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Identification of Banking Stock Risk Factors through Stochastic Search Variable Selection in CoVaR Models Based on Quantile Regression and Quantile Autoregressive

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Abstract

The stability of the banking sector is crucial for maintaining economic balance, particularly in Indonesia where banks play a central role in the financial system. Conventional risk measures such as Value-at-Risk (VaR) mainly capture individual bank risk and are limited in assessing systemic risk arising from interbank spillovers. This study proposes an integrated systemic risk framework that combines Quantile Autoregressive (QAR) based VaR estimation with Conditional Value-at-Risk (CoVaR) derived from quantile regression, while incorporating Stochastic Search Variable Selection (SSVS) to identify key risk factors. The QAR approach accommodates asymmetry and heavy-tailed characteristics of bank return distributions, whereas CoVaR measures the conditional impact of bank distress on the overall financial system. The SSVS is implemented within a Bayesian framework to select significant market and macroeconomic variables based on posterior inclusion probabilities. Model performance is evaluated using the Kupiec Proportion of Failures (POF) test. The results show that QAR-based VaR effectively captures tail risk at the 5% and 1% quantiles. CoVaR estimates reveal heterogeneity in systemic risk exposure, with medium-sized and digital banks exhibiting greater sensitivity to systemic stress than large banks. Overall, the CoVaR–SSVS model demonstrates superior validation performance and estimation stability compared to the conventional CoVaR approach.

Keywords: CoVaR, Quantile Autoregressive, Quantile Regression, SSVS
MSC2020: 62P05

Abstrak

Stabilitas sektor perbankan sangat penting dalam menjaga keseimbangan ekonomi, khususnya di Indonesia di mana perbankan memegang peran sentral dalam sistem keuangan. Ukuran risiko konvensional seperti Value-at-Risk (VaR) menangkap risiko individual bank dan memiliki keterbatasan dalam menilai risiko sistemik antarbank. Penelitian ini mengusulkan pengukuran risiko sistemik terintegrasi dengan mengombinasikan estimasi VaR berbasis Quantile Autoregressive (QAR) dan Conditional Value-at-Risk (CoVaR) yang diperoleh melalui regresi kuantil, serta mengintegrasikan Stochastic Search Variable Selection (SSVS) untuk mengidentifikasi faktor risiko utama. Pendekatan QAR digunakan untuk mengakomodasi karakteristik distribusi return perbankan yang asimetris dan berekor tebal, sementara CoVaR mengukur dampak bersyarat dari kondisi distress suatu bank terhadap sistem keuangan secara keseluruhan. Metode SSVS diterapkan dalam kerangka Bayesian untuk menyeleksi variabel pasar dan makroekonomi yang signifikan berdasarkan probabilitas inklusi posterior. Kinerja model dievaluasi menggunakan uji Kupiec Proportion of Failures (POF). Hasil penelitian menunjukkan bahwa estimasi VaR berbasis QAR mampu menangkap risiko ekor pada kuantil 5% dan 1% secara efektif. Estimasi CoVaR mengungkapkan adanya heterogenitas paparan

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risiko sistemik, di mana bank berukuran menengah dan bank digital menunjukkan sensitivitas yang lebih tinggi terhadap tekanan sistemik dibandingkan bank besar. Secara keseluruhan, model CoVaR–SSVS menunjukkan kinerja validasi estimasi yang lebih baik dibandingkan CoVaR konvensional.

Kata kunci: CoVaR, Regresi Kuantil, Kuantil Autoregressive, SSVS
MSC2020: 62P05

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Introduction

Systemic risk has become a critical issue in financial stability analysis, particularly in banking-dominated financial systems where distress in a single institution can rapidly propagate through interbank linkages, financial markets, and the real economy [1]. Historical episodes such as the Global Financial Crisis of 2008 demonstrate that bank failures can trigger widespread systemic disruptions, undermining investor confidence, economic growth, and financial market stability. In such an interconnected environment, accurate measurement of systemic risk is essential for effective macroprudential supervision and risk management. However, market risk measures such as Value-at-Risk (VaR) primarily focus on individual institutions and fail to capture cross-institutional spillovers and contagion effects [2].

