Asian Journal of Economic Modelling
ISSN(e): 2312-3656
ISSN(p): 2313-2884
DOI: 10.55493/5009.v14i2.5918
Vol. 14, No. 2, 1-16.

URL: www.aessweb.com

Determinants of credit growth in ASEAN banking sector: Insightful understanding from panel quantile regression

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Article History
Received: 22 April 2025
Revised: 29 January 2026
Accepted: 10 February 2026
Published: 4 March 2026

Keywords
Bank
Credit growth
Crisis
Panel data
Quantile regression.

JEL Classification:
G20; G21.

ABSTRACT

This paper investigates the determinants of credit growth in the ASEAN banking sector by employing the Method of Moments Quantile Regression (MM-QR) on an unbalanced panel of 185 banks from ten Southeast Asian countries over the period 2000–2022. Unlike traditional mean-based approaches, MM-QR captures distributional heterogeneity by estimating the effects of both bank-specific and macroeconomic variables across different quantiles of credit growth. This methodology is particularly effective because it provides more comprehensive insights into how determinants influence banks with different levels of credit growth. The findings reveal that non-performing loans (NPLs) negatively impact credit expansion across all quantiles, with the effect intensifying at higher levels of credit growth. Bank size, capital ratio, income diversification, and profitability exhibit non-linear effects that vary depending on a bank's position within the credit growth distribution. On the macroeconomic front, M2 growth consistently stimulates credit, while GDP growth primarily benefits banks with lower lending activity. Inflation exerts a disproportionately negative effect on low-growth banks. The effects of financial crises also diverge: while the 2008 global crisis allowed high-growth banks to expand, the COVID-19 pandemic severely constrained their lending. These findings underscore the need for targeted regulatory and risk management policies that recognize structural differences in bank behavior and resilience across the region.

Contribution/ Originality: This paper contributes to the literature by applying the Method of Moments Quantile Regression (MM-QR) to examine the determinants of credit growth in ASEAN banks. Unlike conventional mean-based approaches, MM-QR captures heterogeneity in the distribution of credit growth, offering novel insights into how both bank-specific and macroeconomic factors influence credit expansion across different quantiles.

1. INTRODUCTION

In recent decades, the role of banks in fostering economic growth has become especially salient in emerging economies, where financial markets remain underdeveloped, and credit intermediation is overwhelmingly bank-centric. Within the ASEAN region, commercial banks are the dominant suppliers of credit, functioning as critical conduits between surplus units and investment-driven sectors. Their operations not only shape the trajectory of aggregate demand but also influence monetary policy transmission, financial resilience, and macroeconomic stability (Casu, Girardone, & Monyneux, 2006; Cetorelli & Goldberg, 2012). However, the centrality of banks in ASEAN financial systems renders them highly susceptible to systemic shocks a vulnerability that was exposed during the

global financial crisis of 2007–2009 and was reaffirmed by the COVID-19 pandemic (Adrian & Shin, 2010; Colak & Öztekin, 2021; Ho, Huang, Lin, & Yen, 2016).

Credit growth, commonly understood as the pace at which banks expand their loan portfolios, serves as both an indicator of banking sector dynamism and a potential precursor to macroeconomic instability. Moderate increases in credit are often associated with heightened investment and economic output (Bernanke & Blinder, 1988; Spatafora & Luca, 2012). However, excessive credit expansion can intensify financial vulnerabilities, lead to capital misallocation, and fuel asset price bubbles (Gourinchas & Obstfeld, 2012; Keeton, 1999; Lane & McQuade, 2014). These tensions are particularly pronounced in ASEAN economies, where rapid financial deepening, varied institutional structures, and uneven regulatory frameworks create intricate patterns of credit development. Empirical data highlight these challenges. From 2000 to 2020, countries such as Vietnam, Malaysia, and Thailand experienced persistent double-digit credit growth, frequently surpassing GDP growth rates (World Bank, 2022). While this trend signals a robust financial sector and greater financial inclusion, it has raised alarms about deteriorating loan quality and potential overheating in the financial system (Foos, Norden, & Weber, 2010; Thiagarajan, Kumar, & Rajendran, 2011). The COVID-19 pandemic further amplified these issues, delivering a severe external shock to credit supply and demand (Colak & Öztekin, 2021). As household incomes plummeted and business revenues contracted, new lending volumes shrank, and non-performing loans spiked, particularly in economies with constrained fiscal resources and inadequate borrower safeguards (Le, Nguyen, Vu, Do, & Tran, 2022). These dynamics underscore the need for a deeper examination of the factors driving credit growth in ASEAN banking systems, especially in the post-pandemic context.

