Article
ECORFAN-Mexico Journal
June 2018 Vol.9 No.20 53-65

Volatility clustering and its asymmetry and leverage effect in the Tehran Stock Exchang

Agrupamiento de volatilidad y su efecto de asimetría y apalancamiento en la Bolsa de Teherán

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Received January 25, 2018; Accepted June 12, 2018

Abstract

The objective of the present study is investigation of the volatility clustering and it's asymmetry and leverage effect in Tehran stock exchange. Great changes in prices intend to changes and small changes intend to small changes, that is named volatility clustering. On the other hand the higher return volatility intend to more clustering in comparison to small volatility that is named volatility asymmetry. The asset return volatility can effect on the exchange options price and stock risk and portfolio, this is an applied and quantitative research. The population is Tehran stock exchange Total index(TEDPIX) and the used sample is time series of Total index return(R-TEDPIX) in time span of the 2008 to 2017. Data was extracted by Rahavarde Novin software and then the logarithmic return was calculated and was analyzed by Eviews software. According to box and Jenkins, the average equation ARMA was prepared and the existence of volatility clustering was confirmed. The TGARCH model shows the asymmetry in volatility and leverage effect. Considering the Akaike statistic for the best model of GARCH family, ETGARCH was introduced for volatility extraction.

Volatility Clustering, Asymmetry, Leverage Effect

Resumen

El objetivo del presente estudio es investigar el agrupamiento de volatilidad y su efecto de asimetría y apalancamiento en la bolsa de Teherán. Los grandes cambios en los precios pretenden cambios y los pequeños cambios pretenden pequeños cambios, que se denomina agrupamiento de volatilidad. Por otro lado, la mayor volatilidad de retorno pretende una mayor agrupación en comparación con la pequeña volatilidad que se denomina asimetría de volatilidad. La volatilidad del rendimiento de los activos puede afectar el precio de las opciones de cambio y el riesgo de acciones y cartera, esta es una investigación aplicada y cuantitativa. La población es el índice total de la bolsa de Teherán (TEDPIX) y la muestra utilizada es la serie temporal de retorno del índice total (R-TEDPIX) en el lapso de 2008 a 2017. Los datos fueron extraídos por el software Ravinvar Novin y luego se calculó el retorno logarítmico y fue analizado por el software Eviews. De acuerdo con Box y Jenkins, se preparó la ecuación promedio ARMA y se confirmó la existencia de agrupamiento de volatilidad. El modelo TGARCH muestra la asimetría en la volatilidad y el efecto de apalancamiento. Teniendo en cuenta la estadística de Akaike para el mejor modelo de la familia GARCH, ETGARCH se introdujo para la extracción de volatilidad.

Agrupamiento de Volatilidad, Asimetría, Efecto de Apalancamiento

Citación: SHIRAZIAN, Zahra, NIKOUMARAM, Hashem, RAHNAMAY-ROODPOSHTI, Fraydoon and TORABI, Taghi. Volatility clustering and its asymmetry and leverage effect in the Tehran Stock Exchang. ECORFAN Journal-Mexico 2018, 9-20: 53-65.

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Introduction

One of the most popular characteristics of financial asset returns is volatility clustering (the great changes in prices intend to great changes and small changes intend to small changes). On the other hand the more volatility in return intend to creating more clustering in comparison to small volatility that is named volatility clustering (the high volatility follow high volatility and low volatility follow low volatility). This model of volatility clustering is very important in financial market since the asset return volatility can effect on the exchange options price and stock risk and portfolio directly and can predict the variance.

The statistic properties study of financial market data show some facts that are conventional in different markets such as asset return wide distribution, extra volatility, un autocorrelation in returns, volume correlation with volatility and volatility clustering. Financial asset such as interest rate have volatility clustering property. Many of statistic models such as GARCH, ARCH and multi fractional models were used by Mandelbrot for volatility clustering study. For example GARCH models as the first study models had this property that lead to volatility clustering phenomenon that is named GARCH effect.

These models assume that the volatility clustering have been created by an external resource. For example the random news clustering in the market and it's agents reaction. The asset volatility is an instrumental property for measuring the risk and is effective in agents investment decisions and need to more extract studies. What lead to volatility clustering, the literature insist on market psychology role or investor feeling. The other studies indicate that the investors are related to the positive and negative waves and create a momentum that lead to volatility clustering. The literature insist on market psychology role or investor feeling.

The other studies indicate that the investors are related to the positive and negative waves and create a momentum that lead to distance prices from their basic temporally. The agent based models try to describe the observed behavior resource of market prices by means of market participants. While the econometric discuss the volatility dependency in short term or long term. The agent based models present a useful part for econometric analysis.

Explanation of the theory scientific in relation to the subject and volatility clustering identify and it's asymmetry in Tehran stock exchange is the main objective of this study that was done in financial knowledge growth field through theoretical bases identify and new models and procedures and help and synergy of science and knowledge in financial area and obtaining the scientific objective in financial field.

Theoretical literature review

Mandelbrot (1963) and Fama (1965) found that high price changes is followed by high price changes and low price changes are followed by low price changes (volatility clustering). One method for volatility clustering illumination is using of the ARCH, GARCH and Engel (1982) models that was developed by Nelson (1991). Engel stated that the volatility clustering originate from the obtained news and information clustering in the financial market. The volatility clustering is asymmetric in asset returns series since the high volatility more than low volatility intend to creating the clustering, with investigation of the volatility clustering persistence in the returns series , the obtained results indicate that the clusters in many of returns series volatility intend to more stability and even after 40 days is not separated from each other.

These findings support from the long-term memory in return volatility. Many research have studied the volatility clustering in financial markets by GARCH models such as Danberg (2003) that identified the important GARCH effect in monthly levels that was proved with Mont Carlo simulation. During several years the price behavior for economic financial experts played an important role. In this area some of primary studies support from prices random step behavior (Fama 1965, Samuelson 1965).

