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Has Tehran Stock Market Calmed Down after Global Financial Crisis? Markov Switching GARCH Approach

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Abstract

We have introduced an early warning system for volatility regimes regarding Tehran Stock Exchange using Markov Switching GARCH approach. We have examined whether Tehran Stock Market has calmed down or more specifically, whether the surge in volatility during 2007-2010 global financial crises still affects stock return volatility in Iran. Doing so, we have used a regime switching GARCH model. The data consist of 3067 daily observations of the closing value of the Tehran stock market from 29/09/1997 to 09/09/2010. The results indicate that during the crisis period, Tehran stock exchange was in the high-volatility regime. Smoothed probability plots show that the volatility in 2007-2009 was in high volatility regime but at 2009-2010, Volatility turned to low volatility regime. Also, we have introduced an early warning system for forecasting high volatility in Tehran Stock Exchange.

Keywords: Tehran Stock Market, Global Financial Crisis, Markov Switching GARCH.
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1. Introduction

The financial crisis of 2006-2007 has developed through the collapse of the housing market in the United States of America and European countries. Collapse in housing market has led to failure of many financial institutions in USA. Crisis developed in financial markets diffused more or less though the entire world. It is considered by many economists to be the worst crisis since the 1930s. It has contributed to the failure of key businesses, declines in household wealth, substantial financial commitments incurred by governments, and a significant decline in economic activities. Many causes and consequences have been suggested, with varying weights assigned by experts. Both market-based and structural solutions have been implemented or are under consideration. The collapse of a global Housing bubble, which peaked in USA caused the values of Security (finance) tied to real estate pricing to plummet thereafter, damaging financial institutions globally. Questions regarding bank solvency, declines in credit availability, and damaged investor confidence had an impact on global Stock market, where securities suffered large losses during late 2008 and early 2009. This situation is partly reflected by the volatility of stock prices. Moreover, stock volatility is also a determinant of investment decisions and the inflow of foreign capital needed for economic recovery. Hence, besides the level of stock prices, also their volatility can be viewed as an indicator for the length of the crisis. Financial returns exhibit sudden jumps that are due not only to structural breaks in the real economy, but also to change in the operators' expectations about the future, that can originate from different information or dissimilar preferences. The real volatility is affected by millions of shocks that anyway never persist for a long time, rendering its behavior mean-reverting.

The aim of this paper is testing whether Tehran Stock Exchange has calmed down after global financial crisis or not. In other word, during the financial crisis (2007-2009) Tehran stock exchange has been in high volatility regime but it calmed down at 2009-2010 (after global financial crisis) and in this period, TSE has been in low volatility regime. In order to test the hypothesis, we have estimated transition matrix of MRSGARCH. Using the MRSGARCH model, the smoothed probability in two regimes has been estimated. Smoothed probability indicates the volatility position of TSE: high volatility or low volatility? Also, we have introduced an early warning system concerning high volatility in TSE. Doing so, we have used the local currency stock market indices in Tehran stock exchange.

2. Review of Literature

This section includes review concerning volatility, the review of Early Warning Systems and the review of literatures regarding financial crisis.

2.1 Review of the Volatility

The volatility of financial markets has been the object of numerous developments and applications over the past two decades, both theoretically and empirically. Portfolio managers, option traders and market makers all are interested in the possibility of forecasting volatility with a reasonable level of accuracy. That is important, in order to obtain either higher profits or less risky positions. In this respect, the most widely used class of models is that of GARCH models [Poon, S. H., and Granger, C. W. (2003)], see e.g. Bollerslev, Engle, and Nelson (1994) for an overview. GARCH models, that introduced by Bollerslev (1986), typically show high volatility persistence. Lamoureux and Lastrapes (1990) attribute this persistence to the possible presence of structural breaks in the variance. They demonstrate that shifts in the unconditional variance are likely to lead to wrong estimates of GARCH parameters in a way that implies persistence. Our focus on the volatility persistence of the global financial crisis combined with the potential importance of breaks for the estimated persistence of shocks makes that we want to allow for breaks in the volatility process. A popular way to do this is by using a Markov regime-switching model. This model was introduced by Hamilton (1989) to study switches between expansions and recessions in the U.S. business cycle. Cai (1994) and Hamilton and Susmel (1994) are the first who applied the seminal idea of regime-switching parameters into an ARCH specification in order to account for the possible presence of structural breaks. They use an ARCH specification instead of a GARCH to avoid the problem of path dependence of the conditional variance which renders the computation of the likelihood function infeasible. This occurs because the conditional variance at time t depends on the entire sequence of regimes up to time t due to recursive nature of the GARCH process. Since the regimes are unobservable, one needs to integrate over all possible regime paths when computing the sample likelihood, but the number of possible paths grows exponentially with t, which renders ML estimation intractable. Gray (1996) presents a tractable Markov-switching GARCH model, and a modification of his model is suggested by Klaassen (2002); see also Bollen, Gray, and Whaley (2000), Dueker (1997), Haas, Mittnik, and Paolella (2004), and Marcucci (2005) for related papers.

