

Comparative Analysis of Value-at-Risk in Market Risk Prediction in Banks Using GARCH Volatility

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Abstract

This study aims to compare the disclosure of Value at Risk (VaR) in market risk prediction among banks in Indonesia. By employing comparative and analytical methods, this research examines the effectiveness of VaR disclosure as a market risk prediction tool. Through the evaluation of VaR models disclosed by Indonesian banks and their comparison to a parametric model using asymmetric GARCH volatility for Variance Covariance Value at Risk, this study identifies the extent to which VaR disclosure can be relied upon to predict market risk. This research contributes to the understanding of risk management practices in the Indonesian banking sector and offers recommendations for improving market risk prediction accuracy through more effective VaR disclosures.

Keywords: Value at Risk; Market Risk; Banks in Indonesia; Asymmetric GARCH Volatility; Risk Management.

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1. Introduction

Indonesian banks face the challenge of managing market risk amid fluctuating economic conditions. This study analyzes the effectiveness of Value at Risk (VaR) disclosures, a key tool for risk assessment. Although VaR is widely used, its accuracy is still debated. Therefore, this research compares the disclosed VaR values by Indonesian banks with those calculated using a parametric method with asymmetric GARCH volatility. The aim is to highlight the importance of effective risk management in ensuring financial stability. This research contributes to both academic discussions and practical regulatory improvements and explores the quality of market risk disclosures in financial reports, comparing the higher VaR figures often reported in Pillar 3 documents to those in annual reports, as noted by Campbell and Smith (2022).

1.1. Problem Formulation

The research problem focuses on measuring market risk using the Value at Risk (VaR) Variance-Covariance method with asymmetric GARCH volatility. The aim is to compare the VaR values reported by banks with those calculated using parametric methods. When banks conduct back-testing of internal models like Credit Scoring Tools, VaR, and stress tests for certain risk exposures, they must use historical data or a set of parameters and assumptions developed by the bank itself, and/or assumptions required by the Financial Services Authority (SEOJK.03/2018). This study focuses on understanding the impact and relationship between certain variables and the VaR market risk value in financial reports. The specific research questions are:

- a. How does Trading Revenue affect the VaR market risk value reflected in the company's financial reports? Is there a significant relationship between these two variables?
- b. How does the return from treasury trading affect the VaR market risk value in the company's financial reports? To what extent does the return from treasury trading influence the VaR value?

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- c. How does treasury trading volatility, calculated using the GARCH model, affect the relationship between Trading Revenue and the VaR market risk value in the company's financial reports? Does this volatility significantly moderate the relationship between these two variables?

1.2. Research Objectives

The objective of this research is to explore the effectiveness of VaR disclosures by Indonesian banks in measuring market risk. There are many doubts about the effectiveness of VaR measurements. Critics argue that managers who choose to disclose quantitative VaR may rely on subjective and questionable assumptions about future events and actions, allowing them to distort the company's net market risk exposure (Lim & Tan, 2007). The objectives of this research are:

- a. To compare the VaR values reported by banks with those calculated using parametric methods with asymmetric GARCH volatility for Variance-Covariance VaR.
- b. To analyze the relationship between banks' VaR measurements and their impact on volatility and treasury trading outcomes.
- c. To understand the accuracy of market risk disclosures made by banks in their financial reports and to evaluate the correlation between market risk measurements and factors such as volatility and trading outcomes.

1.3. Research Benefits

This research is valuable for enhancing knowledge about market risk measurement methods. Practically, the results can be used by those involved in managing, supervising, and regulating banking institutions in Indonesia, especially in the context of market risk control. This research provides an in-depth analysis of the application of VaR in predicting market risk in Indonesian banks, making it relevant for academics in risk management and finance. The findings will contribute to understanding market risk disclosure practices in the banking sector and the effectiveness of the risk measurement methods used.

2. Literature Review

VaR indicates the maximum potential loss on financial assets within a certain timeframe and confidence level, crucial for banks to manage risks and comply with regulations such as Bank Indonesia Regulation (PBI) No. 13/26/PBI/2018 and Basel III, which require sufficient capital to cover risks (Füss & Ruf, 2021). Banks are required to assess market risk daily, choosing from various VaR calculation methods like variance-covariance and Monte Carlo simulations to suit their portfolio characteristics (Lim & Tan, 2007). This study also evaluates the transparency and effectiveness of market risk disclosures in bank financial reports in line with Bank Indonesia's regulations, especially in light of global financial crises. The goal is to improve market risk management by effectively using internal models like VaR and comparing the quality of its disclosure (Berkowitz & O'Brien, 2016).

