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The Development of a Financial Risk Meter for Indonesian Public Banks Using LASSO-QR and LASSO-QRNN

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ABSTRACT

Banking companies will have a domino effect when one company fails that causes systemic risk in Indonesia. Moreover, Indonesia has a history of economic crises. This study presents a series of systemic risk measures for Indonesia, the Financial Risk Meter (FRM) with the LASSO-QR model, a novel application within the context of Indonesian data. Then, this study enhances the FRM methodology by incorporating the QRNN method to account for the nonlinear dependencies of return values across different companies, and applies the novel LASSO-QRNN method to measure FRM for Indonesia. This study employs a quantitative empirical approach using secondary financial and macroeconomic time-series data. This study developed LASSO-QR and LASSO-QRNN models applied to log-return data of public banks in Indonesia and macroeconomic variables to measure the FRM. These models captured financial risk characteristics by adjusting LASSO parameters with a moving window approach. The FRM indicated high-risk periods in mid-2020 and the first quarter of 2021 for the LASSO-QR, extending into the third quarter of 2021 for the LASSO-QRNN. This study contributes new insights into risk measures for individual banks and the banking system in Indonesia. Additionally, this offers solutions for measuring daily systemic risk that can account for both linear and nonlinear dependencies among companies.

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A. INTRODUCTION

Banking has an important role in the economy of Indonesia. In carrying out their functions, banks are very vulnerable to financial risks. Banking is a sector that has a high exposure to systemic risk. Systematic risk is a factor that significantly determines the development of financial system stability in a country (Chen, 2024). The failure of one company can have an impact on the overall financial market system. Systemic risk can be a trigger event, such as an economic shock or company failure, which then spreads simultaneously and affects many other companies (Ellis et al., 2022). One of the most common risk measurement methods used by financial companies is Value at Risk (VaR). VaR is defined as the τ-quantile of the return distribution (Bodnar et al., 2021). However, the VaR cannot always describe the size of systemic risk because the VaR only focuses on the risk of financial companies individually, even though each financial company is interconnected.

Adrian and Brunnermeier (2016) introduced the Conditional Value-at-Risk (CoVaR), a novel measurement methodology utilizing the quantile regression (QR) model. Unlike the traditional

OLS regression model, QR offers greater flexibility in examining the relationships between variables, making it particularly suitable for financial applications where it is used to measure risk through CoVaR. Its mathematical properties have been formally established and proven in the study by (Liu et al., 2025). This model quantifies the risk of extreme loss events in the financial sector by assessing the impact of one company on the entire sector (Adrian & Brunnermeier, 2016). Several studies have accommodated and further developed the CoVaR methodology in various contexts. For instance, Leballo & Mba (2026) propose an extended framework for improving CoVaR estimation. Meanwhile, Benbachir & Beraich (2025) apply CoVaR as a systemic risk detection tool in the Moroccan banking sector. In the Asian context, Rusmanto et al. (2020) examine systemic risk within the banking industry across Asian countries. Furthermore, Orhan et al. (2020) investigate systemic risk spillovers in the financial systems of the United States and Europe using the CoVaR approach.

Hardle et al. (2016) further applied the QR model using a moving window approach, emphasizing the selection of risk-relevant variables for each financial entity via the Least Absolute Shrinkage and Selection Operator (LASSO) (Härdle et al., 2016). Building on these methodologies, Mihoci et al. (2020) devised the Financial Risk Meter (FRM), applied to banking data in the US to aggregate the risk values of all firms into a unified measure that reflects collective exposure. FRM evaluates tail event risks based on the average of the penalty periods (Mihoci et al., 2020). Yu et al. (2023) detailed the FRM's measurement approach, which utilizes daily log-returns from financial entities and macroeconomic variables. This approach applies linear quantile regression with variable selection governed by the L1-norm (LASSO) penalty parameter, λ, which averages the series data across observed firms, aligning the shape and volatility of the series with market fluctuations and significant financial events impacting systemic risk. Thus, this average series data is recognized as FRM (Yu et al., 2023). The FRM based on the LASSO-QR model has been applied in several studies to measure systemic risk across different countries. For example, implementation of the LASSO-QR-based FRM to assess systemic risk applied in China (Wang et al., 2023), Kuwait (Ulussever et al., 2025), Vietnam (Nguyen et al., 2024), and United States, where it was further developed using the expectile approach (Ren et al., 2022).

This study makes three key contributions to the field of systemic risk measurement. Firstly, this study presents a series of systemic risk measures for Indonesia, using the FRM with the LASSO-QR model, a novel application within the context of Indonesian data. Secondly, this study enhances the existing FRM methodology by incorporating the Quantile Regression Neural Network (QRNN) method to account for the non-linear dependencies of return values across different companies. This enhancement builds upon the traditional LASSO Quantile Regression (LASSO-QR) method by integrating a neural network into the penalty parameters to develop the LASSO-QRNN method. This approach is supported by findings from Keilbar & Wang (2022), which demonstrate the superior performance of the QRNN method over linear QR in capturing non-linear dependencies among companies (Keilbar & Wang, 2022; Zeng et al., 2023). The LASSO method's penalty parameters, which articulate systemic risk, are calculated as the average across all observations for each company. Finally, this study calculates the systemic risk measure for Indonesia, the FRM, using the LASSO-QRNN model, which effectively accommodates non-linear interactions within each banking firm.

B. LITERATURE REVIEW

1. Quantile Regression (QR)

Koenker & Bassett (1978) introduced quantile regression (QR) as a development of the OLS regression model. The QR model does not require residual assumptions as the OLS regression model, such as being identical, independent, normally distributed, and homogenous (Koenker & Bassett, 1978). The general linear QR equation for conditional quantile $Q_{Y_i}(\tau|X_{1t}, X_{2t}, \dots, X_{pt})$ is presented in Equation 1.

$$Y_t(\tau) = \beta_0(\tau) + \beta_1(\tau)X_{1t} + \cdots + \beta_p(\tau)X_{pt} + \varepsilon_i(\tau) \tag{1}$$

Then, an objective function that can minimize the absolute amount of weighted residuals, i.e., the Weighted Least Absolute Deviation (LAD) estimation method, is used to estimate the parameters in the QR (Gao & Feng, 2018). The weights on the residuals are given differently. For the residual $u_t \geq 0$, the residual will be given a weight of τ, while for the residual $u_t < 0$, the residual will be given a weight of $1 - \tau$ (Koenker & Bassett, 1978). Then, to get a solution, a loss function is given that is the multiplication of the weighted residuals, presented in Equation 2.

$$\rho_\tau(u) = \sum_{t=1,u_t\geq 0}^{T} \tau|u_t| + \sum_{t=1,u_t<0}^{T} (1-\tau)|u_t| \tag{2}$$

so that, the objective function obtained to obtain the estimation of the QR parameter is by minimizing the loss function in Equation 2 as written in Equation 3.

$$\min_{\beta\in\mathbb{R}^p} \sum_{t=1}^{T} \rho_\tau(y_t - Q_Y(\tau|X)) = \min_{\beta\in\mathbb{R}^p} \sum_{t=1}^{T} \rho_\tau(y_t - \mathbf{X}_t'\boldsymbol{\beta}(\tau)) \tag{3}$$

where $\tau \in (0,1)$ and $\rho_\tau(u_t)$ is a function of the absolute value, called the check function, defined in Equation 4.

$$\rho_\tau(u_t) = \begin{cases} \tau|u_t| & \text{, for } u_t \geq 0 \\ (1-\tau)|u_t| & \text{, for } u_t < 0 \end{cases} \tag{4}$$

Thus, a solution is obtained stated in Equation 5.

$$\hat{\beta}(\tau) = \underset{\beta\in\mathbb{R}^p}{\operatorname{argmin}} \left\{ \tau \sum_{t=1;y_t-\mathbf{X}_t'\boldsymbol{\beta}(\tau)\geq 0}^{T} |y_t - \mathbf{X}_t'\boldsymbol{\beta}(\tau)| + (1-\tau) \sum_{t=1;y_t-\mathbf{X}_t'\boldsymbol{\beta}(\tau)<0}^{T} |y_t - \mathbf{X}_t'\boldsymbol{\beta}(\tau)| \right\} \tag{5}$$

Quantile regression can capture outliers well because quantile regression is a generalization of linear combinations of sample quantiles (Koenker, 2005). In finance, quantile regression is needed because this method can measure risk using VaR and CoVaR, which measure negative tail events (Cai, 2018).