To address this limitation, Conditional Value-at-Risk (CoVaR) was introduced as a systemic risk measure that evaluates the risk of a financial institution conditional on another institution being in distress [3],[4]. CoVaR enables the identification of systemic risk contributions and spillover effects across banks and has become an important tool in macroprudential risk assessment [5]. Given the asymmetric and volatile nature of financial returns, CoVaR estimation based on Quantile Regression and its dynamic extension, Quantile Autoregressive (QAR), provides a flexible and robust framework without imposing restrictive distributional assumptions. Compared to standard models, QAR directly models the conditional quantiles of returns, allowing it to better capture tail behavior, asymmetry, and the persistence of extreme shocks. Moreover, by incorporating lagged quantiles, QAR can more effectively reflect nonlinear dynamics and time-varying dependence in the distribution of returns, which are often overlooked by standard approaches [6].

In addition, systemic risk is influenced by various market, macroeconomic, and global factors [7]. In this study, JCI returns, LQ45 returns, and financial sector returns, were used to capture the interaction of domestic market sentiment, sectoral dynamics [8],[9]. While S&P 500 returns, and global market volatility (VIX) were chosen as macroeconomic proxies for global financial conditions that affect extreme risks in Indonesia's banking sector [10]. However, combining a large set of explanatory variables can lead to overfitting and multicollinearity. Therefore, Stochastic Search Variable Selection (SSVS) is used in a Bayesian framework to identify the most relevant risk factors through the probability of posterior inclusion [11]. Previous studies have shown that integrating CoVaR with SSVS improves model parsimony and estimation stability in dynamic quantity-based systemic risk models.

Methods

Data and Research Variables

This study uses data from finance.yahoo.com. The main data set consists of the daily closing of the share prices of 15 banking companies with the largest market capitalization listed on the Indonesia Stock Exchange (IDX). Data period from July 4, 2022 to June 30, 2025. In addition, this analysis combines external risk factors represented by domestic and global financial market macro variables, namely the Jakarta Composite Index (JCI), the return of the LQ45 Index, the return of the financial sector, the return of the S&P 500 index, and the global market volatility index (VIX)

Table 1. Parameters chosen for numerical simulation

Bank Stock Returns			Macroeconomics	
Emiten	Bank	Variable	Factor	Variable
BBCA	Bank Central Asia	$Y_{1,t}$	Jakarta Composite Index (IHSG)	$X_{1,t}$
BBRI	Bank Rakyat Indonesia	$Y_{2,t}$	Return Indeks LQ45	$X_{2,t}$
BMRI	Bank Mandiri	$Y_{3,t}$	Financial sector returns	$X_{3,t}$
BBNI	Bank Negara Indonesia	$Y_{4,t}$	Return Indeks S&P 500	$X_{4,t}$
BRIS	Bank Syariah Indonesia	$Y_{5,t}$	Global market volatility index	$X_{5,t}$
BNLI	Bank Permata	$Y_{6,t}$		
BNGA	Bank CIMB Niaga	$Y_{7,t}$		
MEGA	Bank Mega	$Y_{8,t}$		
BBHI	Allo Bank Indonesia	$Y_{9,t}$		
NISP	Bank OCBC NISP	$Y_{10,t}$		
ARTO	Bank Jago	$Y_{11,t}$		
PNBN	Bank Pan Indonesia	$Y_{12,t}$		
BINA	Bank Ina Perdana	$Y_{13,t}$		
BDMN	Bank Danamon Indonesa	$Y_{14,t}$		
BTPN	Bank SMBC Indonesia	$Y_{15,t}$		

Theoretical Framework for Methodology

This subsection presents the theoretical framework underlying the methodology employed in this study, explaining the conceptual foundations for analyzing systemic risk in the banking sector.

