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Modeling Stock Return Volatility in Mongolian Stock Market

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Modeling Stock Return Volatility in Mongolian Stock Market

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By

Munkhtsog Altankhuu

We hereby certify that this Master of Science Thesis submitted by Munkhtsog Altankhuu conforms to acceptable standards, and as such is fully adequate in scope in quality. It is therefore approved as the fulfillment of the Thesis requirements for the Degree of Master of Science in Finance.

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ABSTRACT

Modeling Stock Return Volatility

in the Mongolian Stock Exchange

By:

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This paper is one of the first research works to examine the stock index volatility in the Mongolian Stock Exchange. The study utilizes the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models to estimate volatility of stock market return of the Mongolian Stock Exchange. A number of prior research work demonstrated that ARCH and GARCH models are fruitful models for modeling volatility of time series data. However, they recommend using different versions of GARCH–type models for different distributions (Normal, Student's t, Skewed Student's t and Generalized Error Distribution) for emerging markets or developing markets. This paper compares the GARCH(1,1) model and EGARCH(1,1), a version of the GARCH model, in terms of two different conditional distributions of error, normal distribution and student's t distribution by using the daily stock market return from February 2001 to October 2013. Findings show that the EGARCH(1,1) model gives a better explanation than GARCH(1,1) for the Mongolian Stock Exchange.

Key words: Volatility, Mongolian Stock Exchange, ARCH, GARCH, EGARCH model

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CHAPTER ONE

INTRODUCTION

Any financial asset's return is typically considered as a random variable, and the spread of outcomes of this variable factors as the main role in a variety of financial applications. This is known in the financial field as asset volatility. Volatility is a key parameter for risk management and portfolio management because one of the usages of volatility is to estimate the value of market risk. For the rapidly developing market, estimating the current value of the volatility is a crucial issue, as well as predicting their future values. Volatility forecasting is important for any financial institution, especially those which are involved in option trading and portfolio management. Additionally, to determine the cost of capital and evaluate asset allocation decisions, discovering the sources and dynamics of volatility in a stock market is a crucial issue.

As a number of models allow studying stock return volatility, researchers are still working on it. Whitelaw (2000) found that stock market volatility and stock return have a negative correlation. Bekaert and Wu (2000) and Wu (2001) also concluded this finding. French (1987) asserted that the relationship between stock return and volatility is positive, and significant relationships exist among them. However, Baillie and DeGennaro (1990) and Theodossiop and Lee (1995) found that although there is a positive relationship between stock return and volatility, an insignificant relationship exists. In addition to Bekaert and Wu, other studies such as Nelson (1991), Glosten et al.,

(1993) and Brandt confirmed that a negative and significant relationship exists. While the findings and empirical results of these studies are challengeable issues among researchers, they agree that stock return volatility is an important issue.

Most academic research and empirical tests of return-volatility focus on the advanced stock markets, and there are a number of works on the developed markets, whereas in recent years, interest to study the developing and emerging markets has risen due to enormous opportunities for international investors to diversify their portfolio. As a result, the studies examining the efficiency and behavior of these markets are delivering a valuable benefit to investors and policy makers.

As a result of the US sub-prime crisis, the entire financial market began to uniquely fluctuate in 2007-2010, and investors were attracted by the emerging and frontier markets to obtain uncorrelated return. With this interest, some of the emerging markets defined as less developed nations with huge growth potential have benefited remarkably. One of them was the Mongolian market. In fact, in 2010, with the signing of the Oyu-Tolgoi mine contract, which is estimated to house 79 billion pounds of copper and 45 million ounces of gold and is expected to have a lifespan of 40 years, allow foreign companies to develop its assets.

According to the International Monetary Fund (IMF), Mongolian GDP is expected to grow, up to 20% a year, until 2020 with the help of foreign direct investment. Experts say that Mongolia has a huge opportunity to become the next emerging market to make long-term investors wealthy.

After the recent global financial meltdown, the Mongolian equity market was one of the best performing stock markets in the world in 2010 and 2011, with growth over 130% and 47%, respectively[1]. With such impressive returns, it began to attract more investors, and the interest in earning the return is continuously growing and will continue to grow in the next decades.

<u>The Mongolian Equity Market</u>

Even though Mongolia's GDP is only around $11 billion, Mongolia has quietly emerged as the fastest-growing economy in the world in terms of annual growth rate. Over the last decade, the economy had high growth rates, and GDP growth was 17.5%, 12.3%, and 11.7% in 2011, 2012, and 2013 respectively, and expected to grow 9.5% in 2014 due to declining foreign direct investment and the falling of some mineral exports[2]. According to the International Monetary Fund (IMF), the Mongolian economy is expected to grow by 15.3%, which would make it one of the fastest-growing economies in the world over the next decade[3]. In addition, there is $2 trillion worth of mining commodities in the ground, and experts are expecting that Mongolia could be a $100 billion economy by 2025. Currently, real estate is the best and the most conservative way to play the Mongolian market's growth story because Mongolia is a frontier market in the very early stages of development.

Following this dramatic growth, one of the financial developments in the Mongolian economy is the increasing stock market. As a result of the transition from the

[1]Mongolian Stock Exchange
[2]Asian Development Bank
[3] IMF report in 2013

centrally planned economy to the market economy system started by democratic revolution in 1989, the Mongolian Stock Exchange (MSE) was established in 1991. Its main aim was to implement the privatization of State-Owned entities to the public through the MSE administering voucher system. During the privatization, 475 Stated-Owned entities and factories were transferred to the public with vouchers[4].

After approving the Securities and Exchange Law in 1994 and Corporate Law in 1995, the secondary market trading began, and twenty-nine brokerage firms financed by the government were privatized; subsequently the new status for the MSE was approved by the Government resolution in 1995. In consequence of adopting a new Securities and Exchange Law in December 2002, MSE was re-organized as a fully State-Owned Shareholding Company, and entitled to engage in any legal business activities for making a profit. Technologically, MSE has integrated Millennium IT, which is used by 30 different financial organizations across the world including the London Stock Exchange Group, the London Metals Exchange, and the Johannesburg Stock Exchange. It is a highly sophisticated trading and post-trading technology that has the capacity to handle high trading volumes and a variety of securities classes. Starting in April 2013, half the brokerage firms trading on the MSE began trading from their offices remotely. Now, most of the industry is moving towards Internet trading. On the MSE, Government bonds, corporate bonds, and company stocks have been the major trading securities since 2000. From 2000-2012, the government bonds traded had a total value of 344.7 million USD. As of 2013, there are 400 joint stock companies listed on the MSE. At the end of the

[4]Factbook of Mongolian Stock Exchange 2008

2013 reporting period, the average MSE TOP-20 index reached a level of 15,094.94 and decreased by 7.9% compared to the end of the previous year. During 2013, the MSE TOP-20 index reached its peak, hitting 18,301.93, and then lowered to 13,188.46.

The young MSE market has not been deeply researched in terms of its volatility in the academic field. To my knowledge, this paper is the first to systematically examine the market volatility of the MSE. Theoretically, I am expecting the young emerging capital market, the MSE, to have vastly different characteristics than advanced capital markets. As Bekaert and Harvay (1997) discovered, the average return is higher for emerging markets, correlations with developed market return is low, returns are more predictable, and volatility is higher. The objective of this paper is to focus on the volatility of the MSE and its forecasting, and the study findings are expected to confirm these characteristics to investors. Higher volatility implies higher capital costs, and increases the value of the option to wait, and delay investments.

