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The Study of Value-At-Risk Calculation and Back-testing Using the ARMA-GARCH Model Based on Stock Returns: An Overview

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Abstract

Stocks are investment instruments that provide returns but tend to be risky. The most important component of investing is volatility, where volatility is identical to the standard conditional deviation of stock price return. The important thing in investing in addition to return is a risk. Value-at-Risk (VaR) is a statistical method of estimating maximum losses. To evaluate the quality of VaR estimates, models should always be back-tested with appropriate methods. Back-testing is a statistical procedure in which actual gains and losses are systematically compared to appropriate VaR estimates. To evaluate the quality of VaR estimates, models should always be back-tested with appropriate methods. Back-testing is a statistical procedure in which actual gains and losses are systematically compared to appropriate VaR estimates. The goal of the study was to estimate the Autoregressive Moving Average-Generalized Conditional Heteroscedastic (ARMA-GARCH) model to determine Value-at-Risk and back-testing. ARMA is a combination of AR and MA models, while GARCH is a time series model with symmetrical properties. The method in this study is systematic browsing of libraries. Systematic library tracing is an attempt to identify, evaluate, and interpret all research relevant to a particular phenomenon.

Keywords: Stock, Return, Risk, ARMA-GARCH, Value-at-Risk

1. Introduction

Investment is the placement in the form of other assets over a period of time with certain expectations. Investors choose to invest shares in a company based on the desire to get profits in the future that can be seen from the number of stock returns (Tandelilin, 2010). Investing in stocks is faced with high risk because stock returns are volatile. Stock returns change in a very fast span of time so the value of stock indices also changes, this movement is known as stock return volatility. High volatility will result in high risk as well if low volatility results in low risk. The variance features of stock returns have a significant impact on the volatility characteristics. In general, there are two types of variance: homoscedastic (constant variance) and heteroskedastic (variance that changes over time). It is necessary to comprehend the variance features of the data return in order to effectively model the volatility (Maruddani et al., 2021).

Risk is a fundamental attribute of financial activities. When investors make decisions, they consider not only potential returns but also potential risks. There are different types of risks in the financial industry. For example, an investment bank may hold a portfolio of shares for a period of time and the value of the portfolio may expand randomly over that period. Then, banks face market risks that the value of the portfolio may fall below its initial value (Hong and Liu, 2014). People that invest hope to obtain a return after a given amount of time, but they also risk losing their money. To reduce the risk of loss, risk assessment is required (Miftahurrohmah et al., 2021). A risk measure is a formula that converts random variables into numerical values. People can now focus on one number instead of considering the entire distribution of losses when using risk metrics. Numbers like these are easy to interpret and understand (McNeil et al., 2015). Risk measures pave the way for more efficient financial hazard checks (Jorion, 2001).

The most commonly used financial risk is Value-at-Risk (VaR). VaR is widely used in the banking sector and other industries. Value-at-Risk (VaR) has grown in popularity among practitioners in the insurance and financial services industries for measuring and managing risk (Leung et al., 2021). A complete overview of the nature of mathematics, forecast methods, and applications for VaR is provided by Nadarajah and Chan (2016). Investment decisions made by investors are based on average rates of return and variance. Return is the level of profit that investors get in investing. In return, usage has two main reasons (Campbell et al., 1998). First, for the average investor, return is a complete and opportunity-free summary of an investment. Both return series are easier to handle than price series because they have more interesting statistical properties (Tsay, 2005).

Time series models can cope with financial data and most of those models have conditional variances depending on the past (Horv & Kokoszka, 2003). One of the most commonly used models in time series on financial matters is the Autoregressive Conditional Heteroscedasticity (ARCH) model (Engle, 1982). The development of the ARCH model is GARCH, where the GARCH model has a more flexible structure to accommodate the nature of volatility in financial data (Bollerslev, 1986). The GARCH model is a well-defined variance equation, but the symmetrical response to standard deviation to shocks ignores asymmetric (Hentschel, 1995).