Quantile Regression (QR)

Quantile Regression (QR) estimates conditional quantiles of the dependent variable, allowing it to capture extreme behavior and data heterogeneity [12]. The quantile function of a random variable Y_t is defined as

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

In a linear quantile regression framework, the relationship between the dependent and independent variables is expressed as

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

Parameter estimation is obtained by minimizing the asymmetric Least Absolute Deviation (LAD) loss function,

$$\hat{\beta}(\tau) = \arg \min_{\beta \in \mathbb{R}^p} \sum_{t=1}^{T} \rho_\tau \left(y_t - x_t' \beta(\tau)\right) \tag{3}$$

Quantile Autoregressive (QAR)

Quantile Autoregressive (QAR) models extend QR to time-series data, allowing for the analysis of asymmetric and volatile return dynamics across different quantiles[6]. A QAR(p) model is specified as.

$$y_t(\tau) = \phi_0(\tau) + \phi_1(\tau)y_{t-1} + \phi_p(\tau)y_{t-p} + \varepsilon_t \tag{4}$$

where $y_t(\tau)$denotes the τ-th conditional quantile of returns at time t, and $\phi_i(\tau)$are quantile-dependent parameters.

Value-at-Risk (VaR)

Value-at-Risk (VaR) measures the maximum potential loss of an asset or portfolio over a given time horizon at a specified confidence level [13]. Quantile regression is increasingly used for VaR estimation because it does not rely on distributional assumptions and is robust to outliers and asymmetry [12]. In a dynamic context, the QAR approach incorporates lagged returns to capture time dependence, making it suitable for modeling market risk dynamics [14]. Compared to traditional VaR methods, VaR-QAR better captures heteroskedasticity and asymmetric return behavior and is more resilient to financial shocks. In general, VaR based on the QAR framework is obtained from quantile regression applied to return time series and is expressed as

$$VaR_t(\tau) = \hat{y}_t(\tau) = \hat{\phi}_0(\tau) + \hat{\phi}_1(\tau)y_{t-1} + \hat{\phi}_2(\tau)y_{t-2} + \cdots + \hat{\phi}_p(\tau)y_{t-p} + \varepsilon_t, \tag{5}$$

Here, $\text{VaR}_t(\tau)$ represents the τ conditional quantile of the return distribution given information up to time $t-1$, indicating that VaR at time tis determined by a linear combination of past returns weighted by quantile-specific coefficients.

Conditional Value-at-Risk (CoVaR)

Value-at-Risk (VaR) represents the τ-th quantile of the return distribution and is limited in capturing systemic risk under inter-institutional dependence and external influences. To overcome this limitation, CoVaR measures the risk of institution j conditional on distress in another institution j^*[3], defined as

$$P\left(X^j \mid X^{j^*} \leq \text{CoVaR}_\tau^{(j|j^*)}\right) = \tau \tag{6}$$

CoVaR is estimated using quantile regression, which is robust to asymmetry and outliers [12]. In the systemic risk framework, CoVaR relates the return of institution j to the VaR of institution $j^*$and X macroeconomic variables [15]:

$$y_t = \beta_{\tau,0} + \sum_{k=1}^{K} \gamma_{\tau,k} X_k + \varepsilon_{\tau,t}, t = 1,2,\dots,T. \tag{7}$$

Systemic risk contribution is measured by CoVaR, defined as the difference between CoVaR under distress and normal conditions of institution j^*:

$$CoVaR_{\tau,t}^{j|j*} = \beta_{\tau,0} + \sum\nolimits_{\substack{j^*=1 \\ j^*\neq j}}^{J} \beta_{\tau,j^*} VaR_{\tau,t}^{j*} + \sum\nolimits_{k=1}^{K} \gamma_{\tau,k} X_k + \varepsilon_{\tau,t}^{j} \tag{8}$$

Stochastic Search Variable Selection (SSVS)

Stochastic Search Variable Selection (SSVS) is a Bayesian variable selection method that employs Markov Chain Monte Carlo (MCMC) algorithms to explore the model space efficiently. Originally introduced with Gibs sampling, SSVS adopts a spike-and-slab prior structure, where relevant variables are assigned priors with large variances (slab), while irrelevant variables are shrunk toward zero through priors with small variances (spike) [16]. This framework enables simultaneous parameter estimation and assessment of variable importance through Posterior Inclusion Probabilities (PIP)[17].

By means of MCMC sampling, SSVS identifies the most plausible combinations of explanatory variables based on their posterior frequencies. The flexibility of SSVS has been demonstrated in various extensions of extreme-value modelling, including its integration with the GEV framework, which has proven effective for modelling non-normal and extreme financial data [11].

