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**Article**

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# Liquidity creation and banking stability: an approach using the Bayes method

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## ABSTRACT

This research used the Bayesian method and Gibbs sampling algorithm on an unbalanced database and examined the impacts of the liquidity creation (LC) on the financial stability (FS) of the banks in Southeast Asian countries from 2007 to 2021. With both 'Cat Fat' and 'Cat Nonfat' method, the study results point out that LC has a positive impact on the BS within the ASEAN by enhancing the stability level of banks in these countries. The study findings of the impact of liquidity creation (LC) on banking stability (BS) within the Association of Southeast Asian Nations (ASEAN) are critically important because they provide profound implications for regulators and bank managers in determining LC behavior in emerging markets. These outcomes are particularly relevant to liquidity regulations as per Basel III standards. As such, assets with more liquidity are to be held while loans and deposits with illiquidity might cause unexpected effects when LC is reduced. More importantly, this article also contributes empirical results on the relationship between LC and BS. This is the first study to examine the correlation between LC and financial stability of Southeast Asian banks.

## PRACTICAL IMPLICATIONS

The study findings of the impact of liquidity creation (LC) on banking stability (BS) within the Association of Southeast Asian Nations (ASEAN) are critically important because they provide profound implications for regulators and bank managers in determining LC behavior in emerging markets. These outcomes are particularly relevant to liquidity regulations as per Basel III standards. As such, assets with more liquidity are to be held while loans and deposits with illiquidity might cause unexpected effects when LC is reduced. More importantly, this article also contributes empirical results on the relationship between LC and BS. Originality/value: This is the first study to examine the correlation between LC and financial stability of Southeast Asian banks.

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## 1. Introduction

The recent global financial crisis has shown that bank instability or excessive risk-taking capability is the leading cause of financial chaos (Duan & Niu, 2020). Banks have an incentive to maximize liquidity creation (LC) to increase profitability and bank value (Berger & Bouwman, 2009) because illiquid assets are more profitable than their counterparts. However, LC activities can negatively impact financial stability (FS) in the banking industry (Demirgüç-Kunt & Detragiache, 1998; Fungacova et al., 2021). Once an economic shock occurs, customer confidence drops, causing a bank run and leading to liquidity shortages and financial instability. Eventually, several banks are at risk of bankruptcy, threatening economic growth. Building a stable and thriving banking system, therefore, is a top priority (A. K. Mishra et al., 2020). Revealing that LC has a negative impact on banking stability (BS), Huong et al. (2021) believe that equity capital plays an important role in the relationship between LC and BS because it helps to absorb shocks, reduce banks' asset value. Dahir et al. (2018) concluded that a large equity capital enables banks to expand funding and helps absorb the risks of the above correlation.

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BS in Southeast Asian countries has recently been one of the top concerns among researchers for the region's economic integration, and rapid development has risen to the forefront of global economic growth (Wang & Lin, 2021) with outstanding profits compared to the global banking average (Hasanul & Alam, 2021). Banks in Southeast Asia are of great importance in promoting economic development (Lestari et al., 2023).

Liquidity shortages, one of the top concerns of recent instability and global banking crisis are the leading cause of many banks' failure. Together with the contagion effects, these failures have caused widespread damage to many banks and real economy (P. Mishra et al., 2012). Conversely, the case in which higher LC had led to more bank failure can be explained by the excessive liquidity risks incurred in the total assets of these banks. The LC level in Southeast Asian countries at 62.37% (Le & Pham, 2021) is higher than 50% (Berger & Bouwman, 2009) but lower than 23% (Fu et al., 2015), showing that is quite high in this area. Furthermore, banks in Association of Southeast Asian Nations (ASEAN) are required to hold a minimum of 8% of Common Equity Tier 1 capital, different from the 4.5% required by Jayadev. Stringent capital norms coupled with relatively higher LC levels in ASEAN may be responsible for the notable differences for this region. These contrast findings also explain more clearly why GFC hit the banking growth more heavily in some emerging economies. Le and Pham (2021) pointed out that Southeast Asian banks have a large deposit-to-asset ratio of about 86.5%, but a low loan-to-total asset ratio at an average of approximately 51.88% in the period of 2004–2014. This indicates that banks hold a larger proportion of deposit assets but low loan volume. Banks can increase deposit costs, reduce profits and capitalization rates, which can lead to higher risks or instabilities.

LC is necessary for financial markets to function smoothly, but excessive LC can reduce bank liquidity and increase risks (Berger & Bouwman, 2017; Gupta & Kashiramka, 2024). Therefore, creating the liquidity and stability for a bank plays an important role in developing countries. With the aim to examine the impact of the LC on BS, this study can provide relevant information oriented to guide the economies of the research region. The fact that the banking system in this region has heterogeneous development characteristics, Williams and Rajaguru (2022) provide an opportunity to determine significant factors affecting stability. Thus, the empirical research results will also provide substantial evidence and implications for policymakers in Southeast Asia.

Featured contributions of the article are listed as below:

First, using the similar approach of Berger and Bouwman (2009), the author focuses on banks' ability to create liquidity while other researchers concentrate on LC (Duan & Niu, 2020) *via* different approaches such as LC with bank capital (Berger et al., 2019; Berger & Bouwman, 2009; Toh, 2019); market power (Casu et al., 2019; Fu et al., 2016; T. T. H. Nguyen et al., 2023); profitability (Duan & Niu, 2020; A. Sahyouni & Wang, 2018); competition (Al-Khouri & Aroui, 2019; Jiang et al., 2019). It is rare to find studies on the application of LC measurement to the relationship between LC and BS, in which banks' ability to create liquidity has been standardized by total assets to avoid excessive weight on large banks, yet allowing meaningful comparisons among banks. Except (Berger et al., 2019; Gupta & Kashiramka, 2020), this may be the first study to examine the impact of LC on BS in the banking industry of Southeast Asia.

Second, using the Bayesian statistical method to examine the impact of LC on banking and BS in Southeast Asian countries overcomes the disadvantages of the statistical frequency method (Kruschke & Liddell, 2018). With the same approach, research has been conducted such as (Ha et al., 2021; Oanh et al., 2023; Rashid & Naeem, 2017), yet not in Southeast Asia.