2. Literature Review

Financial markets, especially stocks, play an important role in a country's economic growth. However, risk management becomes complicated because stock price movements are unpredictable and move randomly. A higher volatility means higher risk and lower volatility means lower risk. Therefore, it needs to be overcome with the help of mathematical models. Tamilselvan and Vali (2016) used the GARCH model when investigating Muscat's shares on the stock market and concluded that the GARCH (1,1) model was the best estimate of symmetrical data and that the data used did not use leverage. However, the GARCH model cannot be applied to data with leverage. Therefore, the GARCH model has evolved further into GJR-GARCH.

Bucevska (2013) conducted a test relative to the selected GARCH model on the ability to estimate volatility and expand empirical research on VaR estimates in financial markets. Suitable models for the GARCH family for estimating stock market volatilities are the normally distributed E-GARCH model and GJR-GARCH. So and Philip (2006) tested empirical analysis of the GARCH value-at-risk model. As a result, the GARCH model is stationary, partially integrated, and estimates a risk value of 1%.

Sukono et al., (2019) examined the ARIMA-GARCH model used to estimate and predict some stock shortages in the Indonesian capital market. Based on the analysis, selected shares will be acquired. Mandiri Bank equity has the lowest level of risk, Mustikaratu equity has the highest level of risk, and risky equity value exposure is generally less than expected shortfall. Lesmana et al., (2017) estimated the Value-at-Risk of some equities in the Indonesian capital market based on the ARMA-FIGARCH model. The results of the analysis showed that the Value-at-Risk values for the five stocks were 0.01791, 0.06037, 0.02550, and 0.06030. Value at Risk represents a measure of maximum risk for each stock with a significant portion of 95% and can be taken into account when deciding to invest in a stock.

3. Methods

The method carried out in this study is a systematic literature review. The systematic review is a method of finding, analyzing, and interpreting all relevant literature for a particular research problem, topic area, or phenomenon of interest (Kitchenham, 2004). Systematic library searches serve a variety of purposes, including summarizing issues regarding the use of technology, identifying research gaps, assisting in the positioning of new research, and examining the number of ideas supported or rejected by empirical evidence (Budgen and Brereton, 2006). Looking for references using Google Scholar and Science Direct, the research was published in international journals. The inclusion criteria used are international journals that contain information about the ARMA-GARCH model in the determination of Value-at-Risk.

4. Discussion

4.1. Return

According to Ruppert (2011) return is the return on the results obtained due to making investments. In general, the formula of return is as follows:

$$r_t = \ln\left(\frac{S(t_i)}{S(t_{i-1})}\right) \tag{1}$$

where r_t is the return of the stock at the t, $S(t_i)$ is the stock price in the period to t_i and $S(t_{i-1})$ is the stock price in the period to t_{i-1}.

4.2. Mean Model

The order of the ARMA model is determined by looking at stationary series autocorrelation and partial autocorrelation. Box and Jenkins (1976) presented a theoretical framework as well as practical guidelines for establishing optimal p and q values, p and q are seasonal counterparts (Makridakis & Hibon, 1997). The purpose of the ARMA model is to discuss the average model in a time series. In general, the Autoregressive Moving Average (ARMA) model can be stated in the following equations:

$$r_t = \omega + \sum_{i=1}^{p} \phi_i r_{t-i} + a_t - \sum_{j=1}^{q} \theta_j a_{t-j} \quad (2)$$

where r_t is the return value at the time to t, a_t is a process of white noise or error at time t (Susanti et al., 2018).

ARMA modeling process. In general, the ARMA modeling process is: (i) Identify the model by determining the values p and q with the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the correlogram plot. (ii) Parameter estimation can use the smallest square method or maximum likelihood. (iii) Diagnostic test with white noise and non-correlation test against residual using Box-Pierce or Ljung-Box. (iv) Forecasting, if the model is suitable can be used for predictions made recursively.