Kupiec Proportion of Failures (POF) Test

The Kupiec Proportion of Failures (POF) test is employed to evaluate the accuracy of VaR and CoVaR predictions [18]. The null hypothesis states that the expected violation rate equals the observed violation rate $(H_0: p = \hat{p})$, indicating a valid model, while the alternative hypothesis $(H_1: p \neq \hat{p})$ implies model misspecification. Here, p denotes the theoretical violation probability associated with the chosen confidence level, and $\hat{p} = \frac{x}{n}$ represents the empirical violation rate, where x is the number of exceedances and n is the total number of observations. The test statistic is defined as:

$$LR_{POF} = -2\, ln[(1-\hat{p})^{n-x}\hat{p}^{x}] + 2\, ln\left[\left(1-\frac{x}{n}\right)^{n-x}\left(\frac{x}{n}\right)^{x}\right] \tag{9}$$

The LR_{POF} statistic follows a chi-square distribution with one degree of freedom. If $LR_{POF} > \chi^2_{1,\tau}$ or p-value $< \tau$, the null hypothesis is rejected and the model is considered invalid, which means that the VaR model is considered invalid in predicting the risk of extreme losses.

Analysis Steps

This study follows a structured analytical procedure to estimate systemic risk, identify significant risk factors, and evaluate model performance. The analysis is conducted through the following steps:

1. Collect daily stock price data and relevant risk factors, then compute stock returns in the form of log-returns.
2. Estimate VaR at the 5% and 1% quantiles using the QAR model.
3. Use the estimated VaR-QAR as an input to construct the CoVaR through quantile regression.
4. Apply SSVS within a Bayesian framework to select significant risk factors based on posterior inclusion probabilities greater than 0.5 [17].
5. Re-estimate the CoVaR model using the selected variables to obtain the final CoVaR-SSVS model.
6. Evaluate the performance of the CoVaR, and CoVaR-SSVS models using the Kupiec POF test.

Results and Discussion

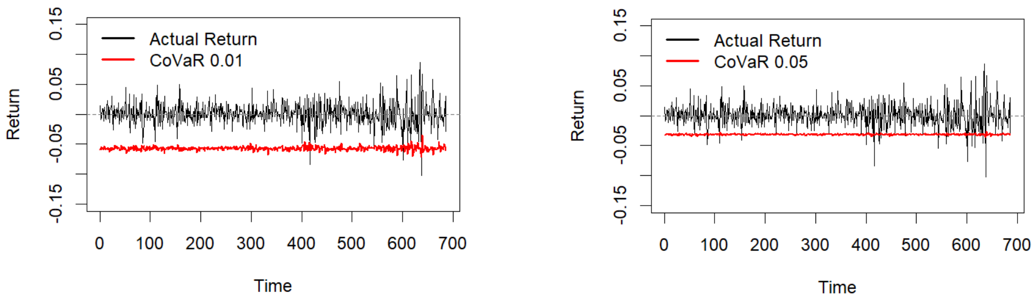
Stock Risk Modeling with CoVaR

In this study, VaR is estimated using a QAR model applied to bank return series, capturing time dependence, volatility clustering, and asymmetric tail behavior. VaR at the 1% and 5% levels is derived from the conditional quantiles of the QAR model. These VaR estimates are then used as conditioning variables in a quantile regression framework to compute CoVaR, which measures a bank's risk conditional on distress in other banks. Macroeconomic and market variables are included as exogenous factors to account for systemic conditions and tail dependence within the banking system.

As an illustration, the CoVaR model for Bank Mandiri (BMRI) is specified by relating BMRI's return to the VaR of other banks and macroeconomic variables within a quantile regression framework. Specifically, BMRI's CoVaR is estimated by conditioning on the extreme risk states of other banks, represented by their VaR-QAR measures, while controlling for macroeconomic factors such as market indices and global financial conditions. The estimated CoVaR for BMRI, denoted as $\widehat{\text{CoVaR}}_{\tau,t}^{(\text{BMRI}|j^*)}$, is obtained based on Equation (8). In this specification, the intercept term is excluded, and the CoVaR value is expressed solely as a function of the conditioning banks' VaR and the included explanatory variables, as presented below.