CHAPTER TWO

REVIEW OF LITERATURE

One of the fundamental questions concerning capital markets is their volatility. Stock return volatility is one of the most popular topics in the financial field for practitioners and researchers. Investors are willing to earn high return from their portfolio, and they are facing an abnormal return from investment performance volatility during various periods of time. Also, Fama (1965) has found that large changes in stock prices follow large changes, and small changes follow small changes. As mentioned in the introduction, for any financial asset, the main characteristic is its return volatility. However, volatility is unobservable, or a latent variable, which is the significant problem in forecasting volatility (Patton, 2006). On the other hand, we cannot observe it directly, but it can be inferred from other observable variables, and mathematical models help to estimate a quantitative forecast of volatility. In finance, volatility of stock return is defined as a statistical measure of the dispersion of return for given security and market index. Specifically, volatility is associated with the sample standard deviation of returns over some period of time, and variance could also be used as a measure of volatility. Volatility is a quantified measure of market risk - it is not exactly the same as risk, but it is related. Risk is the uncertainty of a negative outcome of some event, whereas volatility shows the spread of outcomes.

Finance theory and empirical evidence shows the relation between stock return and its own variance. Roll (1992), Harvey (1995a), Bekaert and Harvey (1997), and Aggarwal et al. (1999) confirmed that the volatility for a particular financial market is related to the variability of volatility across different countries. This finding creates a problem in forecasting volatility. Mathematical modeling assists in investigating the relationship between the current value of financial variables and their expected future value. Quantitative forecasts provide financial institutions and financial analysts with a valuable estimation of market trend. The Value-at-Risk methodology is mostly used to estimate the market risk in the financial world. The concept of volatility is a key role in this methodology. This methodology estimates its parameters over the different time periods such as yearly, monthly, weekly, and daily. The daily based estimation is most adequate. Dynamic Risk Management, which is the technique used to monitor the market risk on a daily basis provides a short term forecast in addition to the correct estimation of the historical volatility. This forecast is described as conditional volatility. In addition, Harvey (2001) and Li (2002) indicated through their empirical research that the relationship between return and volatility depends on the specification of the conditional volatility. The volatility of the daily stock returns changes over time. For instance, during periods of time, the daily stock returns show high volatility, whereas other times they show low volatility. This phenomenon is commonly observed in a financial time series.

According to Mandelbrot (1963), high volatility (small volatility) in some periods of time tends to be followed by high volatility (small volatility) in another period of time. In other words, volatility comes in clusters. Therefore, linear models are not reasonable to investigate the unique behavior of financial time series data due to the assumption of the linear model, homoscedasticity.

Since Engle (1982) has introduced the Autoregressive Conditional Heteroskedasticity (ARCH) in investigation of the variance of United Kingdom inflation, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) by Bollerslev in 1986 and Exponentially Weighted Moving Average (EWMA) to estimate the conditional volatility have been developed. The GARCH model is able to reduce a large number of lags to catch the nature of the volatility compared with ARCH. However, these models fail to model the leverage effect, first noted by Black (1967), because their distribution is symmetric. To solve this problem, extensions of the GARCH model, including Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) by Nelson (1991), Glosten, Jagannathan and Runkle GARCH (GJR-GARCH) by Glosten*et al.* (1993), and Asymmetric Power ARCH (APARCH) by Ding *et al.* (1993), which estimate the conditional volatility, have been proposed.

More precisely, the GARCH model can capture two important characteristics. These include fat tails and volatility clustering in financial time series. However, the GARCH models are not fully capable of incorporating a widely observed behavior of stock prices - thick tails property of high frequency financial time series. To solve this problem, Baillie and Bollerslev (1989), Kaiser (1996) and Beine et al. (2000) suggested using non-normal and Student-t distribution. Furthermore, a number of scientists suggested ideas such as Generalized Error Distribution, normal-Poison, the normal-lognormal, the Bernoulli-normal, and skewed Student's t-distribution.

Although there are fewer studies in the emerging stock market than in the developed market, such research has been experiencing considerable growth covering emerging markets worldwide. Harvey (1995a, 1995b), Havey and Bekaert (1997), Bekaert (1995), Haque and Hassan (2000), Kim and Singal (1999), Choudhury (1996), Lee and Ohk (1991), and Classens et al. (1995) investigated the volatility in the emerging stock market, and they confirmed that returns of emerging markets are more predictable and volatility in emerging markets is higher than in developed markets.

To my knowledge, there is no intended study in MSE, but there are a number of studies of particular emerging markets. In most studies that involve measuring equity market return volatility and the forecasting of it, GARCH family models are widely used. The studies individually recommended that dissimilar types of GARCH models can be better for forecasting stock market volatility. For instance, Alberg et al. (2006) estimated stock return volatility in Tel Aviv Stock Exchange indices of Israeli using asymmetric GARCH models, and they found that the EGARCH model is the most fruitful to forecast the TASE indices that is the Tel Aviv 25 index is a capitalization-weighted index of 25 stocks (free-float adjusted) traded on the Tel Aviv Stock Exchange.

In 2008, the daily closing prices of the Karachi Stock Price Index of Pakistan, the best emerging market in Asia with returns in fiscal year 2011-2012 between 40% and 50%, was studied through linear and non-linear models (Rashid & Ahmad, 2008). They concluded that non-linear GARCH models provided the most successful forecasting for the volatility of the index. According to studies of long memory properties of the Istanbul Stock Exchange Market, the FIGARCH model is able to adequately provide the evidence of long memory dynamics in the conditional variance (Kilic, 2004). Su (2010) concluded that the EGARCH model, rather than the GARCH model, satisfies the data in his study of modeling the volatility of Chinese stock return based on daily data from 2000 to 2010. Gokcan (2000) studied comparison between linear and non-linear models, which captured the volatility characteristics in the daily prices of the 7 emerging markets, Argentina, Brazil, Colombia, Malaysia, Mexico, the Philippines, and Taiwan. This comparison was made between linear GARCH(1,1) and non-linear EGARCH(1,1) using the value of Akaike Information Criterion, AIC value, proposed by Hurvich and Tsai in 1989. This is a measure of the relative quality of a statistical model for a given set of data, and it provides a means for model selection. His empirical results suggested that the GARCH(1,1) model outperforms the EGARCH(1,1) model for all the countries in accordance with AIC values. He concluded that the GARCH model outperforms the EGARCH model in capturing the dynamic behavior of emerging stock market returns. This conclusion might create criticism, as AIC will not provide any guarantee if all the candidate models fit poorly. In most recent studies, Tuyen (2011) examined the volatility of the Vietnamese stock market using GARCH, EGARCH, TGARCH and GARCH-M, and Floros (2008) examined the volatility of market indices for Egypt and Israel using GARCH, EGARCH, T-GARCH, asymmetric component GARCH, the component GARCH, and the power GARCH models. Floros concluded that daily returns can be characterized by the GARCH model. Tuyen's findings also showed that the GARCH(0,1) model adequately describes return dynamics. After Floros, in 2011, Abd El Aal noted in an empirical study estimating volatility of Egyptian stock market return that EGARCH is the best model for forecasting volatility in comparison with other models. As mentioned earlier, in one of the initial papers estimating volatility for emerging market, *Emerging Equity Market Volatility,* Bekaert and Harvey (1995) concluded that the GARCH models have difficulty fitting the highly volatile and non-normal returns, and the asymmetric GARCH gives the best results for most countries while examining the return volatility for emerging markets such as Brazil.

