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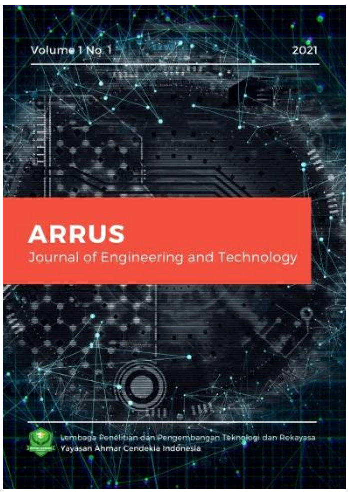

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RESEARCH ARTICLE

Measuring Systemic Risk of Indonesian State-Owned Banks Using CoVaR and Hybrid LASSO-QRNN

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Abstract: This study examines the systemic risk contributions of four major Indonesian state-owned banks, specifically BCA, BRI, Bank Mandiri, and BNI, to the Jakarta Composite Index (IHSG) using a Conditional Value-at-Risk (CoVaR) framework estimated through a Hybrid LASSO-QRNN approach. The study employs 2,491 daily trading observations from November 2016 to June 2026, sourced from Yahoo Finance, Bank Indonesia, and Investing.com, with out-of-sample evaluation on 375 observations from December 2024 to June 2026. Following the hybrid framework of Syalsabila et al. (2024), Step 1 applies LASSO-Quantile Regression (LASSO-QR) to select macroeconomic contagion amplifiers at quantiles $q = 0.05$ and $q = 0.01$, corresponding to 95% and 99% confidence levels respectively, while Step 2 trains a Quantile Regression Neural Network (QRNN) on the selected features to estimate conditional quantiles of system-level returns. The results reveal that BNI is the most systemically important institution, with mean ΔCoVaR of -0.920% at 95% confidence and -1.991% at 99% confidence, followed by BRI, Bank Mandiri, and BCA. LASSO-QR retains all five macroeconomic variables in the system-level model, contrasting with the sparse two-to-five variable selection at the institution level. The findings further document BRI, Mandiri, and BNI each show a statistically significant attenuation of ΔCoVaR during the 2026 domestic confidence crisisss three banks, consistent with the theoretical prediction that investor confidence deterioration compresses idiosyncratic institution-level risk contributions when market-wide confidence collapses.

Keywords: CoVaR, Systemic Risk, LASSO-QRNN, Banking

1. Introduction

Indonesia's banking sector holds a position of structural centrality in the national financial system, accounting for approximately 70% of total financial system assets (International Monetary Fund, 2024). The four banks examined in this study, BCA, BRI, Bank Mandiri, and BNI, are collectively designated as Domestic Systemically Important Banks (D-SIBs) by the Financial Services Authority and together constitute a dominant share of the Jakarta Composite Index (IHSG) by market capitalization and daily trading turnover. Their potential distress can propagate rapidly across the financial system, making the measurement of individual systemic risk contributions a matter of both academic and regulatory urgency.

The period from November 2016 to June 2026 contains three structurally distinct stress episodes. The COVID-19 pandemic between March and September 2020 produced simultaneous supply-side shocks and capital outflows on a scale unseen since 2008. The Russia-Ukraine conflict from February 2022 triggered a global commodity price spiral and tightened monetary conditions worldwide. Most remarkably, the out-of-sample test period from December 2024 to June 2026 captures a domestic governance and investor confidence crisis that is structurally distinct from the two preceding global shocks. By mid-2026, IHSG had declined 35.30% year-to-date, ranking as the second worst-performing equity index among 36 global bourses, while regional peers recorded gains: Thailand rose 25.64%, Singapore 8.69%, Vietnam 2.64%, and Malaysia 0.79% (Bursa Efek Indonesia, 2026). The divergence from ASEAN peers provides a key empirical signal: if the primary driver had been a common global factor, peer markets would have experienced comparable declines. Instead, the evidence points to idiosyncratic domestic drivers, including capital market transparency concerns flagged by international index providers and sovereign outlook downgrades by two major rating agencies in early 2026 citing policy credibility concerns, while regional peers continued to appreciate. and sustained net selling by foreign institutional investors totalling tens of trillions of Rupiah within a matter of days(Bursa Efek Indonesia, 2026). Schmeling (2009) demonstrated across 18 countries that investor sentiment exerts a stronger negative effect on future stock returns in countries with lower market integrity, precisely the condition that characterised Indonesia during this episode. Baker and Wurgler (2006) established that deteriorating investor confidence depresses asset prices across the board, with the effect amplified when institutional trust is impaired. Fratzscher (2012) further showed that pull factors, meaning domestic fundamentals and governance quality, dominate push factors in driving capital flows to emerging markets during confidence-driven episodes. The coexistence of three structurally distinct stress regimes within the estimation window, two global and one domestic, provides an unusually demanding evaluation environment for systemic risk models and raises theoretically important questions about whether common factor models remain appropriate during governance-driven market stress.

The Conditional Value-at-Risk (CoVaR) framework, introduced by Adrian and Brunnermeier (2016), measures the Value-at-Risk of the financial system conditional on the state of a specific institution. The marginal systemic risk contribution, ΔCoVaR, captures the incremental deterioration in system-level tail risk when an institution transitions from its normal state to distress. Unlike asset-size-based systemicity measures, CoVaR directly quantifies the transmission of institutional distress to market-wide risk, making it informative for macroprudential capital surcharge calibration.