Previous empirical research has largely focused on conventional panel data estimation techniques (e.g., pooled ordinary least squares – POLS; fixed-effect model – FEM; random effect model – REM; or generalized method of moments – GMM) (Ivanović, 2016; Vo, 2018). However, these approaches often fail to account for the heterogeneity in the distribution of credit growth across banks, especially when bank-specific factors or economic shocks exert asymmetric effects. For example, a macroeconomic downturn may disproportionately impact banks with different loan sizes or banks with higher exposure to vulnerable sectors. This limitation in the previous literature highlights the need for a more comprehensive methodology that can capture the complexities of bank credit growth dynamics across different lending behavior segments of the banking sector. Therefore, we use the Method of Moments Quantile Regression (MM-QR) proposed by Koenker (2005), Canay (2011), and Machado and Silva (2019), which allows for the estimation of determinants across different quantiles of the credit growth distribution to fill this research gap. This is particularly important because the impact of certain variables, such as bank size, capital adequacy, or non-performing loan ratios, may not be uniform across banks with low and high credit growth. By using MM-QR, this study provides insights into the impact of both bank-specific and macroeconomic variables on credit growth, contributing to more targeted and effective policy recommendations for banking regulators and financial institutions in the ASEAN region. The rest of this paper is structured as follows: Section 2 reviews the relevant literature. Section 3 presents research methodology and data sources. Section 4 discusses empirical findings, while Section 5 concludes our study.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Understanding the determinants of bank credit growth is essential for both policymakers and financial institutions, especially in emerging markets where banks dominate the financial landscape. Prior studies have emphasized that credit expansion is shaped by a combination of internal bank-specific factors and external macroeconomic conditions. However, these influences are neither uniform nor consistent; they vary across institutional settings, economic cycles, and bank performance levels. Therefore, this paper summarizes the literature review by classifying the determinants of credit growth into two main groups: micro-level (bank-specific) variables and macro-level variables.

At the micro level, several bank characteristics significantly affect lending behavior. First, high non-performing loans (NPLs) weaken credit supply by reducing capital adequacy, increasing provisioning needs, and raising credit risk, thereby impairing banks' ability and willingness to lend (Accornero, Alessandri, Carpinelli, & Sorrentino, 2017; Peek & Rosengren, 1995). In contrast, larger banks often benefit from economies of scale and greater diversification, enabling more robust credit growth (Bashir, 2003; Strahan & Weston, 1998), though some evidence suggests excessive size may induce inefficiency and risk aversion (Ibrahim, 2016). Meanwhile, the loan-to-deposit ratio (LDR), which serves as an indicator of how efficiently deposits are utilized, generally facilitates credit expansion when kept within reasonable bounds (Nugraha, Yahya, Nariswari, & Salsabila, 2021). Additionally, strong capital buffers—reflected by the equity-to-assets ratio enhance lending resilience (Bernanke, Lown, & Friedman, 1991; Gambacorta & Mistrulli, 2004), although overly conservative capitalization may temporarily suppress credit activity (Bridges et al., 2014). Bank profitability, especially return on assets (ROA), signals efficient cost management (lower cost-to-income ratio) and internal funding capacity, reinforcing credit expansion (Igan & Pinheiro, 2011). Income diversification also plays a critical role; banks with stable non-interest income streams can absorb shocks more effectively and lend more confidently (Abedifar, Molyneux, & Tarazi, 2018; Lin, Chung, Hsieh, & Wu, 2012). Similarly, bank liquidity enables banks to meet loan demand without jeopardizing financial stability, although excessive liquidity can lead to idle resources (Berger & Bouwman, 2009; Cornett, McNutt, Strahan, & Tehranian, 2011). Overall, these bank-specific variables jointly determine the credit growth across institutions.

The macroeconomic context also significantly influences credit growth, with monetary conditions, economic performance, price stability, and systemic disruptions playing critical roles. An increase in the broad money supply (M2) enhances commercial banks' liquidity and funding capabilities, thereby encouraging lending, particularly in low-interest-rate environments (Akani & Onyema, 2017; Dharmadasa, 2021). Likewise, strong GDP growth boosts loan demand and strengthens borrowers' credit profiles, creating a conducive environment for credit expansion (Calza, Gartner, & Sousa, 2003; Shingjergji & Hyseni, 2015). Conversely, elevated inflation diminishes real returns, undermines borrowers' ability to repay, and heightens uncertainty, all of which constrain credit availability (Boyd, Levine, & Smith, 2001; Huybens & Smith, 1999). Inflation can also trigger restrictive monetary policies, further tightening credit conditions. Finally, crisis periods—such as the 2008 global financial crisis or the COVID-19 pandemic create profound disruptions in lending activity. While banks in some ASEAN countries demonstrated resilience during the 2008 crisis due to conservative banking practices (Claessens & Van Horen, 2015), the COVID-19 pandemic had a more contractionary impact, exacerbating credit risk and curbing both supply and demand (Colak & Öztekin, 2021). Collectively, these macro-level factors highlight the sensitivity of bank lending to broader economic fluctuations and underline the importance of a stable and supportive macroeconomic framework for sustaining credit growth.

3. DATA AND METHODOLOGY

3.1. Data

This paper uses an unbalanced panel dataset comprising 185 banks from ten Southeast Asian countries excluding Timor-Leste due to data unavailability, spanning the period from 2000 to 2022, with 2,518 observations. The sample period from 2000 to 2022 was selected to capture both phases of economic expansion and significant exogenous shocks, including the 2007–2009 global financial crisis and the 2020–2022 COVID-19 pandemic, which have had a profound impact on credit growth patterns in the ASEAN region. By covering this extended timeframe, the study offers a comprehensive view of credit growth dynamics, spanning periods of financial stability to those marked by heightened economic stress, thus allowing for a deeper understanding of the factors influencing credit growth under varying macroeconomic conditions.

Bank-specific data were sourced from the S&P Capital IQ Pro database, while macroeconomic indicators, including M2 money supply growth, GDP growth, and inflation were obtained from authoritative sources such as

the World Bank and the International Monetary Fund (IMF). The variables included in this study were chosen based on both their theoretical importance and empirical relevance in the existing literature on credit growth. Bank-specific variables such as non-performing loans (NPLs), bank size, capital adequacy, profitability (ROA), income diversification, and liquidity are known to significantly affect lending behavior (Bernanke et al., 1991; Gambacorta & Mistrulli, 2004). These variables capture key aspects of a bank's financial health and operational capacity, which directly influence its ability to extend credit. On the macroeconomic side, variables like GDP growth, M2 growth, and inflation are selected because of their established effects on the supply and demand for credit in emerging economies. These factors collectively allow for a holistic view of the determinants of credit growth in the ASEAN banking sector.