In this thesis, I capture the characteristics of the market volatility in the Mongolian equity market by employing linear GARCH and EGARCH models. In the estimation, I am going to use the maximum likelihood method, assuming the normal distribution and student t-distribution for the conditional distribution of the errors, and compare the models based on empirical evidence.

CHAPTER THREE

METHODOLOGY

Variables

The daily market returns are used as an individual time-series variable. There is no indication of the horizon over which the returns should be calculated. Limitation of the organized database of the exchange had a significantly limiting effect on market studies in developing countries (Dickinson and Muragu, 1994). One of the probable solutions to this problem is to use the market index, which is published and readily available at low cost (Sharma and Kennedy, 1977). The daily index prices are selected as daily closing price, and are from the database of the Mongolian Stock Exchange.

The daily market return is calculated as follows:

$$u_t = Ln\left(\frac{P_t}{P_{t-1}}\right) \qquad 3.1$$

Where

- u_t is market return at day t
- P_t is price index at day t
- Ln is Natural logarithm

3.1. Concept of volatility

The return is considered a random variable, and the volatility refers to the spread of all outcomes of an uncertain variable. In terms of a time series of return, its volatility is associated with the sample standard deviation of returns over some period of time. According to formulation of standard deviation in statistic and probability theory, standard deviation of returns over some time period is computed by the following equation.

$$\sigma_n^2 = \frac{1}{m-1}\sum_{i=1}^{m}(u_{n-i} - \bar{u})^2 \qquad 3.2$$

Where;

- σ_n^2 is an unbiased estimate of the variance rate on day n and square of standard deviation, or square of volatility on day n
- u_i is the return during day i or between the end of day $i-1$ and the end of day i
- $\bar{u}$ is the mean of the u_is and computed by $\bar{u} = \frac{1}{m}\sum_i^m u_i$

This equation is the base of all models for measuring volatility of financial asset over some period of time. If mean of return is assumed to be zero because there is no huge effect on estimates of variance and m-1 is replaced by m because there is no big difference on estimate of variance for sufficient observation, there would be a very small difference to the calculations in the formula in equation 3.2, and the variance rate would be:

$$\sigma_n^2 = \sum_{i=1}^{m} \alpha_i {u_{n-i}}^2 \qquad 3.2$$

Where;

- α_i is the amount of weight given to the observation i days ago and $\sum_{i=1}^{m} \alpha_i = 1$, and the weights are not equal to each other. That is, for instance, when $n > m$, if $\alpha_n > \alpha_m$, it tells that the older return contributes to volatility less than recent return.

3.2. ARCH model

Engle's idea in the ARCH model was to assume that the long-run variance rate contributes to the volatility with some weight, and variance of error is non-constant over time or the errors exhibit time-varying heteroskedasticity (1982).

If Ω_{t-1} is all available information set at time t-1, and u_t is a univariate time series, its functional form is as:

$$u_t = E[u_t|\Omega_{t-1}] + \varepsilon_t$$

ε_t are the random innovations and $E[\varepsilon_t] = 0$. According to Engle (1982), the ARCH model that estimates the variance of returns is a simple quadratic function of the lagged values of the innovations.

Therefore, the ARCH model is formulated in terms of the conditional variance of the error term by the following equation:

$$\sigma_n^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{n-i}{}^2 \qquad 3.3$$

Where;

- $\varepsilon_i = z_t\sigma_t$ *and* $z_t \sim i.i.d$ (an independently and identically distributed process with mean zero and variance one, white noise)
- $\alpha_0 = \gamma V_L$ and V_L is the long-run variance, and γ is the weight related to the long-run variance rate. p is the number of autoregressive terms or lag.

3.2. GARCH (1,1) model

The GARCH (p,q) model is an extension of the ARCH model. It was developed by Bollerslev in 1986. The idea behind the extension is that the variance at some time is influenced by its past values, and the model is expressed as a function of past values of variance and past squared error values. It is formulated by the equation 3.4. p and q represent the order of the ARCH terms and the order of the GARCH terms, respectively. β_j is the amount of weight given to the observation i days ago for variance.

$$\sigma_n^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{n-i}{}^2 + \sum_{j=1}^{q} \beta_j \sigma_{n-j}{}^2 \qquad 3.4$$

As noted in the literature review, the GARCH (p,q) model is a fruitful model to estimate and forecast the time-varying volatility of returns of stock markets. The simplest basic GARCH (1,1) model is very reasonable, and it is commonly used for analyzing the high frequency financial time series such as daily stock index returns (Islam, 2013). The GARCH (1,1) model is formulated by the following equation and defined as a function of the last period's squared returns and the last period's volatility:

$$\sigma_n^2 = \alpha_0 + \alpha_1 \varepsilon_{n-1}{}^2 + \beta_1 \sigma_{n-1}{}^2 \qquad 3.5$$

Where;

- $\alpha_0 = \gamma V_L$ and explained in equation 3.3
- $\gamma + \alpha_1 + \beta_1 = 1$ or the term, $\alpha_1 + \beta_1 < 1$, is required in a stable GARCH (1,1).

To estimate the parameters of the GARCH model, γ, α_1, and β_1, the maximum likelihood method (ML) is widely used instead of the usual OLS method due to its non-linear form. With ML, choosing values for the parameters maximizes the chance of data occurring. In my examination, I use EVIEWS 8.0 which is comprehensive statistical software developed by Quantitative Micro Software (QMS).

The second model in my study, the EGARCH model, proposed by Nelson in 1991, emerged from the disadvantage of the GARCH (1,1) model which is that the GARCH (1,1) imposes the assumption that positive and negative innovations affected systematically to the conditional volatility of asset.

3.3. EGARCH model

In the GARCH (1,1) model, alphas and betas parameters are positive constant numbers, completely disregarding the sign of innovations. Nevertheless, a number of researchers such as Bollerslev, Chou and Kroner (1992), Engle and Ng (1993) and Pagan and Schwert (1990) found that negative and positive shocks do not have the same impact on the volatility for equity returns, and positive price shocks tend to increase volatility less than negative price shocks although they have the same size. That is, asymmetry exists in stock market return, and sometimes it is ascribed to a leverage effect. Particularly, falling stock price increases the debt to equity ratio and volatility of returns to equity holders. Consequently, increasing volatility affects the demand for stock fall because of risk aversion. For that reason, GARCH (1,1) cannot capture the asymmetry and skewness of the return series, and a number of extensions for the GARCH model such as TGARCH, EGARCH and APARCH allow capturing of asymmetry. Among these models, EGARCH model is common and formulated as:

$$Log(\sigma_n^2) = \alpha_0 + \sum_{i=1}^{p} \alpha_i g(z_{n-i}) + \delta \frac{z_{n-i}}{\sqrt{\sigma_{n-1}^2}} + \sum_{j=1}^{q} \beta_j Log({\sigma_{n-j}}^2) \qquad 3.6$$

$g(z_t) = \theta_1 z_t + \theta_2[|z_t| - E|z_t|]$, or the value of the function must be the function of both the magnitude and the sign of z_t. $E|z_t|$ depends on the assumption made on the unconditional density.