2. Least Absolute Shrinkage and Selection Operator (LASSO)

The measurement process involves several macroeconomic variables and the return values from other companies. Considering the macroeconomic variables and the returns of other companies, it is expected to provide a good model for estimating the systemic risk that occurs. However, the number of predictor variables included in the model may be irrelevant to the measured financial company and makes the model have high dimensions, so it is necessary to select variables. One of the methods in variable selection is the embedded method. The embedded method is a method that implements an algorithm that produces parameter optimization while simultaneously selecting variables. This method is carried out by representing sparse on irrelevant predictor variables so that variables will be discarded (Hardle & Prastyo, 2014). The LASSO method is a variable selection method in embedded methods that uses penalty parameters as variable selectors. So, the LASSO method can effectively deal with high-dimensional and complex data problems (Geer, 2008; Xia, 2023). The LASSO developed by Tibshirani (1996) has the idea to shrink some coefficients and set other coefficients to 0 so that the best variables are obtained from this selection (Tibshirani, 1996). Tibshirani adds the L1-norm penalty parameter, λ, to the linear regression objective function so that it becomes Equation 6 as follows:

$$\min_{\beta\in\mathbb{R}^p} \sum_{t=1}^{T} \rho_\tau\left(y_t - \mathbf{X}_t'\boldsymbol{\beta}\right)^2 + \lambda\|\boldsymbol{\beta}\|_1, \quad \|\boldsymbol{\beta}\|_1 = \sum_{i=1}^{p}\left|\hat{\beta}_i\right| \tag{6}$$

where $\min_{\beta\in\mathbb{R}^p} \sum_{t=1}^{T} \rho_\tau\left(y_t - \mathbf{X}_t'\boldsymbol{\beta}\right)^2$ is a loss function that measures the error in the model, while $\lambda\|\boldsymbol{\beta}\|_1$ is a penalty function that sets insignificant coefficients to 0. The parameter of λ is a penalty parameter with a positive value. The greater the value of the parameter λ, the more the coefficient is reduced to zero.

3. LASSO-QR

Li and Zhu (2008) developed the LASSO-QR model incorporates a penalty parameter into the loss function of the QR model, utilizing the Weighted LAD estimation method to ascertain the τ-th quantile function (Li & Zhu, 2008). This method is outlined in Equation 7, which describes the loss function of the LASSO-QR model.

$$\min_{\beta\in\mathbb{R}^p} \sum_{t=1}^{T} \rho_\tau\left(y_t - \mathbf{X}_t'\boldsymbol{\beta}(\tau)\right) + \lambda\|\boldsymbol{\beta}\|_1 \tag{7}$$

Furthermore, the check function in the LASSO-QR model is derived from the check function in the standard QR model, as presented in Equation 4, which is based on a weighted absolute deviation (LAD) function.

4. Quantile Regression Neural Network (QRNN)

QR introduced by Koenker & Bassett (1978) is a regression method that can only capture linear relationships between response variables and predictors (Koenker & Bassett, 1978). However, the objective function written in Equation 3 for the QR model is not convex and is used for data that has a non-linear relationship because the QR model is formulated as a linear model (Cannon, 2018). Taylor (2000) introduced the QR method that accommodates non-linear relationships based on the neural network method, called the QRNN model (Taylor, 2000).

Taylor (2000) modified the QR check function in Equation 4 to Equation 8 because the neural network uses the backpropagation algorithm with differentiation.

$$\rho_\tau(u_t) = \begin{cases} \tau g(u_t) & \text{, for } u_t \geq 0 \\ (1-\tau) g(u_t) & \text{, for } u_t < 0 \end{cases} \tag{8}$$

Therefore, the QRNN model form is produced with one hidden layer in Equation 9. X_t is an independent variable with vector dimension p and ε_t is the residual. There are two weights of the neuron, both w^o and w^h, which are the neurons's weights in the output layer and hidden layer respectively. There are also two neuron activation functions, f^o, the activation function in the output layer, and f^h, the activation function of the neuron in the hidden layer. Both are assumed to be fixed and known.

$$(X_{i,t}, \mathbf{w}) = f^o\left[\sum_{k=1}^{K}\left[w_k^o(\tau) f_k^h\left(\sum_{i=1}^{p} w_{i,k}^h(\tau) X_{i,t} + b_k^h\right) + b^o\right]\right] \tag{9}$$

with $\tau \in (0,1)$. The $w_{i,k}^h(\tau)$ parameter represents the estimation of the weighting matrix connecting the input layer and the hidden layer, whereas $w_k^o(\tau)$ denotes the weighting vector linking the hidden layer and the output layer. The estimation of the value of w in the QR-NN model with the objective function in Equation 10, written in Equation 11.

$$\min \sum_t^T \rho_\tau\left[\left(y_t - f(X_{i,t}, \mathbf{w})\right)\right] + \theta_1 \sum_{i,k}\left(w_{i,k}^h\right)^2 + \theta_2 \sum_k (w_k^o)^2 \tag{10}$$

$$\hat{\mathbf{w}} = \operatorname{argmin} \sum_t^T \rho_\tau\left[\left(y_t - f(X_{i,t}, \mathbf{w})\right)\right] + \theta_1 \sum_{i,k}\left(w_{i,k}^h\right)^2 + \theta_2 \sum_k (w_k^o)^2 \tag{11}$$

The check function is written in Equation 8, while θ_1 and θ_2 are penalty parameters that effectively prevent the model from overfitting and increase prediction accuracy.

5. Modeling Design with Moving Window Approach

In establishing our systemic risk measurement model for Indonesia, we organized the data according to the structure shown in Table 1, representing the log-returns of stock for each company. This resulted in 15 company data structure tables within the study. The LASSO-QR model was then applied to each previously selected banking company. For each company, the log-return value serves as the response variable, and the four macroeconomic variables, along with the log-returns from other companies, act as predictor variables.

The LASSO-QR model produces one risk value measurement that represents one trading day. To obtain a series of daily risk values, we add a moving window approach to model and obtain risk values for each trading day. The moving window approach allows us to get more accurate risk values because we can control the window size which represents the number of days used as the number of observations included in the model (Ben Amor et al., 2022). The LASSO-QR model with moving window approach for each j-th company, given $t \in \{1, \dots, T\}$ is a time index with a total number of observations of T days, s is a moving window index with $s \in$

$\{1, \dots, (T-(r-1))\}$, and r is the length of the window size. Equation 12 is the objective function using the moving window approach (Yu et al., 2023).

$$\min r^{-1} \sum_{t=s}^{s+(r-1)} \rho_\tau(y_t^s - \mathbf{X}_t^{\prime,s} \boldsymbol{\beta}^s(\tau)) + \lambda_{QR}^s \|\boldsymbol{\beta}^s\|_1 \tag{12}$$

Then, the estimator function is obtained and presented in Equation 13.

$$f(X_{i,t}^s, \widehat{\boldsymbol{\beta}}^s) = \operatorname{argmin} r^{-1} \sum_{t=s}^{s+(r-1)} \rho_\tau(y_t^s - \mathbf{X}_t^{\prime,s} \boldsymbol{\beta}^s(\tau)) + \lambda_{QR}^s \|\boldsymbol{\beta}^s\|_1 \tag{13}$$

Because Equation 12 has an L_1-norm loss function and an L_1-norm penalty, it is necessary to optimize it to obtain the optimum penalty parameter for each j-th company in the s-th moving window ($\lambda_{j,QR}^s$). The selection of penalty parameters is obtained by minimizing the Generalized Approximate Cross-Validation (GACV) information criteria as follows:

$$\min GACV\ (\lambda_{j,QR}^s) = \min \frac{r^{-1} \sum_{t=s}^{s+(r-1)} \rho_\tau(y_t^s - \mathbf{X}_t^{\prime,s} \boldsymbol{\beta}^s(\tau)) + \lambda_{QR}^s \|\boldsymbol{\beta}^s\|_1}{r - df} \tag{14}$$

where df is a measure of the model dimensions. The advantage of the GACV criteria is that this criterion can work with high dimensions with many covariates greater than the number of observations in one window, $p > r$, so that if the FRM model uses a small window size, the GACV criteria can still be used (Yu et al., 2023). After obtaining the penalty parameter for each company, FRM is measured by calculating the average of the selected parameters for all windows presented in Equation 15 (Mihoci et al., 2020).

$$FRM_{QR}^t = \frac{1}{J} \sum_j^J \lambda_{j,QR}^s \tag{15}$$

Therefore, on each trading day, the FRM_{QR}^t value is obtained. Next, to realize our contribution to the systemic risk measurement literature, we develop the LASSO-QRNN model by estimating the parameters of the LASSO-QRNN model. Estimation is carried out by forming the LASSO-QRNN objective function. Similarly to the LASSO-QR model, we apply a moving window approach for each company so that we obtain a penalty parameter, $\lambda_{j,QRNN}^s$, for each day. Then, we carry out FRM measurements by calculating the average of the selected parameters for the entire window presented in Equation 16.

$$FRM_{QRNN}^t = \frac{1}{J} \sum_j^J \lambda_{j,QRNN}^s \tag{16}$$

Therefore, on each trading day, the FRM_{QRNN}^t value is obtained. Both FRM_{QR}^t and FRM_{QRNN}^t are then interpreted through the risk level indication developed by Yu et al. (2023). The risk level is defined as a ratio interval calculated based on the previous FRM value. The FRM ratio is measured by comparing the FRM value on that day, FRM_{QR}^t or FRM_{QRNN}^t, with the maximum value of the previous series of FRM values (Yu et al., 2023).