There are some studies concerning Tehran Stock Exchange volatility such as Yahyazadehfar, Abounoori and Shababi, (2006), Albadvi, Chaharsooghi, and Esfahanipour (2007), Foster and Kharazi,(2008), Fasanghari, and Montazer (2010), and Ebrahimpour et al. (2011).

Shoghi and Talaneh (2010) have analyzed the volatility behavior of Tehran Stock Exchange returns. Since volatility is an important factor in portfolio selection, asset pricing, and risk management, the main purpose of our study is to model and forecast the returns volatility of the Tehran Stock Exchange. [Shoghi and Talaneh (2010)] using primary index data of TSE for 2003-2008, investigated the appropriateness of several potential models of autoregressive (AR), moving averages (MA), and autoregressive moving averages (ARMA). The ARMA (2, 1) has been chosen as the best process for modeling the conditional means [Shoghi and Talaneh (2010)]. They have used EGARCH and TGARCH models to capture asymmetries in terms of negative and positive shocks and the leverage effect. The ARMA (2, 1)-TGARCH (1, 1) model was the best process to fit the data. They have found no evidence for the presence of the leverage in the news; nor does that bad news have a larger effect on the volatility of returns than the good news. Of the three forecast performance measures, the TGARCH (1, 1) was the best model to forecast the volatility. Abounoori and Nademi (2011) have used daily data from the Tehran stock exchange to illustrate the nature of stock market volatility in an emerging stock market. They have estimated GJR models with both Gaussian innovations and fat-tailed distributions, such as the Student's t and the GED; the results indicate that leverage effect exists in Tehran Stock Exchange due to GJR models with t-student and GED distributions. Also, they have indicated that the effects of bad news on volatility are larger than the effects of good news on volatility. P-Value LR Test for Leverage effect has shown that the differences between the coefficients is not significant for GJR-N model but it is significant at 5% confidence level for GJR models with t student and GED distributions [Abounoori and Nademi (2011)].

2.2 Review of Early Warning Systems

Many studies can be traced concerning Early Warning Systems (EWS) among which are: Demirgüc-Kunt and Detragiache (2005), Davis and Karim (2008), Kaminsky and Reinhart (1999), Borio and Lowe (2002) and Duttagupta and Cashin (2008). Rose and Spiegel (2009) have modeled the causes of the 2008 financial crisis together with its manifestations, using a Multiple Indicator Multiple Cause (MIMIC) model. Their analysis is conducted on a cross-section of 107 countries. They focused on national causes and consequences of the crisis, ignoring cross-country "contagion" effects; the model of the incidence of the crisis combines 2008 changes in real GDP, the stock market, country credit ratings, and the exchange rate. They explored the linkages between these manifestations of the crisis and a number of its possible causes from 2006 and earlier. They have included over sixty potential causes of the crisis, covering such categories as: financial system policies and conditions, asset price appreciation in real estate and equity markets, international imbalances and foreign reserve adequacy, macroeconomic policies, and institutional and geographic features. Despite the fact that they have used a wide number of possible causes in a flexible statistical framework, unable to link most of the commonly-cited causes of the crisis to its incidence across countries. Ahn et al. (2011) extended the EWS classification approach to the traditional-type crisis, i.e., the financial crisis is an outcome of the long-term deterioration of the economic fundamentals. It is shown that Support Vector Machine (SVM) is an efficient classifier in such case. Lin and et. al (2008) have presented a hybrid causal model for predicting the occurrence of currency crises by using the Neural Fuzzy Modeling approach. The model integrated the learning ability of the neural network with the inference mechanism of fuzzy logic. Their empirical results showed that the proposed neural fuzzy model leads to a better prediction of crisis. Significantly, the model can also construct a reliable causal relationship among the variables through the obtained knowledge base. Compared to neural network and the traditionally used techniques such as Logit, the proposed model can thus lead to a somewhat more prescriptive modeling approach based on determinate causal mechanisms towards finding ways to prevent currency crises. Cao (2012) has applied Choquet integral to ensemble single classifiers and proposes a Choquet integral-based combination classifier for financial distress early warning. Also, as the conditions between training and pattern recognition cannot be completely consistent, so he proposed an adaptive fuzzy measure by using the dynamic information in the single classifier pattern recognition results which is more reasonable than the static prior fuzzy density. Finally, a comparative analysis based on Chinese listed companies' real data is conducted to verify prediction accuracy and stability of the combination classifier. The experiment results indicated that financial distress prediction using Choquet integral-based combination classifier has higher average accuracy and stability than single classifiers [Cao (2012)]. Domestic literature about early warning system has been limited to Abounoori and Erfani (2006, 2008). They introduced an early warning system for monetary crisis in Iran and OPEC countries. We have not found any study concerning early warning system for high volatility in Tehran Stock Exchange.

