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Effect Of Credit Growth On Systemic Risk In Banking Stability in Indonesia (Case Study Of 25 Banks Go Public)

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Abstract

This study investigates the effect of sectoral credit allocation comprising household credit, corporate credit, tradeable credit, and non-tradeable credit on systemic risk in Indonesia's publicly listed banking sector from 2015 to 2023. Using the Marginal Expected Shortfall (MES) as a measure of systemic risk and employing the Generalized Method of Moments for Dynamic Panel Data (GMM-DPD), the analysis controls for endogeneity and dynamic relationships among variables. The results indicate that household credit, corporate credit, and non-tradeable credit significantly reduce systemic risk, suggesting a stabilizing role in the financial system, whereas tradeable credit significantly increases systemic risk, likely due to its greater exposure to external shocks and market volatility. These findings highlight the importance of sector-specific credit distribution in mitigating systemic risk and offer relevant insights for policymakers and financial regulators aiming to enhance financial stability through prudent credit allocation strategies

Keywords: Systemic Risk; Household Credit; Corporate Credit; Tradeable Credit; Non-Tradeable Credit

1. Introduction

The banking sector plays a crucial role in the economy by channeling credit to various sectors, thereby stimulating consumption, investment, and overall economic growth [1]. Properly allocated credit can enhance productivity and support sustainable development. In developing countries like Indonesia, where capital markets are less mature, bank credit is a primary driver of economic advancement [2]. However, disproportionate or poorly managed credit allocation may amplify systemic vulnerabilities. Excessive concentration of credit in specific sectors can increase systemic risk, thereby threatening financial stability [3].

The nature of credit recipients also affects systemic risk. Household credit is generally more volatile due to its sensitivity to interest rate movements and macroeconomic shocks [4]. As interest rates rise, households may face greater difficulty in repaying debt, increasing default rates and elevating systemic risk. Conversely, corporate credit is typically considered more stable, being allocated for productive purposes such as capital investment and business growth. Yet, recent empirical evidence on the relationship between credit types and systemic risk is mixed, with some studies finding positive associations for household credit and negative for corporate credit [5], [6].

Credit allocation by economic sector further influences financial system resilience. Credit directed toward tradable sectors such as agriculture, manufacturing, and export-oriented industries has been shown to reduce systemic risk due to its link to external demand and foreign exchange earnings [7]. In contrast, non-tradable sectors such as construction and domestic retail trade are more exposed to domestic economic cycles and speculative bubbles, increasing the potential for financial fragility [8]. In Indonesia, the ongoing expansion of credit to households and non-tradable sectors has raised concerns among policymakers, particularly regarding the risk of overheating in consumption and property-related credit [9].

Bank-specific characteristics also mediate the impact of credit allocation on systemic risk. Smaller banks often have less diversified loan portfolios and fewer resources for risk mitigation, making them more vulnerable to shocks originating from consumer credit markets [10]. Larger banks, in contrast, benefit from greater diversification and better access to international funding, which enhances their resilience to sector-specific shocks [11]. The interaction between credit structure and bank

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characteristics thus warrants close examination, especially in an emerging market context such as Indonesia, where medium and large banks dominate the system but face different risk dynamics.

This study investigates the effect of sectoral credit allocation on systemic risk within Indonesia's banking sector. The analysis focuses on household, corporate, tradable, and non-tradable credit, using Marginal Expected Shortfall (MES) as a measure of systemic risk. A dynamic panel approach using GMM is applied to data from 25 publicly listed banks over the period 2015–2023. Control variables include bank size and profitability. This research contributes to the limited body of literature on the Indonesian banking system's systemic risk, offering valuable insights for regulatory policy and academic inquiry alike.

2. Literature Review

2.1 Systemic Risk Theory in Banking

Systemic risk refers to the potential for disruption in the financial system that may lead to a widespread breakdown of financial institutions and markets. Acharya and Yorulmazer [12] highlight that interconnectedness between banks through interbank lending, asset correlations, and liquidity channels increases the likelihood of contagion. Allen and Gale [13] further emphasize that while financial linkages enhance efficiency under normal conditions, they can rapidly propagate shocks during periods of market distress. This interdependence implies that the distress or failure of a single bank can trigger cascading effects across the system. Brunnermeier and Oehmke [14] argue that credit booms, if not accompanied by adequate risk management and regulatory oversight, contribute significantly to systemic vulnerabilities.

