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Banking Market Risk Modelling Using QAR-Based CoVaR with Quantile Regression

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Abstract

Financial sector stability is essential for economic resilience, particularly in Indonesia's banking industry. Commonly used risk measures such as Value-at-Risk (VaR) capture individual risk but do not adequately account for systemic interdependence. Existing studies often rely on linear models that are less capable of capturing asymmetric and heavy-tailed return behaviour. This study addresses this gap by developing a Conditional Value-at-Risk (CoVaR) framework based on the Quantile Autoregressive (QAR) approach. This study uses daily closing prices of 15 largest market-cap banking firms listed on the Indonesia Stock Exchange from July 4, 2022, to June 30, 2025. VaR is estimated using QAR, followed by CoVaR estimation through quantile regression, and evaluated using the Kupiec Proportion of Failures (POF) test. The results show that the QAR-based VaR model performs consistently well, with all 15 banks passing the Kupiec test at both the 1% and 5% quantiles, indicating robust tail risk estimation. In contrast, CoVaR results are less stable, with 14 banks passing at the 1% quantile and only 7 at the 5% quantile, suggesting challenges in capturing conditional dependence. Banks such as ARTO and BBHI exhibit stronger systemic spillover effects. This study contributes by integrating QAR into CoVaR modelling and provides insights for systemic risk monitoring in emerging banking markets.

Keywords: CoVaR; QAR; Quantile Regression; Systemic Risk; VaR

Abstrak

Stabilitas sektor keuangan sangat penting dalam menjaga ketahanan ekonomi, khususnya pada industri perbankan di Indonesia. Ukuran risiko yang umum digunakan seperti *Value-at-Risk* (VaR) mampu menangkap risiko individual, namun belum memadai dalam merepresentasikan keterkaitan sistemik antar institusi. Studi yang ada umumnya masih mengandalkan model linier yang kurang mampu menangkap karakteristik return yang asimetris dan berekor tebal. Penelitian ini mengatasi kesenjangan tersebut dengan mengembangkan kerangka *Conditional Value-at-Risk* (CoVaR) berbasis pendekatan *Quantile Autoregressive* (QAR).

Penelitian ini menggunakan data harga penutupan harian dari 15 perusahaan perbankan dengan kapitalisasi pasar terbesar yang terdaftar di Bursa Efek Indonesia selama periode 4 Juli 2022 hingga 30 Juni 2025. Estimasi VaR dilakukan menggunakan model QAR, kemudian dilanjutkan dengan estimasi CoVaR melalui regresi kuantil, dengan evaluasi kinerja model menggunakan uji *Kupiec Proportion of Failures* (POF). Hasil penelitian menunjukkan bahwa model VaR berbasis QAR memiliki kinerja yang konsisten baik, dengan seluruh 15 bank lolos uji Kupiec pada kuantil 1% dan 5%, yang mengindikasikan estimasi risiko ekor yang andal. Sebaliknya, hasil CoVaR menunjukkan stabilitas yang lebih rendah, dengan 14 bank lolos pada kuantil 1% dan hanya 7 bank pada kuantil 5%, yang mengindikasikan adanya tantangan dalam menangkap ketergantungan kondisional. Bank seperti ARTO dan BBHI menunjukkan kontribusi risiko sistemik yang lebih tinggi. Penelitian ini memberikan kontribusi dengan mengintegrasikan QAR ke dalam pemodelan CoVaR serta memberikan implikasi praktis bagi pemantauan risiko sistemik pada pasar perbankan di negara berkembang.

Kata Kunci: CoVaR; QAR; Quantile Regression; Systemic Risk; VaR

Introduction

Financial sector stability is a key pillar in maintaining national economic resilience. Disruptions in this sector can have a domino effect on various other sectors, as seen in the 2008 global financial crisis, which originated from the failure of the banking sector (Brunnermeier, 2009) therefore, measuring and mitigating systemic risk has become a critical issue in financial risk management (Acharya et al., 2017). In Indonesia, the banking sector plays a strategic role as a provider of liquidity and a key driver of economic activity. The performance of large banks, especially those with high capitalization, i.e., banks with a big market value, significantly affects the stability of the national financial system (Mishkin, 2007). The failure of one bank can cause widespread systemic risk, so it is necessary to measure risk not only on an individual basis but also by considering the interconnections between institutions (Allen et al., 2012).