2.3 Review of Financial Crisis

There are many studies that analyzed and forecasted financial crisis. We have surveyed some important studies as follows. Berkmen and et al. (2009) provided one of the first attempts at explaining the differences in the crisis impact across developing countries and emerging markets. Using cross-country regressions to explain the factors driving growth forecast revisions after the eruption of the global crisis, they have found that a small set of variables explain a large share of the variation in growth revisions. Countries with more leveraged domestic financial systems and more rapid credit growth tended to suffer larger downward revisions to their growth outlooks. For emerging markets, this financial channel trumped the trade channel. For a broader set of developing countries, however, the trade channel seems to have mattered, with countries exporting more advanced manufacturing goods more affected than those exporting food. Exchange-rate flexibility clearly helped in buffering the impact of the shock. There is also some weaker evidence that countries with a stronger fiscal position prior to the crisis were hit less severely. They have found little evidence for the importance of other policy variables. Chaudhuri and Klaassen (2001) examine whether the volatility has already come down to the level of years before the 1997-98 East Asian crisis. They used regime-switching model to account for possible structural change in the unconditional variance due to the Asian crisis. They found that in June 2000 the stock markets of Indonesia, South Korea, Malaysia, and Thailand, but not the Philippines, were still in the high-volatility regime initiated by the 1997-98 crisis. Hence, markets had not calmed down [Chaudhuri and Klaassen (2001)]. Lee and Teng (2009) have attempted to use MTS to build up a financial crisis early-warning model for Taiwan's companies in two phases; in which they firstly used MTS, logistic regression and neural network to establish the financial crisis early-warning model, followed by a comparative analysis of average accuracy rate of financial prediction in the second phase. Their results showed that the accuracy rate of financial crisis early-warning system established by MTS, logistic regression and neural network are 96.1%, 92.3%, and 96.1%, respectively, indicating that MTS provides greater application effect in predicting financial crisis. Chen and Guo (2011) have employed Z-Score value, which can be used to measure multinomial financial crisis index for forecasting, and utilizes Grey Markov forecasting for valuation. Based on the research results, the accuracy of the Grey Markov forecasting model is as expected, with excellent Z-Score, and the model can rapidly forecast the likelihood of firm financial crises. Their results can provide a good reference for government and financial institutions examining financial risk, and for investors in selecting investment targets. Xinli (2011) has used the global optimization of genetic algorithm to construct a genetic neural network model (GANN) forecasting listed company financial crisis. The model optimized input variables of neural network model forecasting financial crisis. Forecasting of financial distress of listed companies in Shanghai and Shenzhen A share markets indicated that this model bears a better ability to predict financial distress compared with ANN model.

3. Research Method

We have presented Markov Switching GARCH model for testing the hypothesis of the paper. The hypothesis of the paper is: Tehran Stock Exchange has calmed down after global financial crisis.

During the financial crisis (2007-2009) Tehran stock exchange has been in high volatility regime but it calmed down at 2009-2010 (after global financial crisis). In order to test the hypothesis, we have estimated transition matrix of MRSGARCH, so the Smoothed Probability in two regimes has been obtained. Smoothed probability indicates the position of TSE, whether high or low volatility. Also, we have presented an Early Warning System in order to forecast the state of volatility in TSE. Volatility forecasting is an important key in financial economics. Portfolio managers, option traders and market makers, all are interested in the possibility of forecasting volatility, with a reasonable level of accuracy.

3.1 Model Specification

The rate of return is calculated as following:

$$r_t = 100[\log(p_t) - \log(p_{t-1})], \tag{1}$$

in which p_t is the TSE index.

The main feature of regime-switching models is the possibility for some or all of the parameters of the model to switch across different regimes according to a Markov process, which is governed by a state variable, denoted s_t. The logic behind this kind of modeling is having a mixture of distributions with different characteristics, from which the model draws the current value of the variable, according to the more likely (unobserved) state that could have determined such observation [Marcucci (2005) and Klaassen (2002)].

We assumed that state variable is a first-order Markov chain, with the following transition probability:

$$Pr(s_t = j | s_{t-1} = i) = p_{ij} \tag{2}$$

that indicates the probability of switching from state i at time t-1 into state j at t. For simplicity, we have written the matrix concerning two regimes:

$$P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} = \begin{bmatrix} p & 1-q \\ 1-p & q \end{bmatrix} \tag{3}$$

The unconditional probability of being in state $s_t = 1$ is given by $\pi_1 = \frac{1-p}{2-p-q}$.

