Jurnal Keuangan dan Perbankan, 24(4): 474–484, 2020
http://jurnal.unmer.ac.id/index.php/jkdp

Jurnal Keuangan dan Perbankan
UNIVERSITY OF MERDEKA MALANG

Value at risk estimation of exchange rate in banking industry

Siti Saadah[1], Marsiana Luciana Sitanggang[2]

[1]Master of Applied Economics, [2]Department of Management, Faculty of Economics and Business, Atma Jaya Catholic University of Indonesia
Jl. Jenderal Sudirman No.51, Jakarta 12930, Indonesia

Article history:
Received: 2020-07-17
Revised: 2020-08-24
Accepted: 2020-10-02

Keywords:
Asymmetric GARCH; Generalized error distribution; Standard GARCH; Value at risk

JEL Classification: E44, G4, G11

Kata Kunci:
GARCH *asimetris; Distribusi kesalahan umum;* GARCH *standar; Nilai risiko*

Corresponding Author:
Marsiana Luciana:
Tel. +62 21 5727615
E-mail:
marsiana.luciana@atmajaya.ac.id

Abstract

More integrated financial sector has made market risk arising from volatility of exchange rate critical for banking industry. In attempt to mitigate such risk, this study aims to measure risk from IDR/USD exchange rate movement using value-at-risk method by comparing results of estimates using standard and asymmetric generalized autoregressive conditional heteroscedasticity models. Using data on the daily exchange rate of IDR to USD between July 31, 2018 and July 31, 2019, this study found that the asymmetric exponential GARCH using generalized error distribution is the best approach to estimate exchange rate risk. Results of the estimate suggest that standard GARCH model generated a more conservative measure of risk than value-at-risk estimated using exponential GARCH model. Value at risk can be one of the risk indicators for risk managers in banks. The choice of a model is likely to depend on the attitude to risk itself. Risk averse character who does not like risk will choose the most conservative method in calculating the VaR.

Abstrak

Sektor keuangan yang semakin terintegrasi membuat risiko pasar yang timbul dari volatilitas nilai tukar menjadi penting bagi industri perbankan. Dalam upaya memitigasi risiko tersebut, penelitian ini bertujuan untuk mengukur risiko dari pergerakan nilai tukar IDR/USD *menggunakan metode* value-at-risk *dengan membandingkan hasil estimasi menggunakan model heteroskedastisitas* autoregressive *bersyarat standar dan asimetris. Menggunakan data nilai tukar harian* IDR *terhadap* USD *antara 31 Juli 2018 dan 31 Juli 2019, studi ini menemukan bahwa* Asymmetric Exponential GARCH *dengan menggunakan distribusi kesalahan umum adalah pendekatan terbaik untuk mengestimasi risiko nilai tukar. Hasil estimasi menunjukkan bahwa model* GARCH *standar menghasilkan ukuran risiko yang lebih konservatif daripada estimasi nilai risiko menggunakan model* GARCH *eksponensial*. Value at risk *dapat menjadi salah satu indikator risiko bagi pengelola risiko di bank. Pilihan model cenderung bergantung pada sikap terhadap risiko itu sendiri. Karakter* risk averse *yang tidak menyukai risiko akan memilih metode yang paling konservatif dalam menghitung* VaR.

How to Cite: Saadah, S., & Sitanggang, M. L. (2020). Value at risk estimation of exchange rate in banking industry. *Jurnal Keuangan dan Perbankan, 24*(4), 474-484.
https://doi.org/10.26905/jkdp.v24i4.4808

ISSN: **2443-2687** (Online)
ISSN: **1410-8089** (Print)

1. Introduction

The more rapid growth of banking industry, along with the increasing complexity of business, requires implementation of sound and effective banking risk management. Risk management is one of the tools to maintain the quality of assets in order to support prudential banking practices. It protects banks from not only risks from being a financial intermediary (credit risk) but also other types of risk, including market risk from interest rate and exchange rate volatility that contribute to the overall risks.

Market risk from interest rate volatility is one of the most critical risks in banking industry. Fluctuation of interest rate will affect banks' balance sheet and treasury operations. In 2012, America's largest bank, JP Morgan Chase suffered major losses amounted to US$4.4 billion due to high-risk transactions, demonstrating even a banking giant was hard hit by poor market risk management. Despite Q4 earnings totaled US$5 billion throughout the year, billions of losses from derivative transactions have destroyed their reputation. JP Morgan's stock price dropped by 15 percent as they reported losses that soon became public information (BBC News, July 2012).