$$\begin{aligned}\widehat{CoVaR}_{0.01,t}^{\mathrm{BMRI}|j*} = {} & 0{,}78703\widehat{VaR}_{0,01;t}^{BBCA} + 0{,}47414\widehat{VaR}_{0,01;t}^{BBRI} - 0{,}13122\widehat{VaR}_{0,01;t}^{BBNI} \\ & + 0{,}00921\widehat{VaR}_{0,01;t}^{BRIS} + 0{,}01202\widehat{VaR}_{0,01;t}^{BNLI} + 0{,}14946\widehat{VaR}_{0,01;t}^{BNGA} \\ & - 0{,}01888\widehat{VaR}_{0,01;t}^{MEGA} - 0{,}00320\widehat{VaR}_{0,01;t}^{BBHI} - 0{,}01228\widehat{VaR}_{0,01;t}^{NISP} \\ & - 0{,}02364\widehat{VaR}_{0,01;t}^{ARTO} + 0{,}17932\widehat{VaR}_{0,01;t}^{PNBN} - 0{,}05951\widehat{VaR}_{0,01;t}^{BINA} \\ & - 0{,}09942\widehat{VaR}_{0,01;t}^{BDMN} + 0{,}06183\widehat{VaR}_{0,01;t}^{BTPN} + 0{,}03410\ ISHG \\ & + 0{,}01271\ LQ - 0{,}02454SP - 0{,}00456VIX - 0{,}03654\ FIN\end{aligned} \tag{10}$$

Figures 1 (a) and (b) compare BMRI's actual returns with its estimated CoVaR at the 1% and 5% quantile levels. At the 1% quantile, the CoVaR series lies at a markedly lower level, indicating severe systemic risk when the conditioning bank is under extreme distress. Several instances where actual returns approach or breach the CoVaR threshold reflect periods of heightened financial stress, onfirming the model's ability to capture extreme downside risk. At the 5% quantile, BMRI's CoVaR is less extreme and more stable, suggesting that systemic risk spillovers persist under moderate market stress but with lower intensity. The difference between the two quantiles highlights the asymmetric and tail-dependent nature of systemic risk, with stronger risk in extreme market conditions.



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

Figure 1. CoVaR value results chart for BMRI bank shares

Table 2 summarizes the mean and variance of CoVaR estimates at the 1% and 5% quantiles, reflecting expected systemic losses when a bank is in distress. The negative mean CoVaR values indicate that, under stressed market conditions, investors are exposed to potential losses arising from systemic risk transmission across banks, with more negative CoVaR implying stronger spillover effects. At the 5% quantile, ARTO, PNBN, and BBHI exhibit the largest systemic impacts, while banks such as BINA, BTPN, BNGA, and BBCA show relatively lower systemic contributions under moderate stress. At the 1% quantile, systemic losses increase substantially, with BBHI, ARTO, and BNLI displaying the most pronounced spillover effects, highlighting their role in amplifying risk during extreme market conditions. The variance results indicate that MEGA (5%) and BNLI and BBHI (1%) have more volatile systemic risk behavior, whereas banks such as BBRI, BTPN, BNGA, and NISP show relatively stable CoVaR estimates across both quantiles.

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

Bank	$\tau = 1\%$		$\tau = 5\%$	
	Mean	Varians	Mean	Varians
BBCA	-0,03696	$3{,}56 \times 10^{-6}$	-0,02730	$4{,}89 \times 10^{-6}$
BBRI	-0,05927	$9{,}97 \times 10^{-6}$	-0,02847	$2{,}21 \times 10^{-7}$
BMRI	-0,05717	$1{,}15 \times 10^{-5}$	-0,03144	$1{,}17 \times 10^{-6}$