Several major banks, particularly BBCA, BMRI, BBRI, and BBNI, consistently demonstrate high liquidity and attract significant investor attention. Previous empirical studies have shown that these banks exhibit strong trading activity and play a dominant role in market dynamics. For example, an analysis of stock market activity during the Tax Amnesty policy period found that these four banks were among the most actively traded and demonstrated notable market responses compared to other sectors, highlighting their systemic importance within the financial ecosystem (Handayani & Prastyo, 2020).

From a methodological perspective, VaR is widely used to measure potential losses at a given confidence level. Various approaches have been developed to improve its accuracy, including volatility-based models such as GARCH and its extensions. For instance, the ARMAX–GARCHX model demonstrates improved VaR performance when incorporating exogenous variables (Prastyo et al., 2018). In addition to estimating VaR using the ARMA–GARCHX framework, another method that can be used is EVT with the POT approach (Aqsari et al., 2026). Studies in the Indonesian banking sector have also examined VaR and CoVaR using more data-driven methods. Furthermore, studies such as Alimuddin et al. (2025) extend risk measurement by incorporating CoVaR to analyze both individual and systemic risks. While these approaches enhance tail risk estimation, they generally rely on distributional assumptions or static frameworks, limiting their ability to capture dynamic, asymmetric, and time-varying dependencies across financial institutions.

To address these limitations, this study employs the QAR approach to estimate VaR, which directly models return dynamics at specific quantiles and is more flexible in capturing heavy-tailed and nonlinear behavior (Dzhamtyrova & Maple, 2022). However, VaR only measures individual risk and does not account for interdependence among institutions. To overcome this limitation, CoVaR introduced by Adrian & Brunnermeier (2016) is used to measure systemic risk by evaluating the risk of the financial system conditional on an institution in distress.

The QR approach is used to estimate dependence risk among entities without assuming a normal distribution. The predictor in the QR to estimate CoVaR is the entity's VaR. The VaR can be calculated with various approaches, one of which is the QAR approach, which extends the mean-model AR to become a quantile-based model by accounting for time dynamics through lagged returns (Dzhamtyrova & Maple, 2022). Several previous studies have demonstrated the effectiveness of the quantile approach for measuring systemic risk, including Muharam & Erwin (2017), Wijoyo et al. (2022), and Kholishoh et al. (2024). However, these studies generally do not incorporate autoregressive quantile dynamics into the CoVaR framework.

Therefore, the key research gap lies in the limited integration of dynamic quantile-based models, specifically QAR, within the CoVaR framework in the context of Indonesian banking. This study addresses this gap by developing an integrated VaR–CoVaR model that combines QAR and QR. The study is expected to academically contribute advancing systemic risk modeling through dynamic quantile approaches and practically provide insights for regulators in identifying systemically important banks and enhancing macroprudential risk monitoring.

Method

Data and Data Sources

The study used data by documenting and recording historical data from official sources. The main data consisted of daily closing prices of the 15 largest market capitalization banking companies listed on the Indonesia Stock Exchange (IDX) from July 4, 2022, to June 30, 2025. All data were downloaded on August 20, 2025, from credible sources such as Yahoo Finance in Excel or CSV formats. The data were then processed and analysed using RStudio.

Research Variables

The dependent variable in this study was the daily log-return of bank stocks, calculated from daily closing prices. Stock returns were chosen because they reflect the expected gains of investors while considering risk, as proposed by Markowitz (1952), and they capture all market information according to Fama (1970) Efficient Market Hypothesis. The study involved 15 major return banking companies:

Table 1. Bank Stock Returns

Stock	Bank	Variable	Stock	Bank	Variable
BBCA	Bank Central Asia	$Y_{1,t}$	MEGA	Bank Mega	$Y_{8,t}$
BBRI	Bank Rakyat Indonesia	$Y_{2,t}$	BBHI	Allo Bank Indonesia	$Y_{9,t}$
BMRI	Bank Mandiri	$Y_{3,t}$	NISP	Bank OCBC NISP	$Y_{10,t}$
BBNI	Bank Negara Indonesia	$Y_{4,t}$	ARTO	Bank Jago	$Y_{11,t}$
BRIS	Bank Syariah Indonesia	$Y_{5,t}$	PNBN	Bank Pan Indonesia	$Y_{12,t}$
BNLI	Bank Permata	$Y_{6,t}$	BINA	Bank Ina Perdana	$Y_{13,t}$
BNGA	Bank CIMB Niaga	$Y_{7,t}$	BDMN	Bank Danamon Indonesia	$Y_{14,t}$
			BTPN	Bank SMBC Indonesia	$Y_{15,t}$

Theoretical Framework for Methodology

This section presents the theoretical foundations and formulas used in the VaR-QAR modeling, CoVaR estimation, and model evaluation using the Kupiec Test.