And the EGARCH (1,1) model under the normal distribution is written as:

$$Log(\sigma_n^2) = \alpha_0 + \alpha_1 \left[\frac{|\varepsilon_{n-1}|}{\sqrt{\sigma_{n-1}^2}} - \sqrt{2/\pi}\right] + \delta \frac{\varepsilon_{n-1}}{\sqrt{\sigma_{n-1}^2}} + \beta_1 Log({\sigma_{n-1}}^2) \qquad 3.7$$

The parameters, alphas, delta, and beta are constant and can be both negative and positive. The presence of leverage effect can be tested by the hypothesis that is $\delta = 0$ or $\delta \neq 0$. If$\delta \neq 0$, then news impact is asymmetry. To estimate the parameters, I will use the same methodology and software in the estimate GARCH (1,1) parameters.

Before proceeding to applying GARCH models, it is necessary to examine whether or not financial time series data set is stationary, whether it is normally distributed, and whether errors exhibit heteroskedasticity. The last test ascertains the existence of ARCH effects in the residuals.

Most forecasting models are based on the assumption of stationarized time series. The stationary behavior of a time series should be determined before forecasting. That is, a stationary process is one whose statistical properties do not change over time. More precisely, the stationary time series is one whose statistical properties, mean and variance, are constant over time. If time series observe non-stationary, they should be transformed to some stationary time series for analysis. Therefore, it is necessary to investigate the properties of the examining time series data. In academic fields, the unit root test is commonly used.

3.4. Unit root test

The Augmented Dickey-Fuller test is an augmented version of the Dickey-Fuller test proposed by Dickey and Fuller in 1979, and is reasonable and simple in the investigation of existence of unit root in the time series.

ADF unit root test is based on the following regression equation:

$$\Delta r_t = \alpha_0 + \beta t + \theta r_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta r_{t-i} + \varepsilon_t \qquad 3.8$$

Where;

- p is the number of augmenting lags determined by minimizing the Schwardz Bayesian Information Criterion (SIC) or minimizing Akaike Information Criterion (AIC) or lags are dropped until the last lag is statistically significant.

Null hypothesis and alternative hypothesis are stated here as:H_0: $\theta = 0$and H_1: $\theta < 0$. If absolute value of ADF statistic exceeds the McKinnon (1996) critical values at 1%, 5%, and 10% significance level for all returns, ADF test statistic rejects the null hypothesis of the existence of unit root in the return series or data is stationary.

3.5. Testing for ARCH effect

Testing for the following hypothesis is to determine the existence of ARCH effects in the residuals. That is, the ARCH effect test is to ascertain whether or not there is any conditional heteroscedasticity by conducting the squared residuals series. To test for ARCH effects in the conditional variance of ε_t, first the AR(1) model for the returns series of index is considered as

$$r_t = \beta_0 + \beta_1 r_{t-1} + \varepsilon_t \qquad 3.9$$

Second, run the regression on equation 3.9 to obtain residuals ε_t, and run a regression of squared OLS residuals ε_t^2 on p lags of squared residuals. The ARCH(p) specification is noted on equation 3.3, and the hypothesizes are stated as:

$$H_0: \alpha_1 = \alpha_2 = \alpha_3 = \cdots = \alpha_p = 0$$

$$H_1: \alpha_1 \neq 0, \alpha_2 \neq 0,\ \alpha_3 \neq 0, \dots, \alpha_p \neq 0$$

The method to test ARCH effect is Lagrange Multiplier test suggested by Engle (1982). If the value of the test statistic is greater than the critical value from Chi-square distribution with p degree of freedom, then the null hypothesis is rejected. This means there is an ARCH effect in equation 3.9.

3.6. Goodness-of-fit test

Normality is the most common assumption in classical regression model. This is where the residual errors are assumed to be normally distributed. Substantially incorrect statements in the analysis of economic time series models may come from the departures from normality. This requires determining if the normality exists in the examining data set.

3.6.1. Jarque-Bera test and Shapiro-Wilk test

The Jarque-Bera test is a well-known goodness of fit test used to determine how well a random set of data fits a normal distribution. The test was introduced by Jarque and Bera in 1980 and 1987 and is defined as function of the measures of skewness and kurtosis from the sample. The theoretical value of skewness and value of kurtosis are equal to 0 and 3 for normal distribution, respectively.

If F is a continuous function of independent random variables, $\{X_i\}$, null hypothesis is stated as:

$$H_0: F(X) = N(\mu, \sigma^2)$$

$$H_1: F(X) \neq N(\mu, \sigma^2)$$

Test statistic JB is

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \qquad 3.8$$

Where;

- K-kurtosis from sample
- S –skewness from sample
- n –sample size

The statistic value has a chi-square distribution with 2 degrees of freedom,$X^2_{1-\alpha,2}$ (one for skewness, one for kurtosis). JB is asymptotically chi-squared distributed with two degrees of freedom. Therefore, if $JB > X^2_{1-\alpha,2}$critical, H_0 has to be rejected, which means that residuals are non-normally distributed.

Shapiro-Wilktest is based on the probability plot. The regression of the ordered observations on the expected values of the order statistics from the hypothesized distribution is examined, and test statistic is formulated as (X is random variable):

$$SW = \frac{\left(\sum_{i=1}^{n} a_i X_i\right)^2}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \qquad 3.9$$

If SW is less than the critical value, H_0 is rejected. Thaderwald and Buning (2004) investigated the power of several tests, Jarque-Bera, Shapiro-Wilk, and Kolmogorov-Smirnov, for testing normality. Their findings present that the JB test fits well for symmetric distributions with medium up to long tails and for slightly skewed distributions with long tails. Moreover, JB test has poor power for distribution with short tails, and Shapiro-Wilk test would be sensible in this case (Thaderwald and Buning, 2004).

3.6.2.Ljung-Box test / Performance evaluation

R-squared value is a good measure of how well data fit a statistical model for linear regression. The GARCH and EGARCH models deal with the variance equation, and R-squared value is only valid for mean equation. Thus, R-squared value is not significant in model diagnostics for the GARCH models. In other words, if there are no regressors in the mean equation, R-squared value may not be meaningful, and negative values of R-square occur (Jo-Hui Chen, n.d). Therefore, other testing methods are used for checking the validity of the model. In this study, the Ljung-Box test and AIC test are used to evaluate the models. The Ljung-Box test is for testing the autocorrelation within the series. If GARCH models are working well, it should remove the autocorrelation. Also, in order to compare the performance of the two GARCH models that are applied in this study, the Ljung-Box test is employed for the first p lags[5] at 95% confidence interval. The Ljung-Box statistic is computed as below:

$$Q = n(n+2)\sum_{k=1}^{p}\frac{\rho_k^2}{n-k} \qquad 3.10$$

Where

- ρ_k^2 is the square of the autocorrelation for a lag of k
- n is the number of observations

If the Ljung-Box statistic is greater than the critical value of the chi-squared distribution with k degrees of freedom, $\chi^2_{1-\alpha,k}$[6], zero autocorrelation can be rejected.

[5] p represents the number of lags being tested, and a Ljung-Box Test with 15 lagged autocorrelation is widely used Engle (2001).

