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Credit risk and profitability of ASEAN commercial banks: Granger causality test

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Abstract: The purpose of this research is to study the profitability and credit risk causality of ASEAN commercial banks. Using data from 118 ASEAN commercial banks from 2002 to 2017, we measure profitability by the ratio of net return to assets (ROA) and net return to equity (ROE). Banking credit risk is measured by the ratio of loan loss provision to assets (LLP). We set up a panel vector autoregression (PVAR) to estimate this relationship. Our results indicate that there is a two-way causal relationship between ASEAN banks' profitability (measured by ROA) and credit risk. Meanwhile, there is a one-way relationship between profitability by ROE and credit risk, and the opposite direction does not occur. Our results support the "bad management," "skimping," and "moral hazard" hypotheses of Berger and DeYoung [1]. The results of this study provide a basis for informing executive managers to improve the bank's profitability while ensuring safety.

Keywords: *ASEAN, Bank profitability, Credit risk, PVAR.*

1. Introduction

The Asian countries experienced a prolonged severe financial crisis followed by a deep recession in 1997, and were affected by the financial crisis in the US in 2008 [2]. Profitability and credit risk are key issues that bank managers always pay attention to. Bank profitability is often traded off against banks' fragility. In the context of ASEAN countries, after the 2008 financial crisis, the rapid growth of bank mergers and acquisitions led to changes in the banking and financial structure, such as financial integration, privatization, deregulation, financial reform, and foreign banking penetration. Furthermore, investment banks, mutual funds, and insurance companies are now competing with the core business of commercial banks [2]. In this context, profitability and credit risk are very important for the existence and development of commercial banks. Therefore, the relationship between profitability and credit risk has always attracted academics worldwide in recent years [3-5]. However, most studies evaluate the one-way effect between profitability and credit risk, such as [1, 6, 7]. The causal relationship between profitability and credit risk has been studied in Africa [8], America [5], and Asia in China's financial markets [9]. Research on this topic in ASEAN emerging markets is scarce. Therefore, the study of the causal relationship between profitability and credit risk in ASEAN commercial banks is very important and valuable.

2. Related Literature and Hypotheses

Profitability and credit risk in the banking system are identified endogenously, which are interrelated. Because they are both a driving force for banks to improve efficiency and also a factor affecting the financial health of the banking system [4, 6]. If an investor does not expect to receive a return commensurate with the credit risk premium, they will not invest in a credit risk portfolio. In other words, these discussions are not intended to answer the question of why a bank cannot achieve maximum profitability in terms of the credit risk operating environment. The relationship between

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credit risk and bank performance was first studied by Berger and DeYoung [1] and later by Koutsomanoli-Filippaki et al. [10].

2.1. Impact of Credit Risk on Profitability

Research by Berger and DeYoung [1] builds the "bad luck" hypothesis, suggesting that an increase in bad debt will reduce bank efficiency and lead to a decline in profitability. There is a causal relationship between them. At this time, the increase in bad debt is due to bad influences from the economic environment, such as inflation, poor growth from the economy, unemployment, unstable interest rates, and increased money supply. Commercial banks must strengthen their management, tighten credit portfolios, and manage loans near maturity. Banks have to pay expenses for management activities such as debt monitoring and collection, proactive bad debt management, and debt sale. From here, the cost efficiency is reduced, affecting the profitability of the bank. With the above argument, the author hypothesizes:

Hypothesis H1: *The change in credit risk is the cause of the change in profitability*

2.2. The Impact of Profitability on Credit Risk

The goal of maximizing profitability should be easily influenced and achieved at all costs, leading to commercial banks being exposed to many risks. Research by Berger and DeYoung [1] builds the hypothesis of "bad management" and suggests that low bank efficiency, leading to reduced profitability, is a signal of weak business administration performance. There is a causal relationship (Granger–cause) causing high NPLs. Expectations in this relationship are negative between bad debt and bank profitability. That is, low-cost efficiency and declining profitability are signals of poor governance in terms of loan portfolio management, credit monitoring, operating cost management, etc.; besides, the lack of strict control and monitoring of expenses from managers should lead to a decrease in efficiency and an increase in bad debt groups.

In addition to proposing the "bad management" hypothesis, the study of Berger and DeYoung [1] also develops the "skimping" hypothesis and suggests that to maximize profitability in the long term, a bank must choose to cut costs in the short term (such as skipping the costs of credit appraisal, monitoring loans, etc.), thereby bearing the consequences of bad debts in the future. During this period, bank efficiency is higher, and bank profitability increases; however, in the long run, this approach adversely affects credit quality and leads to bad debts. This negative relationship is considered a trade-off between future loan performance (i.e., expected long-term profitability maximization) and short-term bank cost efficiency. The key decision for the bank involves balancing the conflict between short-term operating costs and loan quality issues.