Quantitative analyses were conducted using Stata 16 software to examine the impact of various determinants on credit growth within the ASEAN banking sector. To mitigate the influence of extreme values, all variables were winsorized at the 1st and 99th percentiles. A detailed description of the variables is provided in Table 1.

Table 1. Variables description.

Variables	Definition	Measurement
Dependent variable		
LG	Credit growth (%)	$\left(\frac{\text{Total loans year t}}{\text{Total loans year t} - 1} - 1\right) \times 100$
Independent variables		
Bank characteristics		
Size	Bank size	Natural logarithm of total assets (million USD)
LDR	Loan to deposit ratio (%)	$\frac{\text{Total loans}}{\text{Total deposits}} \times 100$
Capital	Total equity to total assets (%)	$\frac{\text{Total equity}}{\text{Total assets}} \times 100$
ROA	Bank profitability (%)	$\frac{\text{Net income}}{\text{Total assets}} \times 100$
IDIV	Income diversification	$1 - \left(\frac{\text{NII}}{\text{NOP}}\right)^2 - \left(\frac{\text{NON}}{\text{NOP}}\right)^2$ In which: NII: Net interest income NON: Non-interest income NOP: Operating income
Liquidity	Bank liquidity (%)	$\frac{\text{Cash and cash equivalents}}{\text{Total assets}} \times 100$
Macroeconomics variables		
M2Growth	M2 growth rate (%)	$\left(\frac{\text{Total M2 year t}}{\text{Total M2 year t} - 1} - 1\right) \times 100$
GDP	Economic growth rate (%)	World Bank database
Inflation	Inflation rate (%)	IMF database
FC	Financial crisis	Dummy variable representing the period of the global financial crisis; taking the value 1 for the period 2007-2009, and 0 otherwise
COVID	COVID-19 pandemic crisis	Dummy variable representing the period of the COVID-19 crisis; taking value 1 for the period 2020-2022, 0 for otherwise

3.2. Research Methodology

To investigate whether the interplay between bank-specific variables, macro-level variables, and credit growth in the ASEAN banking sector differs across loan growth quantiles, this paper employs the Method of Moments Quantile Regression (MM-QR) proposed by Machado and Silva (2019). Unlike traditional panel estimators that focus

on the conditional mean, MM-QR facilitates the analysis of the entire conditional distribution of the dependent variable. This enables a deeper exploration of distributional heterogeneity across different quantiles of credit growth, thereby offering more nuanced policy insights.

The use of quantile regression is both theoretically and empirically justified for several reasons. Firstly, the ordinary least squares (OLS) estimator is limited by its reliance on mean estimates and the assumption of homogeneity, which may not hold in banking data characterized by asymmetric risks and varied credit behavior. In contrast, quantile regression estimates conditional quantile functions, allowing the model to account for latent heterogeneity in the sample and produce robust estimates even in the presence of outliers and non-normal distributions. Secondly, MM-QR incorporates individual fixed effects and addresses potential endogeneity by using lagged instruments and moment conditions, which improves estimation reliability. Furthermore, this method does not require strict assumptions about the distribution of the dependent variable, and it performs well when traditional mean-based estimators yield biased or inconsistent results. Formally, the MM-QR model used in this study is specified as follows:

$$Q_{y_{it}}(\tau|x_{it}) = \alpha_i(\tau) + x'_{it}\beta(\tau)$$

Where $Q_Y(\tau|X_{it})$ denotes the conditional quantile of the credit growth variable y_{it} for bank i at time t, given covariates x_{it}. The term $\beta(\tau)$ captures the marginal effect of explanatory variables at quantile τ, and $\alpha_i(\tau)$ denotes the quantile-specific fixed effects that absorb unobserved heterogeneity across banks.

Before conducting the quantile regression, following Machado and Silva (2019), Dao, Chu, Shahbaz, and Tran (2024), and Payne, Truong, Chu, Doğan, and Ghosh (2023), several diagnostic tests are carried out to validate the assumptions of the econometric approach. To account for potential interdependence among banks in the panel dataset, the presence of cross-sectional dependence is examined using the test developed by Pesaran (2004). To assess the distributional characteristics of the dataset, normality tests including the Shapiro-Wilk W test, the Skewness/Kurtosis test, and the Jarque-Bera test are implemented. Furthermore, unit root tests are conducted to determine the stationarity of the panel series. Second-generation tests such as the Cross-Sectionally Augmented IPS (CIPS) proposed by Pesaran (2007), are employed depending on the presence of cross-sectional dependence. In instances where variables are found to be non-stationary at level, their first differences are taken before further analysis. Additionally, to examine the existence of long-run equilibrium relationships among variables, panel cointegration tests introduced by Kao (1999), Pedroni (1999), Pedroni (2004), and Westerlund (2005) are utilized.

Once stationarity and cointegration conditions are satisfied, the MM-QR estimation is performed across multiple quantiles. This allows the study to capture the heterogeneous marginal effects of explanatory variables across different points of the conditional distribution of credit growth, thereby offering richer and more policy-relevant insights into the dynamics of banking sector credit expansion within ASEAN economies.

