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# ODHAD MODELOV GARCH S HODNOTOU RIZIKA NA PRÍKLADE MONGOLSKEJ BURZY

# ESTIMATING GARCH MODELS IN MONGOLIAN STOCK EXCHANGE WITH VALUE AT RISK

*Cheng-Wen Lee*[1], *Dolgion Gankhuyag*[2]

Štúdia skúma vplyv autoregresnej podmienenej heteroskedasticity a odhaduje asymetrické modely GARCH i symetrické modely GARCH na príklade mongolského akciového indexu MSE20 od 2. januára 2012 do 27. decembra 2019. Počas štúdie sme zistili významnú prítomnosť autoregresívneho podmieneného účinku heteroscedasticity a vyhodnotili model hodnoty v riziku s cieľom určiť predpovedanú stratu prognózy. Štúdia zistila, že maximálna strata jedného dňa nepresiahne 2 %, zatiaľ čo celý výpočet je nižší ako 2 %. Test ukázal, že pozitívne aj negatívne šoky majú rovnaký vplyv na volatilitu denných výnosov indexu MSE20.
Kľúčové slová: asymetrické modely GARCH, symetrické modely GARCH, hodnota v riziku, akciový trh, manažovanie rizika

This study will examine the effect of Autoregressive Conditional Heteroskedasticity and estimate Asymmetric GARCH models, Symmetric GARCH models, in the Mongolian Stock Index MSE20 time frame from 2 January 2012 to 27 December 2019. During the study, we found significant presence of autoregressive conditional heteroscedasticity effect, and evaluated Value at Risk model to determine predicted forecast loss. The study found that a maximum loss of one day would not surpass 2 percent, while all the calculation is less than 2 percent. The test has shown that both positive and negative shocks have the same effect on the volatility of MSE20 index daily returns.
Key words: Asymmetric GARCH models, Symmetric GARCH models, Value at Risk, Stock market, Risk management
JEL: G32, R15

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## 1 INTRODUCTION

The Value at Risk measures, the potential loss of value of risky assets or portfolios in their most general form over a certain time for a particular confidence duration. While any organization can use Value at Risk for the most widely used risk management measurement for commercial and investment banks to evaluate Value at Risk to catch possible loss in value of their trading assets from adverse market movements over a specified period of time.

In finance, there is conditional heteroskedasticity because of the unpredictable returns on assets, often described as volatile. A series of random variables is heteroskedastic if in the larger set there are subsets of variables that differ from the other variables. Heteroskedastic refers to cases in which the variance of the residual term or error term is very different in a system of regression. When applying regression analyses, including variance analyses, the existence of heteroscedasticity is a significant concern as it can invalidate significant statistical tests, which conclude that modeling errors are uncorrelated and consistent, so that their variances do not vary from model results.

The aim of this study is to check the relative output of a range of GARCH models to estimate and forecast value-at-risk on the Mongolian Stock Exchange for the last 8 years of data.

## 2 LITERATURE REVIEW

The Value at Risk (VaR) and its use have been thoroughly analyzed in calculating the actual potential damages in the financial sector. From a forecasting point of view, Sarma et al. (2003) studied the Indian share market using various VaR models and observed that the VaR models produce varied results.

Bucevska (2013) found EGARCH model at most fitted in the Macedonian stock exchange checking GARCH family models with different forms of VaR models.

Chen and Wang (2009) used GARCH and EGARCH models with normal distribution and student t-distribution to calculate Value at Risk estimates in the Chinese stock market (Shanghai and Shenzhen markets). They reported that daily returns and volatility on the Shanghai and Shenzhen stock markets were highly optimistic, and the features of volatility clustering are apparent.

Lim and Sek (2013) observed that symmetric and asymmetric GARCH family models were operated differently in Malaysian stock market timescales of 1990-2010 and found interesting result of GARCH model were performing the best normal trading days and other GARCH models were outperform during financial recession period.

## 3 DATA AND METHODOLOGY

In this study, we evaluate the actual performance of selected GARCH symmetric models of GARCH (1,1), EGARCH (1,1), GARCH-GJR (1,1), APARCH (1,1), GARCH-M (1,1) and IGARCH (1,1) were used.

