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An Investigation of Leverage Effect in Tehran Stock Exchange; EGARCH Approach

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ABSTRACT

Leverage effect has become an extensively studied phenomenon which describes the negative relation between the stock return and its volatility. In this paper I have estimated EGARCH models with Gaussian innovations. Results indicate that leverage effect exists in Tehran stock exchange. In other words, the effect of bad news on volatility is larger than that of the good news on volatility.
KEY WORDS: Volatility, Stock Exchange, Leverage Effect, Tehran stock exchange.

1. INTRODUCTION

The volatility of financial markets has been the object of numerous developments and applications over the past two decades, both theoretically and empirically. While most researchers agree that volatility is predictable in many asset markets (see for example the survey by Bollerslev et al. 1994), they differ on how this volatility predictability should be modeled. Over the past several decades the evidence for predictability has led to variety of approaches. Leverage effect has become an extensively studied phenomenon which describes the negative relation between the stock return and its volatility. Although this characteristic of stock returns is well acknowledged, most studies about it are based on cross-sectional calibration with parametric models. Other than that, most previous work are over daily or longer return horizons and usually do not specify the quantitative measure of it. The most interesting of these approaches are the "asymmetric" or "leverage" volatility models in which good news and bad news have different predictability for future volatility (see, for example, Black, 1976, Nelson, 1991, Pagan and Schwert, 1990, Campbell and Hentschel, 1992, Engle and Ng, 1993, Henry, 1998, and Friedmann, Sanddorf-Köhle, 2002). In most of these studies researchers have documented strong evidence that volatility is asymmetric in equity markets (see, for example, Cox and Ross, 1976, Engle and Ng, 1993, Henry, 1998). This paper is organized as follows. In section 2 the EGARCH models of stock return volatility are outlined. Section 3 describes the data. Section 4 presents empirical results and estimates of the relationship between news and volatility for the selected models. The final section provides a brief summary and conclusion.

2. RESEARCH METHOD

Let R_t be the rate of return of a stock, or a portfolio of stocks from time $t-1$ to t and Ω_{t-1} be the past Information set containing the Realized value of all relevant variables up to time $t-1$. So the conditional mean and variance are $y_t = E(R_t|\Omega_t), h_t = \mathrm{var}(R_t|\Omega_t)$ respectively. Given this definition, the unexpected return at time t is $\varepsilon_t = R_t - y_t$. In order to model the effect of ε_t on returns I present ARCH models. ARCH models were Introduced by Engle (1982) and generalized as GARCH models by Bollerslev (1986). In developing GARCH (p, q) I will have to provide mean and variance Equation

$$R_t = x_t'\gamma + \varepsilon_t \quad (1)$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \quad (2)$$

where ω, α_i, β_j, γ are constant parameters and x_t contains exogenous and predetermined regressors. As h_t is variance it must be nonnegative which impose the following conditions: $\omega > 0$, $\alpha_1, \ldots\ldots \alpha_p \geq 0$ and $\beta_1, \ldots\ldots\ldots, \beta_q \geq 0$. The conditional variance under ARCH (p) model reflects only information from time $t-p$ to $t-1$ with more importance being placed on the most recent innovation implying $a_i < a_j$ for $i > j$. To avoid long lag lengths on ε_t in ARCH (p) and

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difficulty in selecting the optional length p, and ensuring the non-negativity of coefficients of conditional variance equation (2) , Bollerslev (1986) present GARCH(P, q). A common parameterization for the GARCH model that has been adopted in most applied studies is the GARCH (1, 1) specification under which the effect of a shock to volatility declines geometrically over time.

One problem with ARCH (p) and GARCH (p, q) is that good news and bad news with some absolute size have the same effect on h_t. This fact is symmetric effect. However, the market may react differently to good and bad news. It is important, to be able to test for and allow asymmetry in the ARCH type specification. Nelson (1991) proposes the exponential GARCH (EGARCH) model as a way to deal whit this problem. Under the EGARCH (1, 1) the h_t is given as:

$$\log(h_1) = \omega + \alpha\left[\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| - \sqrt{2/\pi}\right] + \beta \log h_{t-1} + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \qquad (3)$$

The EGARCH news Impact differs from the GARCH new Impact in four ways: (1) it is not symmetric. (2) Big news can have a much greater impact than in the GARCH model. (3) Log construction of Equation 3 ensures that the estimated h_t is strictly positive, thus non-negativity constraints used in the estimation of the ARCH and GARCH are not necessary. (4) Since the parameter of γ typically enters equation 3 with a negative sign, bad news generates more volatility than good news.