Recently the economists assigned high importance to asymmetric distributions modeling and time series residual heavy -tailed and investigated these properties in many of experimental studies. As a sample of this method in modeling the option pricing (fang and lai, 1997), the capital asset pricing (Harvey and Siddique, 2000) and risk reward (smith, 2006) were used and since the remaining of the financial time series include extra skewness and skewness ,usage of Gaussian distribution (or normal distribution) hypothesis for inclusion of the heavy -tailed or return extension is not suitable for residuals heavy –tailed and skewness.

Property of returns may experimental studies have developed the GARCH family models by different distribution of Belerso (1978) include date return extra extension. In addition t-student extension distribution of Lambert and Lorentz (2001) have ability of including the asymmetric distribution and return heavy -tailed. Accordingly the researchers such as Bourmaty et.al (2007) and Tang et.al (2006) have used of non-Gaussian distribution by means of GARCH family models and have used of the studies in abnormal distribution in the ARFEMA-FIGARCH model such as Kang and Vion (2007) and Kasman and Toron (2008) that showed that ARFIMA-FIGARCH with t-student skew distribution presents a better modeling about binary long-term memory in comparison to normal distribution.

The negative news create more shock in comparison to the positive news, and as a result create more volatility that is called leverage effect. Creasty (1982) was the first researcher that investigated the leverage effect. Considering this fact that the stock price changes is the main agent of change toward the leverage. Creasly for examination of the leverage effect tested the relationship of the previous stock return with the volatility changes of the current period by following equation:

$\Delta Ln\boldsymbol{\sigma}t=\alpha 0+\alpha 1Rt\text{-}1+et$

In this equation Rt is stock return and t is standard deviation in t period . If the leverage effect be existed and the stock return be decreased ,the stock volatility will be increased in next period and vice versa. Therefore negativity of coefficient will confirm the leverage effect. Creasty tested his model by data of 400 American companies during the time period of 1962-1987. The obtained results were agreeable with this theory. 1α was obtained by Total index of the companies as 0 , 23. After introduction of conditional variance different auto regression model ARCH by Angel (1982) and a Total model of GARCH by Belersoo (1986) the investigation of the relationship between current period return with the current period expectation was possible instead of examination of the effect of the previous period return effect on the current period volatility (Creasty model).

Accordingly in examination of leverage effect the effectiveness of stock return on the stock exceptional volatility was examined. Many of evidences indicate that the leverage effect is effective in prices decrease. In other words the prices decreasing is more effective in volatility changes. This subject has developed GARCH asymmetry models usage for leverage effect. In the threshold ARCH test the test model by means of the virtual variables considers the stock asymmetry volatility.

In the leverage effect in return increase and decrease impulses present differed behavior this can be one of the main reasons of volatility asymmetry in the stock market. Bekert and Harvy (1997) with investigation of the relationship between the return and stock volatility by means of monthly data of some of new markets have recognized the leverage effect in volatility asymmetry toward return impulse, but the results of Bekret and Voo (20000)indicated that in the Tokyo stock exchange the asymmetry of volatility is not related to leverage effect. Figlosky and Wang (2000) also investigated the asymmetrical behavior of the leverage effect. They tested their New York stock market. Boo ,chayed and Androo and Ponter (2001) studied the leverage effect consistency rate in America, Europe. In the present research they estimated the stock future volatility with the previous prices change. Almost in all of the markets the negative correlation of markets between stock return and stock volatility has been confirmed.

This correlation in America market is more extreme than other markets. Also in the present research it has been showed that the leverage effect has an average rate in the companies and is stable for some month. While this effect is more insensitive in the market it loses its stability rapidly. Tabak and Gooaran (2002) tested the leverage effect by means of Brazil market stock Total index and the prices of 25 companies in time return of 1990-2002.

They used of exponential GARCH method in this research. The test results finally confirmed the leverage effect in Brazil stock exchange. They indicated that when the leverage effect rate is small its durability is more during the time. Vercheneo (2002) in his research used of different models for investigation of the leverage effect. He proved that the exponential GARCH model is more suitable for examination of the leverage effect in comparison to other methods. Verchenco investigated the relationship between stock return and stock volatility.

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682

But this relationship only was significant in half of it thus the leverage effect is confirmed in low number of markets. In the other cases the positive relationship between stock return and its volatility was observed this relationship was only significant in one case. Mehrava and Abdoli 2006 investigated the role of good and bad news in stock return volatility by means of different models of ARCH and GARCH families. The result of this study show that the news effect is asymmetric montmeny and Abonouri 2007 have done a study under the title of “investigation of the leverage effect in Tehran stock exchange. By means of exponential GARCH model and daily time series they examined the leverage effect during the time period of 1992-2006. The stock volatility asymmetry and leverage effect existence confirmed the good and bad news in Tehran stock exchange.

According to stock return leverage effect the stock has a negative effect on the stock volatility. Mohammadi et al 2009 showed that the GARCH models have many abilities in modeling some of Tehran stock exchange market volatility such as leverage effects and long-term memory. They showed that there is a positive relationship between risk and return in portfolio all of the companies in Tehran stock exchange of 50 companies with high cash. Roya Ale Emran in a study under the title of investigation of the volatility process of Tehran stock exchange during the time span of 77-78 concluded that the highest level of volatility and instability in 2003 and after that in 2007 had accrued.

Alfaranoo and Lax (2001) found that there is herd behavior between the market participations mitigate the market return distribution and obtained the heavy-tailed property of the volatility clustering in the financial markets. Yomamoto (2018) used of agent based model for doing simulation in the artificer stock exchange.

Engel and Peten (2001) by means of daily data during 23 years of Daw Jones industrial index predicted the vitality in this index by means of GARCH model (1 ,1). They showed that this index is returning to an average and the effect of shock is loosed after almost 100 days. They also showed that this index has leverage effects thus the asymmetric GARCH models should be used for modeling. Salim (2007) examined the Pakistan Karachi stock exchange.

GARCH model was used for investigation of different volatility and their durability and EGARCH was used for investigation of the leverage effect. The results showed that the positive returns have more volatility in comparison to the negative return and the previous residuals have high effect on the current volatility. Gabich in a study under the title of measurement of volatility clustering in stock exchange market (2007) referred to the GARCH method for description of clustering behavior in complex time series.