There have been significant changes in calculating Capital Adequacy Ratio (CAR) of a bank since the release of "Amendment to the Capital Accord to Incorporate Market Risk" in 1996 by the Bank for International Settlement (BIS). Prior to amendment, calculation took into account only credit risk, but was then amended to allow the addition of market risk to the CAR. In the amendment, the Basel Committee on Banking Supervision recommended two approaches to calculate market risk in CAR namely the Standard Method and the Internal Model. While the Standard Model provides all banks with a standardized approach, the Internal Model allows banks to adopt methods for estimating risks by expanding their own internal risk management models. Banks applying this method must conform to specific quantitative and qualitative requirements and gain consent from supervisory authorities.

Value at Risk (VaR) is an Internal Model commonly applied by banks to calculate market risk exposure. This model will estimate the worst potential losses of a portfolio as a result of changes in risk factors, such as exchange rate, in a set time period and specific confidence level. VaR estimation using parametric approach requires volatility estimation data of risk factors to calculate the overall risks a bank might face in a specific period of time.

Generalized Autoregressive Conditional Heteroscedasticity (GARCH) is a model frequently used by researchers and practitioners in banking industry, including Christianti (2010), Febriana et al. (2014), Fauziah (2014), Bohdalova & Michal (2015), Altun et al. (2017), to estimate volatility of market risk factor such interest rate, exchange rate, and stock price. The standard GARCH approach is widely used. In addition to the ability of GARCH approach to capture the mean reverting characteristic of volatility series, it can also capture the long lag effect by using only few parameters. The standard GARCH accommodates volatility clustering; however, this standard model fails to take into account leverage effect. One of restrictions of this model is the symmetric response of volatility to positive and negative shocks.

To overcome shortcomings of widely used models, this study aimed to estimate and investigate best model with best ability to estimate volatility of exchange rate among some GARCH models. GARCH models investigated in this study included the Standard GARCH (SGARCH) and two asymmetric models namely EGARCH and TGARCH. Results of volatility estimation using the best GARCH model was then added to the calculation of VaR.

Many previous studies adopted VaR formula assuming normal distribution of data on return of exchange rate. Unlike in previous studies, VaR estimation in this study attempted to consider the possibility of non-normal distribution of data on return, as an alternative to normal distribution, due to presence of empirical evidence saying that returns of financial instrument are not normally distributed.

It is expected that accurate estimation of volatility model and use of VaR formula that matches with probability distribution characteristics can yield precise value of VaR and optimal amount of reserves to protect themselves from market risks.

2. Hypotheses Development

According to Bank Indonesia Regulation Number 5/8/PBI/2003, losses may be incurred by occurrence of certain event. In banking context, risk is the potential for occurrence of an event, either expected or unexpected, with negative influences on banks' revenue and capital (Indonesian Banker Association, 2015). Capital is required to cover unexpected loss. In order to implement risk management, banks should be able to identify and understand all risks that may arise. There are eight risks a bank should manage; they include credit risk, market risk, operating risk, liquidity risk, compliance risk, legal risk, reputational risk, and strategic risk.

Market risk is the risk arising from changes in the value in on and off-balance sheet and administrative account positions, including banks' derivative transactions, resulting from the whole movements in the market. In general, market risk can be classified into four categories including Interest Rate Risk, Foreign Exchange Risk, Equity Risk, and Commodity Risk. Market risk may occur in, for example, banks' functional activities, such as treasury (trading book), and investment activities in securities, including loans (banking book).

Measurement of market risk

Risk management principles applied by Indonesian banking industry refer to those set by the Bank for International Settlement (BIS) through the Basel Committee on Banking Supervision (BCBS). According to Basel I Amendment of 1996, with the growth of financial instruments and higher complexity of business in banking sector, banks are exposed to market risk and therefore require adequate amount of capital to protect themselves from potential losses from market risk. Market risk estimation in determining banks' capital adequacy can involve, such as, Internal Model Approach. This approach allows banks to use their own methods that match with their business and risk profile but based on specific quantitative and qualitative standards that banks would have to meet and approval of the banks' supervisory authority.

Quantitative standards the banks should meet include: 1) Application of Value at Risk approach on daily basis using a 99 percent one-tailed confidence interval; 2) Price shock equivalent to a 10-business day holding period; 3) The use of historical data of at least one year; 4) Daily capital charge that is greater than previous day's VaR or three times the average of the VaR for the preceding 60 business days.

Value at Risk is a method of estimating risks by adopting a standard statistical technique. Definitions of VaR vary. According to Jorion (2001), "VaR summarized the worst loss over a target horizon with a given level of confidence". Meanwhile Crouhy et al. (2000) stated that "Value at risk can be defined as the worst loss that might be expected from holding a security or portfolio over a given period of time, given a specified level of probability (known as confidence level)". Referring to the aforementioned definitions, in short, VaR is a measure of the worst potential loss one might expect over a period of time, in normal market conditions, and a given level of probability. VaR measures risks by incorporating three main components including relatively high confidence level (95 percent or 99 percent), a given period of time (day, month, or year), and an estimate of loss expressed in currency or percentage. Some models employed in VaR calculation include, for example, (i) mean variance analysis consisting of exponentially weighted moving average (EWMA) and generalized autoregressive conditional heteroscedastic (GARCH), (ii) simulation (historical simulation dan Monte Carlo simulation, (iii) neural network, and (iv) algorithmic.