Third, unlike previous studies in which data were solely collected from either a particular country or worldwide (Berger et al., 2019; Berger & Bouwman, 2017; Dahir et al., 2018; Fu et al., 2016; Huong et al., 2021), this article has a diverse and updated database of Indonesia, Malaysia, the Philippines, Vietnam and Thailand, the first five nations experiencing ABIF in Southeast Asia<sup>1</sup>.

Fourth, using a database collected from 2007 to 2021, the study provides in-depth insights into LC operations and BS after GFC, following the standard Basel III regulations for research.

Fifth, in addition to contributing to the literature overview in terms of the positive impacts of LC on the BS in the ASEAN, the research also found crucial factors affecting the BS in the region. These findings can be further generalized to provide insights into critical arguments for policy debates on the relationship between LC and BS, which is important to Southeast Asian countries.

By analyzing the impact of LC on BS, the author hopes to contribute important implications for banking supervision and management activities in ASEAN, especially in emerging and developing economies.

This article is structured into five parts. Parts 1 and 2 present the introduction, theoretical basis, and literature overview, respectively. [Section 3](#) establishes the research models and describes the measurement methods of the variables. Based on the constructed empirical model, [Section 4](#) provides statistical evidence and analyzes the research results. Finally, the research conclusions and policy implications are presented in [Section 5](#).

## 2. Liquidity creation and the impact of liquidity creation on banking stability

Banks create liquidity or LC by converting short-term debt with high liquidity into long-term assets with low liquidity by extending the off-balance sheet (Berger & Bouwman, 2009; Bryant, 1980; Diamond, 1996). Berger and Bouwman (2009) proposed a method to calculate liquidity in which banks function as liquidity suppliers for effective operations of the banking system and help promote economic growth (Gupta & Kashiramka, 2020). Note that higher LC is associated with greater profits (Duan & Niu, 2020) and more considerable value (Berger et al., 2019), it is encouraged to maximize LC among banks because illiquid assets generate higher returns than liquid assets. As both borrowers and depositors require liquidity at the same time, balancing the costs and benefits of LC (Berger & Bouwman, 2017) can have two side effects on FS, which has been a leading concern for many banks.

As a bank's main function, LC is considered the core measure of bank efficiency. As such, LC play a critical role in BS (Berger & Bouwman, 2009; Duan & Niu, 2020). Depending on the specific context, different impacts of LC on bank stability have been found in several studies over the years. Fidrmuc et al. (2015) and Gupta and Kashiramka (2020) suggest a higher probability of bank bankruptcy when LC of that bank soars beyond the optimal level based on High Liquidity Creation Hypothesis (HLCH). If the LC exceeds that level, banks will be unable to meet customers' needs for deposits and/or withdrawals due to a shortage of liquid assets. Illiquid assets of the bank must be sold at low prices, increasing the risk of loss for several banks (Allen & Gale, 2004). Liquidity transactions clearly increase banks' financial fragility (Diamond, 1996; Diamond & Rajan, 2005) as short-term deposits and long-term assets are incompatible in terms of duration, resulting in higher risks of financial weaknesses for the studied banks. According to HLCH, many banks face liquidity shortage risks while creating liquidity. In the case of a huge and sudden outflow of deposits, many banks must sell illiquid assets at cheap prices to address the above, which raises the possibility of bankruptcy. Similarly, an increase in LC reflects higher liquidity risks, resulting in an increase in likelihood of bankruptcy yet a drop in bank profits as the bankruptcy cost hypothesis (Tran et al., 2016). Noted the negative relationship between LC and FS, the research of (Berger et al., 2019; Chen & Xie, 2022; A. Sahyouni et al., 2021) has proposed the following hypotheses:

**Hypothesis 1:** LC has a positive effect on FS.

**Hypothesis 2:** LC has a negative effect on FS.

Different results on the relationship between FS and LC have been found in a variety of public banks in comparison with private sector banks applying the SGMM statistical probability method. Berger et al. (2019), Chen and Xie (2022), A. Sahyouni et al. (2021) pointed out a negative association between LC and FS while the opposite has been indicated in the research of Gupta and Kashiramka (2024). Studying the impact of LC on the profitability and FS of 9074 commercial banks from Q1/2001 to Q4/2016 using the FEM method (Duan & Niu, 2020) revealed that LC enhance the FS of banks. Additionally, Zhang et al. (2021) find that excessive LC has a U-shaped impact on systemic risk. Acknowledging inconsistent results from previous studies, and the significantly important role of LC in FS, the author decides to conduct this research to examine the link between LC of the banks and financial stability.

## 3. Research data and research methodology

### 3.1. Research data

Due to the issue of data inconsistency or multiple missing values from the study period of 2007–2021, the sample size of 10 countries was narrowed down to five Southeast Asian nations (Vietnam, Thailand, Indonesia, Malaysia and the Philippines). Singapore was also excluded to achieve the goal of maintain homogeneity in the sample. Our final sample includes 53 commercial banks and 795 observations with

unbalanced panel data for the period 2007–2021. As shown in Table 1, Indonesia had the highest sample size proportion (36%), followed by Vietnam (21%), Thailand (21%), Philippines (11%) and Malaysia (11%). The total assets of the 53 banks in this study account for approximately 75% of the total assets of the ASEAN banking industry, ensuring representativeness of banks in Southeast Asia. The research data were thoroughly reviewed to avoid inconsistencies, errors, and duplications across institutions. The number and percentage of banks in ASEAN -5 are detailed in Table 1.

### 3.2. The research variables

Based on a previous study of Berger et al. (2019), the author established a research model to examine the impact of LC on BS in Southeast Asian countries:

$$Zscore_{i,j,t} = \beta_0 + \beta_1 * Zscore_{i,j,t-1} + \beta_2 * LC_{i,j,t} + \beta_x X_{i,j,t} + \varepsilon_{i,j,t} \quad (1)$$

**Table 1.** Number of banks used in the study.

No	Country	Number of banks (N)	Number of observations	Percentage (%)
1	Vietnam	11	165	21
2	Thailand	11	165	21
3	Indonesia	19	285	36
4	Malaysia	6	90	11
5	Philippines	6	90	11
	Total	53	796	100

Source: Statistics collected by the author.