He says that the effect of volatility clustering by means of GARCH model decreases the volatility clustering significantly, he considered the 500 s &p index from 1995 to 2004 in 5 minute distances and the stock of 28 industries with high cash from 1993 -2002. Alberge et al (2008) estimated the stock market volatility by means of asymmetric GARCH models and used of GARCH, E-GARCH and GJR models. They concluded that GARCH models with skew t-student distribution has been better than other models in Israel stock exchange.

Park showed that herd behavior leads to high increasing in volatility not in exchanges volume. Eminc (2010) investigated the volatility clustering, extension and leverage effect for Nigeria stock exchange return series. By means of GARCH (1 , 2) he found that there is return volatility in Nijeria stock exchange.

By means of model GjR GARCH(1 , 1) the Nigeria stock exchange was recognized. The study that was done by floor (2008) investigated the Egypt stock exchange by means of Egypt stock exchange index daily data. By different GARCH model volatility clustering and board leverage effect the bad news of volatility is increased.

Terpaty et al (2001) in research under the title of “India stock exchange market dynamic analysis” by means of, GARCH, ARCH, EGARCH and TARCH studied the relationship between leverage effect and stock return and exchange volume and volatility for 30 stock from Bombay stock market from time periods January 2005 to June 2009. The results of the research indicate that the effect of ARCH in residuals is existed and stocks and volatility in the market are permanent. Also there is leverage and asymmetric effects in the Bombay stock exchange and bad news have more effect on the exchange and volatility volume in market and asymmetric GARCH models fitting the market conditions better than symmetric GARCH models.

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682

In research under the title of asymmetric volatility in India stock exchange Hojatollah Goodarzi in 2011 investigated good and bad effect on volatility in India stock exchange by means of asymmetric models of ARCH during the years of 2008-2009 of world financial crisis and used of EGARCH and TGARCH and concluded that there is leverage effect in India stock exchange in other words the negative news has more effect on the returns volatility in comparison to positive news with the same rate. Mostafaei et al and Sakhabakhsh (2011) examined the DFA method by means of DFA method and by means of test rate in ARFIMA model predicted open oil price.

Maliba et al (2014) predicted the Bombay stock index volatility. In this study three models of GARCH (1 , 1), EGARCH (1,1) and GGR during the time span of 2010 and 2014 were used. The results of the findings indicate that there is volatility clustering and return to mean behavior and volatility consistency and leverage effect. In research under the title of volatility clustering in junsberg stock exchange that was done by Tevary (2013) GARCH model was used for volatility clustering examination and it was found that the negative shocks have more volatility in comparison to positive shocks on stock prices. He found that there is an asymmetry of negative and positive shocks in the stock exchange. He found that there is volatility clustering and it's asymmetry in stock exchanges by means of GARCH model.

In a study under the title of "what asset return volatility is asymmetric ? that was done by NIG (2015) copula approach was used. By means of daily crenel volatility stock data and high frequency markets were used. And found that the volatility clustering in nonlinear and is asymmetric in the clusters with high volatility and clusters with low volatility. On the other hand volatility clusters were stable for more than one month and during different time periods are asymmetric.

Research methodology

The present research is an applied, quantitative and empirical study. The population is Tehran stock exchange Total index time series(TEDPIX) and the used sample is time series of Total index return(R-TEDPIX) from period of 2008-2017. For compilation of the study theoretical bases the library method was used.

The index rates were extracted from Rahavarde Novin software and then logarithmic return was calculated by the following equation and was analyzed by Eviews software.

$$\boldsymbol{rt} = \boldsymbol{ln}(\frac{Pt}{Pt-1}) \qquad (1)$$

Autoregressive models

When time series coefficients are not zero, random interval variables X have useful data for time series modeling {X_t}. The first-order auto-regression model (AR (1)) is displayed as follows:

$$X_t = \phi_0 + \phi_1 X_t + a_t \qquad (2)$$

Here {a_t} is a white noise process with mean zero and the variance σ_a ^ 2. This model is a simple linear regression model. Where X_ (t-1) is an explanatory variable and X_t is an explanatory variable. In this model we have the condition X_ (t-1):

$$E(X_t|X_{t-1}) = \phi_0 + \phi_1 X_{t-1} \qquad (3)$$
$$V(X_t|X_{t-1}) = V(a_t) = \sigma_a^2$$

That is, with respect to the value X_ (t-1), the value of X_t is equal to the value of φ_0 + φ_1 X_ (t-1) with the standard deviation σ_a. In many cases, only the value X_ (t-1) is used to determine the conditional math expectation X_t It is not enough, so the generalized AR (1) model is represented by AR (p) as follows:

$$X_t = \phi_0 + \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + a_t \qquad (4)$$

This model shows that the previous values of the variables X_ (t-i) (i = 1, ..., p) determine the conditional mathematical expectation X_t. (Alexander, 2008).

Moving Average Model

One of the simplest time series models is the moving average models. If we assume a_t (t = 1,2,3, ...) is a white noise process with E (a_t) = 0 and V (a_t) = σ ^ 2, then the MA (q) model is shown as:

$$X_t = \mu + a_t + \theta_1 a_{t-1} + \cdots + \theta_q a_{t-q} \qquad (5)$$

The MA model is a linear combination of white noise processes, so the value of X_t depends on the values of the present and the present time of the white noise processes.

Autoregressive and Moving Average Models

In many respects, the AR and MA models described in the previous sections may in practice encounter a lot of problems. Because if we want to estimate a large-scale model, we need to estimate many parameters. In order to solve these problems, the moving average motion automation models were introduced by Box, Jenkins and Rieselles in 1994.