The GARCH model

VaR calculation requires an estimation of volatility of market factors that include interest and exchange rates. (Christoffersen & Diebold, 2000). Exchange rate is high-frequency data that often exhibit characteristics such as (i) leptokurtic or a tendency for data to exhibit fat-tailed distribution and higher, narrow peak, (ii) volatility clustering or a tendency for a heteroscedastic volatility, and (iii) leverage effect or a tendency for presence of asymmetry in the volatility. The most popular model that fits for estimating volatility of data with such characteristics is the GARCH model and therefore GARCH can be implemented for modeling and forecasting of volatility (Brooks, 2002). Some specifications of the GARCH model are presented below.

Bollerslev (1986) proposed a Standard GARCH model (SGARCH). The specification of SGARCH (1,1) model is as follows:

$$\sigma_t^2 = \omega + \alpha_1 Z_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad \text{.........................} (1)$$

with $\alpha_1 \succ 0; \quad \beta_1 \succ 0; \quad \omega \succ 0$

In volatility forecasting using SGARCH model, current volatility is influenced by previous volatility and shock. A key feature of this model and other variances of GARCH model is their ability to capture volatility clustering of data. The summation of α_1 and β_1 measures persistence of parameter and indicates the amount of volatility clustering captured by the model.

Other GARCH variance, Exponential GARCH (EGARCH), was developed by Nelson (1990). EGARCH (1,1) can be specified as:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad \text{.............} (2)$$

$\gamma+\alpha$ and $\gamma+\alpha$ reflect asymmetric response to positive dan negative shocks. With $\gamma \prec 0$, negative shock increases volatility more strongly than positive shock. Other asymmetric GARCH model, GJRGARCH, was developed by Glosten et al. (1993). GJRGARCH (1,1) can be specified as:

$$\sigma_t^2 = \omega + \alpha_1 Z_{t-1}^2 + \gamma_1 I_t Z_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad \text{.............} (3)$$

with $I_{t-1} = 1 \ if \ Z_{t-1} \le 0 \ and \quad I_{t-1} = 0 \ if \ Z_{t-1} \succ 0$

γ_1 is parameter of asymmetry. Positive shock increases volatility by α_1 while negative shock increases volatility by $\alpha_1 + \gamma_1$.

VaR measurement

Penza & Bansal (2001) used the following equation to estimate VaR for single instrument:

$$VaR = a \ x \ \sigma \ x \ P \ x \ \sqrt{t} \quad \text{...} (4)$$

with σ is the volatility of market factors

In this study, value at risk was estimated using approach that best fitted its data distribution. For normal distribution,

$$VaR_p = \hat{\mu}_{t+1} + \hat{\sigma}_{t+1} \Phi^{-1}(p), \quad \text{...} (5)$$

where $\Phi(.)$ is a cumulative distribution function of a standard normal distribution

For normal skew distribution (Azzalini, 1985), Where,

$$F(x) = \Phi(x) - 2T(x, \hat{\alpha}) \text{...} (6)$$

for $-\infty < x < \infty$ and $-\infty < \alpha < \infty$, where $T(.,.)$ to show *Owen's T function* (Owen, 1956).

For t Student's distribution (Student, 1908),

$$VaR_p = \hat{\mu}_{t+1} + \hat{\sigma}_{t+1} F^{-1}(p) \quad (7)$$

Where,

$$F(x) = \int_{-\infty}^{x} f(y)dy\,; \quad -\infty < x < \infty \quad (8)$$

Where,

$$f(x) = \frac{2\Gamma\left(\frac{\hat{v}+1}{2}\right)}{\sqrt{\hat{v}(\hat{v}-2)}\,\Gamma\left(\frac{\hat{v}}{2}\right)}\left(1+\frac{x^2}{\hat{v}-2}\right)^{-\frac{\hat{v}+1}{2}}; \quad -\infty < x < \infty \text{ and } v > 0 \quad (9)$$

For skew Student's distribution (Fernandez & Steel, 1998),

$$Var_p = \hat{\mu}_{t+1} + \hat{\sigma}_{t+1} F^{-1}(p) \quad (10)$$

Where,

$$F(x) = \int_{-\infty}^{x} f(y)dy\,; \quad -\infty < x < \infty \quad (11)$$

Where,

$$f(x) = \frac{2\Gamma\left(\frac{\hat{v}+1}{2}\right)}{\sqrt{\hat{v}(\hat{v}-2)}(\hat{\zeta}+\hat{\zeta}^{-1})\Gamma\left(\frac{\hat{v}}{2}\right)}\begin{cases}\left(1+\frac{\hat{\zeta}^2 x^2}{\hat{v}-2}\right)^{-\frac{\hat{v}+1}{2}}, & if\, x<0 \\ \left[1+\frac{x^2}{\hat{\zeta}^2(\hat{v}-2)}\right]^{-\frac{\hat{v}+1}{2}}, & if\, x\geq 0\end{cases} \quad (12)$$

For, $-\infty < x < \infty, v > 0$ and $\zeta > 0$.