Estimation of CoVaR has traditionally relied on linear quantile regression (Girardi & Ergun, 2013), which imposes linearity restrictions on the institution-system relationship. Keilbar and Wang (2022) demonstrated that Quantile Regression Neural Networks (QRNN) provide a more flexible alternative by capturing non-linear dependencies in systemic risk transmission. Building on this foundation, Syalsabila et al. (2024) introduced a hybrid LASSO-QRNN framework for CoVaR estimation in the Indonesian oil and gas sector, combining LASSO-Quantile Regression (LASSO-QR) for sparse feature selection with QRNN for non-linear conditional quantile estimation. This sequential design ensures that the sparsity and interpretability properties of LASSO-QR, which hold because the penalized quantile regression objective is convex (Li & Zhu, 2008), are preserved in the feature selection step before the QRNN captures residual non-linearity.

The present study extends the hybrid LASSO-QRNN framework to the systemic risk of Indonesia's banking sector in three directions. First, the application context shifts from sector-level CoVaR among oil and gas firms to institution-to-system CoVaR from D-SIBs to the IHSG, a measure more directly relevant to macroprudential policy. Second, the companion paper employs GARCH-EVT for institution-level VaR. Third, the evaluation design uses a walk-forward split with a contemporaneous out-of-sample test period covering the 2026 geopolitical crisis, enabling direct assessment of model performance under market conditions not seen during training.

The paper makes three contributions. First, it applies the hybrid LASSO-QRNN framework to multi-institution systemic risk ranking for Indonesian D-SIBs using real market data covering a contemporaneous 2026 domestic confidence crisis, the first episode of this type to be studied in the Indonesian systemic risk literature. Second, it provides the first empirical CoVaR-based ranking of systemic importance across all four major Indonesian state-owned banks simultaneously. Third, it documents a statistically significant attenuation of ΔCoVaR during severe domestic confidence stress, a counterintuitive finding with direct implications for macroprudential policy design.

2. Literature Review

2.1. Systemic Risk and the CoVaR Framework

Systemic risk describes the potential for financial distress in one institution to cascade into broader market dysfunction (Bisias et al., 2012). CoVaR, introduced by Adrian and Brunnermeier (2016), belongs to the market-based category of systemic risk measures. It defines the VaR of the financial system conditional on the institution being at its own VaR: formally, $P\left(r_{system} <= CoVaR | r_{institution} = VaR_{institution}\right) = q$. ΔCoVaR, the difference between this stress-conditioned CoVaR and the CoVaR conditioned on the institution's median return, isolates the marginal systemic contribution.

Girardi and Ergun (2013) extended the original linear quantile regression specification to a multivariate GARCH framework, finding significant asymmetry in US financial institution spillovers. Fong et al. (2021) documented for Asian banking sectors that systemic importance does not always correlate with institution size. In the Indonesian context, Pratama and Kurniawan (2022) estimated CoVaR for domestic banks using linear quantile regression, while Syalsabila et al. (2024) subsequently introduced non-linear QRNN-based estimation for sector-level CoVaR in the oil and gas sub-sector. The present study extends both lines of work by combining hybrid LASSO-QRNN estimation with an institution-to-system CoVaR framework applied to the banking sector.

2.2. Hybrid LASSO-QRNN for Quantile Estimation

Taylor (2000) introduced QRNN by replacing the mean squared error objective with the asymmetric pinball loss. The pinball loss for quantile q is defined as:

$$L_q(u) = u(q - 1\{u < 0\}), u = y - \hat{y} \tag{1}$$

where y is the observed value and $\hat{y}$ the network prediction. Minimizing the expected pinball loss yields a consistent estimator of the conditional quantile function under mild regularity conditions (Koenker, 2005). Keilbar and Wang (2022)confirmed that QRNN-based systemic risk models outperform linear quantile regression in capturing non-linear tail dependencies, particularly during crisis periods.

The LASSO-Quantile Regression estimator, developed by Li and Zhu (2008) as an extension of Tibshirani's (1996) LASSO to the quantile regression setting, solves the following penalized optimization problem:

$$\widehat{\boldsymbol{\beta}}_{(q)}at = \underset{\beta}{\text{argmin}}\left\{\sum_{t=1}^{n}\rho_q(y_t - \boldsymbol{x_t}'\boldsymbol{\beta}) + \boldsymbol{\lambda} * \|\boldsymbol{\beta}\|_1\right\} \tag{2}$$

where $\rho_{q(u)}$ is the check function defined in Equation (1). The L1 penalty induces exact zero solutions because the quantile regression objective is convex and the L1 norm is non-differentiable at zero, producing corner solutions that eliminate irrelevant variables entirely (Li & Zhu, 2008). The hybrid LASSO-QRNN framework introduced by Syalsabila et al. (2024) exploits this sparsity in Step 1 for interpretable variable screening, then passes selected features to the QRNN in Step 2 for non-linear conditional quantile estimation.