a. Quantile Regression (QR)

Quantile Regression (QR) allows conditional quantile estimation of the dependent variable distribution, capturing extreme behavior and data heterogeneity (Koenker & Bassett, 1978). The quantile function of a random variable Y_t is defined as:

$$Q_{Y_t}(\tau) = F_Y^{-1}(\tau) = \inf\{y: F_Y(y) \geq \tau\} \quad (1)$$

where $Q_{Y_t}(\tau)$ is the conditional quantile of Y at level τ. for the linear quantile regression model:

$$\boldsymbol{Y_t} = \boldsymbol{X\beta(\tau)} + \boldsymbol{\varepsilon_t(\tau)} \quad (2)$$

The loss function used is the Least Absolute Deviation (LAD) function:

$$\rho_\tau(u) = \sum_{t=1,u_t\geq 0}^{T} \tau|u_t| + \sum_{t=1,u_t\geq 0}^{T} (1-\tau)|u_t|, \tag{3}$$

so that parameter estimates are obtained through:

$$\widehat{\boldsymbol{\beta}}(\tau) = arg\min_{\beta\in\mathbb{R}^p} \sum_{t=1}^{T} \rho_\tau\left(y_t - \boldsymbol{x}_i'\boldsymbol{\beta}(\tau)\right) \tag{4}$$

b. Quantile Autoregressive (QAR)

Quantile Autoregressive (QAR) extended QR to time series data, capturing the dynamics of quantiles of stock returns that were asymmetric and volatile (Koenker & Xiao, 2006). The QAR(p) model is written as:

$$y_t(\tau) = \phi_0(\tau) + \phi_1(\tau)y_{t-1} + \phi_2(\tau)y_{t-2} + \cdots + \phi_p(\tau)y_{t-p} + \varepsilon_t, \tag{5}$$

If only two specific lags are used, the model can be simplified to QAR($[1, p]$):

$$y_t(\tau) = \phi_0(\tau) + \phi_1(\tau)y_{t-1} + \phi_p(\tau)y_{t-p} + \varepsilon_t \tag{6}$$

This model describs the variation in the return distribution at each quantile, making it suitable for dynamic risk estimation, such as VaR and CoVaR. The lag structure p is determined based on the significance and suitability of lagged variables obtained from the QAR estimation results, ensuring that only relevant lag terms are included in the model.

c. Value-at-Risk (VaR)

Value-at-Risk (VaR) estimates the maximum potential loss over a given time horizon at a specific confidence level (Koenker & Xiao, 2006). In this study, VaR is derived from the QAR model as:

$$VaR_t(\tau) = \hat{y}_t(\tau) = \hat{\phi}_0(\tau) + \hat{\phi}_1(\tau)y_{t-1} + \hat{\phi}_2(\tau)y_{t-2} + \cdots + \hat{\phi}_p(\tau)y_{t-p} + \varepsilon_t, \tag{7}$$

with $VaR_t(\tau)$ is the Value-at-Risk at quantile level τ

d. Conditional Value-at-Risk (CoVaR)

CoVaR measures the risk of a bank j conditional on another bank j^*experiencing extreme losses (Adrian & Brunnermeier, 2016). In quantile regression form, the CoVaR model can be written as:

$$CoVaR_{\tau,t}^{j|j*} = \beta_{\tau,0} + \sum_{\substack{j^*=1 \\ j^*\neq j}}^{J} \beta_{\tau,j^*} VaR_{\tau,t}^{j*} + \varepsilon_{\tau,t}^{j} \tag{8}$$

$$\Delta CoVaR_{\tau,t}^{j|j*} = CoVaR_{\tau,t}^{j|VaR_{\tau,t}^{j*}} - CoVaR_{\tau,t}^{j|VaR_{\tau=0.5,t}^{j*}} \tag{9}$$

Where $CoVaR_{\tau,t}^{j|j*}$ is the Conditional Value-at-Risk of institution j given institution j^* ($j \neq j^*$) is at its VaR level.

e. Kupiec Proportion of Failures (POF) Test

The Kupiec POF Test evaluates the accuracy of predicted VaR or CoVaR (Kupiec, 1995). The hypothesis being tested is:

$$H_0: p = \hat{p} \text{(Model valid)}$$
$$H_1: p \neq \hat{p} \text{(Model invalid)}$$

where p is the expected violation rate and $\hat{p} = \frac{x}{n}$ is the actual violation rate. The test statistics in this study are calculated as:

$$LR_{POF} = -2\ln\left[(1-\hat{p})^{(n-x)}\hat{p}^{x}\right] + 2\ln\left[(1-\tfrac{x}{n})^{(n-x)}(\tfrac{x}{n})^{x}\right] \quad (10)$$

The LR_{POF} value is compared with the chi-square distribution with 1 degree of freedom. If $LR_{POF} > \chi^2_{(1,\alpha)}$, then the model is considered invalid in predicting extreme risk.