Contrary to the "skimping" hypothesis of Berger and DeYoung [1], the "risk-averse management" hypothesis by Koutsomanoli-Filippaki et al. [10] argued that senior executives often tend to avoid risks, thus increasing costs for monitoring, controlling, and guaranteeing loans to reduce bad debts. Therefore, the concern about the effects of the financial crisis and asymmetric information explains the relationship to be in the same direction, meaning that the cost-effectiveness increases proportionally with the rate of increase of the impact of profitability to reduce the bad debt ratio positively.

Finally, the "moral hazard" hypothesis refers to the conflicting relationship between credit risk and bank profitability, and that low-capital banks often have an incentive to invest in risky assets, which, in the long run, increases credit risk. Therefore, banks with relatively low capital will be the cause of inefficient loans. Conversely, high-capital banks often do not face ethical risk or inefficient loans. Meanwhile, these loans assess the cost-effectiveness. This shows that inefficiency in terms of costs will lead to a decline in profitability, forming the basis for increasing banking risks in the future. Based on the above reasoning, this chapter proposes the following hypothesis:

Hypothesis H2: *The change in profitability will be the cause of the change in credit risk*

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3. Methodology

3.1. Data

Data from studies are taken from the Bank Scope source. To avoid frequency issues, we consider the consolidated financial report. We filter the data to include commercial banks, both listed and unlisted, and eliminate banks with fewer than five reporting years and those with incomplete data.

The latest reporting year is earlier than 2016. After cleaning the data, the final sample included 118 commercial banks in eight countries: Cambodia, Indonesia, Laos, Malaysia, the Philippines, Singapore, Thailand, and Vietnam, between 2002 and 2017. It is uniformly converted to USD currency at the local currency/USD exchange rate from the IMF source.

3.2. Calculation Based on Profitability and Credit Risk

Bank profitability is measured by ROA and ROE [4, 11] in particular:

$\text{ROA} = \frac{\text{Net profit}}{\text{Total assets}}$, and $\text{ROE} = \frac{\text{Net profit}}{\text{Total equity}}$

Based on financial statement data, credit risk is measured by the loan loss provision ratio (LLP) [3, 12], and it is determined as follows:

$$\text{LLP} = \frac{\text{Loan loss provision}}{\text{Total assets}}$$

3.3. Panel Vector Autoregression Model-PVAR

We consider the causal relationship between profitability and credit risk through a system of the PVAR model. The two variables included in the model are profitability and credit risk, and lags of the two variables in which the short-term dynamic relationship is defined [6, 13].

Following Berger and DeYoung [1] and Delis et al. [13], the dynamic relationship between endogenous variables is shown in the PVAR asset with $Z_{i,t} = [Pro_{i,t}, LLP_{i,t}]'$ as a vector of k endogenous variables for bank i at time t. The dynamic relationship between endogenous variables is shown in the equation: $\mathrm{Z_{i,t}} = \mathrm{A_{0i}} + \mathrm{A}\ell\mathrm{z_{t-1}} + \mathrm{u}$ (1)

Where, $\mathrm{A_{0}}_i$ is a (k × 1) time constant intercept vector for each specific bank, $A\ell z_{t-1}$ is the matrix (k × k) of the coefficients of lagged variables (parameters for estimation), $\mathrm{A}(\ell) = \sum_{j=1}^{p} \mathrm{A_j}\ell^{j-1}$ to collect the partial and cross-sectional effects of the dependent variable lags in the observations. u is a (1×k) vector of measurement errors with the characteristic:

$$\mathrm{E}(\mathrm{e_{it}}) = 0, \mathrm{E}(\mathrm{e_{it}e'_{it}}) = \sum \mathrm{e}, \mathrm{E}(\mathrm{e_{it}e'_{it}}) = 0 \text{ for all t}$$

The coefficient in eq. (1) is correlated with the error term. Therefore, to address the above problem, especially in panel data with many observations and few time points, GMM estimation and the lag of observations are used as instrumental variables.

After performing the regression system PVAR equation, we estimate the impulse response functions (IRF) and analyze the variance decomposition (VDC) to determine the orthogonal shocks between the variables profitability and credit risk. We use the IRF to assess the current and future responses of profitability to shocks to credit risk and vice versa. VDC is calculated as the percentage change in the proportion explained by the credit risk shock over time and vice versa.