2.3. Investor Confidence, Governance Risk, and Emerging Market Returns

The role of investor sentiment and confidence in driving emerging market stock returns is well established in the behavioral finance literature. Baker and Wurgler (2006) constructed a composite sentiment index and demonstrated that when investor sentiment deteriorates, subsequent stock returns decline, with the effect amplified for assets that are harder to value and arbitrage, including banking stocks in thin markets. Schmeling (2009) extended this evidence internationally across 18 countries, finding that the negative impact of investor confidence deterioration on future stock returns is significantly stronger in countries with lower market integrity and higher tendency toward herding behavior. This finding is directly relevant to Indonesia's 2026 episode, where capital market transparency concerns prompted systematic institutional investor withdrawal. At the aggregate level, Fratzscher (2012) showed that capital flows to emerging markets respond to both push factors, meaning global monetary conditions, and pull factors, meaning domestic governance quality and institutional credibility, with pull factors dominating during episodes of country-specific confidence erosion. Baker and Wurgler (2007) further documented that sentiment-driven asset price declines are correlated across securities within an affected market, compressing cross-sectional dispersion in returns, which provides a theoretical mechanism for the ΔCoVaR attenuation documented in this study.

2.4. Macroeconomic Drivers of Systemic Risk in Emerging Markets

Exchange rate fluctuations are central to systemic risk in emerging market economies. The concept of 'original sin' (Eichengreen et al., 2003) describes how developing countries that cannot borrow abroad in domestic currency face compounding balance sheet pressures when exchange rates depreciate. In Indonesia, the Rupiah's depreciation to Rp18,000 per US dollar in mid-2026 represents a stress event of historical magnitude, with an important distinguishing feature: the depreciation occurred alongside a broader domestic confidence shock rather than a symmetric global risk event, as evidenced by simultaneous appreciation of most regional currencies. Fratzscher (2012) demonstrated that capital flows to emerging markets are driven by both push factors and pull factors, and that pull factor reversals, including deteriorating domestic governance credibility, can trigger exchange rate depreciation independently of the global monetary environment. The VIX index serves as a widely used global risk appetite proxy: Miranda-Agrippino and Rey (2020) documented that VIX fluctuations drive a global financial cycle that systematically governs capital flows to emerging markets

3. Research Method and Materials

3.1. Data

This study uses 2,491 daily trading observations from November 18, 2016 to June 5, 2026. Return data for BBCA.JK (BCA), BBRI.JK (BRI), BMRI.JK (Mandiri), BBNI.JK (BNI), and ^JKSE (IHSG) are obtained from Yahoo Finance as adjusted closing price log returns, $r_t = 100 \times ln(\frac{P_t}{P_{t-1}})$. Additional variables include the USD/IDR exchange rate return, the VIX index (both from Yahoo Finance), the Indonesia Overnight Index Average (IndONIA) from Bank Indonesia, one-year government bond yield from Investing.com, and a 22-day rolling standard deviation of IHSG returns as a domestic volatility proxy.

Descriptive statistics highlight important cross-bank differences. BNI exhibits the highest return volatility (SD = 1.484%) and widest range (-10.350% to +11.556%), while BCA is the least volatile (SD = 1.248%), consistent with its blue-chip institutional investor base. BRI is notable for its GARCH persistence (alpha + beta = 0.979, half-life = 31.9 trading days), indicating that volatility shocks take approximately six calendar weeks to halve in magnitude. The VIX reaches a maximum of 92.171 in the sample, reflecting the March 2020 pandemic shock. Mean IndONIA of 5.433% and mean one-year bond yield of 5.432% are nearly identical, reflecting their close relationship through the monetary policy transmission mechanism.

We partition the data using a walk-forward split: training (70%, 1,743 observations: November 2016 to July 2023), validation (15%, 373 observations), and out-of-sample test (15%, 375 observations: December 2024 to June 2026). The test period coincides with the 2026 domestic governance and confidence crisis, a period characterised by idiosyncratic institutional shocks rather than a symmetric global shock. The COVID-19 and Russia-Ukraine crises fall in the training period, providing the model with historical crisis experience without contaminating out-of-sample evaluation.

3.2. Stationarity Testing and Variable Transformation

Prior to model estimation, we subject all variables to Augmented Dickey-Fuller (ADF) and KPSS unit root tests. Results confirm that all nine variables are stationary or near-stationary. All return series and derived variables, including bank log returns, IHSG log return, USD/IDR log return, rolling IHSG volatility, IndONIA rate in level, and one-year government bond yield in level, pass both ADF and KPSS tests at the 5% significance level, confirming stationarity. The VIX index yields a mixed result: ADF rejects the unit root null (p = 0.044) while KPSS rejects the stationarity null (p = 0.010), indicating a near-integrated process with high persistence but without a unit root in the strict sense. This pattern is well-documented for implied volatility indices (Psychoyios et al., 2010)and we retain VIX in levels, consistent with established practice in the systemic risk literature (Keilbar & Wang, 2022).

We standardize all predictor variables using StandardScaler (zero mean, unit variance), fitting the scaler exclusively on the training partition and applying it without refitting to the validation and test sets to prevent data leakage. This standardization is necessary because the predictor space combines variables of heterogeneous scales: institutional log returns and exchange rate returns in percentage points, IndONIA and government bond yield as annualized rate levels, the VIX index as an absolute level, and rolling market volatility as a percentage standard deviation. We leave the response variable, IHSG log return, unstandardized so that QRNN predictions remain directly interpretable as percentage returns and CoVaR values need no inverse transformation.