This research focuses on quantifying market risk using the Value at Risk (VaR) Variance-Covariance method, enhanced by asymmetric GARCH volatility. The goal is to compare the VaR figures reported by banks with those computed using parametric methods. A key part of this study is back-testing internal models such as Credit Scoring Tools, VaR, and stress tests by banks, using historical data or bank-developed parameters and assumptions, as required by regulations like SEOJK.03/2018. Although VaR-based capital requirements are intended to foster transparent market risk disclosures, there is ongoing debate about the accuracy of VaR calculations. Existing literature, such as Pérignon and Smith (2010), highlights a gap in understanding the correlation between reported VaR values and actual trading outcomes. This research aims to address this gap by examining the effectiveness of VaR metrics in reflecting market risks and their relation to volatility and trading performance. It examines how VaR disclosure impacts investor perceptions and the cost of a company's equity, with Semper and Beltrán (2014) suggesting that risk disclosures can reduce investor uncertainty and lower risk premiums. The study aims to confirm the relevance of VaR disclosures by evaluating their correlation with the risk of future stock returns and their influence on volatility and trading outcomes, as previously investigated by Lim and Tan (2007).

This comprehensive analysis seeks to enhance understanding of market risk disclosure practices within the banking sector and the effectiveness of risk measurement methodologies. It contributes significantly to the discourse on risk management and financial stability in Indonesian banking. According to Wibowo and Fadhila (2019), banks face high

risks, including market risk related to price movements of financial instruments. VaR calculation is a key method for measuring market risk, highlighting its importance for banks in effectively managing risk. This enables banks to take steps such as increasing capital, diversifying their portfolio, or limiting exposure to certain risks, demonstrating the critical role of VaR in strategic risk management practices.

2.1. Market Risk Measurement by Banks in Indonesia

Most banks in Indonesia include market risk measurement tables in their financial reports, although they may use various measurement methods such as VaR Historical Simulation, VaR Parametric (Variance-Covariance), and Expected Shortfall. Banks providing this information tend to be large banks and those with international operations, such as PT Bank Rakyat Indonesia (Persero) Tbk, PT Bank Mandiri (Persero) Tbk, and PT Bank Central Asia Tbk. Conversely, most Islamic banks and digital banks generally do not report their market risk measurement methods in detail. The absence of this information highlights differences in risk reporting within the Indonesian banking sector.

Below is a table summarizing the market risk measurement methods and the availability of measurement value tables used by various banks in Indonesia. The table includes state-owned commercial banks, national private commercial banks, regional development banks, and branches of foreign banks. Each bank is listed with the market risk measurement methods they use, such as VaR Historical Simulation or VaR Parametric (Variance-Covariance) and indicates whether these measurement value tables are available in their financial reports. This information provides an overview of the transparency and risk management practices applied by each bank.

Table 1. List of banks that disclose market risk measurement value tables

Name	Measurement Method	Measurement Table
PT Bank Rakyat Indonesia (Persero) Tbk	VaR Historical Simulation	Present
PT Bank Mandiri (Persero) Tbk	VaR Historical Simulation	Present
PT Bank Central Asia Tbk	VaR Historical Simulation	Present
PT Bank Maybank Indonesia Tbk	VaR Historical Simulation	Present
PT Bank OCBC NISP Tbk	VaR Historical Simulation	Present
PT Bank HSBC Indonesia	VaR Historical Simulation	Present
PT Bank ANZ Indonesia	VaR Historical Simulation	Present
JP Morgan Chase Bank, Na	VaR Historical Simulation	Present
MUFG Bank, Ltd	VaR Historical Simulation	Present
PT Bank Negara Indonesia (Persero) Tbk	VaR Parametric	Present
PT BPD Dki	VaR Parametric	Present
PT Bank Resona Perdania	VaR method not disclosed	Present

Value at Risk (VaR) is a method for calculating market risk to determine the maximum potential loss. Not all banks disclose VaR and their calculation methods in their financial reports. There are three methods for calculating VaR: historical method, variance-covariance method, and Monte Carlo simulation. Different techniques can be used to calculate the VaR of a portfolio, commonly classified into historical simulation, Monte Carlo simulation, and variance-covariance methods (Cabedo Semper & Clemente, 2003). Globally, Historical Simulation is the most frequently used VaR technique, with 73% of banks reporting its use (Perignon & Smith, 2010).

2.2. GARCH Method

Calculations for forecasting stock volatility use ARCH and GARCH models, addressing issues with traditional variance calculation approaches. Asymmetric GARCH models (like GJR and EGARCH) accommodate leverage effects and asymmetry in stock volatility. The GARCH (Generalized Autoregressive Conditional Heteroskedasticity) method is used to calculate volatility in data with heteroscedasticity issues. The ARCH test identifies time-varying patterns in conditional volatility, necessitating models like ARCH/GARCH to account for these fluctuations (Barjaktarović et al., 2014).