In fact, the ARMA model combines the idea of AR and MA models, and at the same time does not increase the parameters of the model. The mathematical representation of an ARMA model (1.1) is as follows:

$$X_t - \phi_1 X_{t-1} = \phi_0 + a_t + \theta_1 a_{t-1} \tag{6}$$

Here a_t is a white noise process. The left part of the equation is AR (1) and the right side of the MA (1) model. In general, the ARMA model (p, q) is displayed as follows:

$$X_t = \phi_0 + \sum_{i=1}^{p} \phi_i X_{t-i} + a_t + \sum_{i=1}^{q} \theta_i a_{t-i}$$

Conditional heterogeneity models

Moving average models for estimating fluctuations are based on the assumption that asset returns are iid. So the oscillation estimates and the correlation coefficient obtained from these models are equal to those estimated for the time being. The fluctuation in the return on financial assets varies over time, and it is assumed that the distribution of return on assets in a simplistic hypothetical practice.

There is plenty of evidence and evidence showing that fluctuations in financial markets tend to be clustered, and the roots of work done in this area are back to Mandelbrot (1963). Clusters of fluctuations have a great impact on risk measurement and management. Variance variance models are considered in cluster variance models. Also, the estimates made from these models are not equal to the estimated values of the present, and may be greater or less than they are.

Autoregressive conditional heterogeneity variance model

In the classical econometric model, the constant of defective sentences is always one of the main assumptions of econometrics. Robert Engel (1982), in order to emancipate this limited assumption, established a new method called ARCH. In this method, it is assumed that the random terms have a mean of zero and serially non-interconnected, but its variance is assumed with the assumption of its past information. Because in this model, the positive and negative shocks of the market (a_t) are of the same importance, it is said to be symmetric. The main idea of the ARCH model is that market shocks do not have a serial solidarity, but are interdependent and their dependence can be modeled by a second degree function of their interruptions. This model is displayed as follows:

$$\begin{aligned} &\sigma_t^2 = \omega + \alpha_1 a_{t-1}^2 + \alpha_2 a_{t-2}^2 + \cdots + \alpha_m a_{t-m}^2 \\ &a_t = \sigma_t \varepsilon_t \\ &\varepsilon_t \sim iid(0,1) \end{aligned} \tag{8}$$

The model is called ARCH (m). In practice, it is assumed that the distribution ε_t is normal or t-studio or .... As highlighted in the model structure, large quantities of previous market shocks increase the conditional variance of a_t. That is, in the ARCH model, large shocks tend to be shaky. To illustrate the features of this model and the models introduced in the next sections, we use them first. The first order of the ARCH model is as follows:

$$\begin{aligned} &a_t = \sigma_t \varepsilon_t \\ &\sigma_t^2 = \omega + \alpha_1 a_{t-1}^2 \end{aligned} \tag{9}$$

To ensure the conditional variance is positive, variations in the equation of variance must be applied. In this model, the limits of the mean equation coefficients are 0> ω and α_1≥0. The mean and non-regular variance a_t are obtained as follows:

$$\begin{aligned} &E(a_t) = E[E(a_t|\Omega_{t-1})] = E[\sigma_t E(\varepsilon_t)] = 0 \\ &V(a_t) = E(a_t^2) = E[E(a_t^2|\Omega_{t-1})] \\ &= E(\omega + \alpha_1 a_{t-1}^2) = \omega + \alpha_1 E(a_{t-1}^2) \end{aligned} \tag{10}$$

Since V (a_t) = E (a_ (t-1) ^ 2) = ω / (1-α_1), therefore, to ensure the positivity of the variance, α_1 <1.

ISSN-Print: 2007-1582- ISSN-On line: 2007-3682

To estimate this model, different exponential functions are used based on the distribution of ε_t. Assuming the distribution of ε_t is normal, the function of the ARCH model (m) is as follows:

$$f(a_1,\dots,a_T|\alpha) = f(a_T|\Omega_{T-1})f(a_{T-1}|\Omega_{T-2})\dots f(a_{m+1}|\Omega_m)f(a_1,\dots,a_m|\alpha) = \prod_{t=m+1}^{T} \frac{1}{\sqrt{2\pi\sigma_t^2}}exp\left(-\frac{a_t^2}{2\sigma_t^2}\right) \times f(a_1,\dots,a_m|\alpha) \quad (11)$$

Here α = (ω, α_1, ..., α_m) and f (a_1, ..., a_T | α) are the joint density function α_1, ..., α_m. The exact form of the complex density function is complex, so when the sample size is large, the high density function is eliminated. The result of the conditional exponential function is the following:

$$ln\,(a_{m+1},\dots,a_T|\alpha,a_1,\dots,a_m) = \sum_{t=m+1}^{T} \left[-\frac{1}{2}ln\,(2\pi) - \frac{1}{2}ln\,(\sigma_t^2) - \frac{1}{2}\frac{a_t^2}{\sigma_t^2}\right] \quad (13)$$

Since the expression ln (2π) has no parameters, the above function converts to the following function:

The symmetric normal GARCH model : This model, which is the generalized ARCH model of the parasite, was introduced by Bolerslo in 1986. The normal GARCH model is symmetric, a simple version of GARCH. The mathematical representation of this model is as follows:

$$r_t = \mu_t + a_t \quad a_t = \sigma_t\varepsilon_t$$
$$\sigma_t^2 = \omega + \alpha a_{t-1}^2 + \beta\sigma_{t-1}^2$$
$$a_t|\Omega_{t-1} \sim N(0,\sigma_t^2) \quad (13)$$

Because in this model, the positive and negative shocks of the market are of the same importance, this model is called GARCH symmetric. Also, because this model assumes that market shocks have a normal distribution, this GARCH model is said to be normal.

Because the second-order conditional moments (conditional variance) depend on each other in the equation above, the process is neither distributed nor independent. If there are no market shocks, the variance of the GARCH model becomes a constant value.