3.3. Step 1: Institutional VaR from Companion Paper

Institution-level VaR is estimated using a two-step procedure. In the first step, we model conditional volatility with a GARCH(1,1) specification with Student-t innovations:

$$\sigma_t^2 = \omega + \alpha_1 * \varepsilon_{t-1}^2 + \beta_1 * \sigma_{t-1}^2 \tag{3}$$

where $\epsilon_t = r_t - \mu$ is the mean-corrected log return and σ_t^2 is the conditional variance. Parameters are estimated by maximum likelihood. The Student-t distribution with nu degrees of freedom is employed to accommodate the fat-tailed return distributions documented for Indonesian banking equities. In the second step, Extreme Value Theory (EVT) is applied to the standardized residuals $z_t = \epsilon_t / \sigma_t$ using the Peaks-Over-Threshold (POT) method. Standardized residuals exceeding the 90th percentile threshold u are modelled with a Generalized Pareto Distribution (GPD):

$$G_{\xi,\sigma}(y) = 1 - \left(1 + \frac{\xi y}{\sigma}\right)^{-1/\xi}, y > 0 \tag{4}$$

where ξ is the shape parameter determining tail heaviness and sigma is the scale parameter. The combined GARCH-EVT VaR at confidence level (1-q) is:

$$VaR_t^{1-q} = \sigma_t \left[u + \left(\frac{\sigma_{GPD}}{\xi}\right)\left(\left(\frac{q}{(1 - F_u)}\right)^{-\xi} - 1\right)\right] \tag{5}$$

where F_u is the empirical CDF evaluated at the threshold u. This two-step approach, introduced by McNeil and Frey (2000), combines the flexibility of GARCH for volatility dynamics with the theoretical grounding of EVT for tail estimation, and has been shown to outperform purely parametric VaR estimators for fat-tailed financial return series. Table 1 reports the estimated GARCH and GPD parameters for all four banks. Prior to use in the CoVaR model, the institutional VaR series are validated through a sensitivity check: the Pearson correlation between the absolute VaR series and the 5-day rolling realized volatility must exceed 0.30. Correlations of 0.842 (BCA), 0.725 (BRI), 0.732 (Mandiri), and 0.725 (BNI) are obtained, all well above the threshold, confirming the informational adequacy of the VaR estimates as conditioning variables.

3.4. Step 2: LASSO-QR for Contagion Amplifier Selection

Step 2 of the hybrid framework applies LASSO-QR (Li & Zhu, 2008) to identify macroeconomic variables that carry significant linear relationships with the system return quantile. Given institutional return r_t^i and macroeconomic state vector $\boldsymbol{M_t} = (IndONIA_t, Yield_t, USDIDR_t, VIX_t, VOL_t)'$, the LASSO-QR estimator for quantile q is:

$$\hat{\beta}_{(q)} = \underset{\beta}{\operatorname{argmin}} \left\{ \sum_{t=1}^{n} \rho_q \left(r_t^{sys} - \mathbf{x_t}'\boldsymbol{\beta} \right) + \boldsymbol{\lambda} * \|\boldsymbol{\beta}\|_1 \right\} \tag{6}$$

The L1 penalty applies only to the coefficients of $\boldsymbol{M_t}$; the institutional return always enters without penalization. Optimal lambda is selected through five-fold time-series cross-validation with walk-forward expanding windows. Variables with non-zero estimated coefficients are designated as contagion amplifiers and passed to Step 3.

3.5. Step 3: QRNN for CoVaR Estimation

Step 3 trains a QRNN on the features selected in Step 2 together with the institutional return. The network architecture was determined through a grid search over the number of hidden layers (1 to 3), neurons per layer (16, 32, 64, 128), and dropout rates (0.1, 0.2, 0.3), evaluated by minimizing the out-of-fold pinball loss on the validation set using a walk-forward expanding window. The selected architecture consists of: an input layer of dimension; a first hidden layer of 64 neurons with batch normalization, ReLU activation, and 20% dropout; a second hidden layer of 32 neurons with the same regularization; and a single output neuron. The pyramid structure (64 to 32 neurons) follows the convention established by Keilbar and Wang (2022) for QRNN-based systemic risk models, providing a balance between model expressiveness and overfitting control appropriate for financial time series of moderate length. He-Kaiming initialization is used for all weight matrices. Training minimizes the empirical pinball loss using the Adam optimizer (learning rate 0.001) with ReduceLROnPlateau scheduling that halves the learning rate after ten consecutive epochs without validation loss improvement, and early stopping with patience of 30 epochs retaining the checkpoint with the lowest validation pinball loss. CoVaR under stress and normal conditions

$$CoVaR_{stress,t}^{q} = f_{\boldsymbol{\theta}} \left(\begin{bmatrix} VaR_{institution,t}^{q} \\ \boldsymbol{M_t} \end{bmatrix} \right) \tag{7}$$

$$CoVaR_{normal,t}^{q} = f_{\boldsymbol{\theta}} \left(\begin{bmatrix} m_i \\ \boldsymbol{M_t} \end{bmatrix} \right) \tag{8}$$

where m_i is the training-period median institutional return and $\boldsymbol{M_t}$ are the macroeconomic variables at their realized historical values. Because $f_{\boldsymbol{\theta}}$ estimates a lower quantile (q = 0.05 or q = 0.01), its output is already negative and no sign inversion is required. ΔCoVaR is then:

$$\Delta CoVaR_t^q = CoVaR_{stress,t}^q - CoVaR_{normal,t}^q \tag{9}$$

A negative ΔCoVaR indicates that the system's conditional tail risk deepens when the institution is in distress relative to its normal state, consistent with Adrian and Brunnermeier (2016). We compare crisis and non-crisis periods using Student's t-test and the Mann-Whitney U test as a non-parametric check