Approach on the research of của Kasman and Carvallo [5] and Saeed and Izzeldin [14], we determine the causal relationship between profitability and credit risk according to the system of PVAR equations, as proposed below:

$$\mathrm{Pro_{it}} = \mathrm{f}(\alpha, \mathrm{Pro_{(i,lag)}}, \mathrm{LLP_{(i,\,lag)}}, \mathrm{u}) \quad (2)$$

$$\mathrm{LLP_{it}} = \mathrm{f}(\beta, \mathrm{LLP_{(i,lag)}}, \mathrm{Pro_{(i,\,lag)}}, \mathrm{u}) \quad (3)$$

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Where, Pro is the bank's profitability. The LLP is the loan loss provision ratio representing credit risk, i is the bank, lag is the number of lag orders (lag = 1,…j), t is the time (t = 2002,...2017, u is the remainder.

4. Empirical Results and Discussion

4.1. Profitability and Credit Risk Results

Table 1 statistics describe the observed variables (Obs), mean (Mean), standard deviation (Std. Dev), minimum (Min), and maximum (Max) of the banks.

Table 1 shows that the average values of profitability, measured by ROA and ROE, are 0.017 and 0.558, respectively, which are much lower than the figures in Indonesia, at 1.54 (ROA) and 10.75 (ROE), and in Malaysia, at 1.24 (ROA) and 9.68 (ROE) during 2011-2015 [15]. Additionally, the credit risk of ASEAN commercial banks, at 0.03, is similar to the findings of Fu et al. [3], who reported an LLP of 0.16 in Asian commercial banks.

Table 1.
Statistics describe the variables for ASEAN banks.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
ROA	1,761	0.017	0.052	-0.052	1.568
ROE	1,761	0.558	0.281	-4.099	0.911
LLP	1,761	0.036	0.489	0.000	20.397

Note: LLP is the loan loss provision ratio; ROA and ROE are Profitability.

4.2. PVAR Model Results

To implement the regression PVAR model, it is necessary to choose the optimal lag length of the independent variable in the system of equations (2) and (3). We select the delay length so that the minimum values of MBIC, MAIC, MQIC, and CD are achieved. The results in Table 2 show that the optimal delay length is 1, similar to Hou et al. [16].

Table 2.
Optimal lag length selection for the PVAR model on the estimation sample.

lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0.4248	.	.	.	.	.
2	-0.2405	.	.	.	.	.
3	-15.496	.	.	.	.	.
4	0.0779	.	.	.	.	.

Note: The values of MBIC, MAIC, and MQIC are minimum, and CD is maximum.

For the PVAR estimation, a necessary condition for performing the analysis of the values obtained from the model is to verify the stability of the variables. In this study, using unbalanced panel data, the Fisher 3 Phillips-Perron (PP) unit root test is consistent with the hypothesis H0 that all panel data are unstable. The ADF test is typically very sensitive to the choice of lag length, so the optimal lag length criterion is determined based on the results in Table 1. The results of the Fisher Phillips-Perron unit root test in Table 2 indicate that all three variables, ROA, ROE, and LLP, have p-values with significance below 5%. Therefore, we reject hypothesis H0 and conclude that all panel data are stationary with respect to ROA, ROE, and LLP. PVAR satisfies the stationarity condition.

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Table 3. Fisher-type unit root test for ROA, ROE, and LLP.

Variable		Statistic	p-value
ROA			
Inverse chi-squared (246)	P	1,114.597	0.000
Inverse normal	Z	-20.557	0.000
Inverse logit t (619)	L*	-26.365	0.000
Modified inv. chi-squared	Pm	39.159	0.000
ROE			
Inverse chi-squared (246)	P	809.897	0.000
Inverse normal	Z	-12.486	0.000
Inverse logit t (619)	L*	-16.787	0.000
Modified inv. chi-squared	Pm	25.422	0.000
LLP			
Inverse chi-squared (246)	P	786.336	0.000
Inverse normal	Z	-11.352	0.000
Inverse logit t (619)	L*	-16.088	0.000
Modified inv. chi-squared	Pm	24.360	0.000

Note: lag length is one, based on the Dickey-Fuller test.

The results of Table 4 show that the absolute value of the characteristic polynomial's inverse is within the unit circle (see Figures 1 and 2), so it can be concluded that the variables in the unbalanced panel data are stable. Pvar satisfies the stability condition.