Table 2. Descriptive statistics.

Variables	Observation	Mean	Std. dev	Min.	Max.
LG	2,518	15.99	67.47	-70.92	2919.88
NPL	2,518	3.58	4.53	0.01	56.05
Size	2,518	8.64	1.78	3.32	13.23
LDR	2,518	89.85	70.53	2.04	2932.87
Capital	2,518	12.21	6.50	-27.49	87.59
ROA	2,518	0.95	3.24	-148.07	8.90
CIR	2,518	55.45	21.62	-7.65	378.80
IDIV	2,518	0.31	0.19	-4.18	0.50
Liquidity	2,518	17.97	10.48	0.85	82.44
M2Growth	2,518	10.73	6.31	-2.05	39.41
GDP	2,518	4.58	3.12	-12.02	14.52
Inflation	2,518	3.51	3.04	-1.26	24.10
FC	2,518	0.07	0.26	0	1
COVID	2,518	0.22	0.41	0	1

4. EMPIRICAL RESULTS

Table 2 presents the descriptive statistics of the dataset used in this paper. Credit growth (LG) among ASEAN banks during the period 2000–2022 ranges from –70.92% to 2919.88%, with a mean value of 15.99% and a standard deviation of 67.47. These figures indicate a substantial disparity in credit growth rates across banks in the ASEAN region. The highest annual credit growth was recorded by MBSB Bank Berhad (Malaysia) in 2018, while the lowest credit growth was observed for Citibank Berhad (Malaysia) in 2022.

Table 3 presents the results of the correlation matrix between independent variables. The results indicate that the correlation coefficients of the independent variables are all below 80%. Therefore, the independent variables exhibit low correlation coefficients (no multicollinearity) and are suitable for regression analysis (Hair, Black, Babin, Anderson, & Tatham, 2006; Judge, Griffiths, Hill, & Lee, 1985).

Table 4 reports the effects of various determinants on Southeast Asian bank credit growth across the sample at the 10^{th}, 30^{th}, 50^{th}, 70^{th}, and 90^{th} quantiles of the dependent variable (LG). Diagnostic tests are presented in Appendix 1.

Table 3. Correlation matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) NPL	1.00												
(2) Size	-0.05	1.00											
(3) LDR	-0.07	-0.09	1.00										
(4) Capital	-0.17	-0.43	0.15	1.00									
(5) ROA	-0.23	0.07	0.05	0.16	1.00								
(6) CIR	0.13	-0.39	-0.06	0.10	-0.23	1.00							
(7) IDIV	0.05	0.31	-0.11	-0.15	0.04	-0.11	1.00						
(8) Liquidity	-0.01	-0.32	-0.16	0.16	0.03	0.03	0.04	1.00					
(9) M2Growth	-0.08	-0.34	0.00	0.09	0.03	0.07	-0.05	0.33	1.00				
(10) GDP	-0.11	-0.13	0.01	-0.01	0.03	0.01	-0.04	0.12	0.23	1.00			
(11) Inflation	-0.02	-0.21	-0.02	-0.01	-0.01	0.04	-0.08	0.14	0.32	0.28	1.00		
(12) FC	0.08	0.05	-0.05	-0.13	-0.05	-0.04	0.10	0.00	0.09	-0.08	0.23	1.00	
(13) COVID	-0.01	0.08	0.01	0.10	-0.02	0.00	-0.03	-0.09	-0.13	-0.45	-0.13	-0.15	1.00

Table 4. Empirical results.

Variables	Q10th	Q30th	Q50th	Q70th	Q90th
	LG	LG	LG	LG	LG
NPL	-0.4090***	-0.5551***	-0.6663***	-0.7921***	-1.0611***
	(0.0858)	(0.0737)	(0.1008)	(0.1483)	(0.2662)
Size	0.9636***	-0.2088	-1.1012***	-2.1106***	-4.2680***
	(0.3062)	(0.2624)	(0.3338)	(0.4720)	(0.8323)
LDR	0.0718***	0.0663***	0.0622***	0.0575**	0.0475
	(0.0175)	(0.0154)	(0.0185)	(0.0250)	(0.0425)
Capital	-0.7173***	-0.4387***	-0.2266*	0.0134	0.5262*
	(0.0843)	(0.0828)	(0.1188)	(0.1749)	(0.3124)
ROA	3.6617***	2.5038***	1.6224**	0.6254	-1.5056
	(0.5204)	(0.4921)	(0.6485)	(0.9173)	(1.6004)
CIR	-0.0161	-0.0234	-0.0291	-0.0354	-0.0491
	(0.0321)	(0.0277)	(0.0354)	(0.0501)	(0.0879)
IDIV	-10.0662***	-4.4452	-0.1667	4.6729	15.0172*
	(3.4221)	(2.9584)	(3.6351)	(5.0270)	(8.7275)
Liquidity	-0.0545	0.0124	0.0634	0.1209	0.2440*
	(0.0488)	(0.0432)	(0.0541)	(0.0751)	(0.1299)
M2Growth	0.5929***	0.6133***	0.6288***	0.6464***	0.6838***
	(0.0773)	(0.0692)	(0.0823)	(0.1097)	(0.1843)
GDP	0.6588***	0.6290***	0.6064***	0.5807***	0.5259
	(0.1188)	(0.0987)	(0.1288)	(0.1868)	(0.3341)
Inflation	-0.9096***	-0.6547***	-0.4606***	-0.2412	0.2279
	(0.1594)	(0.1333)	(0.1463)	(0.1887)	(0.3196)
FC	4.9040***	5.7789***	6.4449***	7.1982***	8.8083**
	(1.3345)	(1.1922)	(1.5547)	(2.2076)	(3.8579)
COVID	-1.2526	-2.7402***	-3.8725***	-5.1533***	-7.8910***
	(0.8700)	(0.7350)	(0.9249)	(1.3103)	(2.3138)
Constant	-13.9453***	0.5282	11.5452**	24.0068***	50.6423***
	(4.7451)	(4.1975)	(5.6259)	(8.1099)	(14.2894)