C. METHODS

1. Data

Initially, we organized the data required for this research, which comprised secondary data including daily log-return data from 15 out of 46 banking sector companies. These companies are among those with the largest market capitalization consistently in Indonesia, covering the period from June 2018 to December 2022. The selection of these 15 companies was based on their representation of over 90% of the market capitalization of all publicly listed banking sector companies in Indonesia. Figure 1 illustrates the cumulative market capitalization percentage of publicly traded banks in Indonesia.

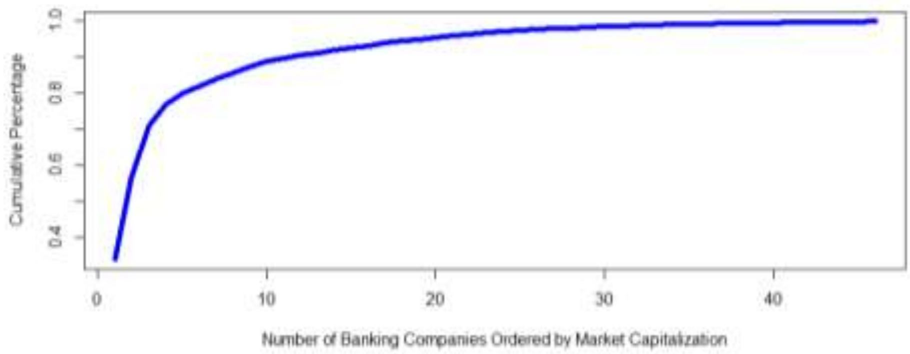

Figure 1. Distribution of Cumulative Market Capitalization among Public Banking Companies in Indonesia

Figure 1 indicates that the 15 largest banking companies in Indonesia collectively contribute 90% of the total market capitalization of all publicly listed banks in the country. Specifically, these 15 companies, which constitute 32% of public banking entities in Indonesia, dominate 90% of the sector's total market capitalization. In contrast, the remaining 31 companies, making up 78% of the public banking firms, are smaller banks holding just 10% of the total market value in the sector. Consequently, the research focused on these 15 major companies to calculate the FRM value. Following the methodology by Yu et al. (2023), the estimated FRM value based on data from companies that represent 85% of cumulative market capitalization showed no significant deviation from the FRM value estimated using data from all companies. This suggests that a limited number of companies with significant market capitalization can effectively represent the entire industry. The study included the top public banking companies in Indonesia by capitalization that had initiated an Initial Public Offering (IPO) before June 2018. These companies, with issuer codes such as BBCA, BBRI, BMRI, BBNI, ARTO, MEGA, BRIS, PNBN, BBHI, BNLI, BNGA, BDMN, BINA, BTPS, and BTPN. Additionally, Figure 2 visualizes the results of the log-return calculations for each company's stock prices, highlighting significant share price volatility in March 2020 due to the onset of the pandemic.

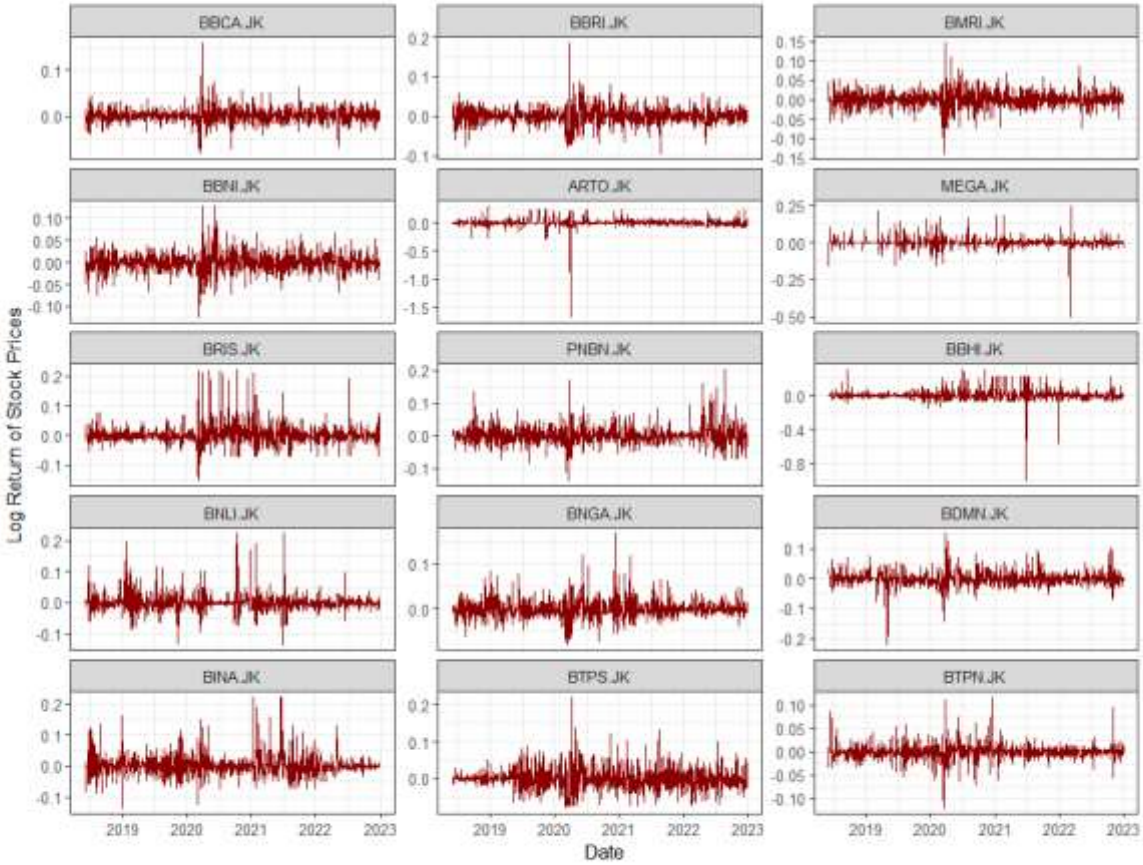

Figure 2. Log-Return Plot

For this study, we selected four macroeconomic variables that reflect the overall economic conditions in Indonesia, particularly those influencing investment instruments. These variables include: (1) the yields on Indonesian bonds with a three-month maturity, (2) the slope of the yield curve, (3) the Composite Stock Price Index (CSPI), and (4) credit spreads. The data for these variables were sourced from Yahoo Finance, investing.com, and the S&P Indonesia websites, as shown in Table 1.

Table 1. *j*-th company

Y_{jt}	Macroeconomic variables				j^*-th other company, $j^* \neq j$			
	X_{1t}	X_{2t}	X_{3t}	X_{4t}				
Y_{j1}	X_{11}	X_{21}	X_{31}	X_{41}	$Y_{(j^*)1}$	$Y_{(j^*+1)1}$	...	$Y_{(J)1}$
Y_{j2}	X_{12}	X_{22}	X_{32}	X_{42}	$Y_{(j^*)2}$	$Y_{(j^*+1)2}$	...	$Y_{(J)2}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	...	$\vdots$
Y_{jt}	X_{1t}	X_{2t}	X_{3t}	X_{4t}	$Y_{(j^*)t}$	$Y_{(j^*+1)t}$	...	$Y_{(J)t}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	...	$\vdots$
Y_{jT}	X_{1T}	X_{2T}	X_{3T}	X_{4T}	$Y_{(j^*)T}$	$Y_{(j^*+1)T}$	...	$Y_{(J)T}$

Table 1 outlines the data framework employed in this study. It details the data structure for a given company, designated as the *j*-th company, with the log-return value from this company serving as the response variable. The explanatory variables include four macroeconomic indicators alongside the log-return values from other companies.