**Table 2.** Detailed description of variables in the model.

	Symbol	Measure	Expectation	Author
<i>Dependent variable</i>				
Bank stability	Zscore	$\frac{\mu(ROAA_{c,t}) + CAR_{i,t}}{\sigma(ROAA_{c,t})}$  In there: $\mu(ROAA_{c,t})$ is the average value of ROAA in country c in year t - $CAR_{i,t}$ is the capital of bank i in year t $\sigma ROAA_{c,t}$ is the standard deviation of ROAA of country c in year t		Berger et al. (2019), Gupta and Kashiramka (2020)
<i>Independent variables</i>				
Liquidity creation	LC	$\frac{\text{Liquidity creation}}{\text{Total assets}} \times 100$ Liquidity creation is determined by two metrics CatFat (LC1) and CatNonFat (LC2).	-	Berger et al. (2019), Berger and Bouwman (2017), Berger and Bouwman (2009), Dang and Huynh (2022); Duan and Niu (2020)
<i>Control variables</i>				
Bank size	SIZE	Ln(Total assets)	+	Gupta and Kashiramka (2020); Hasanul & Alam (2021), Tran et al. (2016), Zheng et al. (2019)
Capital adequacy ratio	CAR	$= \frac{\text{Equity capital}}{\text{Total risk-weighted assets}} \times 100$ (Equity capital)/(Total risk-weighted assets)	+	Gupta and Kashiramka (2020), Zheng et al. (2019)
Non-performing loans	NPL	$NPL = \frac{\text{Bad debts}}{\text{Loan Balance}} \times 100$ (Bad debt)/(Loan balance)	-	Gupta and Kashiramka (2020), Hasanul & Alam (2021), Zheng et al. (2019)
Cost/ income ratio	CIR	$CIR = \frac{\text{Total cost}}{\text{Total income}} \times 100$	-	Gupta and Kashiramka (2020), Hasanul & Alam (2021), Zheng et al. (2019)
Net interest margin ratio	NIM	$NIM = \frac{\text{Interest income} - \text{Interest cost}}{\text{Total assets}} \times 100$ (Interest income - Interest cost)/(Total assets)	+	Gupta and Kashiramka (2020), Hasanul & Alam (2021), Zheng et al. (2019)
Liquidity risk	LIQ	$= \frac{\text{Cash} + \text{deposits of other institutions}}{\text{Total assets}} \times 100$	+	Gupta and Kashiramka (2020), Hasanul & Alam (2021), Zheng et al. (2019)
Gross domestic product growth rate	GDP	$\frac{GDP_t - GDP_{t-1}}{GDP_{t-1}}$	+	Gupta and Kashiramka (2020), Hasanul & Alam (2021), Zheng et al. (2019)
Inflation ratio	INF	$\frac{CPI_t - CPI_{t-1}}{CPI_{t-1}}$	-	Gupta and Kashiramka (2020), Hasanul & Alam (2021), Zheng et al. (2019)

Table 2 summarizes the variables employed in this research and the related previous studies aligning with each variable. The independent variables are Bank Stability (BS). A dependent variable is the LC measures of CatFat and CatNonFat. Other control variables include bank size (SIZE); capital adequacy ratio (CAR); credit risks (NPL); cost income ratio (CIR); net interest margin (NIM); liquidity risk (LIQ); gross domestic product growth rate (GDP); inflation rate (INF).

Source: Summarized by the author.



**Table 3.** Liquidity classification of bank activities.

Illiquid assets (weight = 0.5)	Semiliquid assets (weight = 0)	Liquid assets (weight = -0.5)
Corporate loans	Interbank loans	Cash and due from institutions
Other assets	Loans to individuals	Total securities
Liquid liabilities (weight = 0.5)	Semiliquid liabilities (weight = 0)	Illiquid liabilities and equity (weight = -0.5)
Customer deposits	Deposits from institutions	Other liabilities
Trading liabilities	Other borrowed money	Equity
Illiquid off-balance sheet guarantees (weight = 0.5)	Semiliquid off-balance sheet guarantees (weight = 0)	Liquid off-balance sheet guarantees (weight = -0.5)
Loan guarantee commitments	Other off-balance sheet guarantees	All derivatives
Letters of credit commitments		

Note. Table 3 shows the construction of liquidity creation measurement. Berger and Bouwman (2009) and Fu et al. (2016) developed a measure for bank liquidity creation.

Here,  $Zscore_{(i,j,t)} = \ln$  (Z-score) are the dependent variables representing the BS  $i$  in country  $j$  in year  $t$ ;  $LC_{i,j,t}$  = Liquidity Creation Index of bank  $i$ , country  $j$  in year  $t$ ;  $X_{i,j,t}$  is the specific banking coefficient of bank  $i$  country  $j$  in year  $t$  (such as SIZE, NPL, CAR, CIR, NIM, LIQ) and macroeconomic factors in country  $j$  in year  $t$  (such as GDP and INF).

By using of the average value and estimating the standard deviation of returns over the entire sample period (Berglund & Mäkinen, 2019; Lepetit & Strobel, 2013), Z-score measure is widely used in banking and finance literature to measure the bank stability (Samarasinghe, 2023) for two reasons. First, it helps to eliminate the necessary exclusion of initial observations in rolling moment approach. Second, the 'spurious' volatility is reduced in the measure of bank failure, as shown in Lepetit and Strobel (2013). A higher Z-score implies higher bank stability and vice versa.

After the natural logarithm of the calculated Z-score had been taken, the impact of the extreme values of the Z distribution has declined (Lepetit & Strobel, 2013). As such, the calculation of Zscore in this paper is demonstrated as follows in Table 2.

### 3.2.1. Dependent variables

LC variable: According to the three-step process developed by Berger and Bouwman (2009), two LC measures of CatFat and CatNonFat are presented in Table 3. In Step 1, Berger and Bouwman (2009) classified on-balance sheet and off-balance sheet assets into liquid, semi-liquid, or illiquid assets based on the ease, cost and time required by banks to convert their obligations into liquid cash (for customers) or liquid cash obtained from customers' demands (from the bank). In Step 2, the weights of the classified activities are assigned. Finally, the LC measure is calculated by combining the activities in Steps 1 and 2.