To estimate the model, I follow the quasi-maximum likelihood. Both the conditional mean and the conditional variance are estimated jointly by maximizing the log-likelihood function which is computed as the logarithm of the product of the conditional densities of the prediction errors. The ML estimates are obtained by maximizing the log-likelihood with the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) quasi-Newton optimization algorithm in the MATLAB numerical optimization routines.

3. **Data Description**

The TSE opened officially in February 1967 with only six listed companies compared to the 420 companies that individual and institutional investor trade today. The first ten years of the TSE was marked by a brisk activity where capitalization rose from IRR 6.2 billion to IRR 240 billion and the listed companies grew to 105. After 1978, the Islamic revolution and Iraq's invasion to Iran reduced exchange activities significantly and capitalization fell again to IRR 9.9 billion in 1982. After the Iraq-Iran war ended, the TSE was perceived as one of the most important mechanisms to foster economic development by channeling savings into investment. This goal quickly accelerated the number of listed companies from 56 in 1988 to 422 in 2006.

Between 2000 and 2004, the market capitalization of the TSE grew from IRR 60 billion to IRR 411 billion. The TEPIX index reached an all-time high of 13,882 on August 4, 2004, but within two years, a severe market correction brought the index down 35% to 9069 on July 26, 2006. The stock market plunge was not all negative because it was perceived as a healthy correction in a market that has run ahead of its fundamentals and needed better controls and improved transparency. In fact, the market correction brought major reforms and led, in particular, to the consolidation and merger of many smaller companies. By 2007, the market capitalization has actually risen above its level in 2004, but the number of listed companies was still low because the merger and acquisition activity remained brisk.

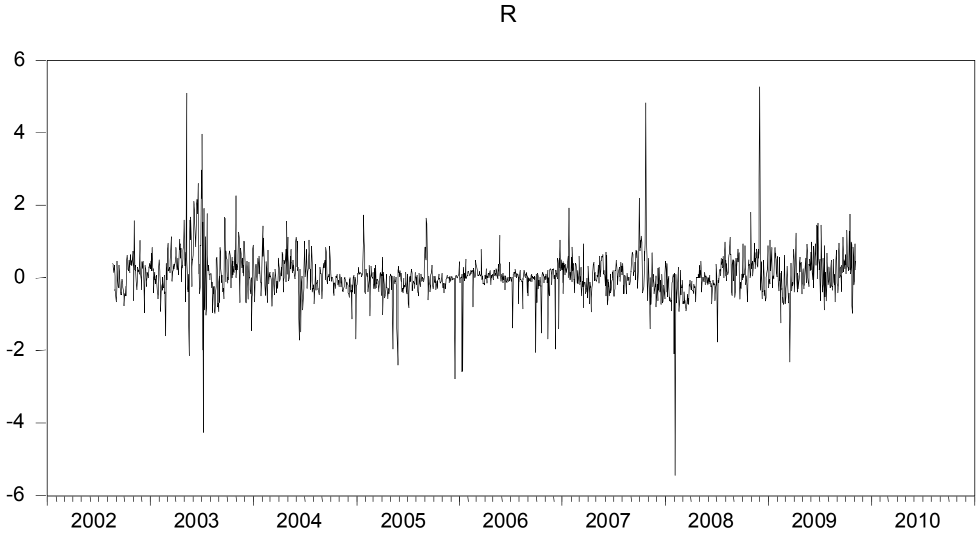
The TSE was not directly affected by the international financial turmoil in 2008, but following the global reduction in prices of copper and steel, the bourse index dropped by 12.5 percent, as most of the companies listed on the exchange are producers of such commodities. TSE experienced an 11% growth at the end of 2008 and ranked second in the world in terms of increase in the volume of trade after Luxembourg's Bourse. On August 2, 2010, the TSE main index (TEPIX) reached a record level of 16,056 points, despite US-sponsored sanctions against Iran. Thus, TEDPIX became the world's second-best performing equity index. Factors such as the global spike in oil and metal prices, government support for industries and oil sectors as well as the growth of stock market liquidity flow contributed to the boom. the growth was also partly due to a government decision to sell off 20 percent of its equity in two major automakers. Given the relative low market valuation of TSE stocks in 2010, the upward trend was expected to continue over the long run, rather than being a bubble. TEPIX reached a new record on September 18, 2010, when it hit 18,658, up from 11,295 at the start of the year. As of December 2010, the TSE index rose about 64 percent since the start of 2010. The Tehran Stock Exchange has been ranked as the best bourse index in Europe, Africa and Middle East in 2010 in terms of performance of the main index.