GARCH is a deterministic variance model where returns and variance are driven by the same randomness source (Lehar et al., 2002). The GARCH method uses an autoregressive (AR) model to model data volatility. An AR model assumes

that the current value of a variable is influenced by its previous values. In the GARCH method, data volatility is modeled as a function of previous data volatility. We compare the predictive accuracy of two volatility measures: VaR calculated by banks and predictions generated by the basic GARCH econometric model (Perignon & Smith, 2010).

GARCH model address issues with traditional variance calculation approaches. Asymmetric GARCH models (like GJR and EGARCH) accommodate leverage effects and asymmetry in stock volatility. The EGARCH model formula is as follows:

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (1)$$

Where: σ_t^2 is the conditional variance (volatility) at time t, ω is a constant, α measures the impact of squared innovations from the previous period, β measures the impact of conditional volatility from the previous period, ϵ_t is the error term at time t, typically assumed to follow a normal distribution with a mean of zero.

The GARCH model allows conditional variance to depend on lag values, with the drawback of not accounting for leverage effects. GJR and EGARCH models introduce asymmetry, explaining higher volatility during negative shocks compared to positive shocks.

2.3. Mincer-Zarnowitz Regression

The Mincer-Zarnowitz regression is an econometric approach used to evaluate the accuracy of economic predictions or projections. Named after economists Jacob Mincer and Victor Zarnowitz, this method assesses forecast quality, such as economic growth or inflation projections. We evaluate the accuracy of VaR and GARCH predictions using the Mincer and Zarnowitz (1969) regression model (Perignon & Smith, 2010).

$$Y = \alpha + \beta Y^{\wedge} + \epsilon \quad (2)$$

Where: Y represents the actual value of the predicted variable, Y^{\wedge} is the predicted or estimated value of Y , α and β are coefficients estimated through regression, ϵ is the error term.

Criteria for good prediction evaluation according to the Mincer-Zarnowitz regression include: The coefficient α should not be statistically significantly different from zero, indicating no systematic bias in the prediction, The coefficient β should be statistically significant and close to one, indicating the prediction is an unbiased estimator of the actual value, A high R-squared value, indicating that a large proportion of the variance in the actual variable can be explained by its prediction. This method, widely used in economic and financial analysis to assess model prediction effectiveness, helps researchers and practitioners identify and improve models that provide the most accurate estimates over time. The research focus is to test the clarity of VaR values in bank financial reports, emphasizing the appropriate volatility model selection to measure the largest market losses.

2.4. Conceptual Framework

Banks, inherently risky due to their financial activities like foreign exchange and investments, use VaR to measure market risk, revealing exposures such as interest rate and currency risks (Professor/Dr Simona Mihai-Yiannaki et al., 2012).

Previous research focused on VaR disclosure and accuracy in Indonesian banks, using data from 2011 to 2015 (Wibowo & Fadhila, 2019). The main focus was to measure the quality of VaR disclosure by Indonesian banks, finding that historical simulation was the most used method. It also found that the parametric VaR method using asymmetric effects showed better quality than the historical simulation method. However, the overall evaluation of VaR disclosure quality did not show significant improvement.

This new research considers market volatility data from the COVID-19 economic crisis in 2020-2021 and uses data from other banks. It aims to answer unanswered questions from previous studies, particularly regarding VaR disclosure quality by banks, through the link between literature and anticipated hypotheses on the effectiveness of VaR disclosure in bank financial reports. Another study analyzed the performance of VaR and actual P&L data from two banks. One bank provided a time series of daily P&L and VaR statistics, while NAB presented its daily P&L and VaR data in annual reports as graphs. We collected data from annual reports and translated it into a machine-readable format.

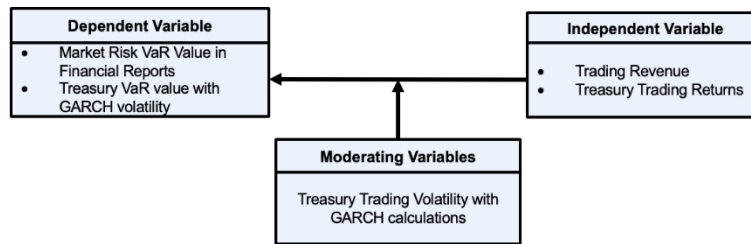


Figure 1. Conceptual Framework of the Research.

The conceptual framework illustrated in the figure outlines the relationships between various variables in the study. The dependent variables are the Market Risk VaR Value in Financial Reports and the Treasury VaR value with GARCH volatility. The independent variables are Trading Revenue and Treasury Trading Returns. Additionally, the framework includes a moderating variable, Treasury Trading Volatility with GARCH calculations, which affects the relationship between the independent and dependent variables. This framework aims to investigate how trading revenue and treasury trading returns impact the market risk VaR value in financial reports and the treasury VaR value, with the moderating effect of treasury trading volatility calculated using GARCH methods.