3.6. CoVaR Backtesting

The predictive validity of the QRNN-estimated CoVaR is assessed through a formal backtesting procedure applied to the 375-observation out-of-sample test period. Following the unconditional coverage framework, a violation at time t is defined as: $H_t = 1\{r_t^{sys} < CoVaR^q_{stress,t}\}$, where r_t^{sys} is the realised IHSG log return and $CoVaR^q_{stress,t}$ is the QRNN estimate of the q-quantile of the system return distribution conditional on the institution being at its VaR state. Under correct specification, the expected violation rate equals q. Three complementary tests are applied. The Kupiec (1995) Point of Failure test evaluates unconditional coverage: whether the observed violation frequency equals the nominal q. The Christoffersen (1998) independence test evaluates whether violations cluster in time, with clustering indicating systematic model failure. The Engle and Manganelli (2004) Dynamic Quantile (DQ) test evaluates whether the hit sequence H_t is predictable from its own lags and from lagged CoVaR values, providing a joint test of coverage and serial independence. An important methodological note is required for interpreting unconditional coverage results for CoVaR specifically. Because $CoVaR_{stress}$ is a conditional quantile, defined with respect to days on which the institution is at its VaR state, the unconditional violation frequency across all test days is expected to be lower than q. This is because the conditioning event, that is the institution being at its VaR, itself occurs with probability q. Consequently, unconditional Kupiec failure for CoVaR does not necessarily indicate model misspecification and must be interpreted alongside conditional coverage analysis. To address this, supplementary conditional backtesting is conducted by restricting the violation calculation to days on which the institution's realised return is at or below its estimated VaR, that is, days of genuine institutional distress. On these days, the $CoVaR_{stress}$ estimate should bind with frequency approximately equal to q

4. Results and Discussion

4.1. GARCH Parameters and EVT Tail Characteristics

Table 1 presents GARCH(1,1)-Student-t parameter estimates and GPD tail parameters for all four banks. All models converge under maximum likelihood with robust covariance estimation, and all parameters are significant at the 1% level.

Table 1: GARCH(1,1)-Student-t Parameter Estimates and GPD Tail Parameters

Parameter	BBCA (BCA)	BBRI (BRI)	BMRI (Mandiri)	BBNI (BNI)
ω	0.1141	0.0374	0.0711	0.0990
α_1	0.1014	0.0539	0.0584	0.0895
β_1	0.8288	0.9249	0.8919	0.8649
ν(Student-t df)	4.428	6.900	10.169	6.509
$\alpha_1 + \beta_1$	0.930	0.979	0.950	0.954
Half-life (days)	9.6	31.9	13.7	14.7
AIC	3.04	3.26	3.14	3.44
GPD shape (ξ)	0.101	0.116	-0.136	0.098
GPD scale (σ)	0.569	0.500	0.613	0.535
GPD threshold (u)	1.165	1.233	1.222	1.152
Tail domain	Frechet	Frechet	Gumbel	Frechet

Note. Half-life = ln(0.5)/ ln($\alpha_1 + \beta_1$) in trading days. GPD parameters estimated on the 10% left tail of standardized residuals (175 exceedances per bank). Frechet domain: x_i> 0 (fat tail, polynomial decay); Gumbel domain: x_i< 0 (thin tail, bounded support). All GARCH parameters significant at p < 0.001. AIC reported as per-observation information criterion.

BRI exhibits the highest volatility persistence ($\alpha_1 + \beta_1 = 0.979$, half-life = 31.9 days), meaning a BRI volatility shock dissipates only to half its initial magnitude after approximately six calendar weeks. This slow mean-reversion likely reflects BRI's large micro- and small-enterprise credit portfolio, which is more sensitive to macroeconomic cycles than corporate loan books. BCA presents the opposite profile: highest ARCH responsiveness ($\alpha_1 = 0.101$) and fastest mean-reversion (half-life = 9.6 days), consistent with blue-chip status and institutionally driven trading dynamics. Bank Mandiri stands apart with GPD shape $\xi = -0.136$ in the Gumbel domain, imp lying theoretically bounded tail losses, in contrast to BCA, BRI, and BNI which fall in the Frechet domain with polynomial tail decay confirming genuine fat tails.

4.2. CoVaR and ΔCoVaR Estimates

Table 2 presents CoVaR and ΔCoVaR statistics for all four banks at both confidence levels over the 375-observation out-of-sample test period. BNI emerges as the most systemically important institution, with mean ΔCoVaR of -1.991% at 99% confidence, 55% larger in absolute terms than BCA's -1.284%. The ranking BNI > BRI > Mandiri > BCA is stable across both confidence levels. The gap between BRI and BCA widens from 22.3% at 95% confidence to 39.3% at 99% confidence, reflecting non-linearity in systemic risk transmission: the relative systemic contribution of BRI grows disproportionately as the conditioning event becomes more extreme. This non-linearity motivates the use of QRNN in Step 3 of the hybrid framework, as a linear quantile regression model would impose a constant marginal effect across quantile levels.