Note: Table 4 presents the results of the quantile regression analysis evaluating the determinants of credit growth among banks in the Southeast Asian region. The dataset has been winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4 reveals several noteworthy findings. Regarding credit risk (NPL), the results indicate a statistically significant negative impact on credit growth across all quantiles, particularly pronounced among banks with high lending growth. Specifically, the coefficient of NPL is -0.4090 at the 10th percentile of credit growth and increases in magnitude to -1.0611 at the 90th percentile more than 2.5 times larger. This suggests that credit risk exerts a more substantial constraining effect on credit expansion among high-growth banks in the Southeast Asian sample. This asymmetry can be attributed to the fact that high-growth banks often pursue more aggressive risk-taking strategies, expanding lending portfolios to riskier customer segments or volatile sectors. While such strategies may yield higher returns under stable conditions, they become increasingly vulnerable during episodes of rising credit risks, such as deteriorating asset quality, liquidity strain, or macroeconomic downturns. In these contexts, banks must increase loan-loss provisions and strengthen risk buffers, thereby limiting their capacity to sustain rapid credit expansion. Moreover, banks operating at higher credit growth percentiles typically manage larger loan portfolios, requiring stricter compliance with capital adequacy ratios and provisioning standards, both internally and under regulatory oversight. When early signals of credit risk emerge, these banks are more likely to tighten lending standards, heighten borrower scrutiny, and reduce exposure to high-risk clients. As a result, their credit growth declines more sharply, given the limited flexibility to swiftly recalibrate large loan books and the pressure from investors to uphold risk governance. Conversely, banks with lower credit growth tend to adopt more conservative lending practices, targeting lower-risk clients and more stable sectors, thereby insulating themselves more effectively from credit risk escalation.

Regarding bank size (Size), the quantile regression results in Table 4 reveal a nonlinear relationship with credit growth across the distribution of bank lending. Among institutions at lower quantiles of credit growth, those with

relatively subdued lending performance—where increasing size is positively associated with higher credit expansion—benefit significantly from scale enhancements. This suggests that smaller banks, which often face constraints in operational capacity, brand recognition, and funding access, benefit from scale improvements. As these banks grow, they are better positioned to expand branch networks, enhance credibility, and access more diversified funding sources. These improvements facilitate greater lending activity, thereby contributing to accelerated credit growth. Moreover, scaling up allows smaller institutions to exploit economies of scale, reducing average operating costs and strengthening their competitive positioning in the credit market. Conversely, for banks at the median and upper quantiles of credit growth, the relationship between size and credit expansion becomes negative. This inversion may be driven by the onset of diseconomies of scale, wherein excessive organizational expansion results in rising managerial and coordination costs, bureaucratic inefficiencies, and reduced agility in credit decision-making. In such cases, larger banks may experience declining marginal benefits from further growth, which dampens their ability—or strategic willingness—to expand credit portfolios. Additionally, large banks tend to adopt more conservative risk management strategies, prioritizing balance sheet stability and long-term sustainability over rapid credit growth. These institutions often diversify into non-interest activities, such as investment banking or fee-based services, reducing their dependence on loan-based income. Furthermore, having already exploited most viable lending opportunities, further expansion in scale may no longer yield proportionate increases in credit growth. Thus, while growth in bank size may catalyze credit expansion for smaller banks, it may instead constrain it among already large, high loan growth rate institutions.

Regarding the loan-to-deposit ratio (LDR), the findings in Table 4 indicate a positive association with credit growth among Southeast Asian banks in the sample, with this effect being more pronounced for institutions operating at lower quantiles of credit growth. This suggests that for banks with limited lending momentum, improving the LDR reflecting a more aggressive deployment of deposits into loans can serve as a key mechanism to enhance credit expansion. Similarly, improvements in operational efficiency, as measured by return on assets (ROA), appear to yield stronger credit growth benefits for banks in the lower quantiles of LG compared to their higher-growth counterparts. Banks with low credit growth often face structural challenges such as suboptimal resource utilization, high operating costs, and weak profitability. As ROA increases signaling more efficient use of assets to generate income, these banks are able to bolster internal capital, improve their reputation, and build investor and depositor confidence. The resulting increase in mobilized funding facilitates greater lending capacity and supports a more robust credit growth trajectory. In contrast, banks situated at higher quantiles of credit growth typically exhibit already optimized operations and strong financial performance. For these institutions, further gains in ROA may not significantly translate into increased credit activity, as their lending portfolios are already well-established and stable. In such cases, improvements in ROA are more likely to enhance profit margins than to stimulate additional loan growth. Thus, for banks in the lower LG quantiles, strengthening ROA carries strategic significance; not only does it sharpen competitive positioning, but it also acts as a critical lever for revitalizing credit growth and elevating their market standing within the financial sector.