3. Methods

3.1. Research Data

Secondary data is obtained from the financial reports of 8 Indonesian banks covering the period from 2015 to 2023. These financial reports include data on treasury trading values and provide Value at Risk (VaR) data. The study involves calculating the percentage returns of treasury trading values, modeling trading value volatility with GARCH, and calculating VaR through volatility estimation using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The impact of VaR with GARCH volatility on trading returns is tested using Mincer-Zarnowitz regression. There is no universal approach for calculating portfolio VaR, and institutions have various techniques to assess VaR (Cabedo Semper & Clemente, 2003).

To evaluate the benefits of VaR disclosure by banks, the study compares the effectiveness of two volatility measurement methods: VaR calculated by banks and parametric VaR using asymmetric GARCH volatility. The analysis tests the ability of VaR to predict future treasury trading volatility and profits. Since VaR is a quantile, it shows a positive correlation between volatility and future treasury trading profits (Jorion, 2002a). This relationship is linear as long as the distribution fits within location-scale distributions, including normal and other asymmetric distributions.

Before testing VaR's ability to predict treasury trading volatility, the study measures VaR values from treasury trading profits using parametric methods that include variance, covariance, and risk with asymmetric GARCH volatility as standard VaR measurement assumptions.

3.2. Research Models and Framework

Value at Risk (VaR) is a standard market risk measure that determines the maximum loss in market value over a specified period (t) and confidence level (p). Commonly used VaR measures are daily with a 99% confidence level, indicating the worst loss is unlikely to exceed the calculated VaR at this confidence level (Jorion, 2007). VaR is calculated as follows:

$$VaR(x) = W_0 \times \alpha \times \sigma \times \sqrt{t} \tag{3}$$

where: W_0 is the total assets, α is the confidence level, σ is the volatility, t is the time period. For a 99% confidence level, VaR assumes that the worst losses over a specified period will not exceed the calculated VaR. VaR should include price movements equivalent to 10 working days, considering banks usually hold exposures over this period.

3.3. Evaluation of VaR Disclosure by Banks

Inconsistent disclosure quantities and methods present a variation in information presentation and calculation. Some banks use Monte Carlo models, while others use historical simulation. Some banks display overall trading positions using pie charts, while others use tables (Mihai-Yiannaki et al., 2012).

To evaluate the quality of VaR disclosure by banks, the study assesses how disclosed VaR values impact treasury trading volatility. Some studies have evaluated bank VaR models by comparing the distribution of exceptions observed by the bank with predicted results if the bank's VaR model was accurate (Campbell & Smith, 2022).

This evaluation not only examines disclosed VaR values but also parametric VaR values using variance-covariance methods based on asymmetric GARCH volatility. Using the E-GARCH model, asymmetric effects on volatility are studied, incorporating them into VaR calculation as a factor determining treasury trading return variation. Hence, the reevaluation examines the impact of parametric VaR variance-covariance values with asymmetric GARCH volatility. After evaluation, results are compared between bank-disclosed VaR values and parametric variance-covariance VaR values with asymmetric GARCH volatility.

When calculating VaR, bank risk management units have more data than researchers, including VaR values based on historical returns and current portfolio weights. Conversely, researchers using the E-GARCH model for parametric variance-covariance VaR calculations can only use current portfolio weight data.

In addition to using asymmetric GARCH volatility, bank VaR quality evaluations are also performed through regression methods. Backtesting relies on daily VaR measurement as it typically does not account for portfolio changes over the VaR range, even if market risk burden is based on bi-weekly VaR measurement (Cuoco & Liu, 2006).

3.4. Bank VaR Data

This study uses financial report data from banks disclosing market risk VaR values. Data includes treasury trading activities from government securities and bond sales, showing financial instrument positions exposed to interest rate risk. Data is obtained from financial reports from Q1 2015 to Q4 2023.

Among all Indonesian banks, ten banks were selected based on data availability in financial reports, bank size relative to others, status as public companies, and consistency with previous research by Wibowo & Fadhila (2019). The ten banks are PT Bank Rakyat Indonesia (Persero) Tbk, PT Bank Mandiri (Persero) Tbk, PT Bank Central Asia Tbk, PT Bank Maybank Indonesia Tbk, PT Bank OCBC NISP Tbk, PT Bank HSBC Indonesia, PT Bank ANZ Indonesia, JP Morgan Chase Bank, Na, MUFG Bank, Ltd, PT Bank Negara Indonesia (Persero) Tbk, PT BPD DKI, and PT Bank Resona Perdania.

