The estimation results of the ARMA(2,1)-EGARCH(1,1) based on Normal, t-student, and GED distributions

	Normal	t-student	GED
$\boldsymbol{\omega}$	-2.370593 (0.0000)	-1.027873 (0.0000)	-1.674044 (0.0000)
$\boldsymbol{\alpha}$	0.469885 (0.0000)	0.478736 (0.0000)	0.492366 (0.0000)
$\boldsymbol{\beta}$	0.810159 (0.0000)	0.932220 (0.0000)	0.877547 (0.0000)
$\boldsymbol{\lambda}$	-0.001572 (0.8856)	0.039648 (0.1359)	0.022038 (0.4382)
Log Likelihood	10177.16	10596.07	10530.45
LM-test statistic	0.272087 (0.6019)	0.242680 (0.6223)	0.014273 (0.9049)

Note: The values reported in parentheses are p-value.

Table 8: The estimation results of the ARMA(2,1)-GJR-ARCH(1,1) based on Normal, t-student, and GED distributions

	Normal	t-student	GED
$\boldsymbol{\omega}$	4.28E-06 (0.0000)	1.90E-06 (0.0000)	2.82E-06 (0.0000)
$\boldsymbol{\alpha}$	0.379417 (0.0000)	0.645232 (0.0000)	0.468904 (0.0000)
$\boldsymbol{\beta}$	0.525614 (0.0000)	0.588949 (0.0000)	0.526639 (0.0000)
$\boldsymbol{\lambda}$	-0.056627 (0.1000)	-0.029043 (0.7993)	-0.002037 (0.9836)
Log Likelihood	10190.17	10580.81	10518.79
LM-test statistic	0.005504 (0.9409)	0.269332 (0.6038)	0.256968 (0.6122)

Note: The values reported in parentheses are p-value.

Table 9: The estimation results of the ARMA(2,1)-APARCH(1,1) based on Normal, t-student, and GED distributions

	Normal	t-student	GED
$\boldsymbol{\omega}$	7.36E-06	0.000763	0.000527
	(0.0777)	(0.1313)	(0.2097)
$\boldsymbol{\alpha}$	0.283242	0.296707	0.324541
	(0.0000)	(0.0000)	(0.0000)
$\boldsymbol{\beta}$	0.569202	0.767731	0.670387
	(0.0000)	(0.0000)	(0.0000)
$\boldsymbol{\lambda}$	-0.001939	-0.011156	-0.016641
	(0.9382)	(0.8560)	(0.7965)
$\boldsymbol{\delta}$	1.894755	0.789405	0.995710
	(0.0000)	(0.0000)	(0.0000)
Log Likelihood	10172.24	10605.21	10531.25
LM-test statistic	0.431738	3.423164	0.762940
	(0.5111)	(0.0643)	(0.3824)

Note: The values reported in parentheses are p-value.

5. Conclusions

The "leverage effect" has become an extensively studied phenomenon which refers to the asymmetric impacts of shocks on the volatility of stock returns such that negative shocks (bad news) increase future volatility more than positive shocks (good news) of the same magnitude. In this paper, we investigated the asymmetry in volatility of returns for the Iranian stock market using the daily closing values of the Tehran exchange price index (TEPIX) covering period from March 25, 2001 to July 25, 2012, with a total of 2743 observations. The descriptive statistics show that the returns series has a non-normal and fat-tailed distribution. On the basis of the Box-Jenkins methodology, the ARMA (2, 1) specification is selected as conditional mean equation of Iranian stock returns series. The results of ARCH-LM test provide strong evidence for rejecting the null hypothesis of no ARCH effect, implying the presence of heteroskedasticity effect in the residuals of the mean equation. Then, we employed the two sets of tests to identify the asymmetry in the returns volatility: the first set is based on the residuals derived from a symmetric

ARMA(2,1)-GARCH(1,1) model, including the sign and size bias tests (Engle and Ng, 1993) and Enders (2004) test. The second set is based on the statistical significance of the asymmetric parameter in the asymmetric GARCH models, including ARMA(2,1)-EGARCH(1,1), ARMA(2,1)-GJR-GARCH(1,1), and ARMA(2,1)-APARCH(1,1) models. To capture the stylized fact that the returns series are fat-tailed distributed, in addition to classic Gaussian assumption, the innovations are also assumed to be distributed as t-student distribution and GED (Generalized Error Distribution).

The results indicate that there is no evidence of asymmetric effects on volatility in the Iranian stock market, meaning that negative and positive shocks (bad and good news) of the same magnitude have the same (symmetric) impacts on the future volatility level. This result is in contrast with the results of most empirical studies, where an asymmetry in volatility of stock returns has been found. This seems to be the result of the governmental or quasi-governmental nature of many companies listed on the Tehran Stock Exchange, and infrastructural restrictions.

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