For skew generalized error distribution (Theodossiou, 1998),

$$VaR_p = \hat{\mu}_{t+1} + \hat{\sigma}_{t+1} F^{-1}(p) \quad (13)$$

Where,

$$F(x) = \int_{-\infty}^{x} f(y)dy \quad \text{for } -\infty < x < \infty \quad (14)$$

Where,

$$f(x) = C\begin{cases}\left[1+\frac{\hat{k}\hat{\theta}^{-\hat{k}}(1-\hat{\lambda})^{-\hat{k}}}{\hat{n}-2}|x|^{\hat{k}}\right]^{-\frac{\hat{n}+1}{k}}, & \text{for } x<0 \\ \left[1+\frac{\hat{k}\hat{\theta}^{-\hat{k}}(1+\hat{\lambda})^{-\hat{k}}}{\hat{n}-2}|x|^{\hat{k}}\right]^{-\frac{\hat{n}+1}{k}}, & \text{for } x\geq 0\end{cases} \quad (15)$$

for $-\infty < x < \infty, k > 0, n > 2$ and $-1 < \lambda < 1$

3. Method, Data, and Analysis

This study aims to estimate risk of exchange rate in state-owned BUKU IV banks and compare Value at Risk of IDR to USD exchange rate using SGARCH and Asymmetric GARCH models. Three GARCH specifications were evaluated using data on daily exchange rate return from July 31, 2018 to July 31, 2019. Lagrange Multiplier test was conducted before GARCH process began to detect ARCH effect in daily exchange rate return data. Using backtesting procedure, the most accurate result of VaR estimation using GARCH model was compared to results of estimation using the other two models.

Data used in VaR calculation were sourced from 243 observations of mid-market rates of IDR to USD on a daily basis from July 31, 2018 to July 31, 2019 retrieved from www.bi.go.id. Mid-market rate is the median average of the bid and ask rate. Data on the size of potential market risk were sourced from financial statements of state-owned banks listed in BUKU IV category, available in The Indonesia Capital Market Institute's financial statement.

VaR calculation was performed by estimating exchange rate return (R_t) using geometric approach.

$$R_t = ln\left[\frac{P_t}{P_{t-1}}\right] x100\% \quad (16)$$

If data on exchange rate return were normally distributed, VaR would be calculated using $VaR = a\ x\ \sigma\ x\ P\ x\ \sqrt{t}$, with an alpha value corresponding to z-score. However, in non-normal distribution of data, VaR calculation would be performed using a formula that fitted its distribution. GARCH model would be applied on daily exchange rate return data to estimate their volatility. Three specified GARCH models to be applied include:

$$SGARCH\ (1,1){:}\ \sigma_t^2 = \omega + \alpha_1 Z_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (17)$$

EGARCH (1,1): $$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad (18)$$

GJRGARCH (1,1): $$\sigma_t^2 = \omega + \alpha_1 Z_{t-1}^2 + \gamma_1 I_t Z_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (19)$$

The use of order (1,1) is based on finding of the simulation results conducted by Hansen & Lunde (2005), the GARCH model with order (1,1) is the best model in predicting the return of assets volatility behavior.

The best GARCH model was determined based upon the lowest error criterion. Exchange rate return volatility forecast would be performed on the best GARCH model. The following variance equation is for SGARCH (1,1) model:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (20)$$

Forecasts for the next 1, 2, and 3 days are (in their respective order):

$$\sigma_{1,T}^{f\,2} = \alpha_0 + \alpha_1 u_T^2 + \beta \sigma_T^2 \quad (21)$$

$$\sigma_{2,T}^{f\,2} = \alpha_0 + (\alpha_1 + \beta) \sigma_{1,T}^{f\,2} \quad (22)$$

$$\sigma_{3,T}^{f\,2} = \alpha_0 + \alpha_0(\alpha_1 + \beta) + (\alpha_1 + \beta)^2 \sigma_{1,T}^{f\,2} \quad (23)$$

Variance equation for TGARCH (1,1) model is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \quad (24)$$