$CatFat = 0.5 \times (\text{illiquid assets} + \text{liquid debt} + \text{illiquid off-balance sheet commitments}) + 0 \times (\text{semi-liquid assets} + \text{semi-liquid liabilities} + \text{semi-liquid off-balance sheet commitments}) - 0.5 \times (\text{liquid assets} + \text{illiquid debt and equity} + \text{liquid off-balance sheet commitments})$ .

$CatNonFat = 0.5 \times (\text{illiquid assets} + \text{liquid debt}) + 0 \times (\text{semi-liquid assets} + \text{semi-liquid debt}) - 0.5 \times (\text{liquid assets} + \text{illiquid debt and equity})$

After a three-step procedure, the final LC variables are obtained to regress on the ratio 'CatFat' or 'CatNonFat' to total bank assets, forming the variables CatFat and CatNonFat, respectively (Berger et al., 2019; Berger & Bouwman, 2017; Berger & Bouwman, 2009; Casu et al., 2019; Dang & Huynh, 2022; Duan & Niu, 2020; Fidrmuc et al., 2015; Fu et al., 2016).

### 3.2.2. Bank-specific variables and macroeconomic variables

In addition, several control variables have been considered important for evaluating banks' financial soundness and stability (Dang & Huynh, 2022; Zheng et al., 2019). For bank-specific factors, the study uses the natural logarithm of total assets to measure bank size (SIZE); Cost-to-income ratio (CIR); Net Interest Margin (NIM variable), CAR capital adequacy ratio to evaluate the quality of banks' capital management (CAR); the ratio of liquid assets to total assets (LIQ) reflects liquidity risk, and the ratio of non-performing loans (NPL). In addition, the Gross Domestic Product rate (GDP) and the inflation rate (INF), are two important factors, controlled for banks' macroeconomic characteristics.

### 3.3. Research methodology

The features of the Bayesian methodology help create appropriate research. With the assumption that the quantities of model parameters are random, conclusions in frequency statistics are based on datasets regardless of prior information Thach (2020) and population parameters are considered unknown fixed constants. According to Bayesian statistics, the parameters are assumed to be random variables following a distribution principle (Block et al., 2014). Conclusions of the Bayesian approach, drawn from a priori information, combined with the collected data set, are therefore considered more accurate (Miočević et al., 2017). Acknowledging the strong points of the Bayesian statistics from which conclusions do not depend on the size of the data and the drawbacks of frequency statistics are withdrawn (Miočević et al., 2017; My et al., 2022), many articles and books have summarized both advantages and challenges applying Bayesian approaches in social science research (Gelman & Hill, 2006; Lynch, 2007; Thach, 2020) and the banking sector (Ha et al., 2021; Oanh et al., 2023; Rashid & Naeem, 2017).

The Bayesian regression method based on the data set regardless of prior information (Miočević et al., 2017) and parameters are considered constants in frequency statistics. On the contrary, parameters in the Bayes statistics are assumed to be random variables, following a distribution law (Block et al., 2014). Different from the frequency statistics, conclusions in the Bayes statistics are based on a priori information that was combined with the collected data set, revealing higher accuracy (Rashid & Naeem, 2017). MCMC chain convergence diagnostics are applied to ensure that the Bayesian results, based on MCMC sample simulations, are reasonable and robust.

Based on the conditional distribution principle, the Bayesian analysis is conducted as follows

$$p(B) = \frac{p(A,B)}{p(B)} \quad (1)$$

The Bayes' principle is established by the formula below

$$p(A) = \frac{p(A|B)p(B)}{p(A)} \quad (2)$$

In which, A and B are two random vectors.

Assuming that the data vector  $y$  is a sample from a model with an unknown parameter vector  $\theta$ , this model can be rewritten using the likelihood function:

$$L(\theta; y) = f(y; \theta) = \prod_{i=1}^n f(y_i | \theta), \quad (3)$$

where  $f(y_i | \theta)$  is the probability density function of  $y$  for a given  $\theta$  value.

Based on Bayes' principle, it can be inferred that the model parameter  $\theta$  is random.

Bayes' principle begins with the definition of a posteriori model. This model combines the collected research data with prior information to describe the probability distribution of the parameters.

The posterior distribution includes of two components: First, the likelihood function which contains information regarding the parameters of the model, based on observed data; second, the prior distribution which contains the available information about the parameters in the model.

Posterior distribution  $\propto$  Likelihood function  $\times$  priori information

Because  $y$  and  $\theta$  are both random variables, we can apply Bayes' theorem to calculate the distribution.

$$p(y) = \frac{p(y|\theta)p(\theta)}{p(y)} = \frac{f(y;\theta)\pi(\theta)}{n(y)} \quad (4)$$

With  $n(y) \equiv p(y)$  is the marginal distribution of  $y$  and has the following form:

$$n(y) = \int f(y;\theta)\pi(\theta)d(\theta) \quad (5)$$

where  $n(y)$  is the posterior prediction probability distribution,  $f(y;\theta)$  is the likelihood function of  $y$  for a given  $\theta$  and  $\pi(\theta)$  is the prior distribution of  $\theta$ .



## 4. Research analysis

### 4.1. Statistical description

As shown in Table 4, the average Z-score variable of 53 banks in Southeast Asian countries reaches 20.23, while the standard deviation is 12.70 during the studied period, indicating that the Z-score index fluctuated strongly and unevenly during the research period. The averages of the LC1 and LC2 measures are 0.32 and 4.05, respectively, meaning that the difference between the ability to create liquidity according to CatFat (LC1) and CatNonFat (LC2) is not large. A very low average NIM is revealed at 0.48, which may be a concern in terms of bank profitability. The calculated data of the research is quite consistent with the estimate of Tran et al. (2016) from 27.53% to 32.19%. Conducted a research on several major listed banks in six-emerging Asia-Pacific economies from 2012 to 2016, Le and Pham (2021) show an average LC in Southeast Asia at 62.37%, consistent with the finding of 50% of Berger and Bouwman (2009), but larger than the estimate of Fu et al. (2015) (23%). The difference in calculations can be explained by the differences in banks size in samples collected from the involved research economies. Table 5 presents the results of the matrix in which the correlation coefficients are all less than 0.8 (Kennedy, 2008) and the VIF of all variables is less than 5 (Neter et al., 1996), thus most collinearity is not a concern in this study. The results table also shows that BS is positively correlated with LC, CAR, NIM, LIQ, GDP and BS is negatively correlated with SIZE, NPL, CIR and INF.