We use the VaR model to estimate the risk for risk assessment. All data from this study were collected on the official website of the Mongolian Stock Exchange. The data shall cover the period from 3 January 2012 to 24 July 2019 and shall contain the findings of 1997 from the observations.

In order to evaluate stock index we used logarithmic return as follow:

$$\mathrm{R_{m,t}} = \ln\left(\frac{\mathrm{X_t}}{\mathrm{X_{t\text{-}1}}}\right), \tag{1}$$

where $X_t$ is MSE20 stock index of day $t$.

## 4 GARCH MODELING

We used the following equations for the GARCH family model for our test. Angabini and Wasiuzzaman (2011) used GARCH (p,q) model:

$$R_t = \mu + \varepsilon_t$$
$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{q} \propto_i + \varepsilon_{t-i}^2$$

Engle, Lilien and Robins (1987) pioneered GARCH-M model:

$$R_t = \mu + \beta_t \sigma_t^2 + \varepsilon_t$$
$$\varepsilon_t \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-i}^2 + \beta_1 \sigma_{t-1}^2$$

Nelson (1991) showed EGARCH model:

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^{p} (\alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \gamma_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) + \sum_{i=1}^{q} \beta_i \log(\sigma_{t-i}^2)$$

Glosten, Jagannatahan and Runkle (1993) pioneered GARCH GJR model:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-1}^2 + \gamma_i I_{t-i} \varepsilon_{t-i}^2$$

Ding, Engle and Granger (1993) introduced APARCH model:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} (\alpha |\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^{\delta} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^{\delta}$$

Ruey S. Tsay,(2010) used IGARCH model:

$$\alpha_t = \sigma_t \varepsilon_t$$
$$\sigma_t^2 = \omega + \sigma_{t-1}^2 + (1 - \beta_1)\, \alpha_{t-1}^2$$

where $p$ is the order of GARCH and $q$ is the order of ARCH process, $R_t$ are returns of the stock index at time $t$ in natural log, $\mu$ are mean value of the returns, $\varepsilon_t$ is the error term at time $t$, zero mean and conditional variance $\sigma_t^2$ and $\alpha, \beta, \omega, \mu$ are parameters. Here $I$ representing as indicator dummy variable.

## 5 VaR MODELING

In view of a confidence level of ρ ∈ (0.1) and using the time index of t and t+α, we would like to see the shift asset of the algorithm ΔV(α) in the financial position over the period.

Let $F_\alpha$ (x) be the cumulative distribution function of ΔV(α). The Value at Risk is defined as the owner of a position, with probability ρ in a given time α, and the financial position as ΔV(α) ≤ 0.

$$\rho = P[\Delta V(\alpha) \leq Value\ at\ Risk] = F\alpha\ (Value\ at\ Risk)$$

Value at Risk systems measure market risk exposure at a user-selected level of confidence. The off the shelf system uses a confidence interval of 95 percent or 99 percent.

In this study, we assume that it follows a distribution of model would be:

$$\mathcal{E}_t = D(\mu_t, 6_t^2),$$

where $\mu_t$ and $6_t^2$ are the mean and variance of $\mathcal{E}_t$.

Value at Risk would be:

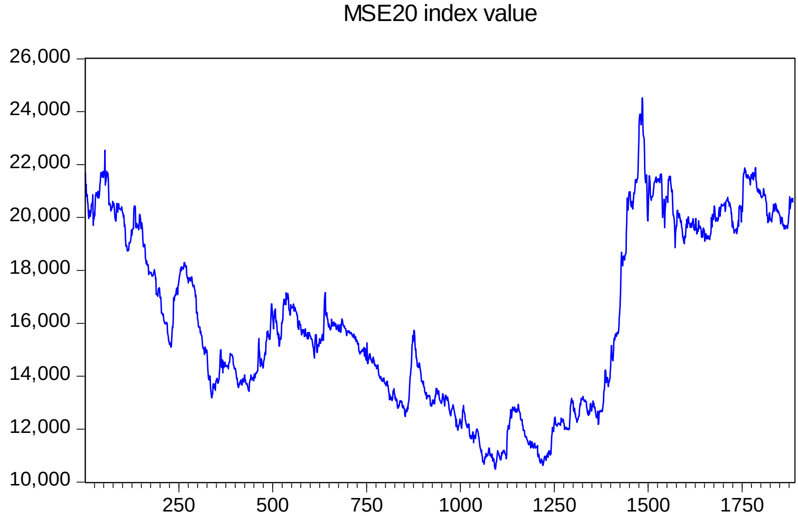
$$VaR_t = E(R_t / F_{t-1}) - \alpha 6_t$$

Where α represents the distribution critical value $\mathcal{E}_t$ to estimate the necessary level of confidence. Alternative measures of conditional variance can be used to replace $\sigma_t$.