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

Bank	$\tau = 1\%$		$\tau = 5\%$	
	Mean	Varians	Mean	Varians
BBNI	-0,05403	$3{,}68 \times 10^{-6}$	-0,03300	$2{,}19 \times 10^{-5}$
BRIS	-0,09549	$4{,}98 \times 10^{-5}$	-0,04008	$1{,}16 \times 10^{-6}$
BNLI	-0,10634	$2{,}70 \times 10^{-4}$	-0,02843	$2{,}09 \times 10^{-6}$
BNGA	-0,04030	$4{,}97 \times 10^{-6}$	-0,01943	$6{,}72 \times 10^{-8}$
MEGA	-0,06293	$6{,}57 \times 10^{-5}$	-0,03581	$2{,}59 \times 10^{-5}$
BBHI	-0,11848	$1{,}43 \times 10^{-4}$	-0,05651	$2{,}71 \times 10^{-6}$
NISP	-0,04955	$3{,}82 \times 10^{-5}$	-0,02089	$5{,}73 \times 10^{-8}$
ARTO	-0,10698	$2{,}38 \times 10^{-5}$	-0,07120	$5{,}18 \times 10^{-6}$
PNBN	-0,08241	$1{,}44 \times 10^{-5}$	-0,05705	$8{,}40 \times 10^{-6}$
BINA	-0,03944	$3{,}45 \times 10^{-5}$	-0,01672	$2{,}25 \times 10^{-6}$
BDMN	-0,03860	$4{,}03 \times 10^{-6}$	-0,02310	$6{,}93 \times 10^{-7}$
BTPN	-0,05059	$3{,}27 \times 10^{-5}$	-0,01857	$1{,}85 \times 10^{-7}$

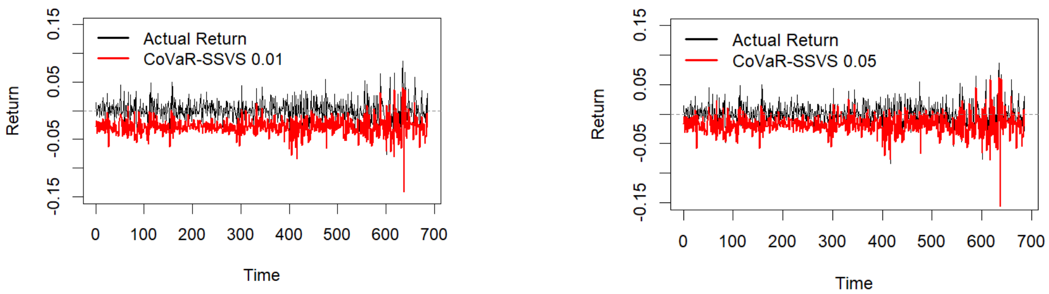
Stock Risk Modeling with CoVaR-SSVS

The CoVaR framework combined with SSVS is employed to provide a more comprehensive assessment of systemic risk in the banking sector. The CoVaR approach evaluates a bank's risk by conditioning on extreme distress events in other banks while accounting for relevant macroeconomic factors. Within this framework, SSVS is implemented by initially including all potential explanatory variables and associating each regression coefficient with a latent binary inclusion indicator governed by a Bernoulli prior and a spike-and-slab prior structure. Parameter estimation and variable inclusion are jointly conducted using MCMC simulation, and posterior inclusion probabilities (PIP) are then used to retain only the most relevant risk drivers.

The estimated CoVaR for BMRI, denoted as $\widehat{\text{CoVaR}}_{\boldsymbol{\tau},\boldsymbol{t}}^{(\text{BMRI}|\boldsymbol{j}^*)}$, is obtained based on Equation (8). In this specification, the intercept term is excluded, and the CoVaR value is expressed solely as a function of the conditioning bank's VaR and selected macroeconomic variables. Based on the SSVS procedure, three macroeconomic factors (IHSG, LQ45, and FIN) are retained from the five initial macroeconomic variables considered in this study, indicating their dominant role in explaining extreme risk spillovers to BMRI. The resulting CoVaR-SSVS model for BMRI is expressed as follows:

$$\widehat{CoVaR}_{\tau,t}^{\text{BMRI}|j*} = 0{,}55874\widehat{VaR}_{0{,}01;t}^{BBNI} - 0{,}91545\, IHSG + 1{,}36022\, LQ + 1{,}00179\, FIN \tag{11}$$

This model demonstrates that not all macroeconomic factors included at the initial stage are relevant in determining CoVaR. Variables such as VIX and the S&P 500 return are excluded for BMRI due to their low posterior inclusion probabilities. Furthermore, the set of selected macroeconomic factors is not identical across banks. Each bank exhibits a different combination of significant macroeconomic drivers, reflecting heterogeneity in risk exposure, business structure, and sensitivity to domestic and global market conditions.



