Available online at https://journal.rescollacomm.com/index.php/ijqrm/index

International Journal of Quantitative Research and Modeling

e-ISSN 2721-477X
p-ISSN 2722-5046

Vol. 5, No. 3, pp. 251-255, 2024

Analysis the Effect of Volatility on Potential Losses Mutual Fund Investments using the ES-GARCH Method

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Abstract

Investing in mutual funds has become a popular choice for investor who looking to participate in the capital markets with more diversified risk. However, the success of mutual fund investments depends on investors understanding the potential losses and opportunities that may arise during the investment period. Analyzing the risk of mutual fund investments is fundamental in helping investors comprehend potential losses. Therefore, research is conducted to understand potential losses by estimating asset price volatility and determining the maximum possible losses. The Expected Shortfall (ES) method proves useful in measuring downside risk and extreme loss potential in investments, but it is less effective in addressing nonlinear trends and the complexity of volatility patterns. Hence, a combination of the Expected Shortfall (ES) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) methods is employed to measure the risk of mutual fund investments. The research findings indicate that volatility has a positive impact on Value at Risk (VaR), and the potential maximum losses (ES) increase with higher volatility, indicating a greater risk.

Keywords: Investment, Mutual Funds, Risk Analysis, ES-GARCH.

1. Introduction

Finding and allocating funds or investments are two important parts of financial management. Investment involves making strategic decisions about allocating readily available funds to various projects, assets or other investments with the aim of achieving an optimal return on investment. In Indonesia, public interest in investment has experienced a significant increase in the last three years and experienced a significant increase in 2022 this is evidenced in the BKPM performance report in 2022.

One investment option that is gaining popularity among Indonesians and continues to increase in investors every year is mutual funds. Mutual funds are financial instruments that allow a number of investors to pool funds in a portfolio managed by professionals, helping to reduce the individual risk associated with investing directly in a particular asset or stock. In addition, mutual funds also offer high liquidity, allowing investors to buy or sell mutual fund shares at any time. This provides greater flexibility compared to some other investments.

While investing in mutual funds has many advantages, investors should consider the risks as well. Market risk is one of the main risks. Mutual funds usually invest in different types of assets such as stocks and bonds that are susceptible to market changes so the value of an equity mutual fund investment may also decrease when the stock market goes down. Portfolio diversification can lower this market risk, but it remains an important component to understand. Although mutual funds are generally liquid some types of mutual funds have liquidity limitations especially if they invest in less liquid assets. Therefore, investors should always consider their own risk profile and conduct careful research before investing in mutual funds.

2. Literature Review

2.1. Investment

Investment is the placement of funds or assets in the financial, economic, or property fields with the aim of obtaining future profits or returns (Masruroh A, 2014). It involves the allocation of current resources to generate greater value in the future. Investors choose to invest in various types of assets, such as stocks, bonds, real estate, or businesses, with the aim of achieving capital growth, passive income, protecting against inflation, and achieving long-term financial goals.

2.2. Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) is a statistical model that recognizes that the volatility of financial assets is often not constant and can change over time. GARCH was chosen to model and forecast volatility in financial data. GARCH combines an Autoregression (AR) approach to volatility with a component of conditional heteroskedasticity, which suggests that current volatility is affected by previous volatility data. The model has two orders, hence the name GARCH(p,q). According to Bollerslev (1986) the GARCH (p,q) model equation can be written as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} a_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2, \tag{1}$$

2.3. Value at Risk (VaR)

Value at Risk (VaR) is a measurement tool that can calculate the amount of the worst loss that can occur by knowing the position of the asset, the level of confidence in the occurrence of risk, and the period of asset placement (Jorion, 2007). VaR_α is expressed as the α-quantile form of the distribution of profits and losses X(t) for t=1,2,3,...,T where T is the investment period. If f (x) is the density function of X(t) and F(x) is the cumulative distribution function, technically Artzner et al. (1999) define that VaR with 100(1-α)% confidence level is as follows:

$$VaR_{1-\alpha}(X) = \mu + \Phi^{-1}(1-\alpha)\sigma \tag{2}$$

$$\Phi = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{\frac{-t^2}{x}} \tag{3}$$