### 4.2. Dependent variable regression results

Table 6 indicates that the Monte-Carlo Standard Error (MCSE) values of the parameters are decimal numbers less than 0.1. The estimation results show that the acceptance rate of the model is equal to one. The acceptance rate in the multivariate regression model was above 0.15, which is optimal. In addition, the smallest effects of the three models were greater than the minimum level of 0.01. Therefore, all

**Table 4.** Descriptive statistics of variables in the model.

Variable	N.o	Average	Standard deviation	Min value	Max value
Z-score	795	20.226	12.706	0.130	90.491
LC1	795	0.317	0.140	−0.265	0.768
LC2	795	4.051	0.702	0.293	5.382
SIZE	795	32.232	1.420	27.194	35.105
CAR	795	4.069	3.773	−1.139	23.115
NPL	795	2.130	5.351	−0.000	31.040
CIR	795	0.333	3.064	0.000	86.302
NIM	795	0.481	1.687	0.000	23.905
LIQ	795	0.207	0.107	0.045	0.610
GDP	795	4.888	2.773	−9.573	8.464
INF	795	4.443	3.013	1.573	9.868

Detailed information regarding the variables Z-score, LC1, LC2, SIZE, CAR, NPL, CIR, NIM, LIQ, GDP and INF is provided in Table 2. The final sample includes 53 commercial banks, 795 observations with balanced panel data over the period of 2007–2021.

Source: Results processed using Stata 17.0 software.

**Table 5.** Autocorrelation results of variables in the model.

	Z-score	LC1	LC2	SIZE	CAR	NPL	CIR	NIM	LIQ	GDP	INF	VIF	Mean
Z-score	1.00												
LC1	0.03	1.00											
LC2	0.03	0.05	1.00										
SIZE	−0.06	0.03	0.02	1.00									
CAR	0.02	−0.01	−0.01	−0.24	1.00								
NPL	−0.08	−0.05	−0.09	−0.01	0.01	1.00							
CIR	−0.06	0.00	−0.04	−0.04	0.01	0.00	1.00						
NIM	0.00	0.06	−0.04	−0.01	0.08	0.05	0.00	1.00					
LIQ	0.15	−0.07	−0.03	−0.02	0.29	−0.08	−0.03	−0.01	1.00				
GDP	0.02	0.00	−0.12	0.04	0.23	0.01	0.02	0.07	0.03	1.00			
INF	−0.07	−0.05	−0.02	−0.01	0.36	0.08	0.02	0.06	0.01	0.01	1.00		
VIF		1.20	1.20	1.20	1.20	1.20	1.20	1.20	1.20	1.20	1.20	1.20	1.28

Table 5 discloses the correlation between all variables and Variance inflation factor (VIF) tests for detecting the severity of multicollinearity, including LC1, LC2, SIZE, CAR, NPL, CIR, NIM, LIQ, GDP and INF.

Source: Results processed using Stata 17.0 software.