Forecasts for the next 1, 2, and 3 days are (in their respective order):

$$\sigma_{1,T}^{f\,2} = \alpha_0 + (\alpha_1 + \gamma) u_T^2 + \beta \sigma_T^2 \quad (25)$$

$$\sigma_{2,T}^{f\,2} = \alpha_0 + (\alpha_1 + \gamma + \beta) \sigma_{1,T}^{f\,2} \quad (26)$$

$$\sigma_{3,T}^{f\,2} = \alpha_0 + \alpha_0(\alpha_1 + \gamma + \beta) + (\alpha_1 + \gamma + \beta)^2 \sigma_{1,T}^{f\,2} \quad (27)$$

4. Results

This research investigated only IDR /USD exchange rate as during study period this exchange rate was more volatile, compared with IDR to other currencies such as Australian Dollar (AUD), Singaporean Dollar (SGD), Japanese Yen (JPY), European Euro (UER), and British Pound sterling (GBP). The following Table 1 illustrates descriptive statistics of exchange rate return between July 31, 2018 and July 31, 2019.

Table 1. Return IDR / USD exchange

Statistics	Value
Mean	-0.0001
Median	-0.0002
Maximum	0.0172
Minimum	-0.0100
Std. Dev	0.0039
Skewness	0.6096
Kurtosis	4.5328

The above table suggests negative mean of IDR/USD exchange rate return. This negative value is in accord with the movement in IDR/USD exchange rate, which, despite exhibiting a trend of appreciation, suffered from greater depreciation at the beginning of the analysis period of 2018. Referring to the website of the Central Bank of Indonesia, within these past 18 years since 2001, IDR reached an all-time low of 8,573 IDR/USD in 2008 and an all-time high of 13,882.62 IDR/USD in 2018.

This 2018 situation is a reminder to the year of 2015 on which IDR plunged by 10.19 percent caused by the Federal Reserve's tapering. Attracted to the higher rates, investors flocked into the US market, causing massive inflow of capital in the country and stronger USD in global market. Table 1 demonstrates that standard deviation of return is higher than its mean. This statistical analysis indicates high volatility of IDR to USD exchange rate within research period as can be seen in the following graph.

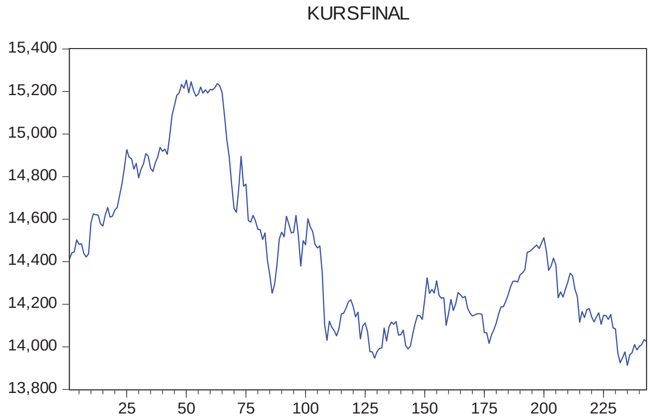

Figure 1. IDR to USD exchange rate movements between July 31, 2018 and July 31, 2019

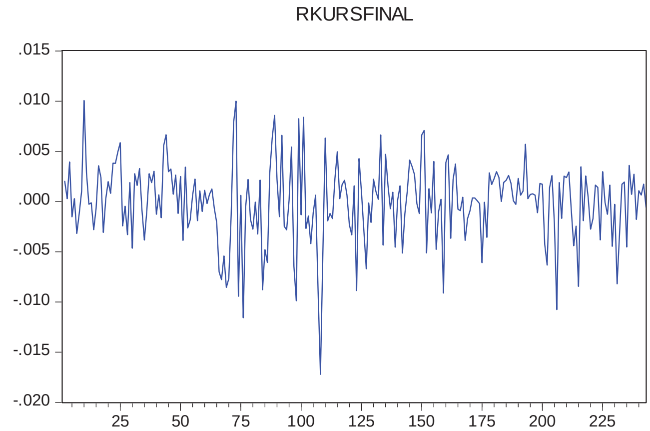

Figure 3. Exchange rate data graph

The Jarque Bera test was performed to test normality of data on IDR/USD exchange rate return. Results are presented in Figure 2.

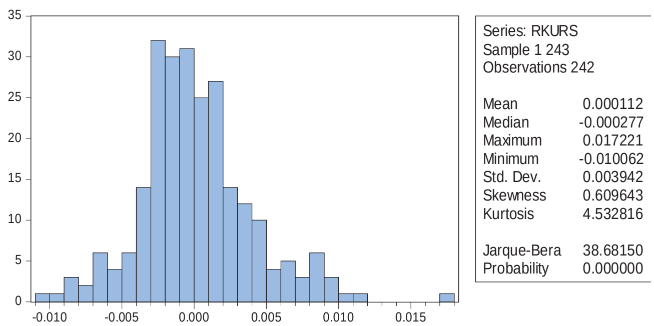

Figure 2. Data return normality test results

The above table and graph indicate statistical evidence of non-normal distribution of data on return collected from observations starting July 31, 2018 to July 31, 2019.