Table 2. Bank Value at Risk data 2015-2023 from financial reports

Year	BRI	Mandiri	BNI	BCA	Maybank
2015	205,770	35,259	179,349	72,751	21,452
2016	762,834	59,770	304,939	144,841	19,545
2017	551,125	33,481	297,219	245,115	23,484
2018	886,298	66,154	410,169	274,335	19,183
2019	1,097,018	81,837	342,758	555,433	28,183
2020	47,366	158,422	471,967	319,289	44,987
2021	534,795	152,202	411,143	280,891	59,685
2022	335,017	73,388	372,486	68,699	18,990
2023	400,687	86,076	348,481	116,142	53,476

Year	OCBC	HSBC	JP Morgan	ANZ	DKI
2015	11,754	7,742	-	-	61.459
2016	14,435	8,189	-	-	65,103
2017	22,445	17,682	-	-	61.407
2018	18,481	13,947	12,513,703	-	59,073
2019	28,684	25,808	14,707,228	1.128.831	53,068
2020	43,468	10,562	72,573,758	1.908.501	202,753
2021	38,718	17,121	18,992,497	1.319.625	67,060
2022	34,515	7,515	45,267,161	1.332.909	120,879
2023	36,603	8,963	15,089,060	683.263	163,592

The selected ten banks have implemented internal VaR models and disclosed market risk VaR values in their financial reports, meeting all standards set by regulatory authorities. This aligns with amendments to the Capital Agreement to include market risk, modified from the 1988 Capital Agreement by the Basel Committee on Banking Supervision. The recommended method for measuring market risk in capital adequacy calculations is using internal VaR models.

This research aims to support improving risk management quality, assuming internal models offer a more accurate risk measurement approach for risk management and capital adequacy calculations.

3.5. Research Variables

In this research methodology, various variables are identified from estimates and secondary data. These variables, along with their descriptions and measurement methods, are summarized as follows: VaR (Value at Risk) is the market risk value exposed to interest rate risk disclosed in bank financial reports, measuring the maximum expected loss at a certain confidence level over a specific period. Trading Revenue refers to the total value of treasury trading held by the bank from government securities and bond sales in the trading book exposed to interest rate risk, including all income generated from these activities. Treasury Trading Returns are measured through the natural logarithm of the ratio of the bank's treasury trading value at time $t+1$ to its value at time t , providing the percentage change in treasury trading value from one period to the next, capturing trading gains or losses.

Treasury Trading VaR is the VaR measurement specific to treasury trading activities, estimated using methodologies like the E-GARCH model to account for volatility and risk in treasury trading. Treasury Trading Volatility is calculated as the variation in the bank's treasury trading returns using the E-GARCH model, which estimates conditional variance based on previous information, capturing volatility effects and predicting changes in treasury trading return variance. Treasury Trading Residual is the residual from the bank's treasury trading return model, interpretable as the component of returns unexplained by the model, useful for further analysis of the model's efficiency in predicting treasury trading returns.

The dependent variables (DV) include the Market Risk VaR Value in Financial Reports and the Treasury VaR value with GARCH volatility. The independent variables (IV) are Trading Revenue and Treasury Trading Returns. The moderating variable (MV) is Treasury Trading Volatility with GARCH calculations. Each variable plays a critical role in analyzing market risk and treasury trading performance, providing insights into how banks manage risk and generate revenue from their trading activities.

3.6. Research Hypotheses

The research hypotheses determine whether bank VaR values accurately reflect market risk and if there is a relationship between these values and treasury trading volatility and returns. The limitations of the research include the use of specific market instruments and a focus on the volatility and returns of treasury trading in Indonesia. The writing systematics include introductory chapters, literature review, research methodology, analysis and discussion, and conclusions and recommendations.

- H1 : Trading Revenue has a significant effect on the Market Risk VaR Value in Financial Reports.
- H2 : Treasury Trading Returns have a significant effect on the Market Risk VaR Value in Financial Reports.
- H3 : Treasury Trading Volatility with GARCH calculations significantly moderates the relationship between Trading Revenue and the treasury VaR value calculated by the bank.

Risk disclosure can reduce equity costs as investor risk perception significantly affects a company's equity cost. Risk disclosure can reduce investor uncertainty, thereby lowering the risk premium demanded by the company (Semper & Beltrán, 2014). This research focuses on comparing bank-reported VaR values with those calculated using parametric methods, tested using financial data from Indonesian banks.

4. Result and Discussions

4.1. Descriptive Statistical Analysis

Financial data from ten major Indonesian banks, including profits from financial asset sales and gains from spot and derivative transactions, is analyzed. Trading revenue is assumed to be the sum of these values. The following table presents the mean, median, and standard deviation (SD) for each category and bank.