[6] In this study, $\chi^2_{1-0.95,15} = 24.99$

HYPOTHESES

The Augmented Dickey-Fuller test /testing stationary/

ADF unit root test is based on the following regression equation:

$$\Delta r_t = \alpha_0 + \beta t + \theta r_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta r_{t-i} + \varepsilon_t$$

Hypotheses are stated here as:

$H_0: \theta = 0$ /non-stationary/

$H_1: \theta < 0.$ /stationary/

The McKinnon (1996) critical values at 1%, 5%, and 10% significance level

ARCH effect test /conditional heteroscedasticity/

Testing method: Lagrange Multiplier

ARCH effect test is based on the following regression equation:

$$\sigma_n^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i {\varepsilon_{n-i}}^2$$

Hypotheses are stated here as:

$H_0: \alpha_1 = \alpha_2 = \alpha_3 = \cdots = \alpha_p = 0$ /no-ARCH effect/

$H_1: \alpha_1 \neq 0, \alpha_2 \neq 0, \ \alpha_3 \neq 0, \ldots, \alpha_p \neq 0$ /ARCH effect/

The critical value is value of Chi square distribution with 3 degree of freedom at 5% of significant level, 7.81.

Jarque-Bera test /normality/

Test statistic JB is

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$$

Hypotheses are stated as:

$H_0: F(X) = N(\mu, \sigma^2)$ /normally distributed/

$H_1: F(X) \neq N(\mu, \sigma^2)$ /non-normally distributed/

The critical value is value of Chi square distribution with 2 degree of freedom at 5% of significant level, 5.99.

Ljung-Box test /autocorrelation/

The Ljung-Box test is employed for the first 15 at 95% confidence interval.

The Ljung-Box statistic is computed as below:

$$Q = n(n+2)\sum_{k=1}^{p}\frac{\rho_k^2}{n-k}$$

Hypotheses are stated as:

H_0: zero autocorrelation

H_1: autocorrelation

Critical value is the value of the chi-squared distribution with 15 degrees of freedom at 5% of significant level, 24.99.

CHAPTER FOUR

DATA COLLECTION AND PRESENTATION

This chapter presents the performance of the Mongolian Stock Market. The dataset is not obtainable from public web-sites or on-sites. The required data of this study was officially obtained from database and research department of the Mongolian Stock Exchange (MSE). The index is composed of the largest 20 companies which constitute 90 percent of the total market capitalization.

4.1. Market condition during the sample period

Figure 4.1 displays the daily market index pattern and the daily return calculated by equation 3.1 during the sample period 2/9/2001-10/18/2013, as shown in Figure 4.2. During February 9, 2001 to April 24, 2006, the market index was low, between 600 and 1100, and had more fluctuation compared to other periods of time (Figure 4.1 and 4.2). The index started increasing from the end of 2006, and reached its first peak of 13519.03, increasing by 634% within 5 months. The following may have impacted its dramatic growth: 1) New regulation of the securities act 2) Consecutive 3 year GDP growth, higher than 8% 3) Attractive environment for foreign investors to play in the MSE 4) Issuing IPO of State-owned enterprises 5) An increase in household income and savings, allowing allocation of household savings in the capital market. The value of domestic investment was tripled to 60 million USD from 22 million in 2006. From the beginning of 2008 to the end of 2009, the index decreased to 4959.43. The average index change in

2008 was -45.5%, which was relatively lower than the average -47.9% of Asian Pacific countries. Total transactions on the MSE were equal to 2.6 % of GDP and 1.005% of GDP in 2007 and 2008, respectively (Mongolian Stock Exchange, 2007, 2008). Subsequently, the index rose to its historical peak of 32955 in February 2011 as a result of the increase in share price of major companies, optimistic expectations from mining output and export. For the last 2 years of the sample period, the market index has been dropping and diminishing due to reducing foreign investment and price of major export goods in the world market.