Forecast about volatility of exchange rate return provides a critical input to VaR calculation. An accurate forecast of volatility determines precision of VaR estimation. The following figure exhibits movements of IDR/USD exchange rate return between July 31, 2018 to July 31, 2019.

The graph visually shows that data on return is most volatile in second semester of 2018, compared with other periods. Results of heteroscedasticity test are presented in Table 2.

Table 2 exhibits statistical evidence of heteroskedastic data on return. Therefore, GARCH model was applied in forecasting volatility. One of restrictions of the GARCH model is that this model assumes that volatility response to positive and negative shocks is symmetric. There are many empirical evidences indicating that negative shocks in financial time series data have more impact in volatility than positive shocks of the same amount. Because of this empirical evidence, researcher attempted to investigate the best model out of two GARCH models: standard GARCH (SGARCH) and Asymmetric GARCH.

The table below illustrates statistics of Akaike information criterion, Schwarz criterion, and Hannan-Quinn criterion generated from the three aforementioned GARCH models. The statistics were adopted as criteria for selecting the best GARCH model.

As demonstrated by two out of three criteria in Table 3, EGARCH model generated the lowest error; therefore, volatility forecast in this study

Table 2. Heteroscedasticity testing results

Heteroscedasticity Test: ARCH			
F-statistic	9.4690	Prob. F(1,239)	0.0023
Obs*R-squared	9.1844	Prob. Chi-Square(1)	0.0024

Table 3. Model selection criteria

	SGARCH	TGARCH	EGARCH
Akaike info criterion	-8.2857	-8.2884	-8.2980
Schwarz criterion	-8.2280	-8.2163	-8.2259
Hannan-Quinn criterion	-8.2625	-8.2594	-8.2689

Table 4. EGARCH model estimation results (1,1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	8.55E-05	0.0002	0.3438	0.7310
C(2)	-2.2280	0.8397	-2.6532	0.0080
C(3)	0.1949	0.0920	2.1181	0.0342
C(4)	-0.1815	0.0571	-3.1779	0.0015
C(5)	0.8143	0.0720	11.3043	0.0000

would be based on this specific model. Results of exchange rate return estimation using EGARCH model during the analysis period are presented in Table 4.

The significance of the coefficient *C(5)* in Table 4 indicates that the data has the characteristic of volatility clustering. The significant negative sign for the coefficient *C(4)* in the same table also indicates that there is an asymmetric phenomenon in volatility. Therefore, we conclude that the data generating process follows the Asymmetric GARCH process.

Table 5. Results of forecasting IDR/USD exchange rate return volatility

Period	Votality
T + 1	0.0029
T + 2	0.0030
T + 3	0.0031
T + 4	0.0032
T + 5	0.0032
T + 6	0.0033
T + 7	0.0033
T + 8	0.0034
T + 9	0.0034
T + 10	0.0034

Referring to results of estimation using EGARCH model in Table 4, volatility forecast was performed up to T+10 days and its results are presented in Table 5.

Estimated daily value at risk exchange rate IDR / USD

The previous section has proven non-normal distribution of data for IDR/USD exchange rate return. Consequently, a simulation using EGARCH modeling with student's t-distribution and generalized error distribution (GED) would be performed in attempt to calculate VaR. As already mentioned, the formula used for VaR calculation depended on the error distribution. According to statistics of AIC, SIC, and Hannan-Quinn criterion presented in Table 6, EGARCH using generalized error distribution (GED) is the best approach for estimating VaR.

Results of daily VaR estimates using both EGARCH and SGARCH models under generalized error distribution (GED), holding period on a daily basis, a 99 percent confidence level, and software R are presented in Table 7. Graph 4, on the other hand, compares both models graphically.

Table 6. Pattern selection error distribution

	Student's t	Generalized Error Distribution (GED)
Akaike info criterion (AIC)	-8.3092	-8.3190
Schwarz criterion (SIC)	-8.2227	-8.2324
Hannan-Quinn criterion (HQ)	-8.2743	-8.2841

Table 7. Daily Value at Risk estimation results based on GED

Period	VaR (EGARCH)	VaR (SGARCH)
T + 1	0.0073	0.0075
T + 2	0.0075	0.0083
T + 3	0.0077	0.0088
T + 4	0.0079	0.0092
T + 5	0.0080	0.0094
T + 6	0.0082	0.0095
T + 7	0.0083	0.0097
T + 8	0.0083	0.0097
T + 9	0.0084	0.0098
T + 10	0.0085	0.0098