Table 3. Table of Descriptive Statistical Analysis Results for Ten Banks

<i>Trading Revenue</i>	<i>BRI</i>	<i>BCA</i>	<i>MANDIRI</i>	<i>BNI</i>	<i>JPMORGAN</i>
Mean	899920.6604	933718.2736	1092283.264	1077342.981	178851.1944
Standard Error	127758.8018	77332.98258	98840.77846	89472.93433	40730.38278
Median	498616.5	745486	826022	761758.5	61310.5
Mode	#N/A	454118	#N/A	1241333	#N/A
Standard Deviation	1315357.37	796191.7863	1017628.098	921180.2395	345608.7583
Sample Variance	1.73017E+12	6.33921E+11	1.03557E+12	8.48573E+11	1.19445E+11
Kurtosis	4.003044051	1.433248212	2.485638092	0.534025492	0.611521285
Skewness	1.739827339	1.2148366	1.713372247	1.124247179	0.867728666
Range	7979579	4021156	4375143	3944894	1816464
Minimum	-1823563	-142471	10476	-270016	-720903
Maximum	6156016	3878685	4385619	3674878	1095561
Sum	95391590	98974137	115782026	114198356	12877286
Count	106	106	106	106	72
<i>Trading Revenue</i>	<i>MAYBANK</i>	<i>HSBC</i>	<i>OCBC</i>	<i>DKI</i>	<i>ANZ</i>
Mean	178022.1981	274639.3491	403202.1698	44183.89623	80835.91667
Standard Error	27895.73798	32169.59448	37020.27071	3887.436849	26003.39928
Median	97378	162273	252513	37231	72225
Mode	#N/A	#N/A	#N/A	0	#N/A
Standard Deviation	287204.2008	331206.2466	381147.0149	40023.61199	201421.4647
Sample Variance	82486252950	1.09698E+11	1.45273E+11	1601889517	40570606451
Kurtosis	1.635817313	0.29390828	2.310941667	1.486918326	4.252311052
Skewness	1.122550052	1.080327027	1.574090075	1.257791482	-1.060546554
Range	1466804	1369748	1745915	179011	1271588
Minimum	-436336	-116511	-35704	0	-753579
Maximum	1030468	1253237	1710211	179011	518009
Sum	18870353	29111771	42739430	4683493	4850155
Count	106	106	106	106	60
<i>VaR Bank</i>	<i>BRI</i>	<i>BCA</i>	<i>MANDIRI</i>	<i>BNI</i>	<i>JPMORGAN</i>
Mean	541880.9434	233815.566	83854.24528	351919.1887	29857.2345
Standard Error	30752.8495	14137.34188	4120.691547	7476.614158	2621.968178
Median	534795	245115	73388	348481	17040.7785
Mode	762834	144841	59770	304939	12513.703
Standard Deviation	316619.9643	145552.8432	42425.1161	76976.45407	22248.13774
Sample Variance	1.00248E+11	21185630162	1799890476	5925374482	494979633
Kurtosis	-0.871004065	0.233578693	-0.686935017	0.305703854	-0.435664374
Skewness	0.214625765	0.897029439	0.747149762	-0.614633584	1.079877724
Range	1049652	486734	124941	292618	60060.055
Minimum	47366	68699	33481	179349	12513.703
Maximum	1097018	555433	158422	471967	72573.758
Sum	57439380	24784450	8888550	37303434	2149720.884

Count	106	106	106	106	72
VaR Bank	MAYBANK	HSBC	OCBC	DKI	ANZ
Mean	32310.5283	13159.09434	27978.55748	95564.24528	1274625.8
Standard Error	1491.741676	570.7448387	1036.511147	5062.625224	51360.6627
Median	23484	10562	28684	65103	1319625
Mode	19545	8189	14435.17153	65103	1128831
Standard Deviation	15358.42057	5876.177764	10671.53541	52122.91685	397837.9826
Sample Variance	235881082.3	34529465.11	113881667.9	2716798461	1.58275E+11
Kurtosis	-1.143947315	-0.148284049	-1.420459633	-0.417361909	-0.604244658
Skewness	0.7556354	0.948697171	-0.114411498	1.079970376	0.150612938
Range	40695	18293	31713.81327	149685	1225238
Minimum	18990	7515	11753.86802	53068	683263
Maximum	59685	25808	43467.68129	202753	1908501
Sum	3424916	1394864	2965727.093	10129810	76477548
Count	106	106	106	106	60

This data provides insight into the distribution and variation of their financial data. This analysis helps in understanding each bank's financial performance, identifying distribution patterns, and variations in each profit category.

4.2. Data Transformation (Shifting and Normalization)

Shifting and normalizing data are crucial steps in calculating Value at Risk (VaR) using historical simulation and variance-covariance methods with EGARCH volatility. Shifting ensures that all return data is above zero, avoiding negative values that could distort risk analysis. Normalizing data addresses different scales in return data, enabling more consistent comparisons. This process reduces excessive skewness and kurtosis, aligning the data distribution closer to normality, which is essential for variance-covariance methods. This improves the accuracy and reliability of VaR calculations, leading to better risk identification and decision-making in financial risk management.