Methodological Justification

This study does not explicitly perform stationarity testing since the analysis is based on return series, which are generally considered weakly stationary in financial literature. Additionally, the QAR model focuses on conditional quantiles, making it less sensitive to strict stationarity assumptions. Robustness checks are implicitly addressed through model validation using the Kupiec POF test across multiple quantiles (1% and 5%). The lag structure in the QAR model is determined based on the statistical significance of estimated parameters, ensuring that only relevant lagged effects are included.

Analysis Steps

The analysis steps were conducted to estimate VaR-QAR and CoVaR, and to evaluate model performance.

a. Estimating VaR-QAR
   1) Collected daily stock prices and relevant risk factors from Yahoo Finance.
   2) Calculated stock returns as log-returns with $ln\, y_t = ln\left(\frac{P_t}{P_{t-1}}\right)$ where $\ln y_t$ is the log return value at time $t, t = 1,2,\dots,T, P_t$ is the closing price of the stock at the time $t = 1,2,\dots,n$, and P_{t-1} is the closing price of the stock at the previous time, i.e., time $(t-1), t = 1,2,\dots,T$.
   3) Modeled QAR to estimate conditional quantiles of stock return distributions.
   4) Calculated VaR at specific quantiles based on QAR estimates.

b. Estimating CoVaR
   1) Computed VaR for each bank as an input to the quantile regression for CoVaR with equation (8)

2) Built a quantile regression model:
   a) Dependent variable: stock return of the bank j
   b) Independent variables: VaR of other banks j^*
   c) Estimated CoVaR bank j conditional on extreme losses of the bank j^*.

c. Model Validation – Kupiec POF Test
   1) Set the expected violation rate p (e.g., 5% for 95% confidence).
   2) Calculated the number of actual violations $x$and proportion $\hat{p} = \frac{x}{n}$.
   3) Computed LR_{POF} using equation (10). Compared LR_{POF} with the χ^2distribution (df=1). Concluded the validity of the model.

Results

Research Algorithm

This study aims to develop VaR and CoVaR models using the QAR and QR approaches on Indonesian banking stock data. The study academically contributes advancing systemic risk modelling and practically provides insights for financial regulators in monitoring banking sector stability.

The analysis consists of three stages. First, VaR is estimated using the QAR model based on daily log-return data at quantile levels $\tau = 0.05$ and $\tau = 0.01$. Second, CoVaR is estimated through quantile regression by regressing the return of bank j on the VaR of another bank j^* to capture distress spillover effects. Third, model performance is evaluated using the Kupiec POF test by comparing the observed and expected violation rates to assess the accuracy of tail risk estimation.

Stock Risk Modeling with VaR-QAR

The VaR estimation in this study is conducted using the QAR model, which enables the direct modelling of conditional quantiles of stock returns. The modelling process begins with identifying the appropriate lag structure for each stock return series through the examination of the Partial Autocorrelation Function (PACF) plot, as presented in Figure 1. The PACF plot is used to identify significant lag dependencies in stock returns. Spikes outside the confidence interval indicate candidate autoregressive lags for the QAR model.

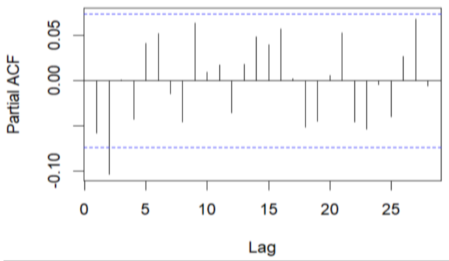
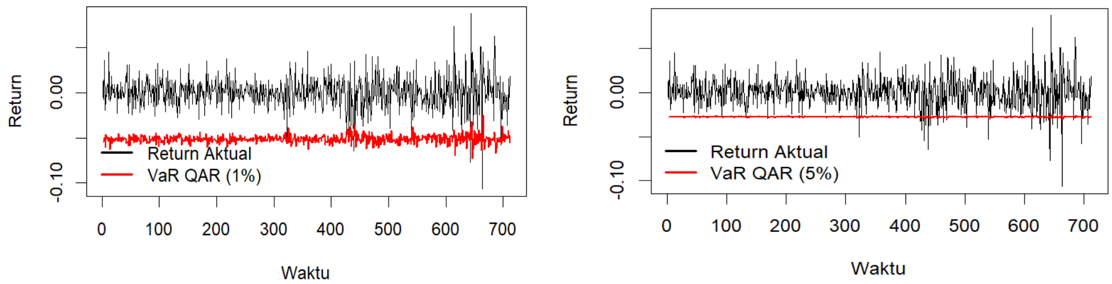