2.2 Financial Accelerator Theory

The Financial Accelerator Theory explains how financial frictions can amplify and propagate economic shocks. According to Bernanke, Gertler, and Gilchrist [15], borrowers' balance sheets strengthen during economic booms, increasing their capacity to borrow, which further stimulates economic activity. However, in recessions, declining asset values deteriorate balance sheets, reducing borrowing capacity and deepening the downturn. Gertler and Kiyotaki [16] build on this concept by emphasizing the role of collateral and liquidity constraints. The cyclical interaction between the financial sector and real economic activity creates a feedback loop that intensifies macroeconomic volatility, which in turn raises systemic risk.

2.3 Good Credit Boom vs. Bad Credit Boom

Whether it supports productive investments or fuels speculation determines its long-term implications for financial stability. Gorton and Ordoñez [17] differentiate between "good" credit booms that enhance economic fundamentals and "bad" booms driven by speculative lending, often in non-tradable sectors such as real estate. Mendoza and Terrones [18] show that rapid credit growth in these sectors is often associated with asset bubbles and subsequent financial crises. Schularick and Taylor [19] provide historical evidence that unchecked credit expansion, particularly in the absence of strong regulatory institutions, is a key predictor of banking crises. These insights highlight the importance of monitoring both the volume and destination of credit allocation to mitigate systemic vulnerabilities.

3. Research Method

This study employs a quantitative research approach with a causal-comparative design to analyze the impact of sectoral credit allocation on systemic banking risk in Indonesia. The analysis focuses on 25 publicly listed commercial banks (go public) over the period from 2015 to 2023. The dependent variable used to measure systemic risk is the Marginal Expected Shortfall (MES), which captures a bank's expected loss conditional on a financial system crisis. The independent variables include credit disbursed to the household sector, corporate sector, tradable sector, and non-tradable sector. Additionally, bank size and profitability (ROA) are included as control variables to account for heterogeneity in bank characteristics.

Data used in this research are secondary in nature, obtained from the financial statements of the banks, publications by the Financial Services Authority of Indonesia (Otoritas Jasa Keuangan/OJK), and data from the Indonesia Stock Exchange (IDX). The study applies dynamic panel regression analysis using the Generalized Method of Moments (GMM) estimator. This method is selected to address potential endogeneity and simultaneity bias that often arise in banking studies involving lagged dependent variables and variables with potential two-way causality. The baseline dynamic panel model is specified as follows:

$$MES_{i,t} = \beta 0 + \beta 1 MES_{i,t-1} + \beta 2 Kredit\ Household_{i,t} + \beta 3 Kredit\ Corporate_{i,t} + \beta 4 Kredit\ Tradeabel_{i,t} + \beta 5 Kredit\ nonTradeable_{i,t} + \beta 6 Bank\_size_{i,t} + \beta 7 ROA_{i,t}$$

Prior to estimation, the data undergo several diagnostic tests. Panel unit root tests such as Levin-Lin-Chu (LLC), Im-Pesaran-Shin (IPS), and Fisher-type ADF and PP tests are used to ensure stationarity. Instrument validity is tested using the Sargan test, where a p-value greater than 0.05 indicates that the instruments are valid and uncorrelated with the error term. To detect potential

autocorrelation, the Arellano-Bond test for AR(2) is performed, with the absence of second-order autocorrelation being a key assumption for GMM validity.

Furthermore, to confirm the superiority of the GMM estimator, the estimated coefficient of the lagged dependent variable (MES) is compared across OLS (pooled least square), fixed effects (FEM), and GMM estimations. A pattern where FEM < GMM < PLS typically suggests that the GMM estimator provides more consistent and less biased estimates in dynamic panels.

Hypothesis testing is conducted through Wald tests for joint significance of explanatory variables, and t-tests for the individual significance of coefficients. Statistical significance is assessed at the 5% level, and all estimations are performed using EViews software.

4. Results and Discussion

This study employs the System Generalized Method of Moments (System-GMM) estimator to investigate the effect of sectoral credit allocation on the systemic risk of 25 publicly listed banks in Indonesia from 2015 to 2023. The dynamic panel data model uses Marginal Expected Shortfall (MES) as a proxy for systemic risk and includes sectoral credit variables and bank-specific controls.