2.4. Expected Shortfall (ES)

In financial analysis, Expected Shortfall (ES), also called Tail Conditional Expectation (TCE), is a risk metric that measures the average of expected losses when facing the worst-case scenario beyond a certain interval.In a continuous distribution with a confidence level of 100(1-α) and at time T, ES is the expectation of conditional losses in excess of VaR. Yamai and Yoshiba (2002) define ES, where X is a random variable of gains or losses of the portfolio and $VaR_\alpha(X)$ with a confidence level of 100(1-α)%, then ES can be formulated as follows:

$$ES_{1-\alpha}(X) = \mu + \sigma \frac{\phi(VaR_{1-\alpha})}{\alpha} \tag{4}$$

3. Materials and Methods

3.1. Materials

The object used in this research is ETF mutual funds on the Indonesia Stock Exchange. The data used is the closing price data of the Pinnacle FTSE Indonesia Mutual Fund (XPFT), Batavia SRI-KEHATI Index ETF (XBSK), Premier ETF Indonesia Financial Mutual Fund (XIIF), Premier ETF Indonesia State-Owned Companies (XISC), and Batavia Smart Liquid ETF (XBLQ) August 2022 - August 2023 from the Yahoo Finance page.

3.2. Methods

a) Stationarity test

Stationarity test is the initial stage of the GARCH model. Stationary test is performed using Augmented Dickey Fuller, if the data is not stationary, differencing is performed.

b) Model Identification

Model identification is the process of finding the right GARCH model to model the data. This process is done by looking for the smallest AIC value.

c) ARCH-LM test

The ARCH-LM test is an evaluation process to determine whether the model used can model the data well, which is indicated by the absence of heteroscedasticity in the residuals.

d) Normality test

The residual normality test is the other model evaluations. If the residuals of the model are normally distributed, the model used is suitable.

e) Volatility estimation

Volatility estimation is the process of calculating price uncertainty through the root of the variance obtained from using the GARCH model.

f) VaR and ES calculation

Finally, potential losses are calculated using VaR and ES.

4. Results and Discussion

a) Stationery test

The initial stage of GARCH modeling is to test the stationarity of the data that has been collected using Augmented Dickey Fuller. The stationarity test results are shown in Table 1.

Table 1: Stasionery Test using ADF

Data	ADF Statistic	p-value
XPFT	-1.36625863	0.598
XBSK	-2.58141891	0.096
XIIF	-1.65625838	0.453
XISC	-2.45569186	0.126
XBLQ	-1.04044202	0.738

After differencing, stationarity testing is performed using ADF on the data. The results of the ADF test on data that has been differenced are shown in Table 2

Table 2: Stasionery Test on Differenced Data

Data	ADF Statistic	p-value
XPFT	-7.16554077	2.89e-10
XBSK	-9.52530468	2.98e-16
XIIF	-9.94182233	2.65e-17
XISC	-8.54009980	9.83e-14
XBLQ	-6.73668690	3.19e-09

The ADF test results after differencing show that the five data are stationary after differencing because the P-Value<0.05.

b) Model Identification

To determine the best model that can model the data, the smallest AIC value is found using python. The results of the AIC value are shown in Table 3.

Table 3: AIC values of data

Model	XPFT	XBSK	XIIF	XISC	XBLQ
1,1	287.564892	395.121082	326.969467	343.042791	274.266638
1,2	289.186063	396.418431	328.969467	345.042791	276.266638
1,3	291.195290	398.168925	330.680610	346.865702	278.266638
2,1	289.564891	396.841175	328.969467	345.042791	276.266638
2,2	291.186062	398.418431	330.969467	347.042791	278.266638
2,3	293.204495	400.168924	332.680616	348.865696	280.266638
3,1	291.564892	396.609893	330.969467	346.063056	278.266638
3,2	293.186062	399.094717	332.969468	349.042792	280.266638
3,3	295.195290	400.265558	334.862091	350.069117	282.266638

From the AIC value in the table above, the best model to use on the five data is the GARCH (1,1) model with the smallest AIC value. Then the GARCH(1,1) model is estimated using the MLE method. The results of parameter estimation using MLE are shown in Table 4.

Table 4: Parameter Estimation Results

Data	ω	α	β
XPFT	22.7474	0	0.5039
XBSK	1.07×10^{-5}	0.1968	0.7502
XIIF	1.5417	2.64×10^{-13}	1
XISC	154.34	0.1010	4.96×10^{-16}
XBLQ	21.8915	0.5316	6.51×10^{-16}

c) ARCH-LM test

Then the residual model is tested to determine whether the model is optimal in identifying data heteroscedasticity using the ARCH-LM test. The ARCH-LM test results on the data are shown in Table 5.