Trading in Tehran stock exchange (TSE) is based on orders sent by the brokers. Trading days in week are: Saturday, Sunday, Monday, Tuesday, and Wednesday except national holidays. The data consist of 3067 daily observations of the closing value of the TSE from 09/29/1997 to 09/09/2010.The return is calculated as $r_t = 100[\log(\frac{P_t}{P_{t-1}})]$ where P_t is the index value at time t. Table 1 shows some descriptive statistics of the TSE rate of return. The mean is quite small and the standard deviation is around 0.3. The Kurtosis (Ku) is significantly higher than the normal value of 3 indicating that fat-tailed distribution are necessary to correctly describe conditional distribution of r_t The Skewness(Sk) is significant, small and negative, showing that the lower tail of empirical distribution of the return is longer than the upper tail, that means negative returns are more likely to be far below the mean than their counterparts.

Table1.Descriptive Statistics r_t

Mean	Standard Deviation	Min	Max	Sk	Ku	$B-J$	$Q^2(12)$	LM(12)
0.0248	0.2910	-5.45	4.83	-0.68	71.75	654376.1	182.89	77.05
p-value:						[0.00]	[0.00]	[0.00]

Note: Sk and Ku are skewness and excess kurtosis. B-J is the Bera-Jarque test for normality distributed as $\chi^2(2)$. The $Q^2(12)$ statistic is the Ljung-Box test on the squared residuals of the conditional mean regression up to the twelfth order. for serial correlation in the squared return data, distributed as $\chi^2(12)$. LM(12) statistic is the ARCH LM test up to twelfth lag and under the null hypothesis of no ARCH effects it has a $\chi^2(q)$ distribution.
LM (12) is the Lagrange Multiplier test for ARCH effects in the OLS residuals from the regression of the returns on a constant, while $Q^2(12)$ is the corresponding Ljung-Box statistic on the squared standardized residuals. Both these statistic are highly significant suggesting the presence of ARCH effects in the TSE returns up to the twelfth order.



Plot.1: The Rate of Return Series

Table 2. Unit Root Tests for Rate of Return Series

Test Type	**Augmented Dickey-Fuller**	**Phillips-Perron**
Statistic	-10.55	-53.17
P-Value	0.00	0.00
Null Hypothesis	Rate of Return has a unit root	

Table 2 shows some unit root tests for rate of return series. Results indicate that the rate of return series has not unit root. So, the rate of return series is a stationary process.

4. Empirical Results

In this section, I have presented the estimation results from EGARCH model as following:

Table 3: Maximum Likelihood Estimates of standard EGARCH Model with Normal conditional distribution.

	EGARCH
δ	0.0284
p-value	0.0
ω	-0.213
p-value	0.0
α	0.246
p-value	0.0
β	0.983
p-value	0.0
γ	-0.0194
p-value	0.0
Log likelihood	-620.1886

Based on the "asymmetric" or "leverage" volatility models, in which good news and bad news have different predictability for future volatility (see, for example, Black, 1976, Nelson, 1991, Pagan and Schwert, 1990, Campbell and Hertschel, 1992, Henry, 1998, and Friedmann, Sanddorf-Köhle, 2002). In most of these studies researchers have documented strong evidence that volatility is asymmetric in equity markets: negative returns are generally associated with upward revisions of the conditional volatility while positive returns are associated with smaller upward or even downward revisions of the conditional volatility (see, for example, Cox and Ross, 1976, Engle and Ng, 1993, Henry, 1998,). Researchers (see Black, 1976, and Schwert, 1989) believe that the asymmetry could be due to changes in leverage in response to changes in the value of equity. Others have argued that the asymmetry could arise from the feedback from volatility to stock price when changes in volatility induce changes in risk premiums (see Pindyck, 1984, French et al., 1987, and Campbell and Hentschel, 1992). The presence of asymmetric volatility is most apparent during a market crisis when large declines in stock prices are associated with a significant increase in market volatility. Asymmetric volatility can potentially explain the negative skewness in stock return data, as discussed in Harvey and Siddique (1999). In this paper, results indicate that leverage effect exists in Tehran stock market, because in EGARCH model with normal distributions, since the parameter of γ typically enters equation 3 with a negative sign, bad news generates more volatility than good news.

5. Summary and Concluding Remarks

In this paper I have estimated EGARCH model with normal innovations. To estimate the model, I follow the quasi-maximum likelihood. Both the conditional mean and the conditional variance are estimated jointly by maximizing the log-likelihood function which is computed as the logarithm of the product of the conditional densities of the prediction errors. The ML estimates are obtained by maximizing the log-likelihood with the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) quasi-Newton optimization algorithm in the MATLAB numerical optimization routines Results indicate that leverage effect exists in Tehran stock exchange. In other words, the effect of bad news on volatility is larger than that of the good news on volatility.

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