With respect to the equity-to-assets ratio (Capital), the results in Table 4 reveal a differentiated impact across credit growth quantiles. For banks positioned in the lower quantiles of credit growth (i.e., lower LG levels), an increase in the capital ratio is associated with a decline in credit growth. In contrast, among high-growth banks (higher LG quantiles), a stronger capital base appears to facilitate further expansion of credit. This divergence may be explained by differences in institutional priorities and strategic orientation. Banks with limited credit growth often focus on strengthening their capital buffers as a defensive strategy to enhance resilience against potential risks, rather than pursuing aggressive lending. Raising the equity-to-assets ratio in these institutions may reflect efforts to develop or adopt more conservative lending policies, thereby constraining credit expansion. Moreover, low-growth banks typically face greater pressure to improve asset quality and financial credibility, leading them to favor safer investment activities over rapid loan portfolio growth. Conversely, high-growth banks often operate with robust

operational frameworks and well-defined expansion strategies. For these banks, a higher capital ratio serves as a facilitator rather than a limitation, enabling them to expand lending while maintaining credit quality. A robust capital foundation supports regulatory adherence, improves access to global funding markets, and bolsters confidence among clients and investors. Collectively, these elements equip banks with the financial strength and reputational credibility needed to sustain and further drive credit growth.

The findings in Table 4 reveal a contrasting relationship between income diversification (IDIV) and credit growth across its distribution. For banks at the lower end of credit growth (notably the 10th percentile), increased income diversification is linked to reduced lending activity. Conversely, for banks at the upper end (90th percentile), greater income diversification tends to bolster credit expansion. This disparity arises primarily from differences in strategic priorities and resource allocation. Banks experiencing low credit growth often prioritize non-interest income streams—such as fees from services, investments in securities, or other non-lending activities—as a means to compensate for weak lending performance. While this strategy may provide short-term revenue stability, it frequently shifts managerial focus and financial resources away from core lending activities. As a result, these banks may exhibit reduced commitment to expanding credit, leading to restrained lending despite enhanced income diversification. In contrast, banks with high credit growth typically benefit from well-established lending frameworks and operational efficiency, enabling them to use non-interest income as a supplementary resource to fuel further credit growth. Revenue from non-lending activities strengthens internal capital reserves and reduces reliance on traditional interest-based income. This, in turn, lowers the cost of capital and enables banks to extend credit more competitively. Additionally, diversified revenue streams provide financial flexibility, enabling these institutions to assume greater lending risk and expand into new borrower segments. The integration of multiple income channels also mitigates overall risk exposure, strengthens financial resilience, and creates favorable conditions for sustained credit expansion.

With respect to macroeconomic variables, the results in Table 4 further reinforce the conclusion that growth in broad money supply (M2) has a positive effect on bank credit expansion across Southeast Asia. Notably, this effect is more pronounced among banks situated in higher credit growth quantiles (i.e., higher LG levels). Increased M2 enhances system-wide liquidity and expands the deposit base, thereby enabling banks with aggressive lending strategies to capitalize on a more favorable funding environment and scale up credit disbursement more efficiently. In contrast, GDP growth exerts a relatively stronger influence on banks operating at lower credit growth levels. During periods of economic expansion, the demand for credit from both households and businesses typically rises, creating ample opportunities for banks to expand lending. Institutions with historically modest credit growth often constrained by competition and limited market presence can leverage macroeconomic tailwinds to regain momentum, enhance financial performance, and attract a broader client base. Moreover, in a buoyant economy, the perceived credit risk declines as borrowers' repayment capacity improves. This favorable environment enables low-growth banks to lend more confidently, supported by reduced concerns over defaults and non-performing loans. These banks may also adopt more flexible lending policies to attract new borrowers and diversify their loan portfolios. By contrast, high-growth banks may already be approaching lending saturation, where further expansion becomes increasingly difficult due to market limitations or heightened competition. Consequently, the marginal benefit of GDP growth on credit expansion diminishes for these institutions. Regarding inflation, the regression results reaffirm earlier findings that higher inflation rates have a detrimental effect on bank credit growth in Southeast Asia, with this impact being significantly stronger among low-growth banks. Several factors explain this asymmetry. First, low-growth banks often serve smaller and more financially vulnerable clientele, who are disproportionately affected by rising borrowing costs in an inflationary environment. As interest rates increase in response to inflation, these customers face reduced credit availability, leading to lower loan volumes. Second, low-growth banks typically operate with narrower funding bases and higher costs of capital relative to larger, more established institutions. When inflation rises, central banks tend to tighten monetary policy, pushing up interest rates and funding costs, thereby compressing interest margins and weakening the incentive to expand credit. Additionally, inflation is frequently accompanied by macroeconomic

instability and rising default risk, particularly for smaller banks with weaker risk management capabilities. Conversely, banks with high credit growth tend to have stronger governance frameworks, better risk provisioning, and greater financial resilience. These institutions are better equipped to weather inflationary shocks and maintain investor and depositor confidence, allowing them to sustain or even expand credit despite adverse macroeconomic conditions. The divergence in customer base composition, managerial capacity, and capital strength between high- and low-growth banks explains why inflation tends to constrain credit more severely at the lower end of the distribution.