Figure 4-1: MSE TOP-20 index pattern

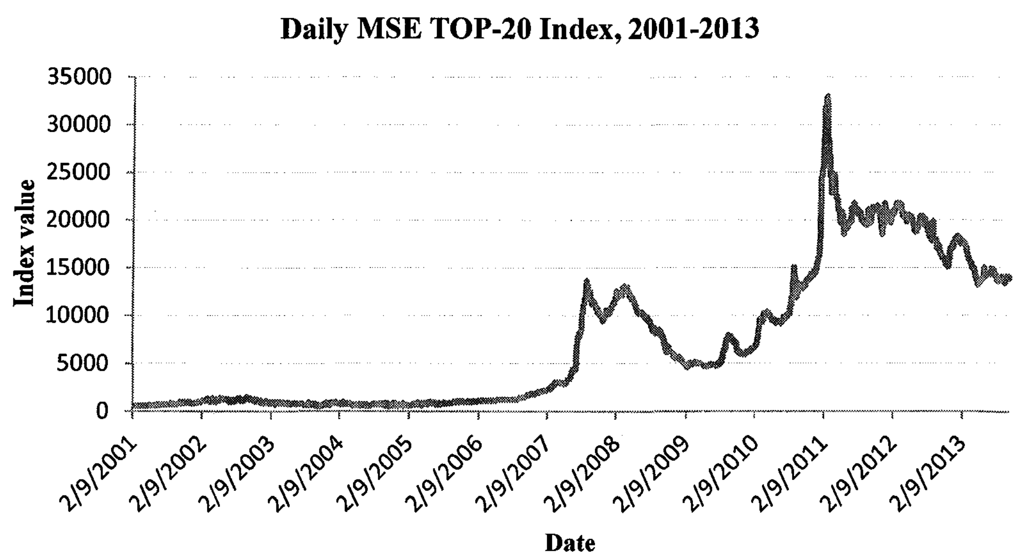


Figure 4-2: MSE TOP-20 Index return

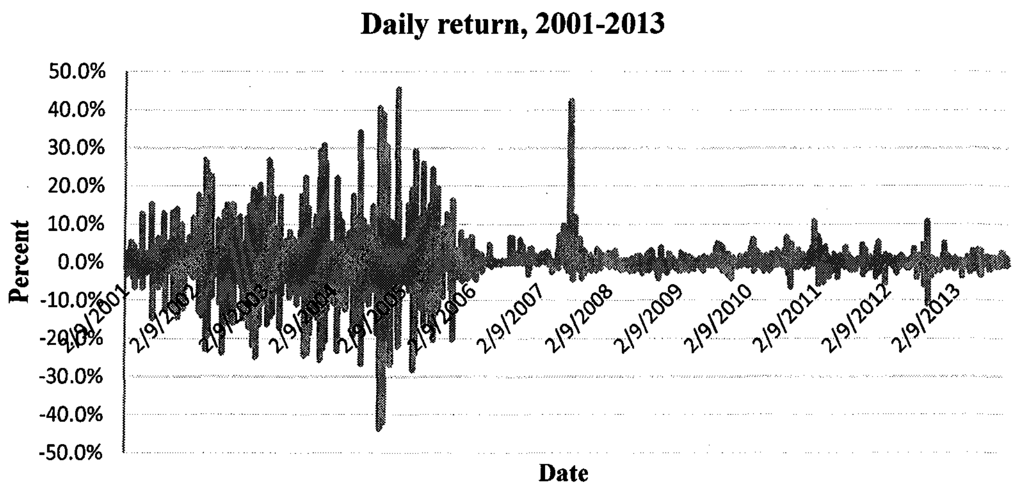


Figure 4-3: MSE TOP-20 Index changes by unit

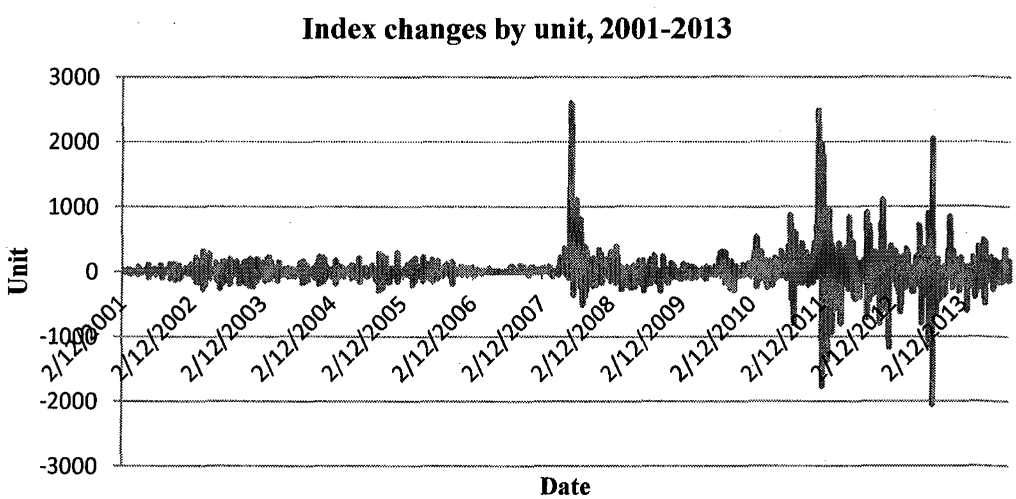


Figure 4.3 demonstrates the index changes as a unit, and indicates that the market has more fluctuation since 2008 than it did before 2008 in terms of unit changes of index. During the low index period, 2001-2008, log return shows high volatility because

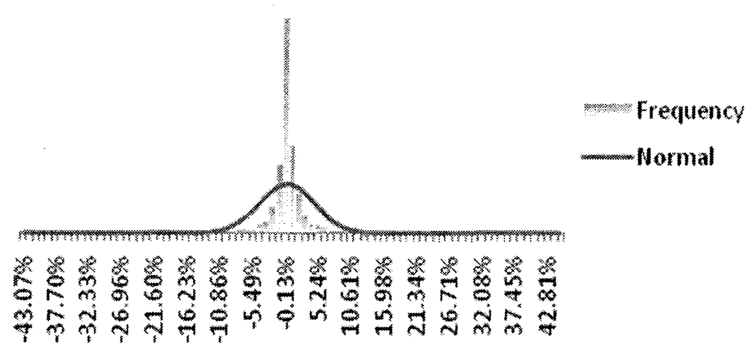
mathematically, small changes in small number give high percentage changes (Figure 4.2).

4.2. Descriptive Statistic

According to results shown in table 4.1, the mean return is 0.1% and the standard deviation is 4.54%. This indicates that MSE has more volatility compared to other markets that have recently been studied. The Indonesian, Malaysian and Singapore markets were studied by Islam in 2013. In addition, Belex 15, DJIA, STOXX TIM and SAX were studied by Lidija et.al in 2014. The higher volatility drives the possibility of the higher rate of returns, but also has more risk.

Table 4-1: Summary statistic for return

Histogram of daily return of MSE



Series: __RET	
Sample 1 3212	
Observations 3212	
Mean	0.001038
Median	0.000000
Maximum	0.454986
Minimum	-0.436037
Std. Dev.	0.045392
Skewness	0.630243
Kurtosis	28.52757
Jarque-Bera	87426.03
Probability	0.000000

The lowest and highest values of return of the MSE in the observed period were -43% and 45%, respectively. These values placed in the high volatile period, before 2007, and after 2008, the volatility is between negative and positive 12%.

The return series shows positive skewness suggesting that the distribution has long right tail. The excess value for kurtosis indicates leptokurtic distribution, which means the future returns will be either extremely large or extremely small, and concludes that the volatility comes in clusters. The extremely large Jarque-Bera statistic shown in Table 4.1 clearly rejects the null hypothesis of normality in the return series. Thus, the test indicates that the distribution of the log-return is non-normal.

Table 4-2: ADF unit root test for the log-return series

Null Hypothesis: __RET has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic - based on SIC, maxlag=28)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-35.21442	0.0000
Test critical values:	1% level	-3.960902	
	5% level	-3.411207	
	10% level	-3.127436	

*MacKinnon (1996) one-sided p-values.

Table 4.2 shows the result of the ADF unit root test explained in the methodology section. The absolute value of the ADF statistic exceeds the absolute value of critical values at all significance levels, which is a good sign. In other words, the time series for return of MSE is stationary, or it allows use of the time series stochastic models in order to investigate the dynamic properties of volatility of MSE.

CHAPTER FIVE

DATA ANALYSIS

Testing ARCH effects

The null hypothesis for testing the ARCH effect is noted in section 3.5 of chapter 3. According to the testing methodology, results shown in Table 5.1 have been found. In the testing, p is equal to 3 (p=3).The ARCH test examines the empirical full period from 2/9/2001-10/18/2013.

Table 5-1: ARCH-LM test for residuals of return of MSE

R-squared	0.067529	Mean dependent var	0.001996
Adjusted R-squared	0.066656	S.D. dependent var	0.009932
S.E. of regression	0.009595	Akaike info criterion	-6.453916
Sum squared resid	0.294969	Schwarz criterion	-6.446343
Log likelihood	10356.08	Hannan-Quinn criter.	-6.451201
F-statistic	77.34398	Durbin-Watson stat	2.006215
Prob(F-statistic)	0.000000		

Note: Significant at the 5% level. The value of Chi square distribution with 3 degree of freedom is 7.81.

The value of ARCH-LM test statistic is calculated by $n*R^2$, and it is 216.97. As a result, the null hypothesis is rejected because the test statistic (the value of LM) is considerably greater than the critical value. This implies that the squared residuals are serially correlated and conditional heteroskedasticity exists in the model. The following results shown in Table 5.2 answer that the daily log returns time series have a presence of serial correlation (no white-noise).

Table 5-2: White-noise test

Test	p-value	SIG?
White-noise	0.00%	FALSE
Normal Distributed?	0.00%	FALSE
ARCH Effect?	0.00%	TRUE

Thus, these results suggest the potential presence of autocorrelation in the MSE and allow investigation to proceed using different types of GARCH models in capturing the dynamic of the MSE.

Estimating parameters for models

As defined in the purpose of this study, the parameters of the GARCH(1,1) and the EGARCH(1,1) is estimated using the maximum likelihood method under the assumptions of the Gaussian distribution and the student-t distribution for the conditional distribution of errors. ML method is the most common method to estimate GARCH parameters, and the method employs trails and errors to determine the optimal values for the coefficients that maximize the likelihood of the data occurring. The results of estimates are presented in Table 5.3, and in Table 3 and 4 in the appendix. The high coefficients, β_1 of 0.90 in the GARCH(1,1) and β_1 of 1.00 in the EGARCH(1,1) model, imply the persistent volatility clustering. The p-values of coefficients show that the volatility from past periods affects the current volatility. For the GARCH(1,1) model, the sum of the two estimated coefficients shown in Table 5.3 ($\alpha_1 + \beta_1 > 1$) are above unity. This signifies that the weight given to the long-term average variance is negative, and the GARCH process is mean fleeing rather than mean reverting. This does not match the assumption for stable GARCH(1,1) process.