## 6 Results of the study

Daily closing value of the Mongolian Stock Exchange index is provided on Figure 1. As we can observe there is no pattern on performance of the index but gradually decline in the first half then appreciated over time for over 8 years of trading.

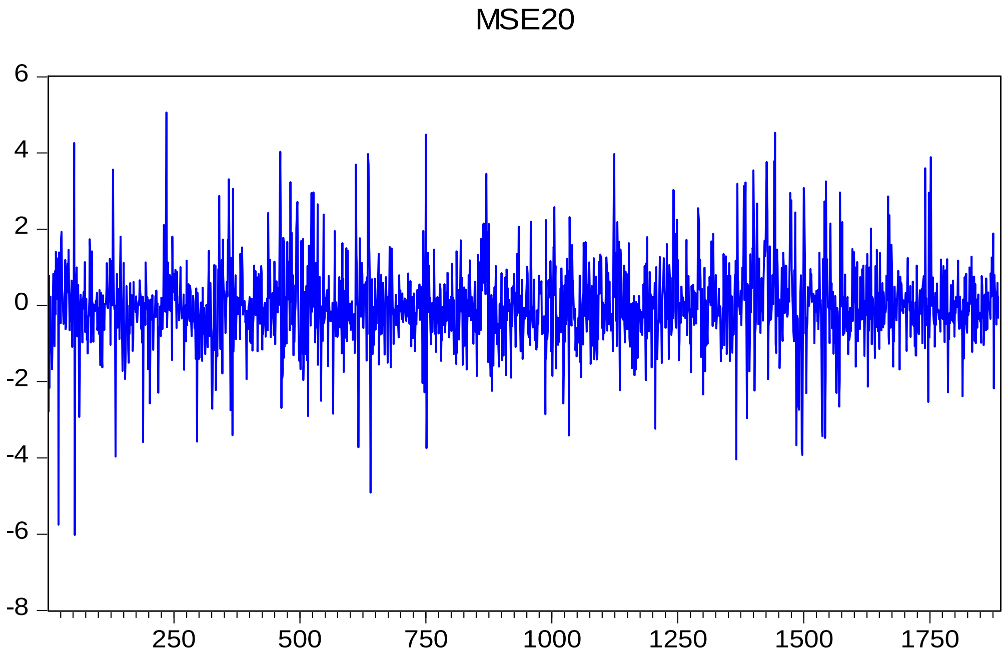
Figure 1: Daily closing values of the Mongolian Stock Exchange index MSE20 in the period from the 3rd January 2012 to 24th July 2019




Source: processed by author

Figure 2 is displaying the daily returns of the Mongolian Stock Exchange index MSE20 and its stationary for daily returns.

Figure 2: Daily closing values of the Mongolian Stock Exchange index MSE20 in the period from the 3rd January 2012 to 24th July 2019




Source: processed by author

Table 1: Augmented Dickey-Fuller test statistic of the Mongolian Stock Exchange index MSE20 in the period from the 3rd January 2012 to 24th July 2019

| | | | | |
|---|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | | -38.3007 | 0.0000 |
| Test critical values: | 1% level | | -3.43361 | |
| | 5% level | | -2.86286 | |
| | 10% level | | -2.56752 | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| MSE20(-1) | -0.874775 | 0.02284 | -38.30074 | 0.0000 |
| C | -0.001066 | 0.02430 | -0.043873 | 0.9651 |
| R-squared | 0.43764 | Mean dependent var | | 0.000304 |
| Adjusted R-squared | 0.437342 | S.D. dependent var | | 1.407528 |
| S.E. of regression | 1.055795 | Akaike info criterion | | 2.947524 |
| Sum squared resid | 2101.214 | Schwarz criterion | | 2.953398 |
| Log likelihood | -2778.989 | Hannan-Quinn criter. | | 2.949687 |
| F-statistic | 1466.946 | Durbin-Watson stat | | 2.010121 |
| Prob(F-statistic) | 0 | | | |