Regarding crisis-related variables namely the Global Financial Crisis (GFC) and the COVID-19 pandemic the results in Table 4 reveal divergent impacts on credit growth across quantiles. During the 2007–2009 global financial crisis, banks in Southeast Asia with higher levels of credit growth (i.e., upper LG quantiles) were more likely to increase lending. In stark contrast, during the COVID-19 crisis (2020–2022), the same group of high-growth banks exhibited a significant contraction in credit provision. During the GFC, Southeast Asian banks particularly those with strong pre-crisis credit growth pursued strategies aimed at market expansion. These institutions capitalized on relatively stable domestic credit demand, which stood in contrast to the sharp contractions observed in advanced Western economies. Additionally, accommodative monetary policy and fiscal stimulus packages implemented by ASEAN governments during this period provided a supportive environment for credit growth. The region was relatively insulated from the systemic financial collapse experienced in the United States and Europe, enabling banks with aggressive lending strategies to expand credit amidst global turbulence. However, the nature of the COVID-19 shock differed fundamentally. The pandemic triggered simultaneous demand and supply shocks across virtually all sectors of the economy, creating severe dislocations in credit markets especially for high-growth banks. These institutions, which typically pursue rapid loan book expansion by targeting high-yield but higher-risk segments such as small and medium-sized enterprises (SMEs), real estate, and retail, were disproportionately affected. These sectors experienced acute distress during lockdowns, supply chain disruptions, and sharp declines in consumer spending, resulting in increased loan defaults and repayment deferrals. Consequently, non-performing loan (NPL) ratios in these banks surged, compelling them to significantly increase loan-loss provisions, thereby limiting their capacity to issue new credit. In addition, the pandemic-induced collapse in aggregate credit demand further exacerbated the decline in lending activity among high-growth banks. Many of these institutions have adopted aggressive pre-crisis growth strategies that relied heavily on short-term or high-cost funding sources. During COVID-19, heightened risk aversion among investors and depositors led to liquidity pressures, as withdrawals accelerated, and funding costs rose. Simultaneously, cash flow disruptions from existing loans impaired the banks' ability to recycle capital, further constraining their lending capacity. Lastly, although government support measures across ASEAN—such as debt moratoria and interest subsidies were designed to ease borrower burdens, they inadvertently increased compliance, monitoring, and provisioning responsibilities for banks, particularly those with large and complex loan portfolios. For high-growth banks, these additional obligations added further strain to already stretched balance sheets, resulting in more cautious lending behavior and a sharp retrenchment in credit growth during the pandemic.

5. CONCLUSIONS AND IMPLICATIONS

This study investigates the determinants of credit growth across different quantiles of credit expansion in the ASEAN banking sector, utilizing the Method of Moments Quantile Regression (MM-QR). This approach enables a detailed analysis at various points within the conditional distribution of credit growth. The findings reveal significant asymmetry in the effects of both bank-specific and macroeconomic variables, emphasizing the importance of moving beyond mean-based models to capture distributional heterogeneity in bank behavior.

Among the bank-specific factors, non-performing loans (NPLs) consistently exhibit a statistically significant negative effect on credit growth across all quantiles, with the most pronounced impact observed among high-growth banks. This reinforces the imperative for robust credit risk management, particularly in institutions with aggressive

lending strategies. Bank size, capital ratio, and income diversification exhibit non-linear impacts: for banks with low credit growth, larger size and higher capital ratios enhance financial resilience, yet for high-growth banks, these factors may lead to inefficiencies or cautious strategies that restrain further lending. Notably, operational efficiency, as measured by return on assets (ROA), serves as a pivotal mechanism for boosting credit activity in underperforming banks. These insights indicate that bank-specific strategies must be customized not only to institutional attributes but also to their placement within the credit growth distribution. Macroeconomic factors also produce varied impacts across credit growth quantiles. Broad money supply (M2 growth) fosters credit expansion across all banks, with stronger effects on banks that have higher lending growth rates. In contrast, GDP growth primarily supports banks with lower credit growth by stimulating loan demand and enhancing borrower creditworthiness. Inflation, however, has a negative effect, particularly on low-growth banks, which often cater to more vulnerable clients and encounter higher funding costs. Crisis-related effects further underscore this asymmetry: while the 2007–2009 global financial crisis appeared to provide lending opportunities for high-growth banks in ASEAN, the COVID-19 pandemic significantly reversed this trend, severely contracting credit growth due to liquidity shocks, rising NPLs, and elevated risk aversion. From a policy perspective, the findings suggest that a one-size-fits-all regulatory framework may be suboptimal. Prudential measures should account for the heterogeneity in bank behavior and risk exposure across the credit growth distribution. Targeted support for low-growth banks particularly in times of crisis or high inflation may help mitigate systemic vulnerabilities. At the same time, capital and risk-based oversight of high-growth banks is essential to prevent excessive credit expansion and maintain financial stability in the region.

Funding: This research is supported by Banking Academy of Vietnam (Grant number: 4990/TB-HVNH).
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: The corresponding author can provide the supporting data of this study upon a reasonable request.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Writing—review & editing, original draft, visualization, validation, supervision, software, resources, project administration, methodology, investigation, funding acquisition, formal analysis, data curation, and conceptualization, Thi Hoang Anh Pham (T.H.A.P.); writing—original draft, visualization, validation, supervision, software, resources, investigation, and formal analysis, Trung Duc Nguyen (T.D.N.); writing—review & editing, original draft, supervision, methodology, investigation, funding acquisition, formal analysis, data curation, and conceptualization, Minh Nhat Nguyen (M.N.N.). All authors have read and agreed to the published version of the manuscript.

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Appendix 1. Diagnostic tests.

Table A1 presents the results of the CD-test for cross-sectional dependence.

Table A1. CD-test for cross-sectional dependence results.