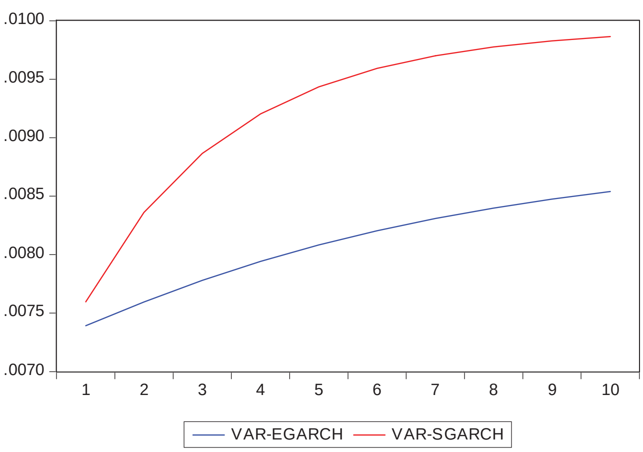

Figure 4. Comparison VaR-EGARCH and VaR-SGARCH

Results indicate that, using data collected from a one-year observation (July 31, 2018 – July 31, 2019) on a daily basis, calculation using SGARCH model generated a more conservative Value at Risk compared with calculation using EGARCH model. As can be seen in Table 7, the average VaR over a 10-day horizon when using EGARCH model was 0.0080 and 0.0092 when using SGARCH model. These results suggest that, according to EGARCH model, banks carrying out transactions in USD face a 1 percent chance of, in average, e"0.8072 percent loss the next day. Meanwhile, the SGARCH model estimates a potential loss of at least 0.9222 percent.

Individual VaR value of each bank is calculated by multiplying each VaR by net open position of each bank. Net open position is the difference between total assets and total liabilities on balance sheet in USD, plus the difference between off-balance receivables and payable. The following graph illustrates the Net Open Position of banks being studied.

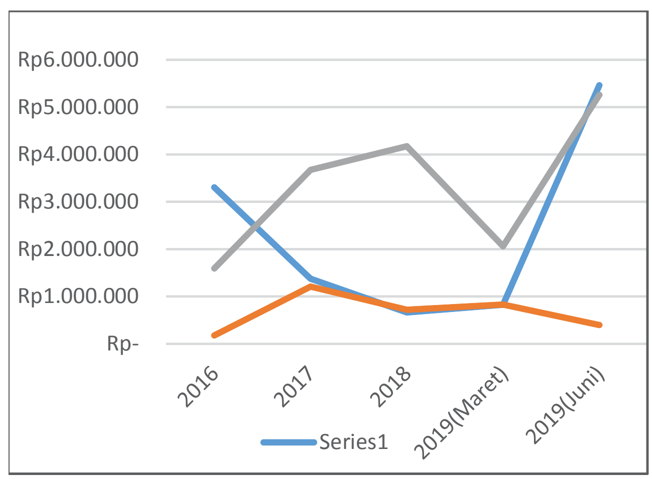

Figure 5. Net open position of state-owned BUKU IV banks

Banks highly engaged in trading must keep certain amount of liquid capital on hand to sustain losses that may be caused by trading activity. For banks adopting the internal model approach, determination of how much capital they must hold to keep them safe from market risk requires VaR estimate. According to the prevailing regulation framework, a bank must estimate their 10-day VaR at a 99 percent confidence level (Basel, 2006). In addition, they should also hold a minimum daily capital charge that is greater than previous day's VaR or three times the average of the VaR for the preceding 60 business days.

In this context, strict backtesting mechanism is important to prevent a bank from underestimating their potential risks. For banks, higher capital reserve equals greater opportunity cost. Therefore, backtesting is critical to help the Basel Committee decide whether they should allow banks to implement their internal VaR model to calculate capital reserve (Jorion, 2001).

According to Kupiec (1995), backtesting is conducted by comparing the estimate of daily VaR to the actual loss within at least 255 observation days. However, with data on daily actual loss resulting from trading transactions carried out by the four banks being unavailable, it was impossible for researcher to perform the expected backtesting procedure. Bank can only publish data on actual loss on yearly basis in their financial statement.

Without backtesting, this research provides banking institutes undertaking trading activities with a model for estimating VaR using parametric approach. This model is capable of capturing characteristics of time series data on a daily basis as well as distribution of the data.