2. Research Procedure

The research steps are systematically structured to measure systemic risk in the Indonesian banking sector using the LASSO-QR and LASSO-QRNN methods through the FRM approach. The research stages are as follows.

a. Data collection and appropriate data sorting were performed in Part 1 of the Methods Chapter. Data preprocessing was then performed in Part 1 of the Results and Discussion Chapter to prepare the data for processing.
b. Modeling using LASSO-QR
Next, the LASSO-QR model parameters were estimated for each trading day using a moving window approach. The parameter estimates refer to the objective function in Equation (13), and the FRM values are obtained using Equation (15).
c. LASSO-QRNN model estimation
The LASSO-QRNN model parameters were estimated by constructing an objective function so that each company obtains a penalty parameter λ for each day. The LASSO-QRNN parameter estimation process is described in Part 4 of the Results and Discussion Chapter.
d. Modeling using LASSO-QRNN
The next step is to estimate the LASSO-QRNN method for each trading day using a moving window approach. Parameter estimation refers to the objective function and FRM values obtained through step 3, namely the LASSO-QRNN model estimation.
e. The next step is to interpret the modeling results by comparing the Financial Risk Meter (FRM) values generated by the LASSO-QR and LASSO-QRNN models. This comparison aims to examine the differences in the ability of the two models to detect periods of systemic risk in the Indonesian banking sector.

D. RESULT AND DISCUSSION

1. Pre-processing Data

Prior to the modeling phase, data preprocessing was conducted to address missing values within the dataset spanning from June 2018 to December 2022. Missing values in the four macroeconomic variables identified for this study were addressed through imputation. The Kalman Smoothing technique, suitable for univariate time series data based on a basic structural model, was selected as the imputation method (Afrifa-Yamoah et al., 2020). Subsequently, transformations were applied to each macroeconomic variable: the CSPI was converted into log-returns, while the 3-month bond yield, the yield curve slope, and the credit spread underwent differencing.

2. LASSO-QR Modeling

The LASSO-QR model was applied individually to each previously selected banking company. For each company, designated as the j-th company, the log-return value functions as the response variable. The predictor variables in this model are the four macroeconomic variables along with the log-returns from other companies. Figure 3 presents the LASSO-QR model equation for each company, highlighting the tail risk level or quantile $\tau = 0.05$.

According to the data presented in Figure 3, it is evident that different variables impact each company uniquely. The numbers listed in the columns of Figure 3 indicate the influence on each company, with the magnitude of the effect denoted by the coefficient values provided in the table. Variable selection depends on the parameter λ, where a larger λ leads to more variable coefficients being reduced to zero, thus diminishing their impact on the model. Among the companies analyzed, the four largest banks—BBCA, BBRI, BMRI, and BBNI—show consistent values. Additionally, BDMN is noted for its stock price being unaffected by the stock price conditions of other companies. On the other hand, companies like MEGA, BNLI, BINA, and BTPS are influenced by several other companies. Notably, BBHI has a significant impact on the stock prices of other companies, particularly influencing ARTO, BNLI, BINA, BTPS, and BTPN, which have lower capitalization orders. These observations suggest that larger companies tend to display consistency and are less influenced by smaller companies, whereas smaller companies are more likely to be influenced by larger ones above them in terms of capitalization.

	$\hat{\beta}_o$	$\hat{\beta}_{BBCA}$	$\hat{\beta}_{BBRI}$	$\hat{\beta}_{BMRI}$	$\hat{\beta}_{BBNI}$	$\hat{\beta}_{ARTO}$	$\hat{\beta}_{MEGA}$	$\hat{\beta}_{BRIS}$	$\hat{\beta}_{PNBN}$	$\hat{\beta}_{BBHI}$	$\hat{\beta}_{BNLI}$	$\hat{\beta}_{BNGA}$	$\hat{\beta}_{BDMN}$	$\hat{\beta}_{BINA}$	$\hat{\beta}_{BTPS}$	$\hat{\beta}_{BTPN}$	$\hat{\beta}_{CSPI}$	$\hat{\beta}_{3MBY}$	$\hat{\beta}_{YIELD}$	$\hat{\beta}_{CREDIT}$
BBCA	0.0704	-															0.1274			
BBRI	0.0869		-														0.1549			
BMRI	0.0853			-													0.1443			
BBNI	0.0966				-												0.1767			
ARTO	0.0658					-		0.0267		0.0313				0.0570			0.0022			-0.0039
MEGA	0.0432		-0.2039	-0.1146		-0.0580	-	-0.0701					0.0480	0.1216		0.2928	0.1578		-0.045	-0.0782
BRIS	0.1136							-									0.1849			
PNBN	0.0895					0.0049			-								0.1301			
BBHI	0.0763									-							0.0167			
BNLI	0.0656					-0.0056			0.0223	0.0395	-			0.0444		0.2311	0.0817			-0.0092
BNGA	0.0864											-					0.1530			
BDMN	0.0976												-				0.1709			
BINA	0.0517						0.0350	0.1197	0.0176	0.0485	-0.0754	-0.1537	-0.0795	-	-0.105	0.1418	0.0790		-0.05	
BTPS	0.0917		0.0396			0.0007		0.0786		0.0030					-		0.1194			
BTPN	0.0748									0.0172					0.0201	-	0.1002			0.0203

Figure 3. Coefficients on Variables Affecting Each Company

Moving on to how macroeconomic variables affect these firms, the CSPI macroeconomic variable positively influences all companies, indicating that the fluctuations in stock prices of these companies generally mirror the overall market price movements. The credit spread affects four companies: ARTO, MEGA, BNLI, and BTPN, while the 3-month bond yield appears to have no impact on their stock prices. However, the yield curve slope, representing the difference between the 10-year and 3-month bond yields, affects ARTO and BINA. This relationship is understandably inverse, as reflected by the negative coefficients, suggesting that stock prices typically move in opposition to bond yields.

Table 2. LASSO Parameter

Bank	**Parameter λ**
BBCA	3.148
BBRI	3.010
BMRI	4.484
BBNI	3.579
ARTO	0.198
MEGA	0.073
BRIS	2.222
PNBN	1.194
BBHI	0.413

Bank	Parameter λ
BNLI	0.175
BNGA	2.097
BDMN	1.146
BINA	0.131
BTPS	0.655
BTPN	0.458

The degree of shrinkage is represented by the LASSO parameter, λ, which is detailed in Table 2. The data shows that the four largest companies possess the highest λ values, correlating with the findings presented in Figure 3. Subsequently, the Financial Risk Meter (FRM) is calculated by averaging the values across all companies, resulting in an FRM value of 1.532. To understand the significance of this value, we can compare it to the maximum value of a previous FRM calculation, thus providing a measure of the current risk level. This risk level is quantified as the ratio of today's FRM value, FRM_t, to the previous FRM value, offering an insight into the relative risk for that day (Yu et al., 2023).