According to Marcucci (2005), the MRS-GARCH model in its most general form can be written as

$$r_t | \zeta_{t-1} \sim \begin{cases} f\left(\theta_t^{(1)}\right) & w.\ P.\, p_{1,t} \\ f\left(\theta_t^{(2)}\right) & w.\ P.\,(1 - p_{1,t}) \end{cases} \tag{4}$$

Where $f(\cdot)$ represents one of the possible conditional distributions that can be assumed, that is Normal (N), student's t or GED, $\theta_t^{(i)}$ denotes the vector of parameters in the i-th regime that characterize the distribution, $p_{1,t} = \Pr[s_t = 1 | \zeta_{t-1}]$ is the ex ante probability and ζ_{t-1} denotes the information set at time t-1. More specifically, the vector of time-varying parameters can be decomposed into three components [Marcucci (2005) and Klaassen (2002)].

$$\theta_t^{(i)} = \left(\mu_t^{(i)}, h_t^{(i)}, \nu_t^{(i)}\right) \tag{5}$$

Where $\mu_t^{(i)} \equiv E(r_t | \zeta_{t-1})$ is the conditional mean (or location parameter), $h_t^{(i)} \equiv Var(r_t | \zeta_{t-1})$ is the conditional variance (or scale parameter), and $\nu_t^{(i)}$ is the shape parameter of the conditional distribution. Hence, the family of density functions of r_t is a location-scale family with time-varying shape parameters in the most general setting [Marcucci (2005) and Klaassen (2002)].

In order to focus on volatility we have used a simple model as:

$$r_t = \mu_t^{(i)} + \varepsilon_t = \delta^{(i)} + \varepsilon_t \tag{6}$$

Where i=1, 2 and $\varepsilon_t = \eta_t\sqrt{h_t}$ and η_t is a zero mean, unit variance process. The conditional variance of r_t, given the whole regime path (not observed by the econometrician) $\tilde{s}_t = (s_t, s_{t-1}, \ldots)$, is $h_t^{(i)} = V[\varepsilon_t|\tilde{s}_t, \zeta_{t-1}]$. For this conditional variance the following GARCH (1,1)-like expression is assumed

$$h_t^{(i)} = \alpha_0^{(i)} + \alpha_1^{(i)}\,\varepsilon_{t-1}^2 + \beta_1^{(i)} h_{t-1} \tag{7}$$

Where h_{t-1} is a state-independent average of past conditional variances. Actually, in a regime switching context a GARCH model with a state-dependent past conditional variance would be infeasible.[18, 20] The conditional variance would in fact depend not only on the observable information ζ_{t-1} and on the current regime s_t which determines all the parameters, but also on all past states $\tilde{s}_{t-1}$[Marcucci (2005) and Klaassen (2002)]. This would require the integration over a number of (unobserved) regime paths that would grow exponentially with the sample size rendering the model essentially intractable and impossible to estimate [Marcucci (2005) and Klaassen (2002)]. Therefore, a simplification is needed to avoid the conditional variance be a function of all past states.

Cai (1994) and Hamilton and Susmel (1994) are the first to point out this difficulty by combining the regime switching approach with ARCH models only, thus eliminating the GARCH term in (7). They realize that many lags are needed for such processes to be sensible. To avoid the path-dependence problem, Gray (1996) suggests integrating out the unobserved regime path $\tilde{s}_{t-1}$in the GARCH term in (7) by using the conditional expectation of the past variance. Dueker (1997) uses a collapsing procedure in the spirit of Kim's (1994) algorithm to overcome the path-dependence problem, but he essentially adopts the same framework of Gray (1996). Klaassen(2002) suggests using the conditional expectation of the lagged conditional variance with broader information set than in Gray(1996). To integrate out the past regimes by also taking into account the current one, Klaassen(2002) adopts the following expression for the conditional variance

$$h_t^{(i)} = \alpha_0^{(i)} + \alpha_1^{(i)} \varepsilon_{t-1}^2 + \beta_1^{(i)} E_{t-1}\{h_{t-1}^{(i)} | s_t\} \quad (8)$$

Where the expectation is computed as

$$E_{t-1}\{h_{t-1}^{(i)} | s_t\} = \tilde{p}_{ii,t-1} \left[\left(\mu_{t-1}^{(i)}\right)^2 + h_{t-1}^{(i)} \right] + \tilde{p}_{ji,t-1} \left[\left(\mu_{t-1}^{(j)}\right)^2 + h_{t-1}^{(j)} \right]$$

$$-\left[\tilde{p}_{ii,t-1}\mu_{t-1}^{(i)} + \tilde{p}_{ji,t-1}\mu_{t-1}^{(j)}\right]^2 \quad (9)$$

And the probabilities are calculated as

$$\tilde{p}_{ji,t} = \Pr(s_t = j | s_{t+1} = i, \zeta_{t-1}) = \frac{p_{ji} Pr(s_t = j | \zeta_{t-1})}{Pr(s_{t+1} = i | \zeta_{t-1})} = \frac{p_{ji} p_{j,t}}{p_{i,t+1}} \quad (10)$$

Typically, in the Markov regime-switching literature maximum likelihood estimation is adopted to estimate the numerous parameters. [3,11] An essential ingredient is the ex-ante probability $p_{1,t} = Pr[s_t = 1 | \zeta_{t-1}]$, i.e. the probability of being in the first regime at time t given the information at time t-1, whose specification is [Marcucci (2005) and Klaassen (2002)].