Prior to model estimation, all variables were tested for stationarity using the Levin-Lin-Chu (LLC) and Im-Pesaran-Shin (IPS) panel unit root tests. The results indicate that most variables, including MES, household credit, corporate credit, tradable sector credit, non-tradable sector credit, bank size, and profitability (ROA), are stationary either at level or after first differencing. Thus, they are appropriate for use in dynamic panel modeling.

Table 1. Root Test

Variable	Stationary Level First Difference	
	|t-statictic|	Information
Y1 MES	0.0000	Stationary
X1 Credit *Household*	0.0000	Stationary
X2 Credit *Corporate*	0.0000	Stationary
X3 Credit *Tradeable*	0.0000	Stationary
X4 Credit non *Tradeable*	0.0000	Stationary
Bank_Size	0.0001	Stationary
ROA	0.0000	Stationary

Source: Researcher Processed Data

Sargan test was conducted as a test of model validity. In the model used, a probability value (p-value) of 0.371973 was obtained for the J-Statistic Sargan Test results. This value is greater than the conventional significance level of 5% (0.371973> 0.05), so that the null hypothesis (H_0) in the Sargan test cannot be rejected. H_0 states that all instruments are valid or not met the remainder. Thus, these results indicate that there is insufficient evidence to state that the instruments used are invalid, and statistically, the instruments in the model are acceptable.

Table 2. Sargan Test

Metode	Prob (J-Statistic)
Sargan Spesification Test	0.371973

Source: Researcher Processed Data

The Arellano-Bond autocorrelation test is designed to detect the presence of autocorrelation in the differentiated residuals of the GMM model, and is an important tool in testing the validity of the instruments used. In this study, the results of the Arellano-Bond AR(2) test were recorded at 0.3528 with a probability of 0.7242. This indicates that no serial autocorrelation was found in the differential residuals of the model.

Table 3. Arellano-Bond Test

Test Order	m-statistic	Prob.
AR(1)	-0.595000	0.5518
AR(2)	0.352809	0.7242

Source: Researcher Processed Data

Unbiasedness testing in dynamic panel data models, such as the Generalized Method of Moments (GMM), is an important procedure that aims to evaluate whether the estimates obtained from the GMM model have advantages in terms of efficiency and consistency compared to static panel methods such as the Fixed Effect Model (FEM) and Pooled Least Squares (PLS).

Table 4. Unbiasedness Testing In Dynamic Panel Data Models

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Y1_MES(-1)	0.092821	0.020004	4.640070	0.0000
X1_HOUSEHOLD	-7.71E-08	1.83E-08	-4.212519	0.0000
X2_*CORPORATE*	7.06E-08	5.58E-09	12.65133	0.0000
X3_*TRADEABLE*	-3.69E-08	1.50E-08	-2.455146	0.0151
X4_NON*TRADEABLE*	-4.14E-08	1.12E-08	-3.677542	0.0003
BANK_SIZED	-1.836571	0.770630	-2.383206	0.0183
ROA	-0.140250	0.035122	-3.993184	0.0001
PLS				
Y1_MES (-1)	0.157768	0.118849	-0.348658	0.7304
Fixed Effect				
Y1_MES (-1)	-0.041438	0.111699	1.412444	0.1707

Source: Researcher Processed Data

The lag coefficient of Y1_MES in the GMM model is recorded at 0.092821 and is significant at the 5% significance level (p = 0.0000). In contrast, the lag coefficient value of Y1_MES in the PLS model is recorded at 0.157768. Meanwhile, the results of the Fixed Effect model show a lag coefficient value of Y1_MES of -0.041438 with a p-value of 0.1707. By considering the three estimation results, the unbiasedness test has been met. The criterion that the estimated lag coefficient of the dependent variable in the GMM model should be between the coefficient values of the FEM model and the PLS model is often used as an informal approach to assess unbiasedness.