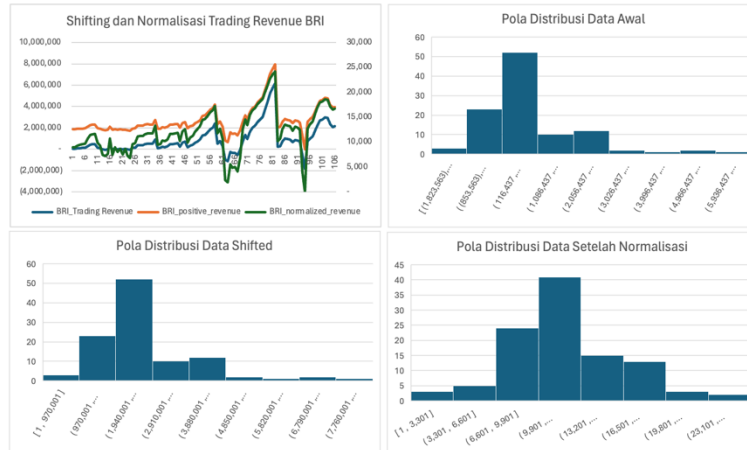


Figure 2. Distribution Patterns of BRI Data Before and After Transformation.

The trading revenue data for BRI shows extreme negative and positive values. To calculate VaR, the data is shifted to positive values by adding the absolute minimum value plus one. This transformation moves all return values upward. Normalizing the data balances the distribution, making it more normal, which is necessary for EGARCH calculations that assume normal distribution.

4.3. Model Fit

After data preparation, the EGARCH model fit is performed to determine the parameters (p, q) for each bank's data. The table shows the estimated EGARCH (p, q) parameters and Akaike Information Criterion (AIC) values for each bank, indicating the best model fit.

Table 4. EGARCH (p, q) Parameter Estimation Results

Data Bank	Optimal_p	Optimal_q	AIC
BRI_normalized_revenue	3	3	-0.361625493
MANDIRI_normalized_revenue	3	1	-9.253599812
BNI_normalized_revenue	3	3	1.533125604
BCA_normalized_revenue	3	2	1.794094676
MAYBANK_normalized_revenue	3	3	0.456072783
OCBC_normalized_revenue	3	3	0.521617545
HSBC_normalized_revenue	1	3	0.479421806
JPMORGAN_normalized_revenue	2	3	-1.604032155
ANZ_normalized_revenue	3	3	-8.214886181
DKI_normalized_revenue	3	1	2.10084717

The AIC values indicate model quality, with lower values representing better fits. For example, BRI's optimal model with (p=3, q=3) and AIC of -0.361625493 shows a good balance for its trading revenue data. Mandiri's model with (p=3, q=1) and AIC of -9.253599812 indicates efficiency with one moving average lag. Other banks show varying optimal parameters, reflecting their specific data characteristics and model needs.

4.4. Results

The analysis of Value at Risk (VaR) across several banks, including BRI, Mandiri, BNI, BCA, Maybank, JP Morgan, OCBC NISP, BPD DKI, HSBC, and ANZ, revealed significant discrepancies between the EGARCH VaR model and the VaR values reported by the banks. Generally, EGARCH VaR tended to be higher for BRI, Mandiri, BNI, and JP Morgan, indicating higher market risk sensitivity, whereas it was often lower for BCA, Maybank, OCBC NISP, HSBC, and ANZ, suggesting lower risk sensitivity. Regression results indicated a significant positive relationship between trading revenue and bank VaR for most banks, with volatility generally not having a significant impact. Notably, BPD DKI showed a significant negative relationship between trading revenue and bank VaR. The findings highlight the varying sensitivity of the EGARCH model to market volatility and its differing alignment with the banks' conservative risk estimates.

The Mincer-Zarnowitz regression analysis results for the banks indicate varying degrees of effectiveness in predicting the VaR values reported by the banks using the EGARCH model. Overall, the results suggest that the EGARCH model generally does not align well with the banks' reported VaR values, showing weak or non-significant relationships.

For BRI, the regression showed a weak positive correlation with an R Square of 0.0441, indicating that only 4.41% of the variability in the reported VaR could be explained by the EGARCH model, although the model was statistically significant, the relationship was weak. Mandiri's regression indicated an almost negligible positive correlation with an R Square of 0.00003, meaning the EGARCH model did not effectively predict the reported VaR values, and the model was not statistically significant. BNI had a weak positive correlation with an R Square of 0.0429, suggesting a similarly weak predictive power. BCA showed a slightly better but still weak positive correlation with an R Square of 0.1046, with the model being statistically significant.