$$p_{1,t} = Pr[s_t = 1 | \zeta_{t-1}]$$
$$= (1-q)\left[\frac{f(r_{t-1}|s_{t-1} = 2)(1 - p_{1,t-1})}{f(r_{t-1}|s_{t-1} = 1)p_{1,t-1} + f(r_{t-1}|s_{t-1} = 2)(1 - p_{1,t-1})}\right]$$
$$+ p\left[\frac{f(r_{t-1}|s_{t-1} = 1)p_{1,t-1}}{f(r_{t-1}|s_{t-1} = 1)p_{1,t-1} + f(r_{t-1}|s_{t-1} = 2)(1 - p_{1,t-1})}\right] \quad (11)$$

Where p and q are the transition probabilities in (3) and $f(\cdot)$ is the likelihood given in (4) [Marcucci (2005) and Klaassen (2002)].

Thus, the log-likelihood function can be written as

$$l = \sum_{t=1}^{T} log\left[p_{1,t} f(r_t | s_t = 1) + (1 - p_{1,t}) f(r_t | s_t = 2)\right] \quad (12)$$

Where $f(\cdot | s_t = i)$ is the conditional distribution given that regime i occurs at time t [Marcucci (2005) and Klaassen (2002)].

Another common finding in the GARCH literature is the leptokurtosis of the empirical distribution of financial returns [Marcucci (2005) and Klaassen (2002)]. To model such fat-tailed distributions researchers have adopted the Student's t or the Generalized Error Distribution (GED). Therefore, in addition to the classic Gaussian assumption, in what follows the errors ε_t are also assumed to be distributed according to a Student's t or a GED distribution. If a Student's t distribution with ν degrees of freedom is assumed, the probability density function (pdf) of ε_t, takes the form [Marcucci (2005) and Klaassen (2002)].

$$f(\varepsilon_t) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\pi}\Gamma\left(\frac{\nu}{2}\right)}(\nu-2)^{-\frac{1}{2}}(h_t)^{-\frac{1}{2}}\left[1+\frac{\varepsilon_t^2}{h_t(\nu-2)}\right]^{-\frac{(\nu+1)}{2}} \quad (13)$$

Where $\Gamma(\cdot)$ is the Gamma function and ν is the degree-of-freedom (or shape) parameter, constrained to be greater than two so that the second moments exist. With a GED distribution instead, the pdf of the innovations becomes [Marcucci (2005) and Klaassen (2002)].

$$f(\varepsilon_t) = \frac{\nu exp\left[-\frac{1}{2}\left|\frac{\varepsilon_t}{\lambda h_t^{\frac{1}{2}}}\right|^{\nu}\right]}{h_t^{\frac{1}{2}}\lambda 2^{\left(1+\frac{1}{\nu}\right)}\Gamma\left(\frac{1}{\nu}\right)} \quad (14)$$

With $\lambda \equiv \left[\frac{2^{-\frac{2}{\nu}}\Gamma\left(\frac{1}{\nu}\right)}{\Gamma\left(\frac{3}{\nu}\right)}\right]^{\frac{1}{2}}$, where $\Gamma(\cdot)$ is the Gamma function, ν is the thickness-of-tail (or shape) parameter, satisfying the condition $0 < \nu \leq \infty$ and indicating how thick the tails of the distribution are, compared to the normal. When the shape parameter $\nu = 2$, the GED becomes a standard normal distribution, while for $\nu < 2$ and $\nu > 2$ the distribution has thicker and thinner tails than the normal respectively[Marcucci (2005) and Klaassen (2002)].

To estimate the model, we 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 as shown in (12). 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.

3.2 Data Description

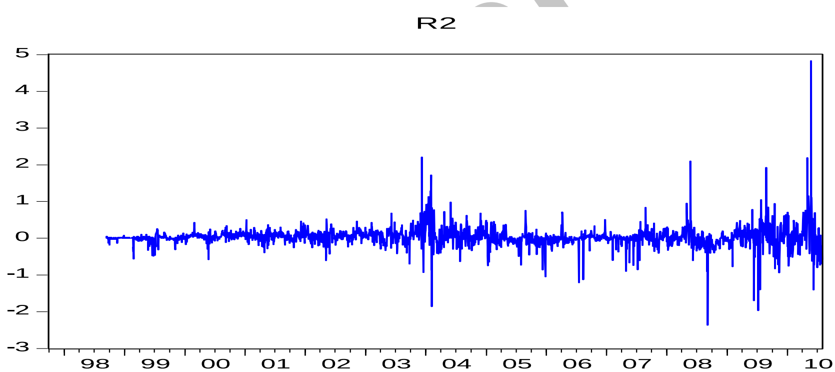
Trading in Tehran Stock Market (TSM) is based on orders sent by the brokers. Trading days in week are: Saturday, Sunday, Monday, Tuesday, and Wednesday except national holidays. The data consist of 3067 daily observations of the closing value of the Tehran stock market from 09/29/1997 to 09/09/2010. 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 TSM 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.