Figure 1. PACF plot for BBRI

For instance, the PACF plot of BBRI stock returns in Figure 1 shows that lag 2 exhibits significant partial autocorrelation, indicating that the return at time t is influenced by the return at time $t-2$. Based on this result, the appropriate specification for BBRI is identified as QAR [2]. The estimated QAR model at the quantile level $\tau = 1\%$ is given by:

$$\hat{y}_t(\tau) = \hat{\phi}_0(\tau) + \hat{\phi}_2(\tau)y_{t-2} = -0{,}05125(0{,}01) - 0.25015(0{,}01)y_{t-2}$$

Using the selected lag structure, VaR is estimated at two quantile levels, namely 1% and 5%, representing extreme downside risks under different confidence levels. The estimated VaR values are then summarized through their mean and variance to further examine risk characteristics. The mean VaR represents the expected maximum loss, where lower values indicate higher risk exposure. Meanwhile, the variance reflects the variability of the VaR estimates, with higher values indicating greater uncertainty in potential losses.



(a) Quantile Level 1% (b) Quantile Level 5%

Figure 2. The graph of BBRI's VaR-QAR results

A summary of the mean and variance of the VaR-QAR estimates at both quantile levels is presented in Table 2. To illustrate the capability of the QAR model in capturing extreme tail behavior, Figure 2. shows the 1% and 5% quantile estimates for BBRI, presenting the model's ability to track lower-tail movements and identify periods of heightened downside risk.

Table 2. Mean and Variance of VaR Estimation Results for Each Quantile

Bank	Quantile 5%		Quantile 1%	
	Mean	Varians	Mean	Varians
ARTO	-0,063216	0,000027	-0,090392	0,000068
BBCA	-0,021928	0,000013	-0,033066	0,000004
BBHI	-0,051443	0,000014	-0,088068	0,000125
BBNI	-0,028112	0,000009	-0,049762	0,000002
BBRI	-0,027526	0,000000	-0,051267	0,000020
BDMN	-0,020045	0,000004	-0,032836	0,000006
BINA	-0,012868	0,000006	-0,024932	0,000019
BMRI	-0,028959	0,000003	-0,049617	0,000020

Bank	Quantile 5%		Quantile 1%	
	Mean	Varians	Mean	Varians
BNGA	-0,018559	0,000000	-0,034401	0,000006
BNLI	-0,023409	0,000022	-0,065836	0,000138
BRIS	-0,036181	0,000006	-0,075646	0,000069
BTPN	-0,017440	0,000001	-0,033202	0,000040
MEGA	-0,023132	0,000060	-0,042969	0,000056
NISP	-0,020195	0,000000	-0,033973	0,000029
PNBN	-0,047252	0,000040	-0,072955	0,000012

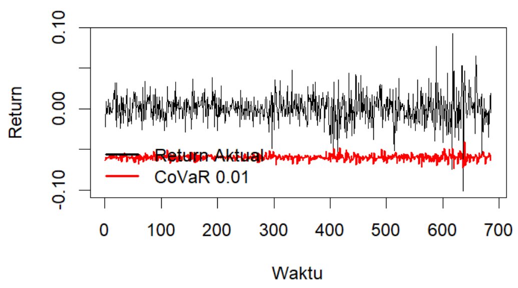
The VaR results indicate that lower quantiles correspond to greater potential losses and higher risk variability. For example, ARTO records a maximum loss of 9.04% at the 1% quantile, compared to 6.32% at the 5% quantile, showing that extreme risk increases as the quantile decreases. At the 1% quantile, the highest-risk stocks are ARTO, BBHI, BNLI, BRIS, and PNBN, with mean VaR values ranging from 6.58% to 9.04%, implying substantial potential losses under extreme market conditions. In addition, BBHI, BNLI, and ARTO exhibit the highest VaR variances, indicating greater instability and uncertainty in risk estimation.