4.3. Volatility Model

The ARCH Generalization (GARCH) model introduced by Bollerslev (1986) met this requirement because it was based on an unlimited ARCH specification that reduced the estimated number of parameters from infinity to two. Both ARCH and GARCH models capture clustering of volatility and leptokurtosis, but because of their symmetrical distribution (Alberg et al., 2008). In general, the GARCH model is as follows:

$$a_t = \sigma_t v_t, \qquad \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + a_t \quad (3)$$

with ϵ_t It is the order of *independent and identically distributed* (iid), σ_t^2 is a residual variance at the t, ω is a constant component, α_i is the I parameter of ARCH, a_{t-i}^2 is the square of the residual in time (t-i), β_j is the j parameter of GARCH, σ_{t-j}^2 is the variance of residual at the time to (t-j). Equation (3) indicates that conditional variance is a shock of the past seen from residual square (p) and past residual variance (q) (Olowe and Ayodeji, 2010).

Volatility model process. In general, the volatility model process is: (i) Estimated ARMA model with time series model. (ii) Use residuals from the ARMA model to test the effects of ARCH. (iii) If there is an ARCH effect, the volatility model estimate, and the combined estimates form the ARMA model and the volatility model. (iv) Perform diagnostic tests to observe the suitability of the model. (v) If the model has matched, use it to predict based on recursive predictions.

4.4. Value-at-Risk

VaR (x) It is a nonconventional and intermittent function for discrete distribution as a confidence-level function (Rockafellar & Uryasev, 2000). According to Dwipa (2016), VaR is defined as the maximum potential loss in a given period with a certain level of confidence under normal (market) circumstances. VaR (x) with a lapse of trust [0, 1] are as follows:

$$VaR = \inf\{r_t | F_l(r_t) \geq \alpha\} \quad (4)$$

where F_l It is a distribution function of return r_t. Then VaR for the next period with a level of trust α can be formulated as follows:

$$VaR = \mu + \sigma_t F^{-1}(\alpha) \quad (5)$$

with μ is average, σ^2 is variant and σ it's a standard deviation.

4.5. Back-testing

The back-test is a method used to measure the expected performance of VaR. If r_t declaring a profit or loss at a time t and VaR_t is a prediction of VaR to t. In 1998 Lopez introduced the following size-adjusted frequency approach (Christoffersen & Pelletier, 2004):

$$C_t = \begin{cases} 1 + (r_t - VaR_t)^2, r_t > VaR_t \\ 0, \qquad\qquad\qquad\quad r_t \leq VaR_t \end{cases} \tag{6}$$

Statistics used to test var risk performance by using *quadratic probability score* (QPS). The QPS equation is as follows:

$$QPS = \left(\frac{2}{n}\right) \sum_{i=1}^{n} (C_t - p)^2 \tag{7}$$

where n That's a lot of data, p it's a probability value. The QPS value is between the [0.2] range with 0 being the minimum value that occurs when $r_t \leq VaR_t$ and 2 is the maximum value that occurs when $r_t > VaR_t$. VaR performance is said to be good when small QPS approach 0 (Sukono et all., 2019).

5. Conclusion

Based on the results of the review some articles have discussed GARCH models such as Tamilselvan and Vali (2016). The advantages possessed in the article are the acquisition of the best GARCH model for symmetric data and the disadvantage is that the GARCH model obtained cannot be used for data that have asymmetrical effects. Furthermore, based on the results of a review of several articles that discuss value-at-risk estimates are Bucevska (2013), So and Philip (2006), Sukono et al., (2019), and Lesmana et al., (2017). The advantage of the four articles is that they can know the maximum risk measure on the stock studied and can be considered in determining stock investments, especially in the stocks studied. The disadvantage of the four articles is that it has not used the risk size performance method to find out how well the risk measure is obtained. So there are several developments in Value-at-Risk by using stock returns, namely averages and variances used in Value-at-Risk obtained from the time series model. The model used for the average is the mean model using ARMA and the model to determine variance is the volatility model using GARCH. Value-at-risk risk measurement is done by determining the value of back-testing.

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