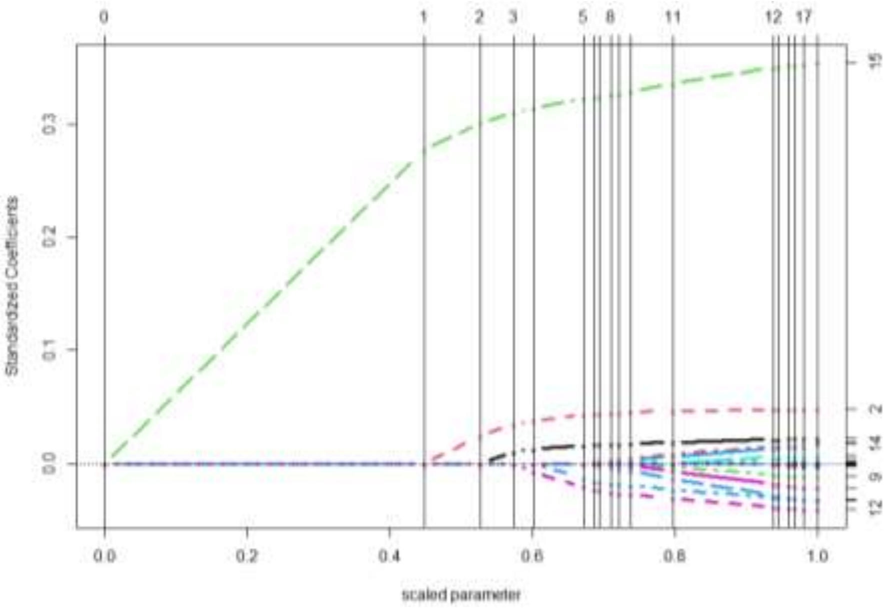

Figure 4. LARS Algorithm Plot

The λ presented in Table 2 are the shrinkage values obtained from the LARS algorithm process. The process of obtaining the scaled parameter $\hat{s}$ as a tuning parameter that corresponds one-to-one with the parameter λ using the LARS algorithm is illustrated in Figure 4. Figure 4 illustrates the movement of LASSO coefficient standardization estimates using the LARS algorithm. The coefficients move from zero to last on the scaled parameter, $\hat{s} = 1$. When $\hat{s} = 1$, the coefficients in LASSO are OLS coefficients. The LASSO coefficients at each step of the LARS algorithm are plotted with $\hat{s} = s / \sum_{i=1}^{p} \left|\hat{\beta}_i^{OLS}\right|$ where s is $\sum_{i=1}^{p} \left|\hat{\beta}_i^{LASSO}\right|$. Next, the optimal s is obtained through the GCV process, which is presented in Figure 5.

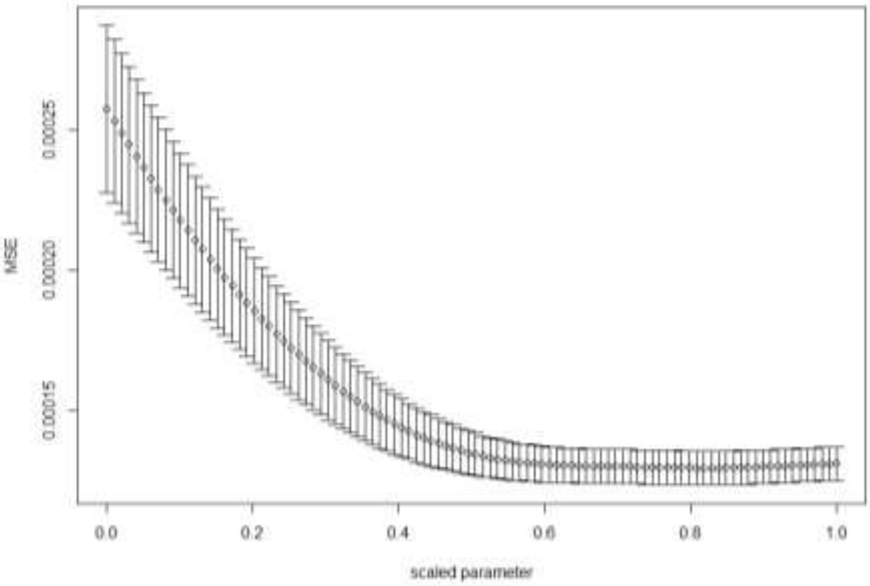

Figure 5. GCV Process

In Figure 5, the optimal scaled parameter value $\hat{s}$ is in the interval $0.4 < \hat{s} < 0.6$. So, if you look again at Figure 4, the optimal value $\hat{s}$ shows the best shrinkage model that obtains the desired variables.

3. LASSO-QR Modeling with Moving Window Approach

In this research, we determine the moving window size r equals 63, which represents 63 trading days or the equivalent of 3 months (1 quarter). This is related to the obligation of public companies to publish financial reports. There are 1144 days for log-return data values from June 2018 to December 2022. Figure 6 illustrates the window movement used in this analysis.

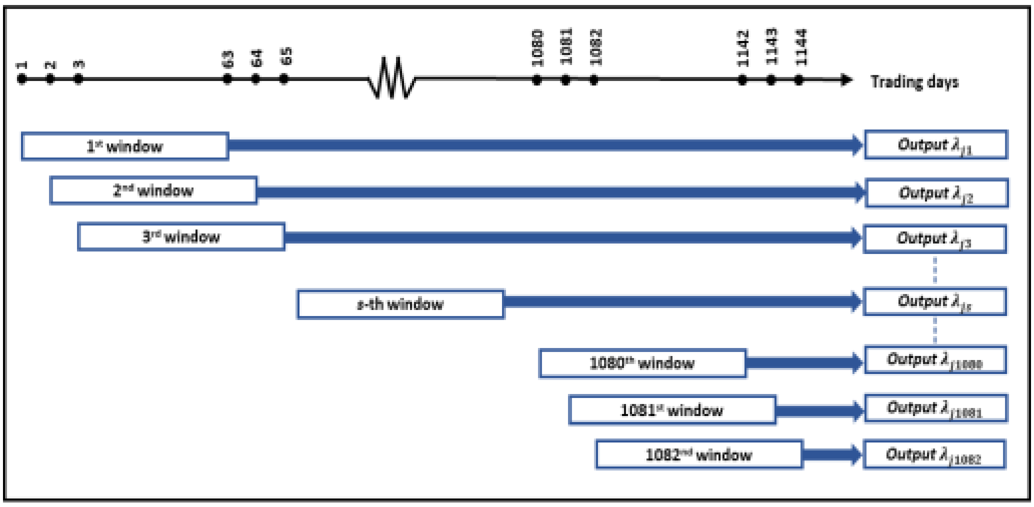

Figure 6. Moving Window

Then, the LASSO parameter of a set window modelled represents the FRM value for one trading day. Figure 6 is a series of LASSO parameters using the moving window approach for each company.

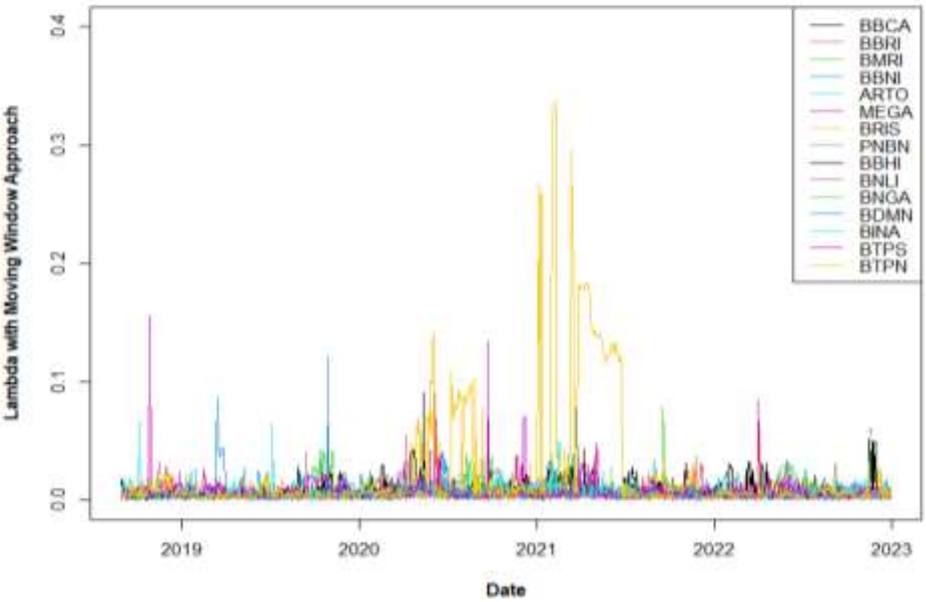

Figure 7. LASSO Parameter with Moving Window using the LASSO-QR Model

Figure 7 displays a series of LASSO parameters calculated using the moving window approach for each company, depicted through 15 line graphs each marked with distinct colors representing different companies. The key for these colors is provided at the top right of Figure 7. The data illustrated in Figure 7 shows variations from those seen in Table 2. Notably, even smaller companies exhibit large lambda values at certain times, particularly during the first quarter of 2021. This variation is possible because the moving window approach allows for the modeling of risk values in a manner that emphasizes the relevance of time. Consequently, this approach ensures that the risk values measured are timely and accurately reflect the assessed period.