Stock Risk Modeling with CoVaR

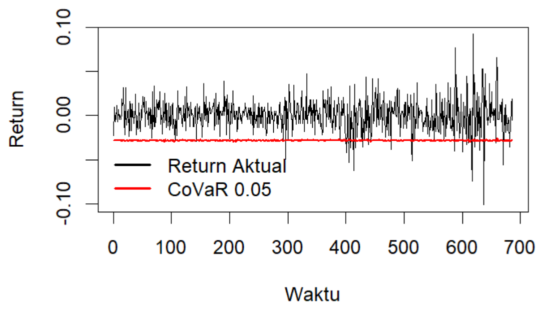
To assess systemic risk, this study extends the analysis from individual risk to CoVaR. While VaR measures standalone extreme losses, CoVaR captures the risk of one bank conditional on another bank being in distress, reflecting interbank dependencies. CoVaR is estimated using quantile regression with VaR-QAR as the conditioning variable, allowing the model to capture nonlinear and tail dependence. For example, the CoVaR model for BBRI at the 1% quantile can be expressed as:

$$
\begin{aligned}
\widehat{CoVaR}_{\tau,t}^{BBRI|j*} = {} & 0{,}3669\widehat{VaR}_{0,01;t}^{BBCA} + 0{,}4934\widehat{VaR}_{0,01;t}^{BMRI} + 0{,}1609\widehat{VaR}_{0,01;t}^{BBNI} \\
& + 0{,}0792\widehat{VaR}_{0,01;t}^{BRIS} - 0{,}0501\widehat{VaR}_{0,01;t}^{BNLI} + 0{,}0978\widehat{VaR}_{0,01;t}^{BNGA} \\
& + 0{,}0181\widehat{VaR}_{0,01;t}^{MEGA} + 0{,}0239\widehat{VaR}_{0,01;t}^{BBHI} + 0{,}0098\widehat{VaR}_{0,01;t}^{NISP} \\
& + 0{,}0719\widehat{VaR}_{0,01;t}^{ARTO} + 0{,}0808\widehat{VaR}_{0,01;t}^{PNBN} - 0{,}1247\widehat{VaR}_{0,01;t}^{BINA} \\
& - 0{,}0809\widehat{VaR}_{0,01;t}^{BDMN} - 0{,}0373\widehat{VaR}_{0,01;t}^{BTPN} - 0{,}0326IHSG - 0{,}0734LQ \\
& + 0{,}0044\,SP + 0{,}0084\,VIX + 0{,}0279\,FIN
\end{aligned}
$$

indicating that the extreme risk of BBRI is influenced by the distress condition (VaR) of another bank j^*.



(a) Quantile Level 1%



(b) Quantile Level 5%

Figure 3. The graph of BBRI's CoVaR results

The results are summarized using mean and variance at the 1% and 5% quantiles, while CoVaR plots in Figure 3 illustrate how systemic risk evolves over time and how shocks in one bank propagate to others.

Table 3. Mean and Variance of CoVaR Estimation Results for Each Quantile

	Quantile 5%		Quantile 1%	
Bank	Mean	Varians	Mean	Varians
ARTO	-0,0710815	0,0000033	-0,107889	0,000022
BBCA	-0,0273482	0,0000050	-0,037254	0,000004
BBHI	-0,0565034	0,0000023	-0,124266	0,000174
BBNI	-0,0326348	0,0000012	-0,054359	0,000004
BBRI	-0,0284429	0,0000002	-0,059847	0,000012
BDMN	-0,0231075	0,0000007	-0,038607	0,000004
BINA	-0,0167684	0,0000016	-0,039771	0,000014
BMRI	-0,0314406	0,0000010	-0,057283	0,000012
BNGA	-0,0194536	0,0000001	-0,039874	0,000003
BNLI	-0,0284910	0,0000020	-0,105960	0,000203
BRIS	-0,0399214	0,0000008	-0,096568	0,000038
BTPN	-0,0186099	0,0000001	-0,052790	0,000034
MEGA	-0,0358105	0,0000173	-0,065436	0,000073
NISP	-0,0208635	0,0000000	-0,049873	0,000031
PNBN	-0,0565225	0,0000041	-0,081967	0,000010

Tabel 3 shows the mean CoVaR values at the 5% and 1% quantiles represent the expected systemic losses when a bank is in distress, where more negative values indicate higher systemic risk contribution. At the 5% quantile, ARTO, BBHI, and PNBN show the largest systemic impacts, while BINA, BTPN, BBCA, and BBRI exhibit relatively lower impacts. At the more extreme 1% quantile, systemic losses increase further, with BBHI, ARTO, and MEGA recording the highest CoVaR values, indicating stronger spillover effects under severe market stress. In terms of stability, MEGA, NISP, and BBHI display higher CoVaR variance, reflecting more unstable systemic risk contributions, whereas BNGA, BBRI, BTPN, and BINA show lower variance and more stable systemic risk estimates.