Table 5-3: Results from the GARCH(1,1) and the EGARCH(1,1) model with normal distribution for the conditional distribution of errors

Coefficients	GARCH(1,1)	Coefficients	EGARCH(1,1)
α_0	0.00000295	α_0	-0.134590
α_1	0.114383	α_1	0.220667
β_1	0.907066	δ	0.044752
		β_1	1.000256

The magnitude of beta coefficient indicates a long memory in the variance. Positive and significant delta coefficient of EGARCH model shows the existence of leverage effect in returns, and the news impact is asymmetry in volatility of the MSE.

Under the assumption of student's t distribution, p-values of parameters for both models are not statistically significant, and the null hypothesis cannot be rejected. (See Table 5 and 6 in appendix). Therefore, the estimates from the assumption that the conditional distribution of errors is the student's t distribution are not considered in comparing the models.

Performance comparison

If a GARCH model is working well, it should remove the autocorrelation. Table 5.4 shows the result of autocorrelations before and after the use of the GARCH models. The first column shows autocorrelation for squared residuals. The last two columns demonstrate autocorrelation structure for variable e_i^2/σ_i^2 after the use of the models. If these show small autocorrelation, the model for volatility has succeeded in explaining autocorrelations in the squared residuals.

Table 5-4: Autocorrelations before and after the use of the GARCH(1,1) and EGARCH(1,1) model for MSE

Time lag	Autocorrelation for e_i^2	Autocorrelation after the use of GARCH	Autocorrelation after the use of EGARCH
1	0.234	0.013	0.009
2	0.056	0.027	0.023
3	0.124	-0.01	-0.008
4	0.079	-0.013	-0.007
5	0.042	-0.003	0.01
6	0.049	-0.012	-0.006
7	0.058	-0.012	-0.007
8	0.042	-0.003	0.003
9	0.059	-0.016	-0.01
10	0.099	0.003	0
11	0.088	-0.011	-0.009
12	0.104	-0.012	-0.007
13	0.215	0.006	0.005
14	0.158	0.007	0.008
15	0.043	-0.008	-0.007

The above results suggest that both models are working well because they show very little autocorrelation. In other words, they significantly removed the autocorrelation. From these results, we cannot tell which model is capable of removing more autocorrelation. To solve the problem, I performed a Ljung-Box test for the first 15 lags at 95% confidence interval in accordance with the test formulation in chapter 3. Engle (2001) stated that a Ljung-Box Test with 15 lagged autocorrelation is acceptable. Before the implementation of models, LB statistic for e_i^2series is 245.91, which means the strong evidence of autocorrelation since zero autocorrelation can be rejected with 95% confidence when LB statistic is greater than critical value.

Table 5-5: Autocorrelations before and after the use of the GARCH(1,1) and EGARCH(1,1) model for MSE: Ljung-Box test

LB		
LB statistic /autocorrelation/	247.91	
LB statistic /GARCH(1,1)/		2.75
LB statistic /EGARCH(1,1)/		1.64

Note: LB critical value with 15 lagged at 95% confidence level is 25

For the e_i^2/σ_i^2 series, the LB statistic values after the implementation of the GARCH and the EGARCH are 2.75 and 1.64, respectively. These numbers are suggesting that autocorrelation has been largely removed by the models. According to the test, the EGARCH model removed more autocorrelation than the GARCH model. This indicates that the EGARCH model outperforms the GARCH model for the return series of the MSE.

Furthermore, with respect to AIC values from Table 3 and 4 in appendix, the EGARCH(1,1) model produces slightly lower AIC value than the GARCH(1,1). This result implies that the GARCH model outperforms the EGARCH model. The sum of alpha and beta parameter of the GARCH model is more than unity, the EGARCH model removes relatively more autocorrelation than the GARCH model does, and the two models produce almost identical AIC values.

In consequence of this, I suggest that the EGARCH model seems to be the realistic model in capturing the dynamic behavior of the Mongolian Stock Market returns.

CHAPTER SIX

DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

In this paper, I compared the performance of two models, the GARCH(1,1) and the version of GARCH (EGARCH(1,1)) used with normal and student's t distribution of error. The dataset is unique in that it is not obtainable from public websites or on-sites. This time series analysis covered a 12 year period, and the daily market prices, Mongolian Stock Exchange Index, were used.

Descriptive statistic shows that the mean return is 0.1% and the standard deviation is 4.54%, and it indicates that the Mongolian Stock Exchange (MSE) is more volatile compared to other markets such as the Indonesian, Malaysian, and Singapore market, and Belex 15, DJIA, STOXX TIM, and SAX indices. This also indicates positive skewness and excess leptokurtic distribution.

The extremely large Jarque-Bera statistic was found and undoubtedly rejects the null hypothesis of normality in the return series. According to the Augmented Dickey-Fuller unit root test, the time series for return of the Mongolian Stock Exchange is stationary. The results from ARCH-LM test reveal that the squared residuals are serially correlated and there is a conditional heteroskedasticity in the model.

The parameters of the GARCH(1,1) and the EGARCH(1,1) are estimated using the maximum likelihood method under the assumptions of Gaussian distribution and student-t distribution for the conditional distribution of errors. For the GARCH(1,1) model, the sum of the two estimated coefficients are above 1. This signifies that the weight given to the long-term average variance is negative and the GARCH process is mean fleeing rather than mean reverting. This does not match the assumption for stable GARCH(1,1) process. Positive and significant delta coefficient of the EGARCH model shows the existence of leverage effect in returns, and the news impact is asymmetry in volatility of the MSE. Under the assumption of student's t distribution, p-values of parameters for GARCH(1,1) and EGARCH(1,1) models are not statistically significant.

The Ljung Box statistics for GARCH(1,1) and EGARCH(1,1) models suggest that autocorrelation has been largely removed by the models. According to the test, the EGARCH model removed more autocorrelation than the GARCH model. The two models produce almost identical Akaike Information Criterion values.

Finally, I suggest that the EGARCH model seems to be the realistic model in capturing the dynamic behavior of the Mongolian Stock Market returns.

In future study, other models and other versions of the GARCH model should be examined by adding more lags in the ARCH term and in the GARCH term, and future research should be made to confirm the appropriateness of the EGARCH model for volatility of the Mongolian Stock Market. In addition, future research should discover the cause of the Mongolian Stock Market's volatility, and compare the cause of the Mongolian Stock Market's volatility with the observations of other similar equity markets.