That is, it converts to σ ^ 2, which is equal to all values of t, σ_t ^ 2 = σσ2. The unconditional variance of GARCH model is σσ2, which is equivalent to the mean of long-term conditional variances.

$$\sigma_t^2 = \sigma_{t-1}^2 = \underline{\sigma}^2$$
$$\underline{\sigma}^2 = \frac{\omega}{1-(\alpha+\beta)} \quad (14)$$

From the above equation it is well established that the constraints ω> 0 and α + β <0 are necessary to ensure the limited and positive nonconformity variance. We also need to use other constraints so that the conditional variance of the GARCH model is always positive. In general, the limitations of the normal GARCH model are symmetric as follows:

$$\{\omega > 0 \;\; \alpha,\beta \geq 0 \;\; \alpha+\beta < 1 \quad (15)$$

The interpretation of the normal symmetric GARCH model parameters in relation to how to respond to market shocks is expressed as follows: The parameter α represents the rate of conditional variance response to market shocks. When α is large, conditional fluctuations are highly responsive to market shocks. The parameter β shows the degree of stability in the conditional fluctuation, regardless of what happened on the market. When β is relatively large, it takes a lot of time to get out of the effects of a shock from the conditional fluctuations The parameters of the GARCH model are obtained by maximizing the value of the logarithm of the following expression:

$$ln\,L(\theta) = -\frac{1}{2}\sum_{t=1}^{T} \left(ln\,(\sigma_t^2) + \left(\frac{a_t}{\sigma_t}\right)^2\right) \quad (16)$$

Here, θ represents the parameters of the equation of conditional variance.

ARMA process

By combining AR (p) and MA (q), the ARMA (p, q) model is obtained. Such a model states that the current value of Y depends on its previous values and the current and past values of the random variable u_t.

The overall form of this model is:

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$$\phi(L)Y_t = \mu + \theta(L)u_t$$
$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p$$
$$\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q$$
$$Y_t = \mu + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + u_t + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q} \quad (17)$$

Note that the following assumptions are made:

$$E(u_t) = . \ , E(u_t^2) = \sigma^2 \ , E(u_t u_s) = . \ , t \neq s$$

Average y_t is equal to:

$$E(Y_t) = \frac{\mu}{1 - \phi_1 - \phi_2 - \cdots - \phi_p}$$

The features of the ARMA model combines the features of the AR and MA models. In particular, the partial correlation function is important here. Note that AC can only distinguish its pure regression model from the pure moving average model. Alternatively, AC can be used to determine whether a time series is followed by the MA process or the AR process. On the other hand, as the ARMA process has a downlink AC, the PAC can be used to distinguish between the AR process and ARMA. AR (P) Has a descriptive self-correlation function, but its partial correlation function reaches zero after the interruption of P, while the partial autocorrelation function for the ARMA process is descending.

Hypothesis

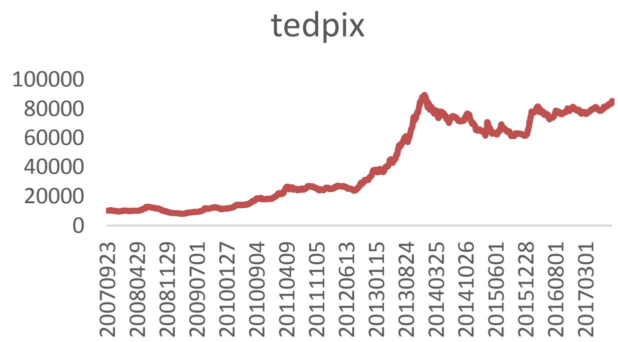
1. Great changes intend to following the great changes and small changes intend to small change in Tehran stock exchange.
2. Stock return volatility is asymmetric in stock exchange.
3. Negative news has more effect on the return volatility in comparison to positive news with the same rate in Tehran stock exchange.
4. Findings

The findings have been obtained in two descriptive and inferential statistics. In the following table descriptive statistics characters for Total stocks index and it's return along with Jarque-Bera for determination data distribution, as you can see and with considering the obtained significant level for this statistic that is less than 0/05, thus the Total index variable and it's return is not normal but until the time that abnormality is the result of Kurtosis not skewness of the results of estimating the least squares is accepted.

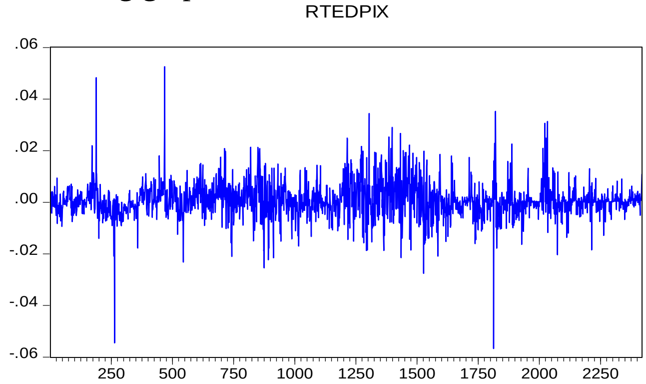
	TEDPIX	RTEDPIX
Mean	42066.29	0.000878
Median	28557.90	0.000319
Maximum	89500.60	0.052608
Minimum	7955.400	-0.056703
Std. Dev.	28025.70	0.006905
Skewness	0.207351	0.273091
Kurtosis	1.335232	10.59614
Jarque-Bera	295.4470	5821.709
Probability	0.000000	0.000000

Table 1 stock index descriptive statistics characteristics (TEDPIX) an it's return (RTEDPIX)

Tehran stock exchange Total index and it's return from the beginning of 2008-2017 is presented in the



following graphs:



Graph 1 stock Total index and it's return

Before modeling a time series it's stability should be confirmed .In financial time series usually instability is the result of this fact that there is not a stable level for returns. In the time series literature the instability time series has single root (Tsay 2005). In this Zero Hypothesis test the single root is existed and the opposite hypothesis is inexistence of single root in time series. Therefore if test statistics has significant distance from zero the zero Hypothesis is rejected. Otherwise it cannot be rejected. As you can see in table 2 for Total index the time series is unstable but is stable Total index return. Therefore the average equation ARMA should be performed on the Total index return series.