Evaluation of Modeling Results

The model is evaluated using the Kupiec POF test. This test is applied to determine whether the number of VaR violations, which occur when actual losses exceed the VaR prediction, is consistent with the confidence level expected from the model. The method compares the observed proportion of violations with the theoretical probability implied by the VaR estimates. The hypotheses used in the test are as follows:

H_0: The model produces accurate risk estimates
H_1: The model does not produce accurate risk estimates

The decision is based on the p-value, where H_0 is rejected if the p-value is less than 0.05. This indicates that the model does not adequately capture extreme risk. The back-testing results for the VaR, QAR, and CoVaR estimates at the 1% and 5% quantile levels are presented in the following discussion.

Table 4. Kupiect Test VaR and CoVaR for Quantile 1%

	VAR-QAR		CoVaR	
Bank	P-Value	Decision	P-Value	Decision
ARTO	0,735956	Fail to Reject H_0	0,028059	Fail to Reject H_0
BBCA	0,735956	Fail to Reject H_0	0,028059	Fail to Reject H_0
BBHI	0,735956	Fail to Reject H_0	0,028059	Fail to Reject H_0
BBNI	0,453297	Fail to Reject H_0	0,095488	Fail to Reject H_0
BBRI	0,453297	Fail to Reject H_0	0,028059	Fail to Reject H_0
BDMN	0,735956	Fail to Reject H_0	0,095488	Fail to Reject H_0
BINA	0,9573	Fail to Reject H_0	0,095488	Fail to Reject H_0
BMRI	0,735956	Fail to Reject H_0	0,233944	Fail to Reject H_0
BNGA	0,735956	Fail to Reject H_0	0,095488	Fail to Reject H_0
BNLI	0,453297	Fail to Reject H_0	0,028059	Fail to Reject H_0
BRIS	0,453297	Fail to Reject H_0	0,095488	Fail to Reject H_0
BTPN	0,735956	Fail to Reject H_0	0,028059	Fail to Reject H_0
MEGA	0,233944	Fail to Reject H_0	0,028059	Fail to Reject H_0
NISP	0,453297	Fail to Reject H_0	0,000205	Reject H_0
PNBN	0,453297	Fail to Reject H_0	0,095488	Fail to Reject H_0

Based on the Kupiec Proportion of Failures test in Table 4, the VaR-QAR model demonstrates strong accuracy for all banks at the 1% quantile level, as all p-values exceed the 0.05 significance level. This indicates that the observed VaR violations are consistent with the expected exceedance rate, confirming the reliability of the model in estimating extreme downside risk. For the CoVaR model, most banks also produce p-values above 0.05, suggesting accurate estimation of conditional systemic risk. However, NISP is an exception, with a p-value below 0.05, indicating that the CoVaR model fails to accurately capture extreme conditional losses for this bank. Overall, the findings show that the VaR-QAR model provides more consistent performance than the CoVaR model at the 1% quantile level, although CoVaR remains adequate for most banks.

Table 5. Kupiect Test VaR and CoVaR fot Quantile 5%

	VAR-QAR		CoVaR	
Bank	P-Value	Decision	P-Value	Decision
ARTO	0,55702772	Fail to Reject H_0	0,00082259	Reject H_0
BBCA	0,68377908	Fail to Reject H_0	0,00036423	Reject H_0
BBHI	0,68377908	Fail to Reject H_0	0,03571086	Reject H_0
BBNI	0,95802859	Fail to Reject H_0	0,12948035	Fail to Reject H_0
BBRI	0,81877361	Fail to Reject H_0	0,34072172	Fail to Reject H_0
BDMN	0,68377908	Fail to Reject H_0	0,00353282	Reject H_0
BINA	0,68377908	Fail to Reject H_0	0,00175227	Reject H_0
BMRI	0,44186614	Fail to Reject H_0	0,18477317	Fail to Reject H_0
BNGA	0,55702772	Fail to Reject H_0	0,44186614	Fail to Reject H_0
BNLI	0,55702772	Fail to Reject H_0	0,00676252	Reject H_0
BRIS	0,68377908	Fail to Reject H_0	0,18477317	Fail to Reject H_0
BTPN	0,81877361	Fail to Reject H_0	0,44186614	Fail to Reject H_0
MEGA	0,44186614	Fail to Reject H_0	0,00353282	Reject H_0
NISP	0,81877361	Fail to Reject H_0	0,55702772	Fail to Reject H_0
PNBN	0,55702772	Fail to Reject H_0	0,0214461	Reject H_0