Source: processed by author

Dickey – Fuller is testing the null hypothesis that the unit root is present in the daily returns of the Mongolian Stock Exchange Index MSE20. If the Augmented Dickey-Fuller test is significant, this means that the null hypothesis that the variable has a root / non-stationary unit is rejected and the daily returns of the stock index are stationary data.

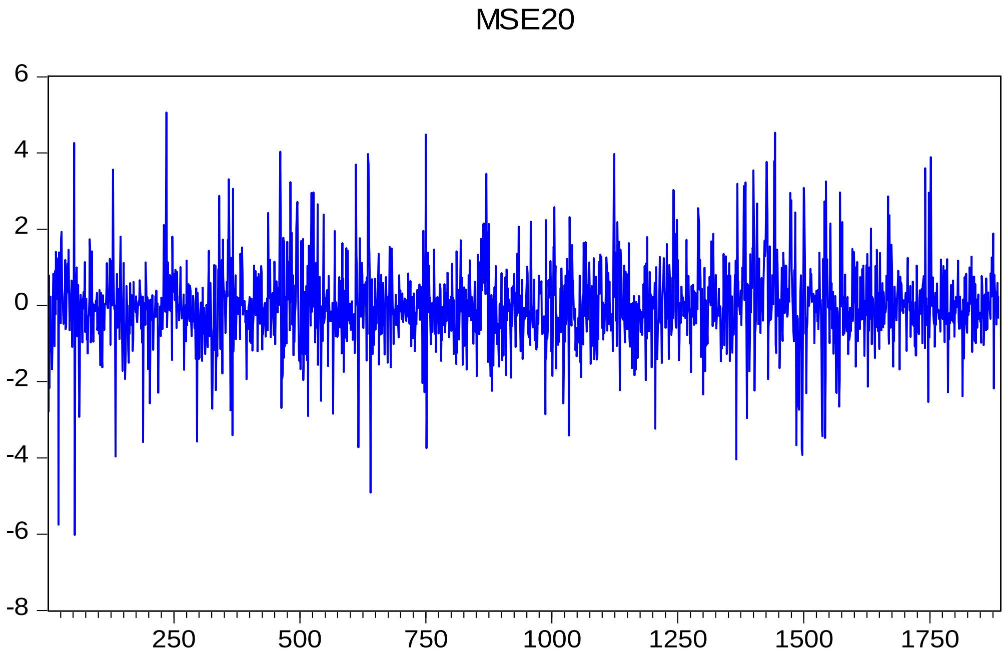
Table 2: Correlogram of daily stock returns of the Mongolian Stock Exchange index MSE20 in the period from the 3rd January 2012 to 24th July 2019