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APPENDIX

Table 1: Test for Arch effect

Dependent Variable: E2
Method: Least Squares
Date: 06/18/14 Time: 10:54
Sample (adjusted): 6 3213
Included observations: 3208 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001349	0.000177	7.625867	0.0000
E2(-1)	0.233407	0.017546	13.30237	0.0000
E2(-2)	-0.025936	0.018018	-1.439392	0.1501
E2(-3)	0.116540	0.017546	6.641872	0.0000

R-squared	0.067529	Mean dependent var	0.001996
Adjusted R-squared	0.066656	S.D. dependent var	0.009932
S.E. of regression	0.009595	Akaike info criterion	-6.453916
Sum squared resid	0.294969	Schwarz criterion	-6.446343
Log likelihood	10356.08	Hannan-Quinn criter.	-6.451201
F-statistic	77.34398	Durbin-Watson stat	2.006215
Prob(F-statistic)	0.000000		

Table 2: Correlogram for squared residuals of return

Date: 06/18/14 Time: 12:23
Sample: 1 3213
Included observations: 3211

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>|** |</td><td>|** |</td><td>1</td><td>0.234</td><td>0.234</td><td>175.79</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>2</td><td>0.056</td><td>0.001</td><td>185.84</td><td>0.000</td></tr>
<tr><td>|* |</td><td>|* |</td><td>3</td><td>0.124</td><td>0.117</td><td>234.90</td><td>0.000</td></tr>
<tr><td>|* |</td><td>| |</td><td>4</td><td>0.079</td><td>0.027</td><td>255.23</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>5</td><td>0.042</td><td>0.015</td><td>260.89</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>6</td><td>0.049</td><td>0.024</td><td>268.56</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>7</td><td>0.058</td><td>0.032</td><td>279.29</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>8</td><td>0.042</td><td>0.016</td><td>285.05</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>9</td><td>0.059</td><td>0.040</td><td>296.38</td><td>0.000</td></tr>
<tr><td>|* |</td><td>| |</td><td>10</td><td>0.099</td><td>0.070</td><td>328.26</td><td>0.000</td></tr>
<tr><td>|* |</td><td>| |</td><td>11</td><td>0.088</td><td>0.044</td><td>353.17</td><td>0.000</td></tr>
<tr><td>|* |</td><td>| |</td><td>12</td><td>0.104</td><td>0.067</td><td>388.31</td><td>0.000</td></tr>
<tr><td>|** |</td><td>|* |</td><td>13</td><td>0.215</td><td>0.169</td><td>537.34</td><td>0.000</td></tr>
<tr><td>|* |</td><td>| |</td><td>14</td><td>0.158</td><td>0.063</td><td>617.55</td><td>0.000</td></tr>
<tr><td>| |</td><td>| |</td><td>15</td><td>0.043</td><td>-0.026</td><td>623.66</td><td>0.000</td></tr>
</table>

Table 3: Estimation results of GARCH(1,1) with Gaussian distribution

Dependent Variable: R
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 06/18/14 Time: 12:24
Sample (adjusted): 3 3213
Included observations: 3211 after adjustments
Convergence achieved after 45 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-3.37E-05	0.000279	-0.120884	0.9038
R(-1)	0.049046	0.017786	2.757635	0.0058
		Variance Equation		
C	0.00000295	1.27E-07	23.32714	0.0000
RESID(-1)^2	0.114383	0.002636	43.39968	0.0000
GARCH(-1)	0.907066	0.001799	504.0880	0.0000

R-squared	-0.020524	Mean dependent var	0.001032
Adjusted R-squared	-0.020842	S.D. dependent var	0.045398
S.E. of regression	0.045869	Akaike info criterion	-4.471706
Sum squared resid	6.751668	Schwarz criterion	-4.462248
Log likelihood	7184.324	Hannan-Quinn criter.	-4.468316
Durbin-Watson stat	2.442726		

Note: *R-squared value is only valid for mean equation. GARCH and EGARCH model deal with variance equation. Thus, R-squared value is not significant in model diagnostics. That is, if there are no regressors in the mean equation, R-squared value may not be meaningful or it is negative (Chen, Jo-Hui, n.d)*

Table 4: Estimation results of EGARCH(1,1) with Gaussian distribution

Dependent Variable: R
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 06/18/14 Time: 16:40
Sample (adjusted): 3 3213
Included observations: 3211 after adjustments
Convergence achieved after 50 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.001526	7.21E-05	-21.16151	0.0000
R(-1)	0.062343	0.014102	4.420934	0.0000
		Variance Equation		
C(3)	-0.134590	0.004781	-28.15057	0.0000
C(4)	0.220667	0.005110	43.18259	0.0000
C(5)	0.044752	0.002703	16.55435	0.0000
C(6)	1.000256	0.000553	1807.755	0.0000

R-squared	-0.029299	Mean dependent var	0.001032
Adjusted R-squared	-0.029620	S.D. dependent var	0.045398
S.E. of regression	0.046066	Akaike info criterion	-4.438623
Sum squared resid	6.809725	Schwarz criterion	-4.427273
Log likelihood	7132.210	Hannan-Quinn criter.	-4.434555
Durbin-Watson stat	2.459002		

Note: *R-squared value is only valid for mean equation. GARCH and EGARCH model deal with variance equation. Thus, R-squared value is not significant in model diagnostics. That is, if there are no regressors in the mean equation, R-squared value may not be meaningful or it is negative (Chen, Jo-Hui, n.d)*

Table 5: Estimation results of GARCH(1,1) with student's t distribution

Dependent Variable: R
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/18/14 Time: 16:35
Sample (adjusted): 3 3213
Included observations: 3211 after adjustments
Convergence achieved after 500 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-9.76E-05	0.000184	-0.530951	0.5955
R(-1)	0.027129	0.013430	2.020068	0.0434
		Variance Equation		
C	0.035837	20.38506	0.001758	0.9986
RESID(-1)^2	368.4884	209629.5	0.001758	0.9986
GARCH(-1)	0.892406	0.009101	98.05906	0.0000
T-DIST. DOF	2.000104	0.059139	33.82045	0.0000

R-squared	-0.011070	Mean dependent var	0.001032
Adjusted R-squared	-0.011385	S.D. dependent var	0.045398
S.E. of regression	0.045656	Akaike info criterion	-4.993722
Sum squared resid	6.689123	Schwarz criterion	-4.982372
Log likelihood	8023.421	Hannan-Quinn criter.	-4.989654
Durbin-Watson stat	2.405106		

Note: *R-squared value is only valid for mean equation. GARCH and EGARCH model deal with variance equation. Thus, R-squared value is not significant in model diagnostics. That is, if there are no regressors in the mean equation, R-squared value may not be meaningful or it is negative (Chen, Jo-Hui, n.d)*

Table 6: Estimation results of EGARCH(1,1) with student's t distribution

Dependent Variable: R
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 06/18/14 Time: 16:57
Sample (adjusted): 3 3213
Included observations: 3211 after adjustments
Convergence achieved after 58 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.41E-05	0.000176	0.080084	0.9362
R(-1)	0.025395	0.013069	1.943056	0.0520
	Variance Equation			
C(3)	-0.204316	0.022019	-9.279071	0.0000
C(4)	0.886273	0.390384	2.270258	0.0232
C(5)	-0.001529	0.049485	-0.030903	0.9753
C(6)	0.984306	0.002486	396.0020	0.0000
T-DIST. DOF	2.023023	0.019988	101.2115	0.0000

R-squared	-0.010244	Mean dependent var	0.001032
Adjusted R-squared	-0.010559	S.D. dependent var	0.045398
S.E. of regression	0.045638	Akaike info criterion	-5.020280
Sum squared resid	6.683660	Schwarz criterion	-5.007038
Log likelihood	8067.059	Hannan-Quinn criter.	-5.015533
Durbin-Watson stat	2.402380		

Note: *R-squared value is only valid for mean equation. GARCH and EGARCH model deal with variance equation. Thus, R-squared value is not significant in model diagnostics. That is, if there are no regressors in the mean equation, R-squared value may not be meaningful or it is negative (Chen, Jo-Hui, n.d)*