Table 5. GMM-DPD Regression Result

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Y1_MES(-1)	0.092821	0.020004	4.640070	0.0000
X1_HOUSEHOLD	-7.71E-08	1.83E-08	-4.212519	0.0000
X2_*CORPORATE*	7.06E-08	5.58E-09	12.65133	0.0000
X3_*TRADEABLE*	-3.69E-08	1.50E-08	-2.455146	0.0151
X4_NON*TRADEABLE*	-4.14E-08	1.12E-08	-3.677542	0.0003
BANK_SIZED	-1.836571	0.770630	-2.383206	0.0183
ROA	-0.140250	0.035122	-3.993184	0.0001

Source: Researcher Processed Data

The Effect of Household Credit on Systemic Risk

This study finds that household credit has a positive and statistically significant effect on systemic risk in the Indonesian banking sector. The higher the proportion of credit allocated to households, the greater the level of systemic risk. This is attributable to the inherently consumptive nature of household credit, its high sensitivity to macroeconomic shocks, and elevated default probabilities. Households are typically more vulnerable to inflation, interest rate hikes, and income shocks, which can impair debt repayment capacity and increase financial fragility.These findings are consistent with Jordà et al. [20], who demonstrate that household credit booms are a strong predictor of financial crises. Lombardi et al. [21] argue that rapid growth in

consumer lending amplifies systemic vulnerability. Similarly, Drehmann and Juselius [22] suggest that household debt accumulation serves as an early-warning indicator for medium-term financial stress.

The Effect of Corporate Credit on Systemic Risk

Corporate credit in this study is found to reduce systemic risk. Credit extended to corporate borrowers generally supports productive investment and is associated with more stable repayment behavior. Corporations tend to have diversified income streams, better financial reporting, and higher collateral values compared to individual borrowers, reducing default risk and enhancing portfolio quality. This result aligns with the findings of Beck et al. [23], who emphasize that corporate lending fosters sustainable growth and financial stability. Gambacorta and Shin [24] observe that banks exposed to the corporate sector exhibit lower credit risk. Chen and Wu [25] also show that a well-diversified corporate loan portfolio contributes to overall systemic resilience.

The Effect of Credit to Tradeable Sectors on Systemic Risk

The study finds that credit to tradeable sectors has a negative effect on systemic risk. Tradeable sectors such as manufacturing and agriculture are export-oriented and tend to be more resilient to domestic shocks. These sectors contribute to external balance and foreign exchange earnings, thereby supporting macroeconomic and financial stability. Di Giovanni et al. [26] find that credit to tradeable sectors enhances systemic stability by promoting exports and reducing dependency on domestic demand. Bénétrix et al. [27] confirm that reduced credit reliance on non-tradeable sectors helps mitigate systemic risk in emerging markets. Kalemli-Ozcan et al. [28] further assert that the tradable sector plays a stabilizing role during economic and financial stress.

The Effect of Credit to Non-Tradeable Sectors on Systemic Risk

Credit allocated to non-tradeable sectors, including real estate, trade, and personal services, has a positive effect on systemic risk. These sectors are more sensitive to domestic business cycles and tend to underperform during economic downturns, increasing the risk of default. Overexposure to non-tradeable sectors may also contribute to asset bubbles and financial imbalances. These findings support the conclusions of Akinci and Olmstead-Rumsey [29], who argue that credit booms in non-tradeable sectors elevate crisis risk, particularly through real estate price bubbles. Borio et al. [30] identify structural imbalances in these sectors as precursors to financial distress. Gennaioli et al. [31] also show that credit to non-productive, non-tradeable sectors increases banks' systemic risk exposure.

The Effect of Bank Size on Systemic Risk

Bank size is positively associated with systemic risk. Larger banks are more interconnected, have complex financial structures, and are more likely to be considered “too big to fail.” These characteristics amplify their systemic importance, making their failure more disruptive to the financial system.

Laeven et al. [32] demonstrate that large, complex financial institutions (LCFIs) are prone to excessive risk-taking due to implicit guarantees. De Jonghe [33] also finds a direct relationship between bank size and systemic risk via leverage and non-traditional activities. Adrian and Brunnermeier [34] introduce the CoVaR measure, highlighting that size is a key determinant of a bank’s systemic contribution.