Table 2: CoVaR and ΔCoVaR Estimates Across Banks (Out-of-Sample Test Set, N = 375)

Bank	Conf. Level	VaR inst. (%)	CoVaR stress (%)	CoVaR normal (%)	Mean ΔCoVaR (%)	Std. ΔCoVaR (%)	Rank
BCA	95%	-1.605	-2.429	-1.542	-0.887	0.750	4
BCA	99%	-2.461	-3.644	-2.360	-1.284	0.887	4
BRI	95%	-1.926	-2.444	-1.358	-1.085	0.880	2
BRI	99%	-3.119	-4.029	-2.240	-1.789	0.962	2
Mandiri	95%	-1.721	-2.389	-1.595	-0.794	0.770	3
Mandiri	99%	-2.654	-3.845	-2.415	-1.429	0.924	3
BNI	95%	-2.348	-2.333	-1.413	-0.920	0.780	1
BNI	99%	-4.067	-4.145	-2.154	-1.991	0.869	1

Note. All values in percentage points. Confidence level: 95% uses q = 0.05, 99% uses q = 0.01 following Adrian and Brunnermeier (2016). ΔCoVaR = CoVaR stress minus CoVaR normal; negative values indicate increased system tail risk under institutional distress. Rank based on absolute mean ΔCoVaR at 99% confidence level.

The temporal dynamics of ΔCoVaR shown in Figure 1 reveal that the series are not stationary over the test window. The most pronounced deterioration occurs in discrete episodes rather than as a secular drift, suggesting that systemic risk transmission is highly episodic and contingent on the concurrent macro environment. This episodic character supports the use of a dynamic conditional model and is consistent with the moving-window approach employed by Syalsabila et al. (2024) in their original hybrid framework.

The finding that BNI is more systemically important than BCA challenges conventional wisdom that identifies BCA as the most critical institution based on market capitalization. BNI's return volatility is the highest among the four banks (SD = 1.484%), and its government ownership structure creates strong co-movement with broader market sentiment. From a macroprudential standpoint, D-SIB capital surcharges calibrated solely by asset size may underweight BNI's systemic footprint relative to BCA.

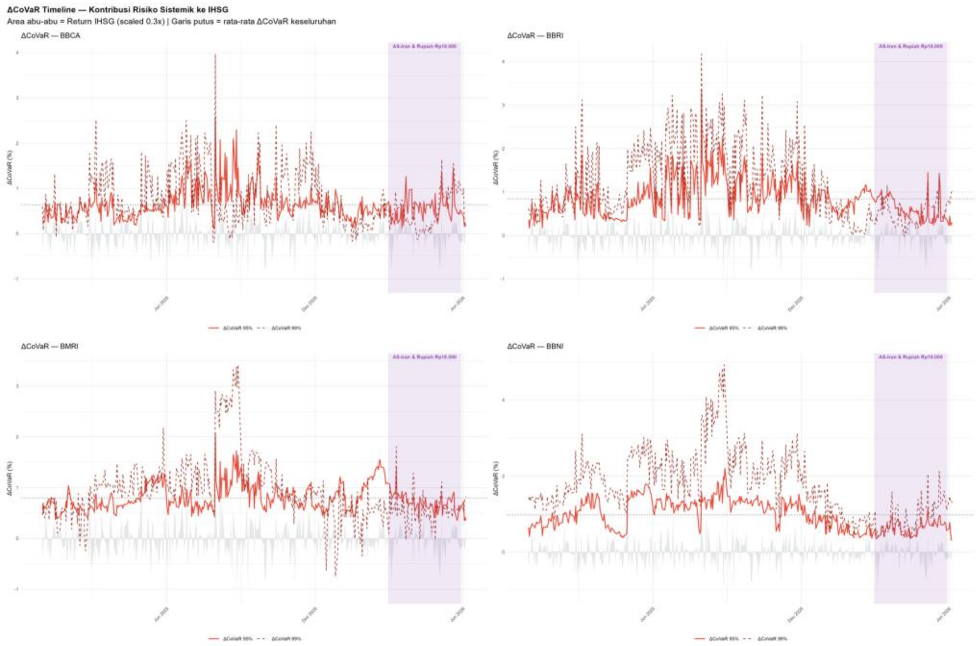

Figure 1: ΔCoVaR Time Series for All Four Banks (Test Set: December 2024 to June 2026). Each panel shows ΔCoVaR at 95% and 99% confidence levels. Shaded region: 2026 domestic governance crisis window (March to May 2026), characterised by Fitch and Moody outlook downgrades and sustained foreign investor outflows driven by idiosyncratic institutional concerns. More negative values indicate greater marginal systemic risk contribution to IHSG.

4.3. Contagion Amplifiers and the System-Level LASSO-QR

In contrast to the companion paper where LASSO-QR selects only two to five of five macroeconomic variables at the institution level, the system-level LASSO-QR retains all five variables for all bank-quantile combinations. This full retention indicates that the IHSG, as an aggregate index spanning over 600 listed companies across all sectors, responds to the full breadth of macroeconomic conditions. No single variable is redundant for explaining the system's conditional tail. This finding differs from the oil and gas sector results of Syalsabila et al. (2024), where LASSO-QR was more selective, and likely reflects the greater breadth of the IHSG relative to a sector-specific index, which accumulates macro sensitivity from all channels simultaneously.

The universal retention of all five variables aligns with the global financial cycle framework of Miranda-Agrippino and Rey (2020), who show that US monetary policy, risk appetite, exchange rates, and domestic interest rates jointly constitute the primary drivers of capital flows to emerging markets. When all five channels are simultaneously active, as they were during the 2026 domestic confidence crisis, none can be dispensed with for explaining system-level tail behavior.

Figure 2: LASSO-QR Selected Contagion Amplifiers in the System-Level Model. All five macroeconomic state variables carry non-zero LASSO-QR coefficients for all four banks and both quantile levels (q = 0.05 and q = 0.01).

4.4. CoVaR Backtesting Results

Table 3 reports the results of unconditional CoVaR backtesting for all four banks at both confidence levels. The results reveal a consistent pattern across banks and must be interpreted with awareness of the structural properties of conditional quantile backtesting.