**Table 6.** LC and BS in ASEAN-5 (the Bayesian regression results).

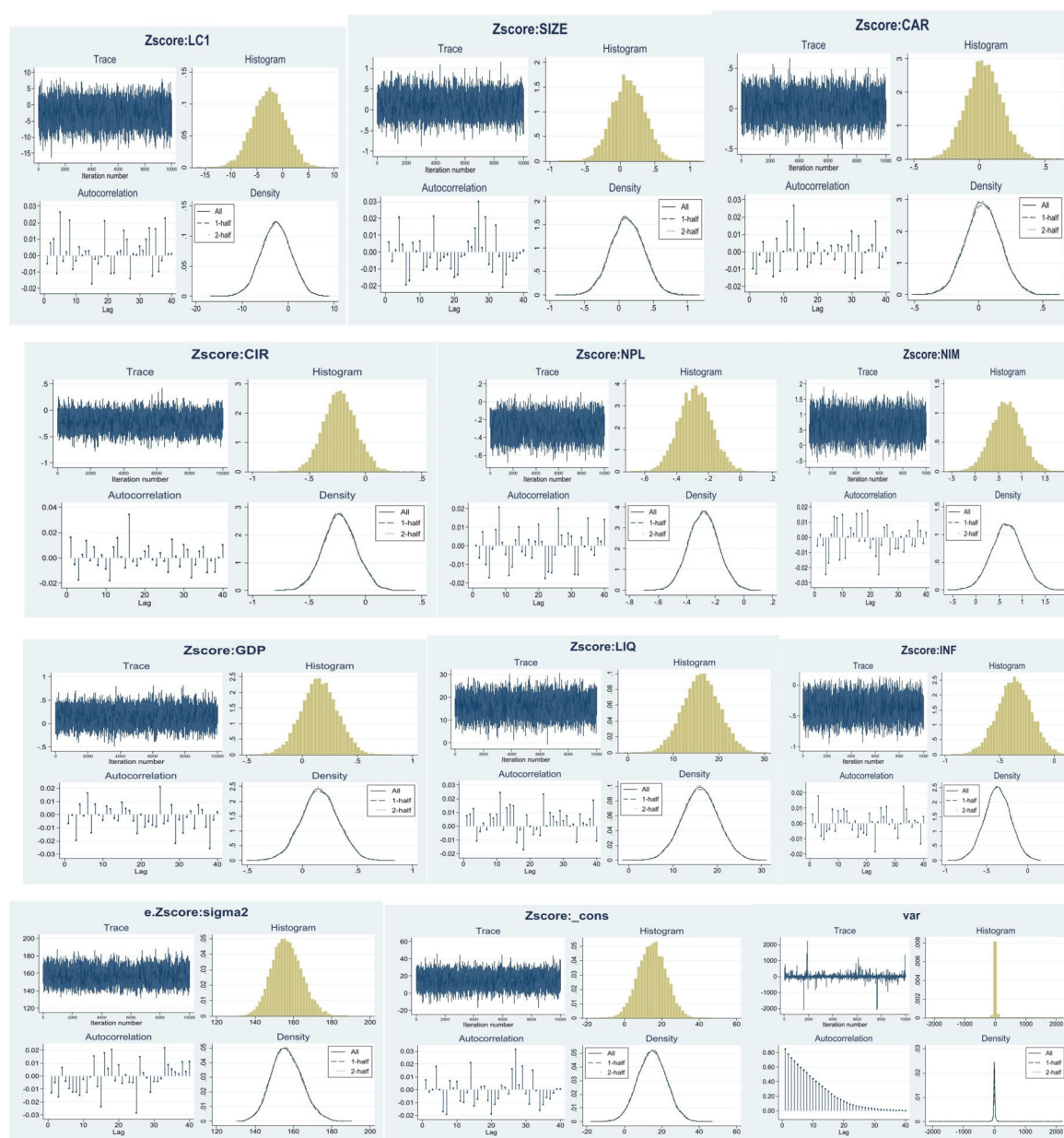
Independent variables	Dependent variables			
	Z-score (CatFat) (1)		Z-score(CatNonFat) (2)	
	Average of parameter series [standard deviation]	Standard error (MCSE)	Average of parameter series [standard deviation]	Standard error (MCSE)
LC1 _Var	2.627 [3.216]	0.032		
LC2 _Var			0.2143 [0.662]	0.006
SIZE	0.122 [0.238]	0.002	0.047 [0.233]	0.002
CAR	0.033 [0.136]	0.001	0.0491 [0.135]	0.001
NPL	−0.283 [0.103]	0.001	−0.275 [0.103]	0.001
CIR	−0.227 [0.145]	0.001	−0.227 [0.146]	0.001
NIM	0.676 [0.331]	0.003	0.643 [0.329]	0.003
LIQ	16.138 [4.012]	0.040	16.330 [4.105]	0.042
GDP	0.155 [0.166]	0.001	0.157 [0.167]	0.001
INF	−0.366 [0.157]	0.001	−0.363 [0.158]	0.001
_cons (Constant)	14.830 [7.567]	0.075	15.426 [7.576]	0.075
Average acceptance rate	0.918		0.911	
Minimal effect	0.050		0.050	
Number of observations	795		795	
Number of banks	53		53	

Source: Results processed using Stata 17.0 software.

regression models met the requirements. Furthermore, convergence diagnostics of the MCMC series have been applied to ensure the appropriateness of Bayesian inference in the MCMC sample simulation. In Bayes, the MCMC series autocorrelation test of variables was carried out using an autocorrelation model and Effective Sample Size (ESS) plots. Unlike the frequency statistical method, many tests of endogeneity or autocorrelation do not have to be executed owing to Bayes' advantage of generality. When the MCMC series converges, Bayesian inference becomes robust, and all the disadvantages of the frequency method are solved accordingly (Miočević et al., 2017; H. T. Nguyen et al., 2019). In addition to graphical convergence diagnosis, testing has also been proposed based on the average acceptance rate and the smallest efficiency (Grzegorzczuk, 2023).

The Bayesian regression results also provide a parameter for the MCSE. The MCSE coefficient shows the robustness of the MCMC chains. The closer the MCSE coefficient is to the value '0', the more robust is the MCMC chain. It is noted that the standard deviation is acceptable the MCSE less than 6.5%, and it reaches the optimal level when the obtained MCSE less than 5%. In order to ensure that the Bayesian inference based on the MCMC model is reasonable, the study conducts a test of the convergence of MCMC using a graphical visual diagnosis method. If the trace graphs run quickly through the distribution, the autocorrelation histogram drops quickly, indicating low autocorrelation, and the shape of the histograms simulating the shape of the probability distributions is identical, it can be concluded that the Bayesian regression is stable. As illustrated in Figures 1 and 2, Bayesian inference was proven to be strong. Figures 1 and 2 show trace plots quickly pass the distribution. The autocorrelation plot drops quickly to show low autocorrelation. The shapes of the probability distribution Histograms are all homogeneous. These graphs also show good mixing with the autocorrelation coefficient fluctuates at 0.02 and below (Miočević et al., 2017; H. T. Nguyen et al., 2019) relevant to the distributed simulation density. Besides, all delays reflected are obviously within the effective limits. The above evidence clearly leads to the conclusion that the Bayesian inference is robust.

Besides, Table 4 shows that the average CatNonFat/Total Assets and CatFat/Total Assets ratios of the Southeast Asia region are 4% and 0.3%, respectively in the period of 2007–2021, which is lower than many developed countries such as United States at 20% in 2003 (Berger et al., 2019), Russia approximately more than 28% in 2007 (Fidrmuc et al., 2015) and 29% in Western Europe during the period of