Table 4.
Eigenvalue stability condition in PVAR.

Eigenvalue Real	Imaginary	Modulus
Model: ROA and LLP		
0.688	0	0.6881
-0.478	0	0.4784
Model: ROE and Z-score		
0.758	0	0.758
-0.120	0	0.120

Note: The stability condition of PVAR when all the eigenvalues lie inside the unit circle (see Figures 1 and 2).

Table 5 presents the results of estimating the Granger causality between profitability and credit risk of ASEAN commercial banks. Model (1), column (2), shows the Granger causality between ROA and LLP; model (2), column (3), shows the Granger causality between ROE and LLP.

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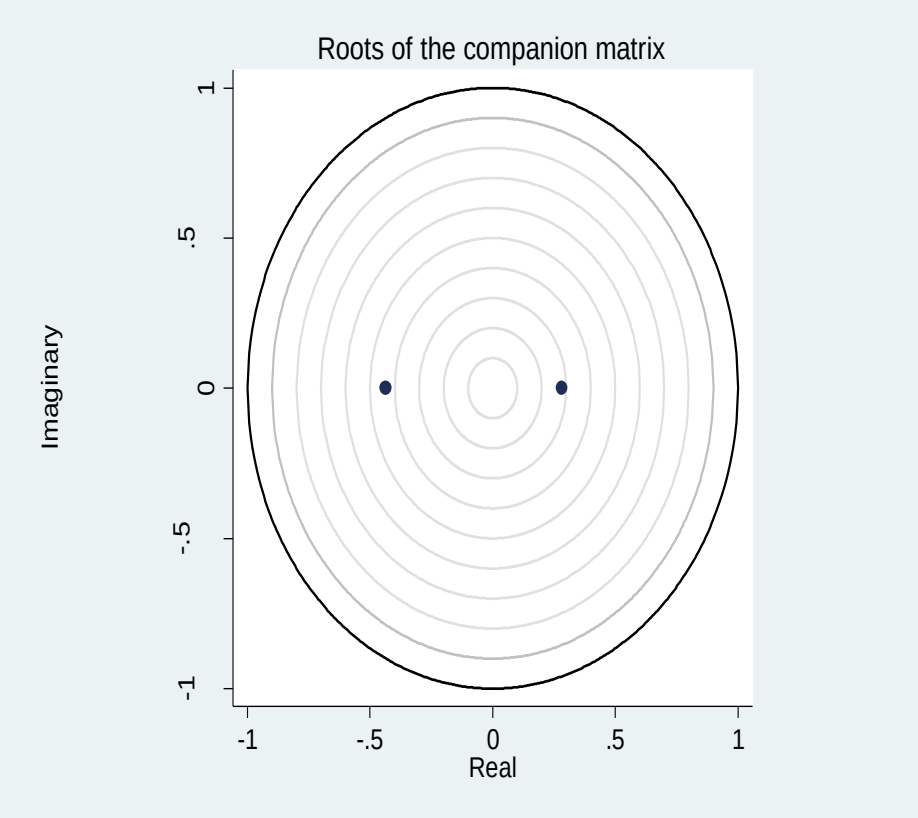

Figure 1.
Stability condition of PVAR: ROA and LLP.