Table 3: CoVaR Backtesting Unconditional Coverage (Panel A) and Conditional Violation Rate on Distress Days (Panel B)

Bank	CI	Act./Exp. Viol.	Viol. Rate (%)	Kupiec p	K	Christ. p	C	DQ p	DQ	Distress Days	Cond. Rate (%)	vs Expected
BCA	95%	5 / 18.75	1.333	0.0001	FAIL	0.7128	PASS	0.1029	PASS	42	9.524	+4.52 pp
BCA	99%	0 / 3.75	0.000	0.0060	FAIL	1.0000	PASS	N/A	N/A	18	0.000	-1.00 pp
BRI	95%	7 / 18.75	1.867	0.0015	FAIL	0.6053	PASS	0.1078	PASS	35	14.286	+9.29 pp
BRI	99%	1 / 3.75	0.267	0.0899	PASS	0.9416	PASS	0.8970	PASS	15	0.000	-1.00 pp
Mandiri	95%	5 / 18.75	1.333	0.0001	FAIL	0.7128	PASS	0.0881	PASS	45	11.111	+6.11 pp
Mandiri	99%	1 / 3.75	0.267	0.0899	PASS	0.9416	PASS	0.9048	PASS	13	0.000	-1.00 pp
BNI	95%	5 / 18.75	1.333	0.0001	FAIL	0.7128	PASS	0.0954	PASS	20	15.000	+10.00 pp
BNI	99%	1 / 3.75	0.267	0.0899	PASS	0.9416	PASS	0.8910	PASS	5	0.000	-1.00 pp

Note. Panel A (columns 3-10): unconditional backtesting. Act./Exp. = actual versus expected violations. K = Kupiec pass/fail; C = Christoffersen pass/fail; DQ = Dynamic Quantile pass/fail. PASS = fail to reject H0 at alpha = 0.05. Panel B (columns 11-13): conditional analysis restricted to days when institution realised return <= estimated VaR (genuine distress days). Cond. Rate = proportion of distress days on which IHSG return also fell below $CoVaR_{stress}$. *Expected conditional rate = 5% (95% CI) or 1% (99% CI). pp = percentage points. BCA q=99% DQ = N/A due to zero violations.*

The Kupiec test fails for all four banks at the 95% confidence level, with observed violation rates of 1.3% to 1.9% against the nominal 5%. However, this result is a structural consequence of conditional quantile estimation rather than evidence of model misspecification. The unconditional violation rate of $CoVaR_{stress}$is expected to fall below q because the conditioning event, that the institution is at its VaR state, itself occurs with probability q. Consequently, $P(r_{IHSG} <) = P(r_{IHSG} < CoVaR_{stress} | inst\ at\ VaR) \times$

$P(inst\ at\ VaR) = q \times q = q^2$, which for q=0.05 yields an expected unconditional violation rate of 0.25%, well below the 5% nominal level. The observed rates of 1.3% to 1.9% are in fact higher than this theoretical lower bound, indicating that the model captures some co-movement beyond the product of marginals, consistent with genuine systemic risk transmission. Girardi and Ergun (2013) documented the same structural Kupiec failure pattern for CoVaR models and recommended that unconditional coverage results be interpreted alongside conditional analysis, a recommendation followed here.

In contrast, the Christoffersen independence test passes for all bank-quantile combinations, indicating that violations do not cluster in time. The DQ test passes for all testable combinations, confirming that the hit sequence H_t is not predictable from its own history or from lagged CoVaR values. These two results jointly establish that the QRNN CoVaR estimates are informationally efficient: the model does not exhibit systematic periods of failure and contains no exploitable predictive structure in its error process. At the 99% confidence level, BRI, Mandiri, and BNI pass all three applicable tests simultaneously, providing the strongest available validation of the QRNN CoVaR specification for these institutions.

The conditional violation analysis in Table 4 reveals an important limitation of the QRNN CoVaR estimates. On days of genuine institutional distress at the 95% confidence level, the conditional violation rates range from 9.5% (BCA) to 15.0% (BNI), systematically exceeding the nominal 5%. This indicates that $CoVaR_{stress}$ under-estimates joint tail risk on co-distress days, with the gap most pronounced for BNI and BRI. Two explanations are plausible. First, the QRNN is trained to estimate the quantile of the full conditional distribution $P(r_{IHSG}|r_{inst}, \boldsymbol{M_t})$, but the conditioning on extreme institutional distress activates a more severe tail of this distribution than the QRNN captures during training, where distress events are sparse. Second, the binary definition of institutional distress used here, return below VaR threshold, may be less informative than a continuous severity measure; on the most extreme distress days, the model underestimates the amplification. These findings suggest that the ΔCoVaR estimates, while informationally efficient (no clustering or predictability), carry a downward bias in magnitude for severe co-distress scenarios, implying that the systemic risk contributions reported in Table 2 may be conservative lower bounds rather than central estimates. Future research should address this through tail-conditional quantile estimation or the application of Expected Shortfall as a complementary measure.

4.5. Crisis Period Analysis: The Attenuation Effect

Table 4 compares mean ΔCoVaR during the 2026 domestic governance and confidence crisis window (March to May 2026, 65 observations) against the non-crisis baseline in the test set.