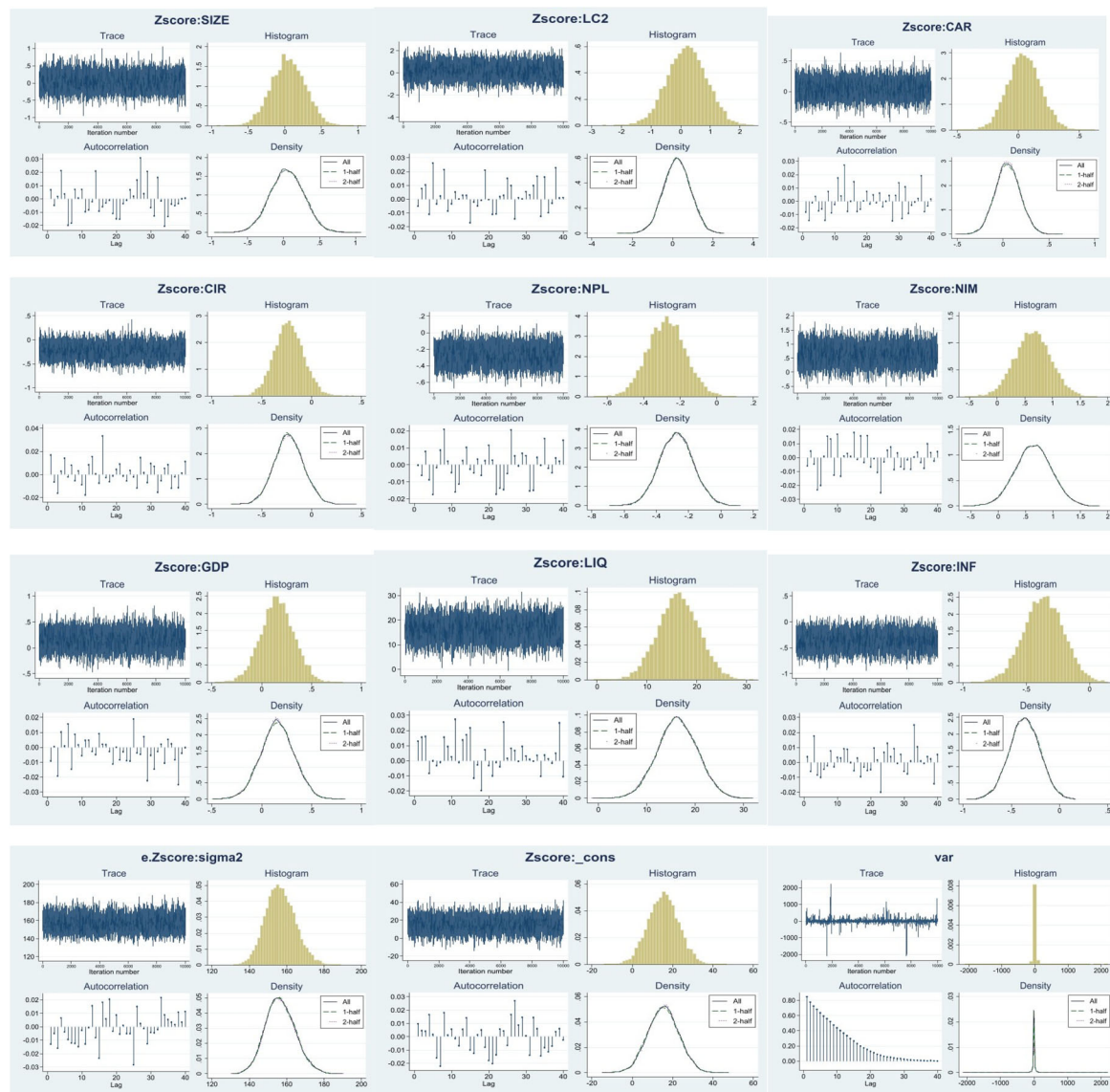


**Figure 1.** Convergence test of MCMC series for Z-score variable (1- CatFat). Figure 1 with the convergence diagnostic results for the Z-score variable (1- CatFat), MCMC test for convergence through visual diagnostics, shows that all parameters in the model are quite appropriate, low autocorrelation is indicated regarding the trace plots and correlograms; homogeneous histograms with standard distribution shapes are also illustrated. Source: Results processed using Stata 17.0 software.

2004–2018 (Yeddou & Pourroy, 2020). The relatively low LC level in ASEAN contributes to the positive impact on BS.

Model (1) for variable (LC1) and model (2) for variable (LC2) in Table 6 both show similar results regarding the same direction of the impact of LC on BS (Zscore), indicating that banks are less interested in engaging in excessive risk-taking liquidity. The results show that LC increases the BS of banks, similar to Gupta and Kashiramka (2020), Javid et al. (2023) and Zheng et al. (2019) yet different from the research results on developed economies in other regions. Noticing that increasing LC together with increasing banks' capital will create a moral hazard channel, many banks try to limit the moral issues by holding more capitals (Nguyen et al., 2019), which promotes the stability of the banks.

Contrast with the above Berger et al. (2019) and Fidrmuc et al. (2015) suggest that liquidity created conventionally increases the risk of bank failure. It is the excessive risk-taking LC in their total assets that leads a number of banks with high LC level in developing countries to failures. Conversely, relatively low



**Figure 2.** Convergence test results of MCMC series for Z-score variable (2- CatNonFat). **Figure 2** with the convergence diagnostic results for the Z-score variable (2- CatNonFat), MCMC test for convergence through visual diagnostics, shows that all parameters in the model are quite appropriate, low autocorrelation is indicated regarding the trace plots and correlograms; homogeneous histograms with standard distribution shapes are also illustrated. Source: Results processed using Stata 17.0 software.

LC levels contribute to the positive impact of LC on bank stability, emphasizing that banks do not engage in excessive risk-taking liquidity activities. H. T. Nguyen et al. (2019) suppose that a franchise channel will be created by a raise of LC and funding in which the greater capital of the banks reduces their future periodical profits, thereby damaging their franchise values. This encourages banks to take more risks (H. T. Nguyen et al., 2019) and consequently reduces their FS. Stemming from the uneven level of development of the banking systems among ASEAN countries, the LC restrictions implemented in emerging and developing economies may be a prudent decision to avoid an increase in the system-wide 'bank fragility' (Berger et al., 2019). In addition, the standard errors of the MCMC chain are quite small decimal numbers, demonstrating the high reliability of the estimated parameters. Additionally, the model's acceptance rates are 0.9182 and 0.9113, respectively (higher than the required level of 0.15). Overall, the Metropolis-Hastings sampling algorithm is effective (Gelfand et al., 1990). If the MCMC chains converge, it can be concluded that the model is strong (Thach, 2020).

Besides, as shown in [Table 6](#), variables of SIZE, CAR, NIM, LIQ, GDP affect Zscore in the same direction while the rest NPL, CIR, INF show a reverse impact in both models (1) and (2).