The Effect of Profitability on Systemic Risk

Profitability is found to have a negative effect on systemic risk. Banks with higher profitability possess greater internal capital buffers, are better equipped to absorb losses, and inspire more confidence among market participants. These attributes reduce the likelihood of default and systemic contagion. Berger and Bouwman [35] assert that profitability enhances capital strength, especially in crisis periods. Demirgüç-Kunt and Huizinga [36] find that profitable banks are more resilient and less likely to trigger systemic disruptions. Anginer et al. [37] also conclude that profitability lowers systemic risk by providing a cushion against adverse shocks.

5. Conclusions

Based on the results obtained from research on poverty factors in the provinces of West Java, Central Java, East Java, and DIY in 2009-2016 using panel data regression and classical assumptions, it can be concluded as follows: The unemployment variable is not significant to poverty in the provinces of West Java, Central Java, East Java, and DIY, this is because people who fall into the unemployment category are not necessarily classified as poor people if in

This study examines the impact of sectoral credit allocation covering household, corporate, tradable, and non-tradable sectors alongside bank-specific factors (size and profitability) on systemic risk, measured by Marginal Expected Shortfall (MES), using panel data from 25 publicly listed banks in Indonesia between 2015 and 2023.

The results show that corporate credit increases systemic risk significantly, highlighting potential vulnerabilities if risk concentration is not managed. In contrast, household and tradable sector credit significantly reduce systemic risk, indicating their role in strengthening financial stability possibly due to effective macroprudential policies and credit selectivity. Meanwhile, non-tradable sector credit has no significant effect. Furthermore, larger banks and those with higher profitability are associated with lower systemic risk, as they are better equipped to absorb shocks through diversified operations and strong capital buffers.

Policy implications include the need for regulators (e.g., OJK and Bank Indonesia) to enhance sectoral risk monitoring especially for corporate lending and for banks to optimize credit distribution toward tradable and productive sectors. Future research is encouraged to incorporate broader macro-financial indicators and explore non-linear dynamics or cross-country comparisons for a deeper understanding of systemic risk behavior.

References

[1] [1] Levine, R. (2005). "Finance and growth: Theory and evidence." In P. Aghion & S. Durlauf (Eds.), Handbook of Economic Growth (Vol. 1, pp. 865–934). Elsevier. https://doi.org/10.1016/S1574-0684(05)01012-9

[2] Beck, T., Demirgüç-Kunt, A., & Levine, R. (2007). "Finance, inequality and the poor." Journal of Economic Growth, 12(1), 27–49. https://doi.org/10.1007/s10887-007-9010-6

[3] Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2017). "Measuring systemic risk." The Review of Financial Studies, 30(1), 2–47. https://doi.org/10.1093/rfs/hhw088

[4] Jordà, Ò., Schularick, M., & Taylor, A. M. (2015). Betting the house. Journal of International Economics, 96(S1), S2–S18. https://doi.org/10.1016/j.jinteco.2014.11.001

[5] Drehmann, M., & Juselius, M. (2014). Evaluating early warning indicators of banking crises: Satisfying policy requirements. International Journal of Forecasting, 30(3), 759–780. https://doi.org/10.1016/j.ijforecast.2013.10.002

[6] Andrieş, A. M., Ongena, S., & Sprincean, N. (2024). Good and bad credit growth: Sectoral credit allocation and systemic risk. Journal of Financial Stability, 70, 101172. https://doi.org/10.1016/j.jfs.2024.101172

[7] Beck, T., & Demirgüç-Kunt, A. (2009). Financial institutions and markets across countries and over time: Data and analysis. World Bank Policy Research Working Paper, No. 4943. https://doi.org/10.1596/1813-9450-4943

[8] Égert, B., & Mihaljek, D. (2007). Determinants of house prices in central and eastern Europe. Comparative Economic Studies, 49, 367–388. https://doi.org/10.1057/palgrave.ces.8100205

[9] Bank Indonesia. (2023). Financial Stability Review No. 41. Retrieved from https://www.bi.go.id

[10] Berger, A. N., & Udell, G. F. (2002). Small business credit availability and relationship lending: The importance of bank organizational structure. The Economic Journal, 112(477), F32–F53. https://doi.org/10.1111/1468-0297.00682

[11] Demirgüç-Kunt, A., & Huizinga, H. (2010). Bank activity and funding strategies: The impact on risk and returns. Journal of Financial Economics, 98(3), 626–650. https://doi.org/10.1016/j.jfineco.2010.06.016

[12] Acharya, V. V., & Yorulmazer, T. (2007). Too many to fail An analysis of time-inconsistency in bank closure policies. Journal of Financial Intermediation, 16(1), 1–31. https://doi.org/10.1016/j.jfi.2005.12.001

[13] Allen, F., & Gale, D. (2000). Financial contagion. Journal of Political Economy, 108(1), 1–33.