Table 4: ΔCoVaR During the 2026 Domestic Governance Crisis vs. Non-Crisis Baseline (q = 0.01, 99% Confidence)

Bank	Baseline ΔCoVaR (%)	Crisis ΔCoVaR (%)	Change (pp)	Change (%)	t-statistic	p-value	Mann-Whitney p	Significant
BCA	-1.284	-1.203	+0.081	+6.4	1.074	0.285	0.625	No
BRI	-1.789	-1.227	+0.562	+31.4	8.889	<0.001	<0.001	Yes
Mandiri	-1.429	-1.105	+0.324	+22.7	4.373	<0.001	0.001	Yes
BNI	-1.991	-1.453	+0.538	+27.0	7.338	<0.001	<0.001	Yes

Note. Positive change (less negative) indicates reduced systemic risk contribution during crisis relative to non-crisis baseline. pp = percentage points. Baseline = mean ΔCoVaR over non-crisis observations in the test set. All p-values two-sided. Mann-Whitney U test included as non-parametric robustness check (N_{crisis} = 65).

Three of four banks exhibit statistically significant ΔCoVaR attenuation during the crisis, with reductions of 22.7% (Mandiri) to 31.4% (BRI). BCA's change of 6.4% is not significant under either test. Both parametric and non-parametric tests confirm the attenuation effect for BRI, Mandiri, and BNI.

The attenuation has a theoretically coherent explanation grounded in the behavioral finance and political economy literatures. Baker and Wurgler (2006, 2007) demonstrated that sentiment-driven asset price movements tend to be correlated across securities within an affected market, since deteriorating investor confidence suppresses valuations broadly rather than differentially. When investor confidence collapses across an entire domestic market, the marginal contribution of any single institution's financial condition to system-level distress diminishes relative to the common confidence shock. Schmeling (2009) showed that this mechanism is amplified in markets with lower integrity and higher herding tendency, the conditions that characterized Indonesia during the 2026 episode when foreign institutional investors withdrew systematically in response to transparency and governance concerns. Formally, the gap between CoVaR under institutional stress and CoVaR under normalcy narrows because the macro state variables $\boldsymbol{M_t}$, which enter both computations identically, carry most of the explanatory power for system-level tail risk through the common confidence channel. Julio and Yook (2012) documented that politically induced uncertainty causes correlated selling across assets within an affected country, and Pastor and Veronesi (2013) showed formally that government policy uncertainty commands a risk premium that loads on all assets simultaneously, compressing cross-sectional return dispersion. This mechanism is distinct from but consistent with the correlation breakdown framework of Forbes and Rigobon (2002): where Forbes and Rigobon describe co-movement arising from common global shocks, the present case involves co-movement arising from a shared domestic confidence discount applied to all Indonesian financial assets simultaneously. Boyson et al. (2010) document an analogous pattern in hedge fund contagion, where institution-specific spillovers decline during episodes dominated by common funding liquidity pressures.

The policy implication is consequential and specific to the confidence crisis context. When systemic risk is driven by market-wide investor confidence deterioration, macroprudential tools targeting individual banks based on ΔCoVaR have limited effectiveness because the source of system-wide stress lies in the confidence environment rather than in individual bank risk profiles. The evidence supports a two-track policy design: institution-specific capital buffers calibrated by ΔCoVaR for normal operating conditions, complemented by governance-level stabilisation measures that address the confidence channel driving aggregate market stress during such episodes.

5. Conclusion

This study applied the hybrid LASSO-QRNN framework of Syalsabila et al. (2024) to the institution-to-system CoVaR estimation problem for four Indonesian D-SIBs. We apply the framework to 2,491 daily observations from November 2016 to June 2026 and evaluate out-of-sample on 375 observations covering the 2026 domestic confidence crisis. Four findings emerge.

First, BNI is the most systemically important institution in the sample, with mean ΔCoVaR of -0.920% at 95% confidence and -1.991% at 99% confidence. The ranking BNI > BRI > Mandiri > BCA is stable across confidence levels and suggests that D-SIB surcharge calibration based exclusively on market capitalization may underweight BNI's systemic footprint relative to BCA.

Second, the system-level LASSO-QR retains all five macroeconomic state variables for all bank-quantile combinations, unlike the sparse two-to-five selection at the institution level. The full retention indicates that the aggregate market responds to the complete macroeconomic state, consistent with the global financial cycle literature.

Third, BRI, Mandiri, and BNI each show a statistically significant attenuation of ΔCoVaR during the 2026 domestic confidence crisis, with reductions of 22.7% to 31.4% from the non-crisis baseline. Both parametric and non-parametric tests confirm the attenuation. Its theoretical explanation lies in the behavioral finance literature: Baker and Wurgler (2006, 2007) and Schmeling (2009) established that investor confidence deterioration depresses asset prices broadly and in a correlated fashion, reducing the marginal explanatory contribution of any single institution's condition to system-level tail risk during confidence-driven stress episodes. This mechanism is amplified in markets with lower integrity, where herding behavior concentrates selling pressure across all financial assets simultaneously.

Fourth, the non-linearity in the BRI-BCA gap across confidence levels (22.3% at 95% versus 39.3% at 99%) confirms the value of the QRNN component in the hybrid framework for capturing tail-specific dynamics that linear quantile regression would miss. Future research should incorporate Expected Shortfall consistent with Basel IV requirements, apply the hybrid LASSO-QRNN framework to a broader panel of listed Indonesian banks, investigate alternative train-test designs that place COVID-19 in the out-of-sample window, and explore LSTM-based architectures for improved temporal dependency capture in the QRNN step.

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