5. Conclusion

Referring to results of analysis and discussion of data concerning IDR to USD exchange rate as well as state-owned BUKU IV banks' exposure to market risk, it can be concluded that data on daily exchange rate of IDR to USD demonstrated heteroscedasticity. Therefore, estimation of volatility, a key input to Value at Risk (VaR) calculation, was performed using the GARCH approach. Based on some specific criteria, EGARCH was considered the best model; As GED was considered the best distribution pattern of daily exchange rate return data, calculation of Value at Risk was performed based on formula that best fitted this distribution pattern; Value at Risk estimation using SGARCH (Standard) model under GED distribution pattern resulted in a more conservative estimation of VaR compared with estimation using EGARCH; Value at risk can be one of the risk indicator for risk managers in banks. The choice of a model is likely to depend on the attitude to risk itself. Risk averse character who does not like risk will choose the most conservative method in calculating the VaR. However, for banks, a more conservative estimate of Value at Risk implicates that banks must hold higher minimum capital. The high minimum capital maintained will ultimately have implications for increasing the opportunity cost for banks to carry out their intermediation function. This in turn will have an impact on the high cost of funds.

References

Altun, E., Alizadeh, M., Kadilar, G. O., & Tatlýdil, H. (2017). Forecasting Value-at-Risk with two-step method: GARCH exponentiated odd log-logistic normal model. *Romanian Journal of Economics Forecasting, 20*(4).

Azzalini, A. (1985). A class of distributions which includes the normal ones. *Scandinavian Journal of Statistics, 12*(2), 171-178.

Basel Committee on Banking Supervision. (1996a). Supervisory framework for the use of "backtesting" in conjunction with the internal models approach to market risk capital requirement. *BIS.*

Basel Committee on Banking Supervision. (1996b). Amendment to the capital accord to incorporate market risk. *BIS.*

Brooks, C. (2002). *Introductory Econometrics for Finance*. 3rd Edition. Cambridge: Cambridge University Press.

Bohdalova, M., & Michal, G. (2015). Estimating Value-at-Risk based on non-normal distributions. *CBU International Conference Proceedings, 3,* 188-195. https://doi.org/10.12955/cbup.v3.601

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Christoffersen, P. F., & Diebold, F. X. (2000). How relevant is volatility forecasting for financial risk management? *Review of Economics and Statistics, 82*(1), 12-22. https://doi.org/10.1162/003465300558597

Christianti, A. (2010). Risiko Pasar: perbandingan model EWMA dan GARCH pada nilai tukar rupiah terhadap US Dollar. *Jurnal Riset Manajemen dan Bisnis, 5*(2), 153-172.

Crouhy, M., Galai, D., & Mark, R. (2000). A comparative analysis of current credit risk models. *Journal of Banking & Finance, 24*(1-2), 59-117. https://doi.org/10.1016/S0378-4266(99)00053-9

Fauziah, M. (2014). Analisis risiko pada portfolio saham Syariah menggunakan Value at Risk dengan pendekatan Generalized Pareto Distribution (GPD). *Jurnal Konvergensi, 4*(2), 85-104.

Febriana, D., Tarno, T., & Sugito, S. (2014). Perhitungan Value at Risk menggunakan model integrated generalized autoregressive conditional heteroscedasticity (Studi kasus pada return kurs rupiah terhadap dollar Australia). *Jurnal Gaussian, 3*(4), 635-643. https://doi.org/10.14710/j.gauss.v3i4.8074

Fernandez, C., & Steel, M. On Bayesian modeling of fat tails and skewness. *Journal of the American Statistical Association, 93*(441), 359-371. https://doi.org/10.1080/01621459.1998.10474117

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance, 48*(5), 1779-1801. https://doi.org/10.1111/j.1540-6261.1993.tb05128.x

Hansen, P. R., & Lunde, A. (2005). A forecast comparison of volatility models: Does anything beat a GARCH(1,1)? *Journal of Applied Econometrics, 20*(7), 873–889. https://doi.org/10.1002/jae.800

Jorion, P. (2001). *Value at Risk: The New Benchmark for Managing Financial Risk*. 3nd Edition. Boston: McGraw Hill.

Kupiec, P. H. (1995). Techniques for verifying the accuracy of risk measurement models. *The Journal of Derivatives Winter, 3*(2), 73-84. https://doi.org/10.3905/jod.1995.407942

Nelson, D. B. (1990). Stationarity and persistence in the GARCH(1,1) Model. *Econometric Theory, 6*(3), 318–334. https://doi.org/10.1017/s0266466600005296

Owen, D. B. (1956). Tables for computing bivariate normal probabilities. *Annals of Mathematical Statistics, 27*(4), 1075-1090. https://doi.org/10.1214/aoms/1177728074

Penza, P., & Bansal, V. K. (2001). *Measuring Market Risk with Value at Risk*. New Jersey: John Wiley & Sons.

Student. (1908). The probable error of a mean. *Biometrika, 6*(1), 1-25. https://doi.org/10.2307/2331554

Theodossiou, P. (1998). Financial data and the skewed generalized t distribution. *Management Science, 44*(12 part 1), 1650-1661. http://dx.doi.org/10.1287/mnsc.44.12.1650