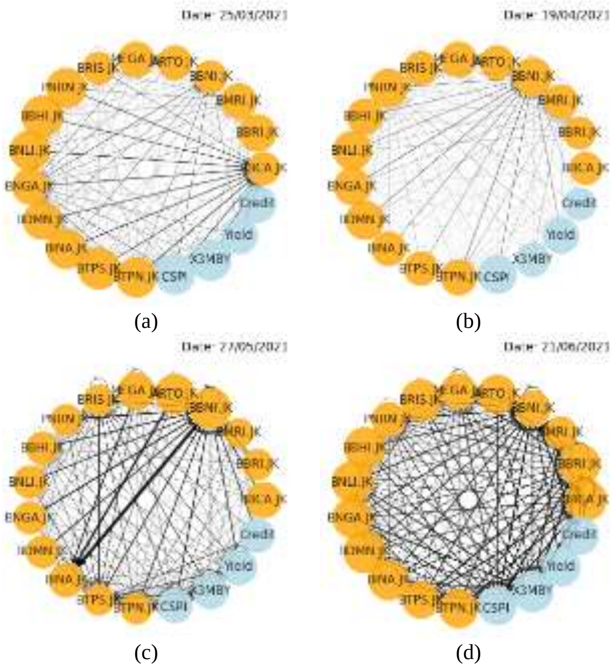

Figure 8. Sample Network using the LASSO-QR Model

Figure 8 shows some samples of network images for each day. The network continues to change every day. The circle's size describes the variable's strength in influencing the network, and the thick arrows explain the coefficients.

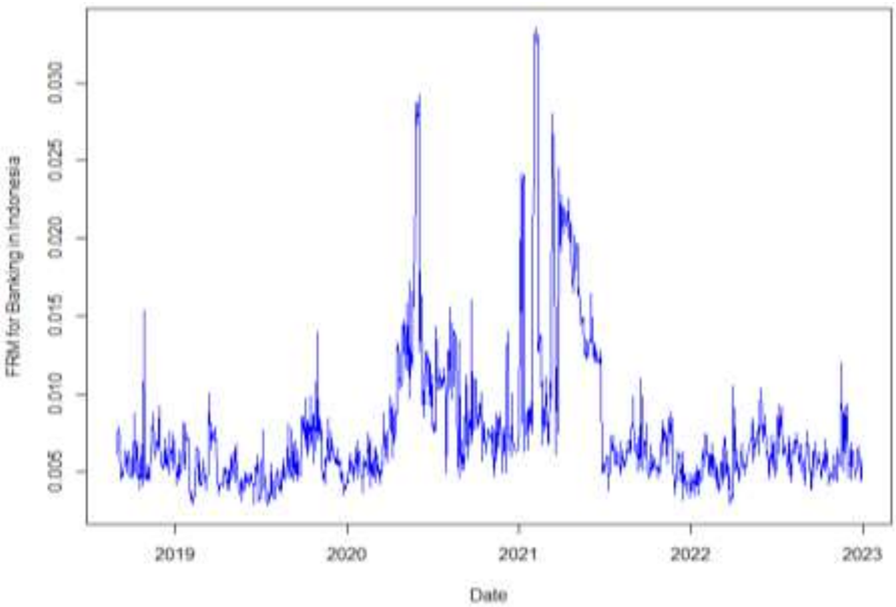

Figure 9. FRM Plot using the LASSO-QR Model

We proceed by calculating the average lambda values across all companies over time to determine the FRM value, which is displayed in Figure 9. The peak FRM value recorded in this series was 0.033510 on February 4, 2021. During this quarter, the FRM values were generally higher, coinciding with a period where investors were largely focused on economic recovery, influenced by the recession triggered by the COVID-19 pandemic. This peak value, 0.033510, serves as a benchmark to assess risk levels in subsequent days. On the final day of this analysis, December 30, 2022, an FRM value of 0.00576 was recorded. Comparing this value to the maximum gives a ratio of 17.20%. According to the risk level classification framework by Yu et al. (2023), this ratio places the risk at the green level, indicating a low risk of crisis within the financial market.

4. LASSO-QRNN Modeling

In this subsection, we develop the LASSO-QRNN model to accommodate each company's non-linear relationship. We estimate the parameter of the LASSO-QRNN model by adding the L_1-norm penalty parameter to the loss function of the QRNN model in Equation 17.

$$\min \sum_t^T \rho_\tau\left[\left(y_t - f(X_{i,t}, \mathbf{w})\right)\right] + \theta_1 \sum_{i,k}\left(w_{i,k}^h\right)^2 + \theta_2 \sum_k (w_k^o)^2 \tag{17}$$

Therefore, the loss function of the LASSO-QRNN model is obtained, which is written in Equation 18. We refer to Li & Zhu (2008) who defined the loss function of LASSO-QR by adding the L_1-norm parameter to the loss function of the QR model.

$$\min \sum_t^T \rho_\tau\left[\left(y_t - f(X_{i,t}, \mathbf{w})\right)\right] + \theta_1 \sum_{i,k}\left(w_{i,k}^h\right)^2 + \theta_2 \sum_k (w_k^o)^2 + \lambda \|\mathbf{w}^h\|_1 \tag{18}$$

From Equation 18, we obtain the estimator function presented in Equation 19.

$$\widehat{\mathbf{w}} = \operatorname{argmin}_{\mathbf{w}^h, \mathbf{w}^o} \sum_t^T \rho_\tau\left[\left(y_t - f(X_{i,t}, \mathbf{w})\right)\right] + \theta_1 \sum_{i,k}\left(w_{i,k}^h\right)^2 + \theta_2 \sum_k (w_k^o)^2 + \lambda_{QRNN} \|\mathbf{w}^h\|_1 \tag{19}$$

The check function (objective function) in Equation 18 and the estimator function in Equation 19 refers to the QRNN model's objective function (in ten forms of check function), written in Equation 20.

$$\rho_\tau(u_t) = \begin{cases} \tau g(u_t) & \text{, for } u_t \geq 0 \\ (1-\tau) g(u_t) & \text{, for } u_t < 0 \end{cases} \tag{20}$$

Furthermore, adjustments need to be made using the moving window approach to apply the objective function of the LASSO-QRNN model that has been formed to this research data. For each j-th company, given $t \in \{1, \dots, T\}$ is a time index with a total number of observations of T days, s is a moving window index with $s \in \{1, \dots, \left(T - (r-1)\right)\}$, and r is the length of the window size. Parameter estimation using the moving window approach in the LASSO-QR-NN model, which refers to Equation 18, is written in Equation 21.

$$\min r^{-1} \sum_{t=s}^{s+(r-1)} \rho_\tau\left[\left(y_t^s - f(X_{i,t}^s, \mathbf{w})\right)\right] + \theta_1 \sum_{i,k}\left(w_{i,k}^h\right)^2 + \theta_2 \sum_k (w_k^o)^2 + \lambda_{QR-NN}^s \|\mathbf{w}^{h,s}\|_1 \tag{21}$$

So that the estimator function presented in Equation 22 is obtained.

$$\left(X_{i,t}^s, \widehat{\mathbf{w}}^{\mathbf{s}}\right) = \operatorname{argmin} r^{-1} \sum_{t=s}^{s+(r-1)} \rho_\tau\left[\left(y_t^s - f(X_{i,t}^s, \mathbf{w})\right)\right] + \theta_1 \sum_{i,k}\left(w_{i,k}^h\right)^2 + \theta_2 \sum_k (w_k^o)^2 + \lambda_{QR-NN}^s \|\mathbf{w}^{h,s}\|_1 \tag{22}$$

The selection of penalty parameters is carried out by minimizing the GACV information criteria as follows:

$$\min GACV\ (\lambda_{QR-NN}) = \min \frac{1}{(r-df)} \left\{ r^{-1} \sum_{t=s}^{s+(r-1)} \rho_\tau \left[\left(y_t^s - f\left(X_{i,t}^s, \mathbf{w}\right)\right)\right] + \theta_1 \sum_{i,k}\left(w_{i,k}^h\right)^2 + \theta_2 \sum_k (w_k^o)^2 + \lambda_{QR-NN}^s \|\mathbf{w}^{h,s}\|_1 \right\} \tag{23}$$

where df is the size of the model dimensions.

5. LASSO-QRNN Modeling with Moving Window Approach

Prior to employing the LASSO-QRNN model, it is essential to ascertain the presence of any non-linear relationships between the response and predictor variables. To achieve this, we conducted non-linearity tests for each data set within every company model involved in the study. Consequently, we obtained non-linearity test results for each of the 15 company models that the p-value in the Terasvirta test is less than 0.05. Therefore, Terasvirta's testing of each variable relationship in each model showed that it had a non-linear relationship. So, we can proceed to the next step, i.e., LASSO-QRNN modeling.