Maybank and JP Morgan both exhibited weak positive correlations with R Squares of 0.0529 and 0.0306, respectively, neither being statistically significant. OCBC NISP, BPD DKI, and HSBC all showed very weak correlations with R Squares of 0.0083, 0.0068, and 0.0022, respectively, and none were statistically significant. Finally, ANZ showed a very weak negative correlation with an R Square of 0.000009, also not statistically significant. These results collectively indicate that the EGARCH model generally does not provide accurate predictions for the banks' reported VaR values, as evidenced by the low R Square values and the lack of statistical significance in most cases.

From the summary table, it is evident that trading revenue is significant for 9 out of 10 banks, with a positive direction except for HSBC. Only BRI shows significant volatility with a positive direction, while volatility in other banks is either insignificant or negative. VaR GARCH is significant only for BCA and BNI, with a positive relationship for BRI, BCA, BNI, JPMorgan, and ANZ. Most banks use the Historical Simulation method, while BNI and DKI use Variance Covariance. According to Perignon and Smith (2010), an ideal market risk measurement has a positive relationship with volatility and trading returns, and the summary results indicate that most banks align with this principle. However, some banks show negative or insignificant results, which may require further analysis or model adjustments.

Table 5. Summary of regression results for 10 banks

Bank	BRI	BCA	Mandiri	BNI	JPMorgan
Trading Revenue (Significance)	Significant	Significant	Significant	Significant	Significant
Trading Revenue (Correlation)	Positive	Positive	Positive	Positive	Positive
Volatilitas (Significance)	Significant	Not Significant	Not Significant	Not Significant	Not Significant
Volatilitas (Correlation)	Positive	Positive	Positive	Positive	Negative
VAR GARCH (Significance)	Not Significant	Significant	Not Significant	Significant	Not Significant
VAR GARCH (Correlation)	Positive	Positive	Negative	Positive	Positive
Internal Model	Historical Simulation	Historical Simulation	Historical Simulation	Variance Covariance	Historical Simulation

Bank	Maybank	HSBC	OCBC	DKI	ANZ
Trading Revenue (Significance)	Not Significant	Significant	Significant	Significant	Significant
Trading Revenue (Correlation)	Positive	Negative	Positive	Negative	Positive
Volatilitas (Significance)	Not Significant	Not Significant	Not Significant	Not Significant	Not Significant
Volatilitas (Correlation)	Positive	Negative	Negative	Positive	Negative
VAR GARCH (Significance)	Not Significant	Not Significant	Not Significant	Not Significant	Not Significant
VAR GARCH (Correlation)	Positive	Negative	Negative	Positive	Negative
Internal Model	Historical Simulation	Historical Simulation	Historical Simulation	Variance Covariance	Historical Simulation

The relationship between various financial indicators and the Value at Risk (VaR) reported in the financial statements of the ten tested banks can address the following hypotheses:

H1: There is a significant influence of Trading Revenue on the Value of Market Risk VaR in Financial Statements

Based on the summary table, 9 out of 10 banks show that trading revenue significantly influences market risk VaR values. This supports hypothesis H1, indicating that trading revenue indeed significantly affects market risk VaR in financial statements.

H2: There is a significant influence of Treasury Trading Returns on the Value of Market Risk VaR in Financial Statements

This hypothesis can be equated with H1 in the context of the given data because treasury trading returns are part of trading revenue. Therefore, the data shows that trading revenue (treasury trading returns) significantly affects market risk VaR for most banks, supporting hypothesis H2.

H3: Treasury Trading Volatility, as calculated by the bank, significantly moderates the relationship between Trading Revenue and Treasury VaR with bank volatility

From the summary table, only BRI shows significant volatility, while volatility in other banks is insignificant. Additionally, bank VaR is only significant for BCA and BNI. This indicates that bank-calculated volatility does not significantly moderate the relationship between trading revenue and treasury VaR for most banks. Therefore, hypothesis H3 is not supported by the available data, as bank volatility does not show a significant moderating effect on this relationship.

The results of this study can be used by parties involved in the management, supervision, and regulation of banking institutions in Indonesia, especially in the context of market risk control. This study also offers an in-depth analysis of the application of VaR in predicting market risk in Indonesian banks.

5. Conclusions

Based on the findings of this study, several recommendations can be made to improve market risk management in banks, including: Banks should continue to develop and optimize the use of VaR methods, particularly historical simulation and variance-covariance with GARCH volatility, in market risk assessment. These methods have proven to provide more accurate and relevant risk estimates compared to simple return methods. Given the significant relationship between Trading Revenue and Financial Statement VaR, banks should enhance monitoring and analysis of trading revenue. This can help in identifying potential market risks early and taking timely mitigation actions.

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