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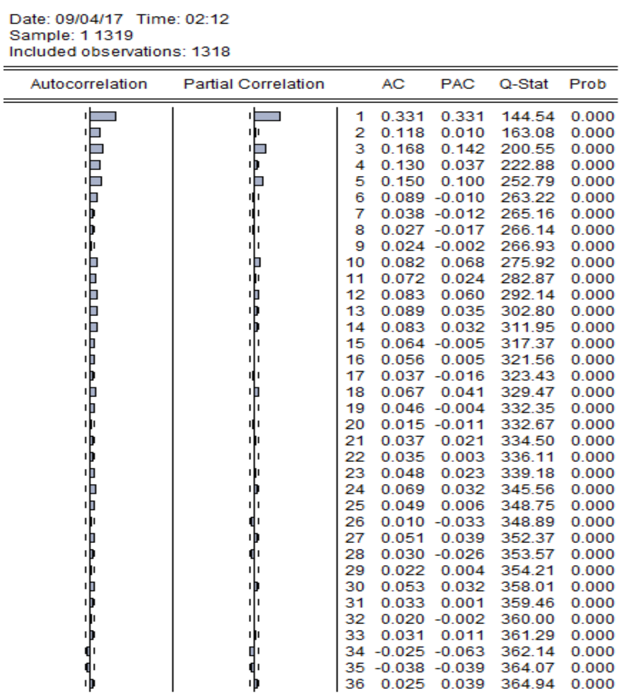
RTEDPIX	TEDPIX
0.0000	0.6796

Table 2 The results of the generated Dicky Fuller on the Total index and it's return

Hypothesis test

H1: The great change intend to following the great change and small change intend to following the small change in Tehran stock exchange. For examination of this hypothesis ARMA average equation is performed on the Total index return based on the Box-Jenkins method. Box and Jenkins (1976) were the first persons that presented a method for estimation of ARMA models. Their method is an operational method that has three stages of recognition, estimation and review. This method Totally use from auto correlation coefficients and partial autocorrelation coefficient.

Accordingly the series correlation graph and out regression (AR), mobile variable (AM) and their ranking should be identified and added to the average equation. In the following graph the return series are presented.



Date: 09/04/17 Time: 02:12
Sample: 1 1319
Included observations: 1318

Lag	AC	PAC	Q-Stat	Prob
1	0.331	0.331	144.54	0.000
2	0.118	0.010	163.08	0.000
3	0.168	0.142	200.55	0.000
4	0.130	0.037	222.88	0.000
5	0.150	0.100	252.79	0.000
6	0.089	-0.010	263.22	0.000
7	0.038	-0.012	265.16	0.000
8	0.027	-0.017	266.14	0.000
9	0.024	-0.002	266.93	0.000
10	0.082	0.068	275.92	0.000
11	0.072	0.024	282.87	0.000
12	0.083	0.060	292.14	0.000
13	0.089	0.035	302.80	0.000
14	0.083	0.032	311.95	0.000
15	0.064	-0.005	317.37	0.000
16	0.056	0.005	321.56	0.000
17	0.037	-0.016	323.43	0.000
18	0.067	0.041	329.47	0.000
19	0.046	-0.004	332.35	0.000
20	0.015	-0.011	332.67	0.000
21	0.037	0.021	334.50	0.000
22	0.035	0.003	336.11	0.000
23	0.048	0.023	339.18	0.000
24	0.069	0.032	345.56	0.000
25	0.049	0.006	348.75	0.000
26	0.010	-0.033	348.89	0.000
27	0.051	0.039	352.37	0.000
28	0.030	-0.026	353.57	0.000
29	0.022	0.004	354.21	0.000
30	0.053	0.032	358.01	0.000
31	0.033	0.001	359.46	0.000
32	0.020	-0.002	360.00	0.000
33	0.031	0.011	361.29	0.000
34	-0.025	-0.063	362.14	0.000
35	-0.038	-0.039	364.07	0.000
36	0.025	0.039	364.94	0.000

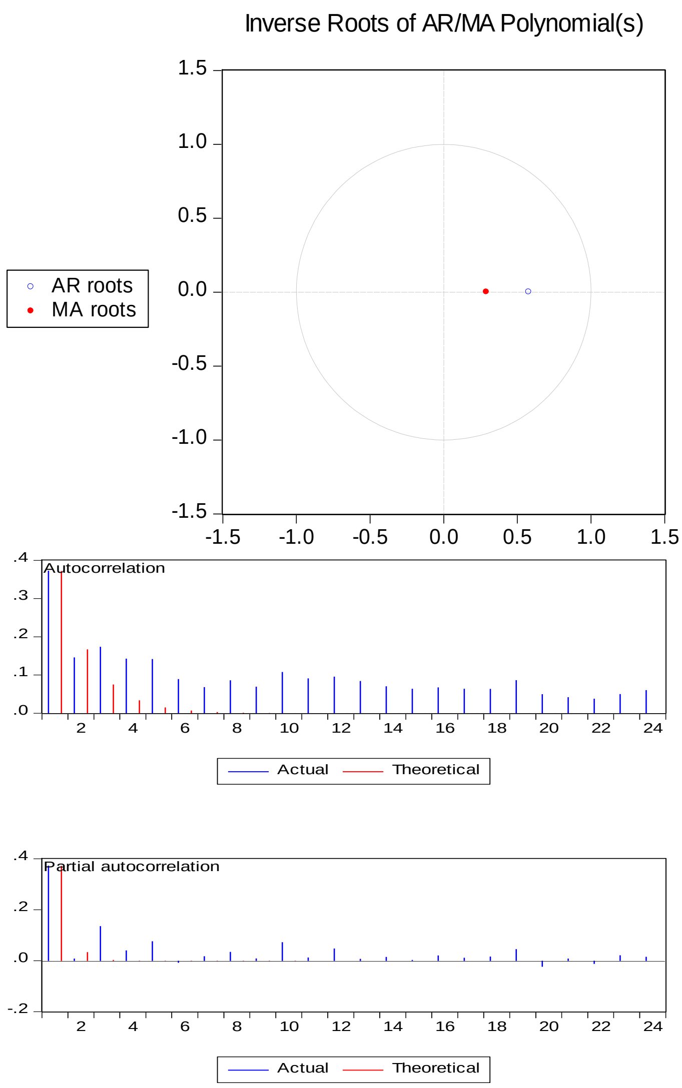
Graph 2 Correlated graph

In the first stage and considering This fact that autocorrelation and partial correlation in pause have an outstanding at the first the ARMA (1,1) model is performed that it's results are as follows:

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000881	0.000216	4.085180	0.0000
AR(1)	0.449166	0.048644	9.233826	0.0000
MA(1)	-0.089526	0.054216	-1.651294	0.0988

Table 3 ARMA model

Then homogeneous section roots of ARMA differential are observed and the ARMA Correlated graph graph are examined for identifying the estimated rates overlap with real rates.