In this research, we limit the number of neurons in the hidden layer to 1 hidden layer ($K = 1$) with one neuron ($Z = 1$) in the LASSO-QRNN modeling because the model is simple and almost identical to the LASSO-QR model. In the learning process, we determine an initial learning rate of 0.5. We also determine the activation function used in the model is the tanh activation function, the quantile level of $\tau = 5\%$, and a threshold of 0.01 for the LASSO-QRNN modeling. The architecture of the LASSO-QRNN modeling results is presented in Figure 10.

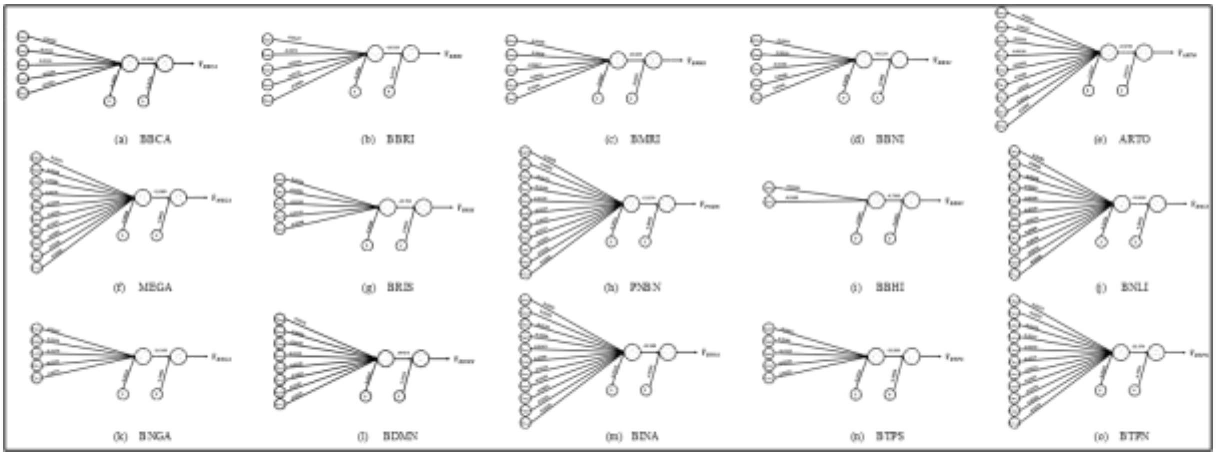

Figure 10. Architecture of LASSO-QRNN Model

Figure 10 provides a visual representation of the LASSO-QR-NN model architecture for each company. Among these, the four largest banking companies—BBCA, BBRI, BMRI, and BBNI—exhibit less influence compared to others. Consistent with the findings from the LASSO-QR model, the CSPI macroeconomic variable impacts all companies, with the exception of BBHI. Additionally, the 3-month bond yield macroeconomic variable affects seven companies. Similarly, the yield curve slope variable impacts seven different companies, whereas the credit spread variable only affects MEGA and BTPN, as shown in Table 3.

Table 3. LASSO Parameter using LASSO-QRNN Model

Bank	**Parameter λ**
BBCA	0.002104
BBRI	0.002986
BMRI	0.002765
BBNI	0.001997
ARTO	0.008387
MEGA	0.003167
BRIS	0.011116
PNBN	0.005145
BBHI	0.007893
BNLI	0.005011
BNGA	0.003974
BDMN	0.006920

Bank	Parameter λ
BINA	0.003391
BTPS	0.006680
BTPN	0.005366

Table 3 is the result of the λ parameter as a penalty parameter in the LASSO-QRNN model. Based on Table 3, it can be seen that if the λ parameters in the LASSO-QRNN model are compared with Table 2, the λ parameters in the LASSO-QR model, the difference in the magnitude of these parameters is visible. The LASSO-QR model has a much larger λ value than the LASSO-QRNN model. In the LASSO-QRNN model, more input variables are used for each company than in the LASSO-QR model. Next, the FRM calculation is carried out by calculating the average of all companies. In this modeling, the FRM value is 0.005127.

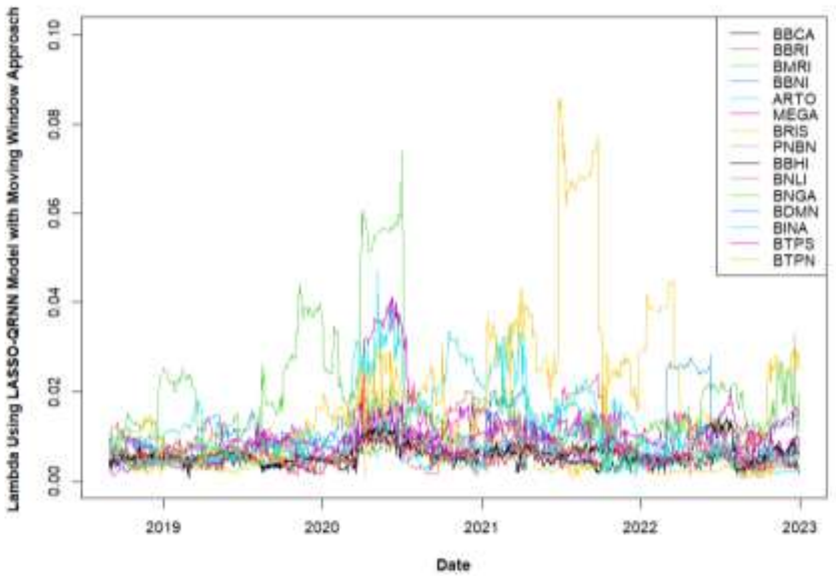

Figure 11. LASSO Parameter using LASSO-QRNN Model with Moving Window

The moving window approach in LASSO-QRNN modeling has the same concept as that in LASSO-QR modeling, written in the previous subsection. Figure 11 displays a series of LASSO parameters calculated using a moving window approach for each company. The analysis identifies BNGA and BTPN as having notably large λ values at specific times compared to other companies. To determine the Financial Risk Meter (FRM) value, the average λ value is computed for all companies at each time point. This FRM value is illustrated in Figure 12. The peak FRM value in this data set occurred on June 8, 2020, reaching 0.020693. The FRM values were particularly high during mid-2020, the first quarter of 2021, and the third quarter of 2021, periods during which the FRM tended to surpass other values. Corresponding to the data characteristics shown in Figure 12, this period also saw a general decline in share prices, triggered by the onset of the COVID-19 pandemic.

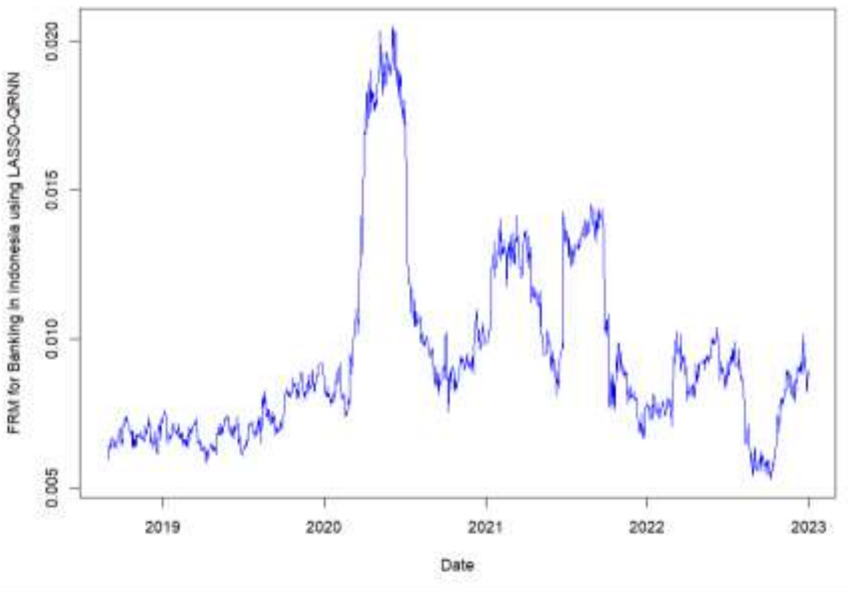

Figure 12. FRM Plot using LASSO-QRNN Model

This peak value serves as a benchmark to assess the risk level in subsequent days. On the final day of this study, December 30, 2022, the FRM value recorded was 0.008762. When this value is compared to the maximum value by calculating their ratio, it results in 42.34%. According to the risk level classification system established by Yu et al. (2023), this places the risk at the yellow level, indicating that it is moderately higher than usual.