Tabel 5 shows the Kupiec Proportion of Failures test at the 5% quantile level describing that the VaR-QAR model performs well for all banks, as all p-values exceed the 0.05 significance level. This indicates that the observed VaR violations are consistent with the expected exceedance probability, confirming the reliability of the model in estimating downside risk. In contrast, the CoVaR results show mixed performance. Several banks, including ARTO, BBCA, BBHI, BRIS, and MEGA, produce p-values below 0.05, indicating that the model fails to accurately estimate conditional extreme losses for these institutions, while banks such as BBRI, BMRI, and NISP show satisfactory results. Overall, the findings suggest that the VaR-QAR model provides more consistent performance than the CoVaR model, highlighting the greater complexity of modeling systemic risk and the need for further refinement of the CoVaR framework.

Discussion

The descriptive results indicate substantial heterogeneity in return characteristics across banks. While mean returns are close to zero, volatility differs markedly, with digital and mid-sized banks such as ARTO and BBHI exhibiting significantly higher dispersion than large-cap banks like BBCA and BMRI. This finding is consistent with previous empirical studies by Wijoyo et al. (2022) and Alimuddin et al. (2025), which highlight that smaller or less mature banks tend to exhibit higher return volatility and risk exposure. These differences justify the use of quantile-based methods, as they are more capable of capturing asymmetric and heavy-tailed distributions compared to mean-based approaches.

The VaR results obtained from the QAR model further confirm this heterogeneity. High-volatility banks such as ARTO and BBHI consistently produce larger VaR estimates, indicating greater downside risk. This aligns with prior findings that quantile-based autoregressive models outperform conventional volatility-based models in capturing tail risk (Koenker & Xiao, 2006). The strong performance of VaR-QAR, as validated by the Kupiec test, suggests that modeling dynamic quantiles provides a more reliable representation of extreme losses than traditional approaches that rely on distributional assumptions.

In contrast, the CoVaR results reveal more complex and less stable patterns of systemic risk. ARTO, BBHI, and PNBN emerge as major contributors to systemic spillovers, which is in line with studies such as Adrian & Brunnermeier (2016) that emphasize the role of certain institutions as key transmitters of financial distress. However, the variability in CoVaR across banks and quantiles indicates that systemic risk is not solely driven by individual volatility but also by interdependence structures that are more difficult to capture.

The Kupiec test results reveal a clear difference between VaR and CoVaR performance. While all banks pass the VaR backtesting at both quantile levels, CoVaR shows weaker performance, particularly at the 5% quantile where several banks fail the test. This may occur because CoVaR depends on VaR estimates as inputs, so estimation errors can propagate into the conditional model. In addition, the quantile regression approach assumes a linear relationship between bank returns and the VaR of other banks, which may not fully capture nonlinear and time-varying market dependencies. Furthermore, systemic risk is influenced by unobserved factors such as market sentiment, liquidity conditions, and macroeconomic shocks that are not explicitly included in the model.

Overall, the results show the VaR-QAR framework provides robust and consistent estimates of individual tail risk, whereas CoVaR is more sensitive to model specification and dependence structure. This indicates that systemic risk modelling requires more flexible approaches to capture dynamic interconnections among financial institutions. The findings also emphasize the importance of interconnected risk measures in financial stability analysis, particularly in emerging banking markets.

Conclusion

The results show heterogeneous risk profiles across banks, where digital and mid-sized institutions exhibit higher volatility and greater tail risk than large banks. The QAR approach produces reliable VaR estimates at both quantiles, as all banks pass the Kupiec test, confirming its effectiveness in capturing nonlinear tail behaviour. CoVaR analysis reveals that certain banks, particularly ARTO and BBHI, generate stronger systemic spillovers. However, CoVaR performance is less stable, with several banks failing the Kupiec test at the 5% quantile. This indicates that modelling conditional dependence is more complex and sensitive to model.

From a practical perspective, these findings highlight the importance of combining individual and systemic risk measures in financial supervision. For regulators such as OJK and Bank Indonesia, the VaR-QAR framework can serve as a reliable tool for monitoring extreme individual risk, while CoVaR provides early signals of systemic spillovers across banks. This dual approach can support macroprudential policy, stress testing, and early warning systems to maintain financial stability.

Overall, while VaR-QAR performs robustly, improving CoVaR modelling remains essential to better capture interbank linkages. Future research may enhance CoVaR estimation by incorporating feature selection techniques and machine learning such as LASSO-QRNN Syalsabila et al. (2024) or Bayesian approaches like SSVS Prastyo et al. (2025), enabling more accurate identification of key systemic risk drivers.

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