| ***Lag*** | ***AC*** | ***PAC*** | ***Q-Stat*** | ***Prob*** | ***Lag*** | ***AC*** | ***PAC*** | ***Q-Stat*** | ***Prob*** |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.123 | 0.123 | 28.529 | 0.000 | **16** | -0.001 | 0.000 | 53.186 | 0.000 |
| **2** | 0.066 | 0.052 | 36.791 | 0.000 | **17** | -0.003 | -0.001 | 53.200 | 0.000 |
| **3** | 0.017 | 0.003 | 37.312 | 0.000 | **18** | -0.002 | -0.004 | 53.210 | 0.000 |
| **4** | -0.010 | -0.016 | 37.501 | 0.000 | **19** | 0.006 | 0.012 | 53.287 | 0.000 |
| **5** | 0.032 | 0.034 | 39.407 | 0.000 | **20** | 0.036 | 0.033 | 55.751 | 0.000 |
| **6** | 0.017 | 0.011 | 39.973 | 0.000 | **21** | -0.030 | -0.038 | 57.511 | 0.000 |
| **7** | 0.041 | 0.035 | 43.142 | 0.000 | **22** | 0.007 | 0.012 | 57.600 | 0.000 |
| **8** | 0.061 | 0.051 | 50.306 | 0.000 | **23** | -0.022 | -0.021 | 58.569 | 0.000 |
| **9** | -0.018 | -0.035 | 50.903 | 0.000 | **24** | 0.017 | 0.024 | 59.141 | 0.000 |
| **10** | 0.028 | 0.027 | 52.375 | 0.000 | **25** | 0.029 | 0.024 | 60.725 | 0.000 |
| **11** | -0.018 | -0.023 | 53.017 | 0.000 | **26** | 0.032 | 0.026 | 62.672 | 0.000 |
| **12** | 0.001 | 0.003 | 53.020 | 0.000 | **27** | 0.070 | 0.057 | 71.987 | 0.000 |
| **13** | -0.001 | -0.004 | 53.021 | 0.000 | **28** | 0.038 | 0.021 | 74.738 | 0.000 |
| **14** | -0.009 | -0.009 | 53.182 | 0.000 | **29** | -0.001 | -0.011 | 74.741 | 0.000 |
| **15** | 0.000 | -0.004 | 53.182 | 0.000 | **30** | -0.006 | -0.014 | 74.813 | 0.000 |

Source: processed by author

In all log returns the return data are checked for autocorrelation. We use ACF, PACF and Q-statistics to check for the existence of autocorrelation in log returns. If autocorrelation is observed during the study, series heteroskedasticity can be reduced by filling out the simplest possible GARCH model. The effect of ARCH is detectable in all data series throughout the Q-Statistics test. The first lag of the sample shows strong autocorrelation during the test and the second, fifth, twentieth, twentieth, twentieth and twentieth lag shows significant autocorrelation effects from the Q-statistics of the stock index.

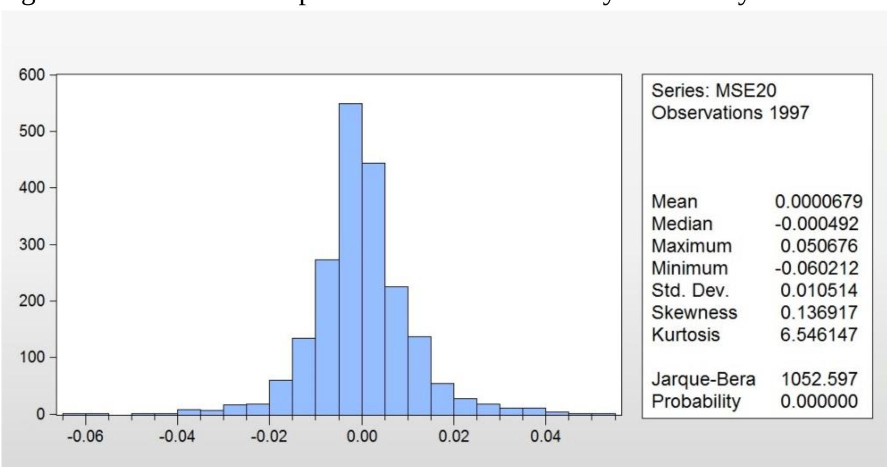
Figure 3: Q-Q plot of daily stock returns of the Mongolian Stock Exchange index MSE20 in the period from the 3rd January to 24th July 2019




Source: processed by author

Q-Q plot, is a graphical resource to help us determine whether a data set is likely to originate from some quantitative distribution, as we can assume the data is normally distributed.

Figure 4: Summary descriptive statistics for the daily returns of the Mongolian Stock Exchange index MSE20 in the period from the 3rd January to 24th July 2019




Source: processed by author

The descriptive statistics on the daily returns from the stock index are shown in Figure 4.