Table 1: Descriptive Statistics r_t

Mean	St. Dev	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]	[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 statistic 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 TSM returns up to the twelfth order.



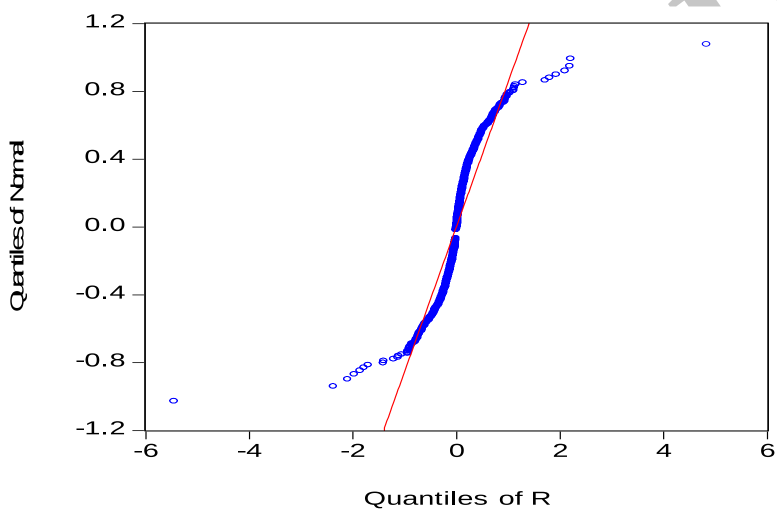
Plot 1. The rate of return series

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	

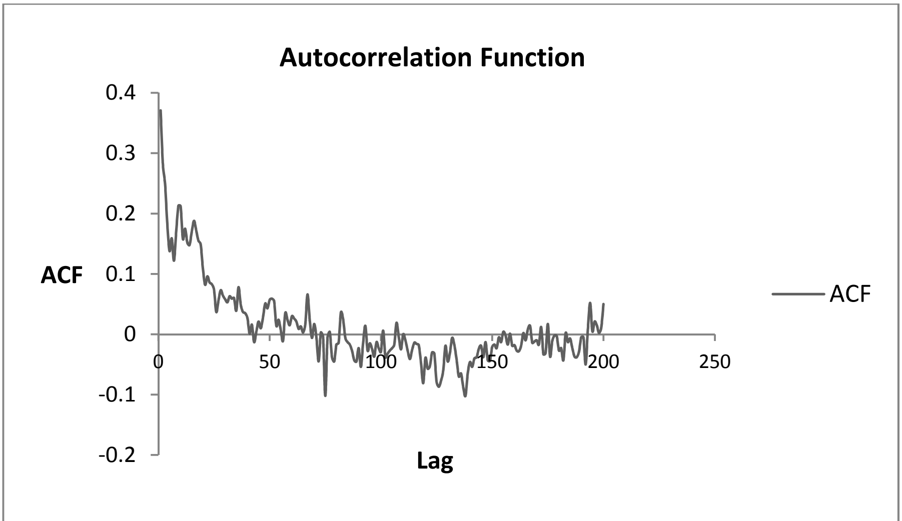
Table 2 shows the unit root tests for the TSE rate of return, R(t). Results indicate that the rate of return series has not unit root. So, the rate of return series is a stationary process.

The Quantile-quantile plot of R(t) distribution against Gaussian PDF with the same mean and standard deviation is depicted in Plot 2. If the PDF of returns was gaussian, all points should have fallen on a straight line. It is seen that the gaussianity is not a good approximation of this distribution and the tails are much fatter than the gaussian distribution and therefor displays the leptokurtic behavior of the returns.



Plot 2. Quantile-quantile plot of R(t) distribution against Gaussian PDF with the same mean and standard deviation

Also autocorrelation is a commonly used method for checking randomness in a data set. This can be seen in Plot 3.



Plot 3. Autocorrelation Function for Rate of Return Series

Note: All of the P-Values for the Ljung-Box test for these 200 lags were zero. If the time series is random, the autocorrelations should be near zero for any and all time lag separations. Otherwise then, one or more of the autocorrelations will be significantly non zero.

Plot 3 indicates the rate of return has a memory of several trading days. There is an evidence of considerable positive autocorrelation for the values of lag < 40, after which the autocorrelations are at the level of noise. The autocorrelation function of the modulus time series displays a very long term memory. This indicates that the volatility is clustered in time.

4. Empirical Results

The estimated parameter concerning MRS-GARCH models are presented in Table 3. Both the models with constant degrees of freedom and the one where the degrees-of-freedom parameters are allowed to switch between the two regimes show highly significant in-sample estimates. The conditional mean estimates and the conditional variance parameters are all significant. The estimates confirm the existence of two states: the first regime is characterized by a low volatility and almost nil persistence of the shock in the conditional volatility, whereas the second one reveals high volatility and a higher persistence. The transition probabilities are all significant, showing that almost all regimes are particularly persistent in MRS-GARCH with t-student and GED distributions, but in MRS-GARCH with normal distribution, there is an absorbing regime in low volatility regime. Table 3 also reports the unconditional probabilities for each MRS-GARCH model. The unconditional probability π_1 of being in the first regime, ranges between 14% for the model with Gaussian innovations and 61% for the model with t-student innovations.