The size of the bank measured through the SIZE indicator/variable has a positive relationship with the BS. The hypothesis of the franchise values suggests that large banks have an incentive to mobilize additional capital to limit unforeseen risks (Ahmad et al., 2008). The existence of a few restrictions on the capital access in the markets allows the majority of large banks to raise more external capital easily, thereby their financial flexibility increases, following a lower capital ratio (Le & Pham, 2021). The capital of the bank measured by CAR has a positive association with the bank stability. As a cushion, the capital, if large enough, can mobilize external funding to the risky LC. However, certain liquid liabilities that are considered stable funding sources of the bank can be replaced by its capital when the bank faces greater illiquidity situations (Fu et al., 2015). Banks at risks are subject to stricter legal supervisions with greater requirement for the capital proportion. However, great risk-taking liquidity activities combined with lower capital proportions are obviously indicators of the banks with moral risks. Profitability measured through NIM has a significant positive association with the bank's stability (Berger et al., 2019; Fidrmuc et al., 2015). The bank's profitability raising higher equity capital can affect the LC of the banks (Berger & Bouwman, 2017). Because of the difference between assets and liabilities, banks can hold more liquid assets to control liquidity risk. Liquid assets usually generate lower returns than illiquid assets, so holding more liquid assets will reduce the bank's profits. The significant negative coefficient of credit risk indicators (NPL, CIR) in model (1) and model (2) shows that the higher credit risks result in the greater instability of the banks, consistent with the results of Zhang et al. (2021). LC of the banks is expected to have a positive impact on the credit risks (Diamond & Rajan, 2005), which can be greater if the banks do not evaluate and monitor borrowers effectively before financing numeral economic projects via loans. For a better operation management, the ratio of non-interest expenses to total assets (CIR) is used. If the management system is weak, banks may not be able to control operating costs and borrower monitoring costs effectively, which may lead to higher liquidity risks. However, according to the cost management hypothesis, many banks tend to save operating costs by reducing credit monitoring costs and collateral pricing to achieve economic efficiency, in the short term. These activities cause a decline in loan quality, resulting in higher risks. Similar to the research findings of Berger et al. (2019), the GDP growth rate positively affects the stability of the banks, reflecting that the stability of banks increases during the economic development, but decreases during economic contraction. A reduction in the inflation rate (INF) is likely to improve the financial conditions for many households, enabling them to repay loans quickly and regularly (Le & Pham, 2021). On the other hand, when banks react less to changes in interest rates and remain lending rates, based on the inflation forecasts, at a high enough level, the bad debts are likely to be reduced due to an increase in the inflation rates.

## 5. Conclusion and policy implications

Applying a new approach of Berger and Bouwman (2009) with the use of the Bayesian method on an unbalanced database of 53 ASEAN banks to analyze the impact of LC on banking FS in the period 2007–2021, the researcher has drawn the following implications.

First, the analysis focuses only on the Southeast Asia region, with the most recently updated database of several representative banks. The study's findings can be generalized to provide in-depth insights into critical policy debates on the relationship between LCs and BS. These research outcomes directly impact BS in the studied countries. Either a lower or higher LC can signal BS because the result directly affects banks' balance sheets. It is noted that different sizes of the banks indicate different levels of stability when LC varies (Gupta & Kashiramka, 2024), therefore, 'one-size-fits-all' regulations should be taken into account by policy makers.

Second, this study adds to the empirical literature on the positive impact of LC on BS, within the Southeast Asian countries studied. Banks with lower LC are less likely to withdraw capital because they are independent from core funding sources (transaction deposits). However, they rely on volatile long-term funding sources (syndicated loans and bonds). Consequently, a higher risk of failure is revealed because of the possibility of unexpected declines in alternative financial sources. A lower LC limits the supply of credit, and subsequently increases the likelihood of bank failure (Chatterjee, 2018). This implies that maintaining a high liquidity buffer (and creating less liquidity) may have negative externalities, resulting in illiquidity in the market and greater risk of bank failure. Using different strategies, banks facing higher liquidity risk may choose to hoard more liquidity for anticipated future financial difficulties. Thus, creating more liquidity can be a healthy financial sign for many banks.

By the research findings, this article has proposed implications for bank managers and policy makers in emerging and growing markets.

First, bank regulators need to be cautious in setting capital-related regulations so that commercial banks can avoid higher liquidity risks, in case of over-optimal LC.

Second, the LC process significantly reduces the bad debts. It is recommended that more bank reforms should be implemented to offer a diversity of liquidity services to the economy. According to the LC process, an increase of the credit quality is recorded as borrowers have more opportunities to repay their debts.

Third, following the Basel II standard can create lower liquidity for the banking system. LC, however, at a higher level can lead to more failures. Therefore, it is essential for regional authorities to balance the benefits of greater LC and a stronger the FS via implementing tighter capital requirements to strengthen the banking sector.

The research results have several policy implications. A trade-off between BS for the larger capital requirements as proposed by Basel III and the benefits of greater LC. Tightening capital requirements can reduce the credit risks as well as liquidity generation, which hinders the economic growth. However, creating greater liquidity may reduce the bank's capital following higher risks. Either of the decision can be beneficial in both directions, all the research governments are highly recommended to take this antagonistic relationship into consideration while implementing new capital requirements based on the Basel framework. Regarding the LC implications, the Government needs to further promote the competitiveness in the banking system so that the LC of the economy can be greatly enhanced.

Noticing that the research has been conducted within a short time with the research sample of five emerging markets, the author suggests that future studies should be done in other developed economies to ensure the reliability of the result trends.

### Author contribution statement

Thanh Nga Thi Tran ([ngatcnh@ufm.edu.vn](mailto:ngatcnh@ufm.edu.vn)): conceived and designed the experiments, performed the experiments, analyzed and interpreted the data, and wrote the first and final drafts of the manuscript.

### Disclosure statement

No potential conflict of interest was reported by the author.

### Note

1. The research data gathered from five largest ASEAN economies (accounting for more than 87% the region's total GDP from the period of 2007–2016) is considered sufficient to represent for the whole region. Limited data resources from the other five (Cambodia, Brunei Darussalam, Laos, Myanmar) are the main drawbacks to conduct an appropriate research for the entire area.

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## Data availability statement

The [Excel File] data used to support the findings of this study are available from the corresponding author upon request.

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