6. Comparison of FRM using the LASSO-QR and the LASSO-QRNN Models

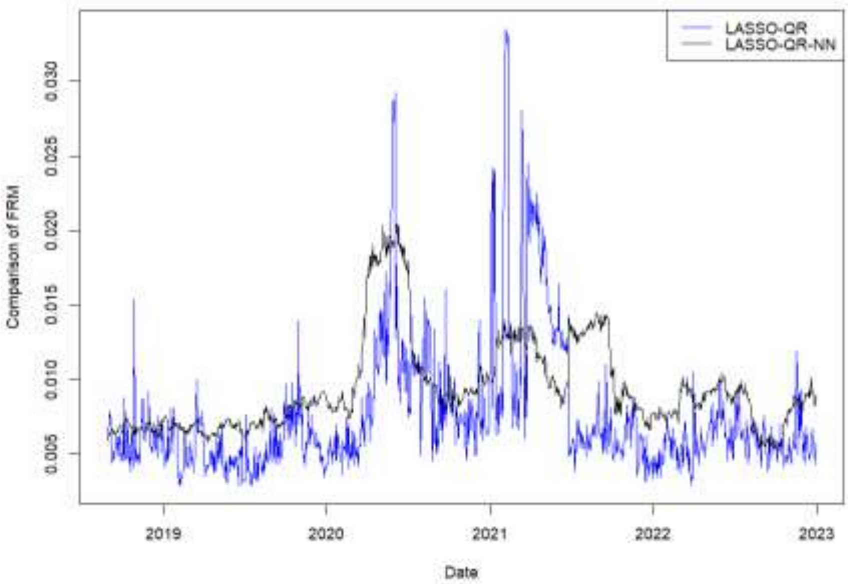

Figure 13. Comparison of FRM Plots

The FRM values generated by both the LASSO-QR and LASSO-QRNN models show similar trends, with elevated risk levels occurring in mid-2020 and the first quarter of 2021. This pattern aligns with the underlying share price data, which typically showed a decline during these periods. Notably, the FRM values from the LASSO-QR-NN model capture a broader spectrum of risk compared to those from the LASSO-QR model, despite the LASSO-QR-NN model having a narrower range. This comparative analysis is depicted in Figure 13.

To assess the models' performance, we calculated the Root Mean Square Error (RMSE) based on the actual response variable values and the estimated values produced by each model for each company. The average RMSE for the LASSO-QR model is 0.0469, while for the LASSO-QRNN model, it is 0.0454. Although the RMSE values for both models are quite similar, the LASSO-QRNN model shows a slight improvement over the LASSO-QR model. Specifically, the LASSO-QR model outperforms the LASSO-QRNN model for the MEGA, PNBN, and BNLI companies.

The COVID-19 pandemic, which spanned 2020 and 2021, significantly impacted the global economy and markets, including those in Indonesia. In the first quarter of 2020, the CSPI value in the capital market declined due to exchange rate issues and liquidity challenges. The CSPI covers all market prices in Indonesia, including property prices in it. This is in line with the results of , that property prices significantly affect the stability of the financial system (Tham et al., 2022). Other macroeconomic factors that are not included in the four macroeconomics that are already in the model also need to be considered. Research by Pangestuti et al. (2022) revealed that the macroeconomic variables of gold prices, exchange rates, and oil prices affect the price of mining stocks used to measure changes in the economy. This will also indirectly have a domino effect on stock prices in the banking sector. However, in cases where the market deviates substantially from efficiency, the assessment needs to consider microeconomic variables. On a micro scale, each company has its variables that will have a domino effect on other companies. Pangestuti et al. (2022) explains that the variables of profitability, intellectual capital, and business risks are variables that need to be considered because they have a significant influence, as shown in Figure 13.

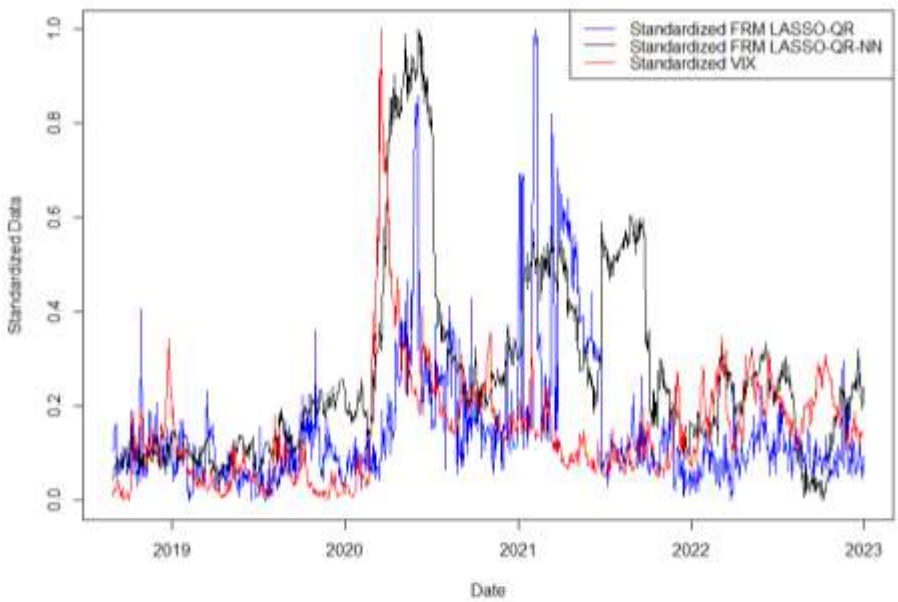

Figure 13. Standardized VIX and FRM

The COVID-19 period saw investors facing business and income difficulties. Six banks experienced liquidity problems during this time, including BBTN, MAYA, BBKP, BBYB, BEKS, and BANK. Although these banks have smaller capitalizations, they can influence larger-capitalization banks that dominate the credit and capital markets, potentially leading to systemic risk. To further understand how the FRM reflects global market volatility, we compared it with the Volatility Index (VIX) of the US market, which is commonly used as a benchmark to gauge market sentiment, including in Indonesia.

A comparison of the standardized FRM values from the two models and the VIX is illustrated in Figure 14. The figure reveals that the standardized VIX and FRM values for both models were elevated at the beginning of 2020, and the fluctuation patterns of these three data sets tend to be similar. However, the standardized VIX remained relatively stable in the first quarter of 2021. While the VIX measures volatility in the US market and not specifically in the Indonesian market, it can still be used to compare the risk conditions of the Indonesian financial market with those of the global financial market. A high VIX value indicates heightened global financial market risk (Goswami et al., 2025).

E. CONCLUSION AND SUGGESTIONS

The estimation of the Financial Risk Meter (FRM) for the banking sector in Indonesia involved adjusting the LASSO parameters based on the LASSO-QR model and LASSO-QRNN. These parameters successfully captured the characteristics of financial risk. Among the major banking companies—BBCA, BBRI, BMRI, and BBNI—consistent stock price log-return values were observed. The IHSG macroeconomic variable uniquely impacted all evaluated companies. The FRM outcomes indicated elevated risks during mid-2020 and the first quarter of 2021 for the LASSO-QR model, and additionally in the third quarter of 2021 for the LASSO-QRNN model. On the final day of this study, 30 December 2022, the LASSO-QR model classified a low risk of crisis, whereas the LASSO-QRNN model indicated a slightly higher than usual risk. Despite having a narrower range, the LASSO-QRNN model was more effective in detecting crises. In terms of performance, the average RMSE for the LASSO-QRNN model was better compared to the LASSO-QR model.

The standardized FRM values of both models provide comparative values that are not very different from prices in the global. In addition to the global market through the VIX, several things also need to be considered in assessing systemic risk in a country. Macroeconomic variables such as (1) the yields on Indonesian bonds with a three-month maturity, (2) the slope of the yield curve, (3) the CSPI, and (4) credit spreads have been included in this FRM. However, this study has limitations in the model-building process. Other macroeconomic variables can be added in further research with the same parameter estimation, while microeconomic variables in each company can be added by developing a model with multivariate analysis that can include microvariables for each company.

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