For the Student's t version of the MRS-GARCH with constant degrees of freedom across regimes, the shape parameter is below four, indicating the existence of conditional moments up to third. This means that by allowing state-dependent parameters, it is possible to model most of the leptokurtosis in the data. In the GED case the $\boldsymbol{\nu}$ parameter is below the threshold value of 2, showing that the distribution has thicker tails than the normal.

The MS-GARCH model with Student's t innovations is presented in the version in which the degrees of freedom are allowed to switch, implying a time-varying kurtosis as in Hansen (1994) and Dueker (1997). While Hansen suggests a model in which the Student's t degrees-of-freedom parameter is allowed to vary over time according to a logistic function of variables included in the information set up to time t-1, and Dueker allows only such a parameter to be state-dependent, in this paper, according to Marcucci (2005), the degrees-of-freedom parameter is allowed to switch across regimes together with all the other parameters.

Table 3: MLE of MS-GARCH Models with different Conditional Distributions

	MRS-GARCH-N	MRS-GARCH-t	MRS-GARCH-GED
$\boldsymbol{\delta^{(1)}}$	0.03302	0.23794	0.22917
p-value	0.01	0.04	0.03
$\boldsymbol{\delta^{(2)}}$	-0.0296	-0.00803	0.0
p-value	0.00	0.02	0.02
$\boldsymbol{\alpha_0^{(1)}}$	0	0.0024	0.07682
p-value	0.03	0.04	0.00

	MRS-GARCH-N	MRS-GARCH-t	MRS-GARCH-GED
$\boldsymbol{\alpha_0^{(2)}}$	0.45989	0.02056	0.00003
p-value	0.05	0.06	0.02
$\boldsymbol{\alpha_1^{(1)}}$	0.4988	0.11501	0.83863
p-value	0.00	0.01	0.03
$\boldsymbol{\alpha_1^{(2)}}$	0.63258	0.7954	0.20352
p-value	0.00	0.05	0.04
$\boldsymbol{\beta_1^{(1)}}$	0.27144	0.88403	0.00351
p-value	0.03	0.00	0.00
$\boldsymbol{\beta_1^{(2)}}$	0.33881	0.16614	0.7962
p-value	0.02	0.00	0.00
p	0.83821	0.96049	0.93477
p-value	0.00	0.00	0.00
q	0.0	0.97465	0.95597
p-value	0.00	0.00	0.00
$\boldsymbol{\nu^{(1)}}$	-	3.31724	0.74701
p-value		0.01	0.00
Log (L)	-809.79925	-580.6226	-568.81478
N. of Par.	10	11	11
$\boldsymbol{\pi_1}$	0.14	0.61	0.60
$\boldsymbol{\pi_2}$	0.86	0.39	0.40

4.1 An Early Warning System for High Volatility in TSE: Policy Implication

In order to modeling the high volatility concerning Tehran Stock Exchange we have estimated Markov Switching GARCH model. So, we have obtained transition matrix of probability. Using this matrix, we have estimated forecasted probabilities regarding high and low volatility regime in TSE for future horizons. Thus, the policy makers can develop a suitable policies controlling high volatility in TSE based on the early warning system.

The Akaike Information Criterion (AIC) and the Schwarz Criterion (BIC) both indicate that the best model among the MRS-GARCH models is the MRS-GARCH with GED distribution that fits the best. So, we have used this model for modeling Early Warning System.

We have introduced the Early warning System following the models:

$$r_t|\zeta_{t-1} \sim \begin{cases} f\left(\theta_t^{(1)}\right) & w.\ P.\, p_{1,t} \\ f\left(\theta_t^{(2)}\right) & w.\ P.\, (1-p_{1,t}) \end{cases}$$

$$f(\varepsilon_t) = \frac{\nu exp\left[-\frac{1}{2}\left|\frac{\varepsilon_t}{\lambda h_t^{\frac{1}{2}}}\right|^{\nu}\right]}{h_t^{\frac{1}{2}}\lambda 2^{\left(1+\frac{1}{\nu}\right)}\Gamma\left(\frac{1}{\nu}\right)}$$

$$\mathrm{h}_\mathrm{t}^{(\mathrm{i})} = \alpha_0^{(\mathrm{i})} + \alpha_1^{(\mathrm{i})}\varepsilon_{t-1}^2 + \beta_1^{(\mathrm{i})}h_{t-1}$$

$$P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} = \begin{bmatrix} 0.93 & 0.04 \\ 0.07 & 0.96 \end{bmatrix}$$

The value 0.93 is the probability of transition from low volatility to low volatility, 0.07 is the probability of transition from low volatility to high volatility, 0.04 is the probability of transition from high volatility to low volatility and 0.96 is the probability of transition from high volatility to high volatility.