Graph 3 Roots of homogeneous section in ARMA and comparison of actual and theoretical values

Then the remind parts series Correlated graph graph in the above model is examined and according to property value of the Q-STAT statistic about the existence or inexistence of AR and MA systematic elements in the reminder series of this model are determined.

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As you can see the significance of Q-stat is less than 0/05 thus the fives hypothesis of inexistence of systematic elements in the above model remained parts is rejected and it shows that the elements of AR and MA are not observed and reconsidering this subject that the model based on AR (1) and MA (1) that is performed is not the final model thus considering the outstanding pauses in auto correlation and partial auto correlation function we add the AR and MA elements and finally omit the insignificant elements so that we can reach to the least Akaike statistic and in this state we have reached to the final model that accordingly the following model is determined as average equation.

Date: 09/23/17 Time: 11:34
Sample: 11 2419
Included observations: 2409
Q-statistic probabilities adjusted for 2 ARMA terms

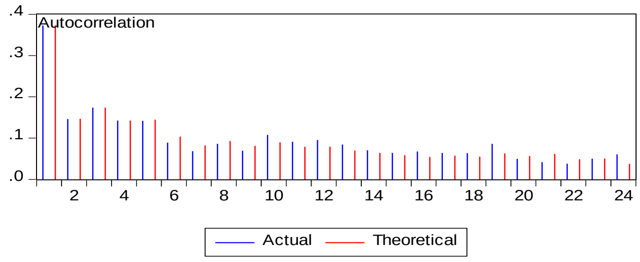
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.006	0.006	0.0780	
		2	-0.072	-0.072	12.617	
		3	0.090	0.091	31.954	0.000
		4	0.050	0.043	37.884	0.000
		5	0.083	0.096	54.428	0.000
		6	0.023	0.021	55.716	0.000
		7	0.010	0.015	55.967	0.000
		8	0.050	0.035	61.902	0.000
		9	0.006	-0.005	61.991	0.000
		10	0.070	0.066	73.711	0.000
		11	0.031	0.019	76.095	0.000
		12	0.048	0.054	81.596	0.000
		13	0.037	0.022	84.987	0.000
		14	0.026	0.023	86.643	0.000
		15	0.022	0.004	87.847	0.000
		16	0.032	0.018	90.288	0.000
		17	0.025	0.011	91.800	0.000
		18	0.018	0.006	92.622	0.000
		19	0.063	0.055	102.34	0.000
		20	0.010	-0.006	102.57	0.000
		21	0.014	0.011	103.07	0.000
		22	0.008	-0.016	103.23	0.000
		23	0.023	0.011	104.54	0.000
		24	0.045	0.025	109.50	0.000
		25	0.010	0.003	109.72	0.000
		26	-0.024	-0.031	111.15	0.000
		27	0.029	0.012	113.14	0.000
		28	0.015	-0.002	113.66	0.000
		29	0.008	-0.003	113.83	0.000
		30	0.048	0.042	119.47	0.000
		31	0.024	0.017	120.93	0.000
		32	-0.011	-0.014	121.23	0.000
		33	0.017	0.004	121.92	0.000
		34	-0.001	-0.017	121.92	0.000
		35	-0.038	-0.054	125.52	0.000
		36	0.017	0.007	126.22	0.000

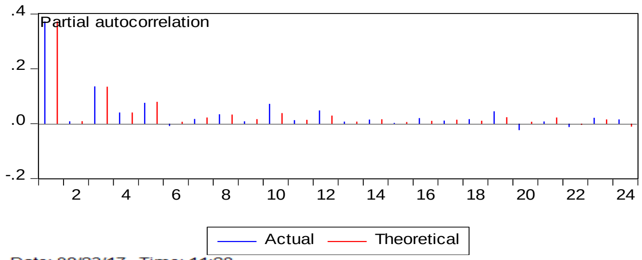
Graph 3 Correlation graph

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000887	0.000407	2.178213	0.0295
AR(1)	1.441654	0.563887	2.556636	0.0106
AR(2)	-0.120415	0.441485	-0.272750	0.7851
AR(3)	-1.193093	0.359594	-3.317892	0.0009
AR(4)	0.819043	0.551666	1.484671	0.1378
AR(5)	0.487848	0.208444	2.340426	0.0193
AR(6)	-0.604494	0.426728	-1.416577	0.1567
AR(7)	0.134633	0.120928	1.113329	0.2657
AR(8)	0.013823	0.047659	0.290046	0.7718
AR(9)	-0.054960	0.044355	-1.239112	0.2154
AR(10)	0.038595	0.025251	1.528431	0.1265
MA(1)	-1.085732	0.564697	-1.922680	0.0546
MA(2)	-0.322927	0.265138	-1.217960	0.2234
MA(3)	1.263314	0.420925	3.001283	0.0027
MA(4)	-0.477929	0.491623	-0.972147	0.3311
MA(5)	-0.711595	0.212178	-3.353757	0.0008
MA(6)	0.444824	0.414361	1.073518	0.2831
SIGMASQ	3.94E-05	5.14E-07	76.80862	0.0000

Table 4 the results of ARMA model

ARMA Correlated graph and the Residual of the above model are as follow:





Date: 09/23/17 Time: 11:28
Sample: 11 2419
Included observations: 2409
Q-statistic probabilities adjusted for 16 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0010	
		2	0.001	0.001	0.0042	
		3	0.001	0.001	0.0049	
		4	0.003	0.003	0.0239	
		5	-0.002	-0.002	0.0341	
		6	-0.011	-0.011	0.3456	
		7	-0.016	-0.016	0.9390	
		8	0.001	0.001	0.9436	
		9	-0.021	-0.021	2.0105	
		10	0.026	0.026	3.6802	
		11	0.003	0.003	3.7027	
		12	0.014	0.014	4.1640	
		13	0.009	0.009	4.3793	
		14	-0.002	-0.002	4.3884	
		15	-0.001	-0.001	4.3893	
		16	0.009	0.009	4.5820	
		17	0.005	0.006	4.6519	0.031
		18	0.000	0.000	4.6520	0.098
		19	0.030	0.032	6.8920	0.075
		20	-0.011	-0.012	7.2035	0.126
		21	-0.018	-0.018	7.9880	0.157
		22	-0.007	-0.007	8.1015	0.231
		23	-0.006	-0.007	8.1930	0.316
		24	0.034	0.034	10.983	0.203
		25	-0.014	-0.014	11.495	0.243
		26	-0.028	-0.027	13.356	0.204
		27	0.001	-0.001	13.357	0.271
		28	0.002	0.003	13.371	0.343
		29	-0.011	-0.014	13.670	0.397
		30	0.033	0.033	16.297	0.296
		31	0.008	0.009	16.461	0.352
		32	-0.026	-0.027	18.051	0.321
		33	-0.001	0.000	18.056	0.385
		34	-0.022	-0.024	19.240	0.377
		35	-0.043	-0.044	23.779	0.205
		36	-0.001	0.000	23.784	0.252

Graph 5 Correlated graph

As you can see significant level for Q-STAT statistics Totally is more than 0/05 that indicate that there is not systematic element in the remainder parts of model thus this model is the final model and ARCH test is used for determination of variance dissimilarity that it's results are as follows:

Heteroscedasticity Test: ARCH			
F-statistic	130.0190	Prob. F(1,2406)	0.0000
Obs*R-squared	123.4556	Prob. Chi-Square(1)	0.0000

Table 5 ARCH test results

According to above test results and considering the obtained significance level for this test the first hypothesis of inexistence of non-similarity variance as a result of auto correlation is rejected and thus there is a problem that it means the performance of ARCH and GARCH model and it this part the clustering is confirmed. At the first ARCH and GARCH model are performed.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.92E-06	2.34E-07	8.212114	0.0000
RESID(-1)^2	0.249862	0.018654	13.39437	0.0000
GARCH(-1)	0.739899	0.017438	42.42984	0.0000

Table 6 the results of GARCH model

In above table the GARCH model has been performed on ARMA equation considering the obtained significance level for GARH equation elements (that are less than 0/05). It is determined that all of these elements in variance equation are significant. In continue other models of The is family such as MGARCH , ETGARCH , TGHARCH , EGARCH was performed , considering the Akaike statistic the best model of GARCH family is ETGARCH because it has the least Akaike thus this model as the final model is considered for extraction of the volatility.

Akaike	Model
-7.5660	M GARCH
-7.5733	E TGHARCH
-7.5580	T GHARCH
-7.5641	E GARCH
-7.5519	GARCH

Table 7 models comparison according to Akaike statistic

H2: The volatility of stock return in stock exchange is asymmetric .

In order to examination of this hypothesis the TGHRCH was used. Considering the threshold element significance is determined that stock output volatility in stock exchange is asymmetry.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.71E-06	2.12E-07	8.042750	0.0000
RESID(-1)^2	0.313200	0.024392	12.84044	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.133859	0.025937	-5.160957	0.0000
GARCH(-1)	0.748989	0.015884	47.15256	0.0000

Table 8 the results of TGARCH model

H3: Negative news has more effect on return volatility than positive news with the same rate in Tehran stock exchange. Considering the negativity of threshold element in T GHARCH in the second hypothesis(table8) we find the leverage effect and negativity of this coefficient indicate the exponential model that con be exponential with ETGHARCH model.

Conclusion

According to the first hypothesis considering GHARCH effect we concluded that there is volatility clustering in Tehran stock exchange and can effect directly on the exchange options price and stock risk and portfolio. The result of this study is in consistent with the research of Roya Aleoman, Engel and peten , Malibaet.al(2014). According to H2 test that was examined with T GHARCH model we concluded that volatility clustering in Tehran stock exchange is asymmetric and it is consistent with the researches of Flour , Tripaty et.ai , Kang and Vion (2007) and Kasman and Toron (2007).

The obtained results of the H3 indicated that in Tehran stock exchange the negative shocks have more effect on volatility in comparison to positive shocks. This result is consistent with the research by Mehr Ara, Abdoli, Motamani and Abu Nuri, Goudarzi, Flora, Tripaty and colleagues. According to the obtained results we can say that: Measuring and correct prediction of financial market risk are very important for market agents and economic and financial policy makers. As a management the company should know the probability of asset basket value decrease.

The option risk of option contract, for covering the risk of this contract he also intend to know the rate of prediction volatility. An asset basket manager my wait to sell a stock before it be very disturbed. Tehran stock exchange as the most important financial market of Iran in one hand because of increasing growth and high investment absorb and on the other hand as one of the main tools the Privatization of governmental companies play on important role in Iran economy. However this market during the last years has faced to many volatility that con increase the cost of this activity in this market for investors and dealers.

As a result the modeling and prediction of risk in this new market can be an important guidance for investors and policy makers so that they can predict the volatility rate of this market and decide about stock buy and sell or suitable policy considering the increasing growth of financial markets , existence of one kind of change in these markets can has a wonderful effect on the global economy. Generally the change can be created as a result of economic , social and cultural and political accidents that lead to intense bewilderment of investors and un safety of financial markets operation that leads to decrease of investor general confidence to these markets and many negative effect on the global economy.

This subject is an evident of a strong relationship between un confidence of financial markets and investors general confidence .As a result financial policy makers of countries mostly estimate and predict the financial markets prices as a criteria of suitable policy making for decrease of national and global economy vulnerability thus the prediction of the most important task of financial markets that has attracted researchers and policy makers attention during two recent decades so that the can use of them in examination and pricing of assets , optimal assignment of financial resources and examination of risk management performance.

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