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

Figure 2. CoVaR-SSVS value results chart for BMRI bank shares

Figure 2. presents the time-varying CoVaR-SSVS estimates for BMRI at the 1% and 5% quantiles alongside actual returns. The CoVaR-SSVS series consistently lies below the realized returns, indicating BMRI's downside risk threshold when other banks are under distress and selected macroeconomic factors are considered. At the 1% quantile, CoVaR-SSVS values are more negative and volatile, reflecting strong systemic risk spillovers under extreme market conditions. At the 5% quantile, the estimates are smoother and less negative, indicating lower but still meaningful systemic risk under moderate stress. Overall, the results confirm that the CoVaR-SSVS model effectively captures the dynamic and quantile-dependent nature of BMRI's systemic risk exposure.

Table 3. presents the mean and variance of CoVaR-SSVS estimates at the 1% and 5% quantiles, capturing the magnitude and stability of banks' systemic risk contributions under extreme and moderate market stress. The negative mean CoVaR values indicate that, when the market is under stress, investors are exposed to potential losses arising from systemic risk transmission across banks, with more negative values reflecting stronger spillover effects. At the 1% quantile, ARTO, PNBN, BBHI, and BRIS exhibit the largest systemic spillovers, while BBCA and BTPN show relatively limited effects even under severe stress. At the 5% quantile, systemic risk is generally smaller, though ARTO, PNBN, and BBHI remain key contributors, whereas large banks such as BBCA, BBNI, BBRI, and BMRI display more contained impacts.

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

Bank	$\tau = 1\%$		$\tau = 5\%$	
	Mean	Varians	Mean	Varians
BBCA	-0,00066	$1{,}19 \times 10^{-4}$	-0,01498	$8{,}21 \times 10^{-5}$
BBRI	-0,02854	$2{,}06 \times 10^{-4}$	-0,01774	$2{,}34 \times 10^{-4}$
BMRI	-0,02850	$2{,}35 \times 10^{-4}$	-0,01813	$3{,}00 \times 10^{-4}$
BBNI	-0,02789	$2{,}42 \times 10^{-4}$	-0,01791	$2{,}56 \times 10^{-4}$
BRIS	-0,05632	$3{,}33 \times 10^{-4}$	-0,02934	$1{,}68 \times 10^{-4}$
BNLI	-0,05877	$7{,}65 \times 10^{-5}$	-0,02054	$4{,}11 \times 10^{-5}$
BNGA	-0,02520	$1{,}13 \times 10^{-4}$	-0,01482	$6{,}60 \times 10^{-5}$
MEGA	-0,04682	$1{,}51 \times 10^{-4}$	-0,02394	$6{,}36 \times 10^{-5}$
BBHI	-0,07894	$3{,}10 \times 10^{-4}$	-0,04776	$1{,}21 \times 10^{-4}$
NISP	-0,02654	$5{,}62 \times 10^{-5}$	-0,01749	$5{,}45 \times 10^{-5}$
ARTO	-0,07027	$5{,}01 \times 10^{-4}$	-0,05456	$4{,}34 \times 10^{-4}$
PNBN	-0,07064	$2{,}02 \times 10^{-4}$	-0,04450	$2{,}54 \times 10^{-4}$
BINA	-0,02981	$7{,}12 \times 10^{-6}$	-0,01217	$1{,}07 \times 10^{-6}$
BDMN	-0,02926	$3{,}72 \times 10^{-5}$	-0,01685	$3{,}63 \times 10^{-5}$
BTPN	-0,00004	$6{,}41 \times 10^{-6}$	-0,01544	$2{,}36 \times 10^{-5}$

The variance results indicate that ARTO, PNBN, BRIS, and BMRI have more volatile systemic risk dynamics, while BINA, BTPN, BDMN, and BNGA exhibit stable and consistent CoVaR-SSVS estimates.

Overall, the results confirm that the CoVaR-SSVS approach effectively distinguishes banks based on both the level and stability of systemic risk across different tail conditions.