Variables	CD-test	p-value	Conclusion
LG	85.91	0.00	Cross-sectional dependence between banks
NPL	19.33	0.00	Cross-sectional dependence between banks
Size	279.42	0.00	Cross-sectional dependence between banks
LDR	33.24	0.00	Cross-sectional dependence between banks
Capital	18.73	0.00	Cross-sectional dependence between banks
ROA	53.21	0.00	Cross-sectional dependence between banks
CIR	13.16	0.00	Cross-sectional dependence between banks
IDIV	13.98	0.00	Cross-sectional dependence between banks
Liquidity	60.48	0.00	Cross-sectional dependence between banks
M2Growth	171.19	0.00	Cross-sectional dependence between banks
GDP	363.64	0.00	Cross-sectional dependence between banks
Inflation	217.13	0.00	Cross-sectional dependence between banks
FC	107.45	0.00	Cross-sectional dependence between banks
COVID	445.04	0.00	Cross-sectional dependence between banks

Table A2 presents the results of the diagnostic tests for the normality distribution of the residuals.

Table A2. Diagnostic test for residuals' normality distribution.

Shapiro-Wilk W test for normal data				
Observations	***W***	***V***	***p-value***	***Conclusion***
2,518	0.84311	229.362	0.000	Residuals are not normally distributed
Skewness/Kurtosis tests for normality				
Observations	*Pr(Skewness)*	*Pr(Skewness)*	*p-value*	*Conclusion*
2,518	0.000	0.000	0.000	Residuals are not normally distributed
Jarque-Bera normality test				
Chi (2)		*p-value*		*Conclusion*
8486.00		0.000		Residuals are not normally distributed.

Figure 1 illustrates the Kernel density estimate.

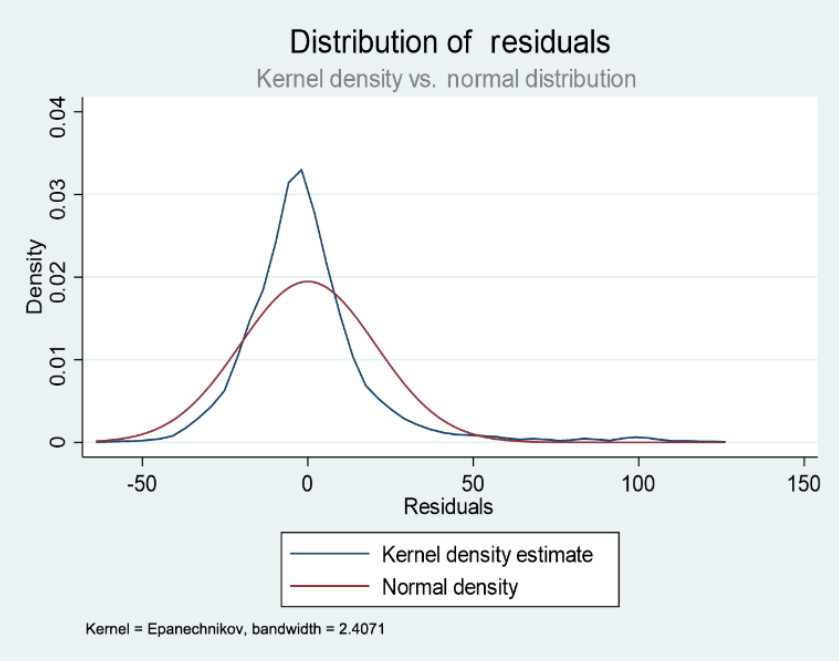

Figure 1. Kernel density estimate.

Table A3 presents the results of the panel unit root tests.

Table A3. Panel unit root test results.

Variables	Level		First difference		Conclusion
	Zt-bar	p-value	Zt-bar	p-value	
LG	-16.299	0.000	-27.332	0.000	Variable is stationary at both levels and first differences.
NPL	-7.364	0.000	-19.090	0.000	Variable is stationary at both levels and first differences.
Size	-6.091	0.000	-12.892	0.000	Variable is stationary at both levels and first differences.
LDR	-3.812	0.000	-21.490	0.000	Variable is stationary at both the level and the first difference.
Capital	-5.665	0.000	-20.887	0.000	Variable is stationary at both the level and the first difference.
ROA	-8.136	0.000	-24.301	0.000	Variable is stationary at both levels and first differences.
CIR	-6.542	0.000	-24.160	0.000	Variable is stationary at both the level and the first difference.
IDIV	-4.556	0.000	-24.576	0.000	Variable is stationary at both level and first difference.
Liquidity	-9.642	0.000	-27.483	0.000	Variable is stationary at both levels and first differences.
M2Growth	-15.955	0.000	-31.616	0.000	Variable is stationary at both levels and first differences.
GDP	-17.711	0.000	-35.077	0.000	Variable is stationary at both levels and first differences.
Inflation	-6.682	0.000	-27.396	0.000	Variable is stationary at both the level and the first difference.

Table A4 presents the results of the co-integration tests.'

Table A4. Co-integration test results.

Co-integration test	Statistic	p-value	Conclusion
Modified Dickey-Fuller	-11.1069	0.000	All panels are cointegrated
Dickey-Fuller test	-20.7087	0.000	All panels are cointegrated
Augmented Dickey-Fuller	-12.7605	0.000	All panels are cointegrated
Unadjusted Modified Dickey-Fuller	-30.4734	0.000	All panels are cointegrated
Unadjusted Dickey-Fuller	-28.2890	0.000	All panels are cointegrated