Table 5: ARCH-LM Test Results

Data	ARCH-LM Statistic	P-Value
XPFT	10.9137024	0.999
XBSK	0.4016419	1
XIIF	5.2268995	1
XISC	4.2479292	1
XBLQ	11.152353	0.999

The results above show that the residuals of the five data no longer contain heteroscedasticity because the P-Value> 0.05 so that the GARCH (1,1) model used is suitable for modeling the data.

d) Normality test

Then the Jarque-Bera test is performed to evaluate whether the residuals of the model are normally distributed. The results of the Jarque-Bera test are shown in Table 6.

Table 6: Jarque-Bera Test Results

Data	Jarque-Bera Statistic	$X^2(2, 0{,}05)$
XPFT	1.1483911	5.9914645
XBSK	2.3194444	5.9914645
XIIF	1.8006282	5.9914645
XISC	1.6410128	5.9914645
XBLQ	2.5004833	5.9914645

The results above show that the residuals of the five data are normally distributed because $JB < \chi^2(2, \alpha)$ so that the GARCH (1,1) model used is proven suitable for modeling the data.

e) Volatility estimation

Using the variance value obtained from the GARCH model, volatility estimation is then carried out. The volatility estimation results are shown in Table 7.

Table 7: Volatility Estimation Result

Data	Mean	Median	Standard Deviation	Min	Max
XPFT	12.251	10.795	5.725	6.205	25.709
XBSK	33.449	27.799	28.268	2.492	125.553
XIIF	17.497	15.689	7.356	8.987	39.344
XISC	18.942	16.887	6.806	11.910	45.714
XBLQ	11.501	7.555	7.765	2.739	27.222

f) VaR and ES calculation

From the results of the calculation of conditional volatility using the GARCH model, the Value at Risk and Expected Shortfall values are then calculated at the 95% confidence level. The calculation results are shown in Table 8.

Table 8: VaR and ES Calculation Result

Data	VaR	ES
XPFT	2.8335	24.0616
XBSK	-13.0488	91.7601
XIIF	5.3977	32.6706
XISC	7.7472	32.9816
XBLQ	-1.2721	27.5197

5. Conclussion

In this article, investment risk is analyzed by comparing the standard deviation obtained from the GARCH model volatility estimate with the maximum potential loss measured using ES. The results show that volatility value and maximum potential loss have a positive effect on mutual fund investment. This is shown in 4 out of 5 mutual funds where the greater the volatility value, the greater the potential maximum loss that may occur. However, the relationship between volatility and potential maximum loss is not always in line. This is shown in XBLQ where this occurs because the potential maximum loss is related to the extremity of price movements, which is not always in line with the level of volatility.

References

Bollerslev, T. 1986. Generalized Autoregressive Conditional Heteroskedasticity. Journal of Econometrics. Vol. 31, 1986, pp. 307327.

Cryer, J. D., and Chan, K. S., 2008, Time series analysis: with applications in R. Springer.

Irwandi, K. R. 2021. Estimation of Investment Risk of Consumer Sector Company Shares Using Value at Risk and Expected Shortfall.

Klugman, S., Panjer, ,HWillmot, G., 2004. Loss Models: From Data to Decisions, Wiley Interscience, New Jersey

Liu, Q., Charleston, M. A., Richards, S. A., & Holland, B. R. 2023. Performance of Akaike Information Criterion and Bayesian Information Criterion in Selecting Partition Models and Mixture Models. *Systematic Biology*, *72*(1), 92–105.\

Ratnasari, V., & Nitivijaya, M. (2018). Modeling Inflation in Indonesia Using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model Approach. *Inferensi*, *1*(2), 71.

Rizani, N. F. F., Mustafid, M., & Suparti, S. (2019). Application of Expected Shortfall Method in Measuring Stock Investment Risk with Garch Volatility Model. *Jurnal Gaussian*, *8*(1), 184–193.

Yamai, Y. and Yoshiba, T. 2002. On the Validity of Value at Risk: Comparative Analysis with Expected Shortfall. Monetary and Economic Studies.