In order to calculate the transition matrix for *m* period ahead, we can multiply the transition matrix by *m* multiple. In other word:

$$P_{t+m} = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix}^m = \begin{bmatrix} 0.93 & 0.04 \\ 0.07 & 0.96 \end{bmatrix}^m$$

Using this matrix, we have estimated the forecasted probabilities concerning high and low volatility regime in TSE for future horizons as shown in Figure 1.

Figure 1. Smoothed Probability in two regimes

Smooth 1 is forecasted probability in the high volatility regime and smooth 2 is forecasted probability in low volatility regime for 2008- 2010 period.

The system above is an early warning system forecasting high volatility in Tehran stock exchange. The system can be used to predict the volatility crisis in Tehran stock exchange concerning future periods.

Why we need to forecast Volatility and EWS for it?

Volatility is the most important variable in pricing derivative securities, whose trading volume has quadrupled in recent years. To price an option, we need to know the volatility of the underlying asset from now until the option expires. In fact, the market convention is to list option prices in terms of volatility units. Nowadays, one can buy derivatives with known estimated volatility, in which case the definition and measurement of volatility will be clearly specified in the derivative contracts. So volatility forecast and a second prediction on the volatility of volatility over the defined period is needed to price such derivative contracts. Financial risk management has taken a central role since the first Basle Accord was established in 1996. This effectively makes volatility forecasting a compulsory risk-management exercise for many financial institutions around the world [Poon and Granger (2003)]. Also, financial market volatility can have a wide repercussion on the economy as a whole. The incidents caused by the terrorists' attack on September 11, 2001, and the recent financial crisis in the United States have caused great turmoil in financial markets on several continents and a negative impact on the world economy. This is clear evidence of the important link between financial market uncertainty and public confidence. For this reason, policy makers often rely on market estimates of volatility as a barometer for the vulnerability of financial markets and the economy. In the United States, the Federal Reserve explicitly takes into account the volatility of stocks, bonds, currencies, and commodities in establishing its monetary policy [Sylvia Nasar 1992]. The Bank of England is also known to make frequent references to market sentiment and option implied densities of key financial variables in its monetary policy meetings [Poon and Granger (2003)].

Has Tehran Stock Exchange Calmed Down after Global Financial Crisis?

The hypothesis here has been that "Tehran Stock Exchange has calmed down after global financial crisis." Estimation results indicate that during the financial crisis (2007-2009) Tehran stock exchange had been in high volatility regime: smoothed probability of high volatility has been between 0.8 and 0.95 while smoothed probability of low volatility is between 0.0 and 0.2. This situation has calmed down at 2009-2010-after global financial crisis-(smoothed probability turned to low volatility regime because smoothed probability of high volatility is between 0.6 and 0.8). In this period, TSE has been in low volatility regime (smoothed probability of low volatility is between 0.2 to 0.4). During the crisis period, Tehran stock exchange was in the high-volatility regime. Smoothed probability plots show that the volatility in 2007-2009 was in high volatility regime but at 2009-2010, Volatility turned to low volatility regime.

5. Conclusion

The volatility of financial markets has been the object of numerous developments and applications over the past two decades, both theoretically and empirically. Portfolio managers, option traders and market makers all are interested in the possibility of forecasting volatility with a reasonable level of accuracy. That is important, in order to obtain either higher profits or less risky positions. In this respect, the most widely used class of models is that of GARCH models [Poon, S. H., and Granger, C. W. (2003)]. Given the important role of volatility forecasting and that so much has been written on the subject, this paper aims to introduce an early warning system for the high volatility Tehran Stock Exchange. Also, we have examined whether Tehran Stock Exchange has calmed down or more specifically, whether the surge in volatility during 2007-2010 global financial crises still affects stock return volatility in the year 2010. We have used a regime switching GARCH model. This model allows for the possibility that the crisis has caused a temporary rise in the unconditional variance of stock returns (switch from a low to a high-volatility regime) and it uses GARCH dynamics to govern the conditional variance within a regime. The model is more flexible regarding the volatility persistence of shocks than standard single-regime GARCH, which is important given the focus of the paper. The data consist of 3067 daily observations of the closing value of the Tehran stock market from 09/29/1997 to 09/09/2010.

During the crisis period, Tehran stock exchange was in the high-volatility regime. Smoothed probability plots show that the volatility in 2007-2009 was in high volatility regime but at 2009-2010, volatility turned to low volatility regime. Also, we have introduced an Early Warning System for forecasting high volatility in Tehran Stock Exchange. Volatility forecasting is very important for policy makers because financial market volatility can have a wide repercussion on the economy as a whole. Also, the recent financial crisis in the United States has caused great turmoil in financial markets on several continents and a negative impact on the world economy. This is clear evidence of the important link between financial market uncertainty and public confidence. For this reason, policy makers often rely on market estimates of volatility as a barometer for the vulnerability of financial markets and the economy.

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