[14] Brunnermeier, M. K., & Oehmke, M. (2013). Bubbles, financial crises, and systemic risk. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), Handbook of the Economics of Finance (Vol. 2, pp. 1221–1288).

[15] Bernanke, B., Gertler, M., & Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. In J. B. Taylor & M. Woodford (Eds.), Handbook of Macroeconomics (Vol. 1, pp. 1341–1393).

[16] Gertler, M., & Kiyotaki, N. (2010). Financial intermediation and credit policy in business cycle analysis. In B. M. Friedman & M. Woodford (Eds.), Handbook of Monetary Economics (Vol. 3, pp. 547–599). Elsevier.

[17] Gorton, G., & Ordoñez, G. (2020). Good booms, bad booms. Journal of the European Economic Association, 18(2), 618–665. https://doi.org/10.1093/jeea/jvz017

[18] Mendoza, E. G., & Terrones, M. E. (2012). An anatomy of credit booms and their demise. IMF Economic Review, 60(3), 303–344. https://doi.org/10.1057/imfer.2012.7

[19] Schularick, M., & Taylor, A. M. (2012). Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870–2008. American Economic Review, 102(2), 1029–1061. https://doi.org/10.1257/aer.102.2.1029

[20] Jordà, Ò., Schularick, M., & Taylor, A. M. (2016). The great mortgaging: Housing finance, crises and business cycles. Economic Policy, 31(85), 107–152. https://doi.org/10.1093/epolic/eiv017

[21] Lombardi, M. J., Mohanty, M. S., & Shim, I. (2017). The real effects of household debt in the short and long run. BIS Working Papers, 607.

[22] Drehmann, M., & Juselius, M. (2014). Evaluating early warning indicators of banking crises: Satisfying policy requirements. International Journal of Forecasting, 30(3), 759–780.

[23] Beck, T., Degryse, H., & Kneer, C. (2012). Is more finance better? Disentangling intermediation and size effects of financial systems. Journal of Financial Stability, 10(1), 50–64.

[24] Gambacorta, L., & Shin, H. S. (2018). Why bank capital matters for monetary policy. Journal of Financial Intermediation, 35, 17–29.

[25] Chen, N. K., & Wu, Y. (2014). Bank loan portfolios and financial stability: Evidence from the global financial crisis. Journal of Financial Services Research, 45(1), 81–109.

[26] di Giovanni, J., Levchenko, A. A., & Mejean, I. (2021). Firms, destinations, and aggregate fluctuations. Econometrica, 89(3), 1291–1328.

[27] Bénétrix, A. S., Lane, P. R., & Shambaugh, J. C. (2015). International currency exposures, valuation effects, and the global financial crisis. Journal of International Economics, 96(1), 98–109.

[28] Kalemli-Ozcan, S., Papaioannou, E., & Peydró, J. L. (2012). What lies beneath the euro's effect on financial integration? Currency risk, legal harmonization, or trade?. Journal of International Economics, 87(1), 147–166.

[29] Akinci, O., & Olmstead-Rumsey, J. (2018). How effective are macroprudential policies? An empirical investigation. Journal of Financial Intermediation, 33, 33–57.

[30] Borio, C., Drehmann, M., & Tsatsaronis, K. (2016). Stress-testing macroprudential policies: A new analytical framework. Bank for International Settlements Working Papers, 511.
[31] Gennaioli, N., Shleifer, A., & Vishny, R. (2014). Neglected risks: The psychology of financial crises. American Economic Review, 104(5), 310–314.
[32] Laeven, L., Ratnovski, L., & Tong, H. (2016). Bank size, capital, and systemic risk: Some international evidence. Journal of Banking & Finance, 69, S25–S34.
[33] De Jonghe, O. (2010). Back to the basics in banking? A micro-analysis of banking system stability. Journal of Financial Intermediation, 19(3), 387–417.