Model Evaluation with Kupiec Proportion of Failures Test

This study conducts backtesting using the Kupiec Test with the POF approach. The POF test evaluates the adequacy of the CoVaR model by comparing the observed proportion of CoVaR violations when actual losses exceed the estimated CoVaR with the expected violation probability implied by the confidence level. The hypotheses are formulated as follows:

$H_0: p = \hat{p}$ (The model is valid).

$H_1: p \neq \hat{p}$ (The model is invalid).

The decision is based on the p-value, where H_0 is rejected if P-value$< \tau$, indicating that the risk model fails to achieve the required accuracy. The backtesting results for CoVaR, and CoVaR-SSVS at the 1% and 5% quantiles are reported in Table 4.

Tabel Error! No text of specified style in document.**.** Kupiec Test CoVaR and CoVaR-SSVS

Bank	CoVaR (1%)		CoVaR-SSVS (1%)		CoVaR (5%)		CoVaR-SSVS (5%)	
	P-Value	Decision	P-Value	Decision	P-Value	Decision	P-Value	Decision
ARTO	0,0955	VALID	0,9573	VALID	0,0004	INVALID	0,8188	VALID
BBCA	0,0281	VALID	0,0000	INVALID	0,0004	INVALID	0,9580	VALID
BBHI	0,0281	VALID	0,2339	VALID	0,0357	INVALID	0,7676	VALID
BBNI	0,0955	VALID	0,7360	VALID	0,0876	VALID	0,9580	VALID
BBRI	0,2339	VALID	0,2339	VALID	0,3407	VALID	0,5570	VALID
BDMN	0,2339	VALID	0,9573	VALID	0,0035	INVALID	0,9580	VALID
BINA	0,0049	INVALID	0,9573	VALID	0,0018	INVALID	0,9027	VALID
BMRI	0,2339	VALID	0,9573	VALID	0,1295	VALID	0,4419	VALID
BNGA	0,0955	VALID	0,4333	VALID	0,4419	VALID	0,6403	VALID
BNLI	0,0281	VALID	0,7360	VALID	0,0123	INVALID	0,9027	VALID
BRIS	0,0281	VALID	0,1441	VALID	0,1295	VALID	0,8188	VALID
BTPN	0,0049	INVALID	0,0000	INVALID	0,4419	VALID	0,8188	VALID
MEGA	0,0955	VALID	0,4533	VALID	0,0000	INVALID	0,6838	VALID
NISP	0,0002	INVALID	0,9573	VALID	0,5570	VALID	0,9027	VALID
PNBN	0,0955	VALID	0,2339	VALID	0,0123	INVALID	0,8188	VALID

The Kupiec test results indicate that the CoVaR-SSVS model consistently outperforms the standard CoVaR across both 1% and 5% quantiles. At the 1% quantile, CoVaR exhibits several violations for specific banks, while CoVaR-SSVS achieves a higher pass rate, indicating improved accuracy in capturing extreme risk. At the 5% quantile, the performance gap becomes more pronounced, with CoVaR failing the backtesting for many banks, whereas CoVaR-SSVS passes the Kupiec test for all banks. These findings confirm that incorporating SSVS substantially enhances the reliability and stability of systemic risk estimation.

Conclusion

This study provides evidence on systemic risk modeling in the Indonesian banking sector using the CoVaR and CoVaR-SSVS frameworks. The results indicate pronounced tail dependence and asymmetric spillover effects, with systemic risk being substantially higher at the 1% quantile than at the 5% quantile. Banks such as BBHI, ARTO, and BNLI exhibit strong risk transmission under extreme market stress, while others remain relatively stable under moderate conditions. Incorporating SSVS into the CoVaR framework improves model parsimony and interpretability by retaining only statistically relevant risk drivers, leading to more stable estimates and clearer differentiation of systemic risk across banks. Backtesting results based on the Kupiec POF test further confirm that CoVaR-SSVS consistently outperforms the standard CoVaR model at both quantiles, passing the test for all banks while the standard CoVaR often fails at the 5% level. Overall, the findings demonstrate that CoVaR-SSVS provides a more accurate and reliable tool for identifying systemic risk contributors and monitoring financial vulnerability, with important implications for risk management and macroprudential supervision.

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