Table 3: Tested asymmetric and symmetric GARCH models for daily returns of the Mongolian Stock Exchange index MSE20

| | ***GARCH*** | | | | ***EGARCH*** | | | |
|---|---|---|---|---|---|---|---|---|
| | Coefficient | Std.Error | t-value | t-prob | Coefficient | Std.Error | t-value | t-prob |
| Alpha0 | -0.000679 | 0.00023692 | -2.865 | 0.0042 | -0.000462 | 0.0002464 | -1.877 | 0.0607 |
| ARCH(Alpha1) | 0.204891 | 0.041798 | 4.902 | 0.0000 | -0.221541 | 0.11728 | -1.889 | 0.0590 |
| GARCH(Beta1) | 0.583709 | 0.084438 | 6.913 | 0.0000 | 0.751484 | 0.058738 | 12.79 | 0.0000 |
| EGARCH(Theta1) | | | | | 0.123006 | 0.033742 | 3.645 | 0.0003 |
| EGARCH(Theta2) | | | | | 0.40245 | 0.059606 | 6.752 | 0.0000 |
| GJR(Gamma1) | | | | | | | | |
| APARCH(Delta) | | | | | | | | |
| ARCH-in-mean(var) | | | | | | | | |
| Log-Likelihood | 6366.432 | | | | 6370.26 | | | |

| | ***GARCH-GJR*** | | | | ***APARCH*** | | | |
|---|---|---|---|---|---|---|---|---|
| | Coefficient | Std.Error | t-value | t-prob | Coefficient | Std.Error | t-value | t-prob |
| Alpha0 | -0.000507 | 0.00022269 | -2.276 | 0.0230 | -0.000506 | 0.0002217 | -2.284 | 0.0225 |
| ARCH(Alpha1) | 0.275827 | 0.060135 | 4.587 | 0.0000 | 0.083392 | 0.045489 | 3.826 | 0.0001 |
| GARCH(Beta1) | 0.585785 | 0.080117 | 7.312 | 0.0000 | 0.571522 | 0.08193 | 6.976 | 0.0000 |
| EGARCH(Theta1) | | | | | | | | |
| EGARCH(Theta2) | | | | | | | | |
| GJR(Gamma1) | -0.168237 | 0.058532 | -2.874 | 0.0041 | -0.224618 | 0.078491 | -2.862 | 0.0043 |
| APARCH(Delta) | | | | | 2.237732 | 0.57118 | 3.918 | 0.0001 |
| ARCH-in-mean(var) | | | | | | | | |
| Log-Likelihood | 6376.26 | | | | 6376.76 | | | |

| | GARCH-M | | | | IGARCH | | | |
|---|---|---|---|---|---|---|---|---|
| | Coefficient | Std.Error | t-value | t-prob | Coefficient | Std.Error | t-value | t-prob |
| Alpha0 | -0.002003 | 0.00051463 | -3.893 | 0.0001 | -0.00155 | 0.000338 | -4.586 | 0.0000 |
| ARCH(Alpha1) | 0.199682 | 0.039246 | 3.591 | 0.0000 | 0.364669 | 0.067176 | 5.429 | 0.0000 |
| GARCH(Beta1) | 0.590999 | 0.079996 | 7.388 | 0.0000 | 0.635331 | | | |
| EGARCH(Theta1) | | | | | | | | |
| EGARCH(Theta2) | | | | | | | | |
| GJR(Gamma1) | | | | | | | | |
| APARCH(Delta) | | | | | | | | |
| ARCH-in-mean(var) | 14.253591 | 5.1403 | 2.773 | 0.0056 | 7.34984 | 1.9613 | 3.747 | 0.0002 |
| Log-Likelihood | 6371.12 | | | | 6340.09 | | | |

Source: processed by author

Table 3 displaying ARCH effect for all asymmetric and symmetric GARCH models. All models have significant presence of autoregressive conditional heteroscedasticity effect. According log-likelihood parameter, APARCH model is preferred to be the best one with highest log-likelihood parameter.

Table 4: Engle and Ng Joint test for sign and size bias

| *Variable* | *Coefficient* | *Std. Error* | *t-Statistic* | *Prob.* |
|---|---|---|---|---|
| C | 0.0000428 | 0.0000115 | 3.7098 | 0.0002 |
| DUMMY1 | 0.0000271 | 0.0000158 | 1.7228 | 0.0851 |
| DUMMY1*REST(-1) | -0.003511 | 0.001078 | -3.2562 | 0.0011 |
| DUMMY2*REST(-1) | 0.011003 | 0.001037 | 10.6084 | 0.0000 |
| R-squared | 0.062271 | Mean dependent var | 0.00011 | |
| Adjusted R-squared | 0.060858 | S.D. dependent var | 0.00026 | |
| S.E. of regression | 0.000252 | Akaike info criterion | -13.73401 | |
| Sum squared resid | 0.000126 | Schwarz criterion | -13.72278 | |
| Log likelihood | 13710.54 | Hannan-Quinn criter. | -13.72988 | |
| F-statistic | 44.09341 | Durbin-Watson stat | 1.9560 | |
| Prob(F-statistic) | 0.0000 | | | |

Source: processed by author

Estimation of the GARCH models, run the test, and we concluded that there can be residual asymmetry from the sign and bias test, which lead us to use asymmetric GARCH models were good choice. Engle and Ng bias test showing that models have strong evidence of asymmetric effects.

Table 5: Engle and Ng Joint test descriptive statistic for sign and size bias

| Wald Test: | | | |
|---|---|---|---|
| Test Statistic | Value | df | Probability |
| F-statistic | 44.09341 | (3, 1992) | 0 |
| Chi-square | 132.2802 | 3 | 0 |

Null Hypothesis: C(2)=0, C(3)=0, C(4)=0

| Null Hypothesis Summary: | | | |
|---|---|---|---|
| Normalized Restriction (= 0) | | Value | Std. Err. |
| C(2) | | 0.0000271 | 0.0000158 |
| C(3) | | -0.003511 | 0.001078 |
| C(4) | | 0.011003 | 0.001037 |
| Restrictions are linear in coefficients. | | | |

Source: processed by author

It is unlikely that positive and negative shocks would have the same effect on the volatility of stock returns. The test has demonstrated that positive and negative shocks have the same impacts on volatilities of daily returns of MSE20 index.

Table 6: Forecasted Value at Risk estimation

| | ***Forecasted return*** | ***Forecasted conditional vatiance*** | ***90*** | ***95*** | ***99*** |
|---|---|---|---|---|---|
| **GARCH** | 0.0006788 | 0.00006147 | -0.937% | -1.222% | -1.756% |
| **EGARCH** | 0.0004623 | 0.00005832 | -0.932% | -1.210% | -1.730% |
| **GARCH-GJR** | 0.0005067 | 0.00006209 | -0.959% | -1.245% | -1.782% |
| **APARCH** | 0.0005063 | 0.00006350 | -0.971% | -1.260% | -1.803% |
| **GARCH-M** | 0.0011240 | 0.00006170 | -0.894% | -1.180% | -1.715% |
| **IGARCH** | 0.0007999 | 0.00004615 | -0.791% | -1.037% | -1.500% |

Source: processed by author

Table 6 reveals that projected loss or gains for the forecasting for the one day ahead estimation. According to our test, we can assume one day maximum loss would be no greater than 2 percent although all the estimation is lower than 2 percent. It is usually ignore negative sign in study of estimation of Value at Risk models due to use them as indicator of projected loss. That means we can expect the cumulative loss due to MNT 1000000 stocks on the Mongolian stock exchange to be around MNT 17560 in one day, with a probability of 99 percent.

## 6 CONCLUSION

This research examines acceptable GARCH models for day-to-day trade on the Mongolian Stock Exchange. To evaluate for stationarity, the "unit root test" was applied, and all series were found to be stationary. We observed a strong concentration of ARCH effect in the residuals using ARCH-LM test at different lags. The Gaussian normal distribution considered for the GARCH family models were used in this study. The analysis summarizes six asymmetric and symmetrical GARCH models. Using GARCH models are suggested from the ARCH-LM study for significance existence of auto-regression heteroscedasticity effects were reported.

For each of the GARCH(1,1), EGARCH(1,1), GARCH-M(1,1), GARCH-GJR(1,1), APARCH(1,1), and IGARCH models, different lags were examined.. Under the assumed our model the observed data is most probable is APARCH model, which is considered to be the optimal one with the maximum log-likelihood parameter according to the log-likelihood parameter.

The Value at Risk with 90%, 95% and 99% were used to assess which model has the strongest-predicted precision. From our perspective, IGARCH has the lowest projectile loss for prediction forecast with 1.5 percent for most accurate prediction.

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