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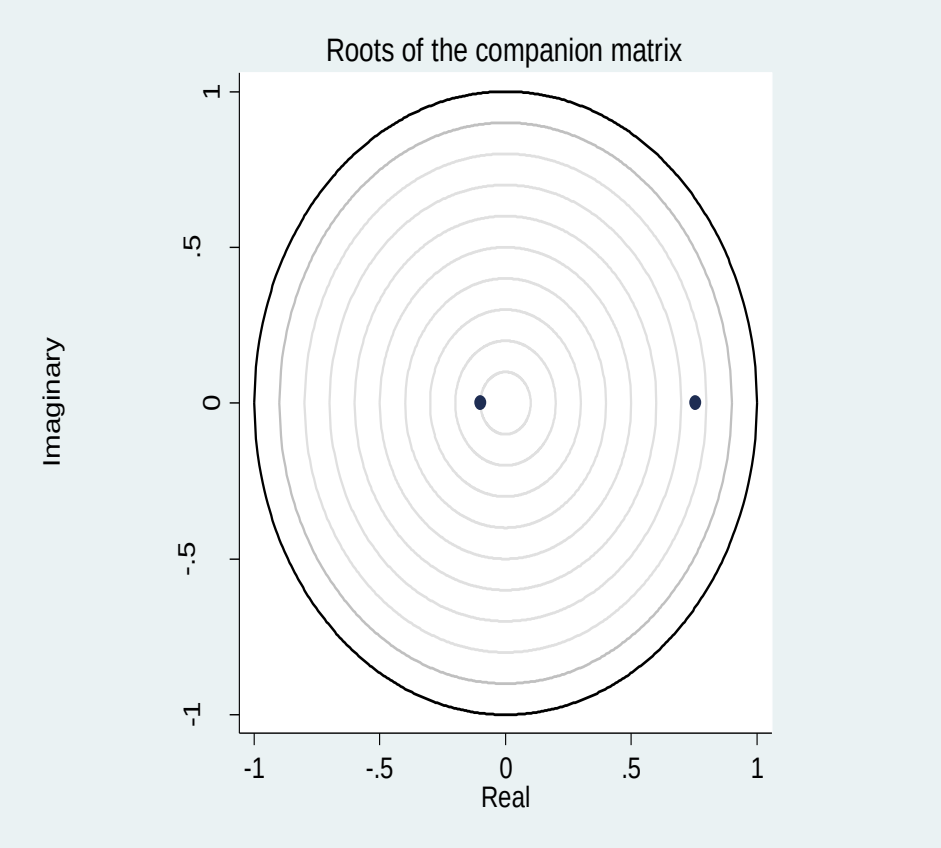

Figure 2.
Stability condition of PVAR: ROE and LLP.

Table 5.
Analysis of Granger causality, model (1) between ROA and LLP; model (2) between ROE and LLP.

Variable	ROA	ROE
	Mô hình (1)	**Mô hình (2)**
ROA_{t-1}	-0.436***	
	[-2.91]	
LLP_{t-1}	0.00952***	0.0113
	[11.07]	[1.48]
ROE_{t-1}		0.105
		[0.85]
LLP		
ROA_{t-1}	0.0850***	
	[3.49]	
LLP_{t-1}	0.281***	0.042
	[11.01]	[1.54]
ROE_{t-1}		-0.140**
		[-2.22]
N	1512	1512
Hansen's J $chi^2(24)$	32.698	32.356
p-value	0.111	0.118

Note: This table presents PVAR estimates with (1) the Granger causality between ROA and LLP variables; (2) the Granger causality between ROE and LLP. The symbols *, **, and *** represent significance at 10%, 5%, and 1%. PVAR-Granger causality Wald test: H0 is the hypothesis that the excluded variable does not Granger-cause the equation variable; H1 is the hypothesis that the excluded variable Granger-causes the equation variable.

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An interesting aspect of this research result, in model (1), column (2) of Table 5, shows that the increase in credit risk is the cause of the increase in profitability measured by ROA at a 1% significance level. Conversely, an increase in ROA profitability also leads to an increase in credit risk at a 1% significance level. This indicates a positive causal relationship between profitability, as measured by the ROA ratio, and credit risk, as measured by the credit risk provision ratio to total assets (LLP). These findings are consistent with the proposed research hypotheses H1 and H2.

Besides, in model (2), column (3) of Table 5 shows that the change in credit risk does not affect ROE profitability. In contrast, the change in ROE profitability is the cause of the change in credit risk. That is, when ROE decreases, credit risk increases at a 5% significance level. This result is consistent with hypothesis H2, supporting the hypothesis of bad management, "skimping" and "moral hazard" of Berger and DeYoung [1], similar to the study of Duho et al. [17] and Abdelaziz et al. [18]. Thus, this result indicates that there is no causal relationship between the ratio of the net return on equity (ROE) and credit risk, as measured by the loan loss provision ratio to total assets ratio (LLP). This is a sign of attention in the management of bank administrators.

4.3. Impulse Response Functions and Variance Decompositions (IRFs and FEVD)

Estimating through the PVAR model also analyzes the IRFs' repulsion function along with the decaying variance matrix (FEVDs). For the IRF push-response function, a shock to the credit risk ratio results in a slight change in ROA profitability at the first stage, then gradually disappears in the subsequent stages (lower left corner of Figure 3.a). In contrast, the ROA profitability shock remained unaffected by credit risk at all stages (upper right corner of Figure 3.a).

Meanwhile, a shock to the credit risk ratio slightly reduces profitability measured by ROE in the first stage and is not affected in subsequent periods (bottom right corner of Figure 3.b). In contrast, the shock to profitability by ROE remains unaffected by credit risk at all stages (top right corner of Figure 3.b).

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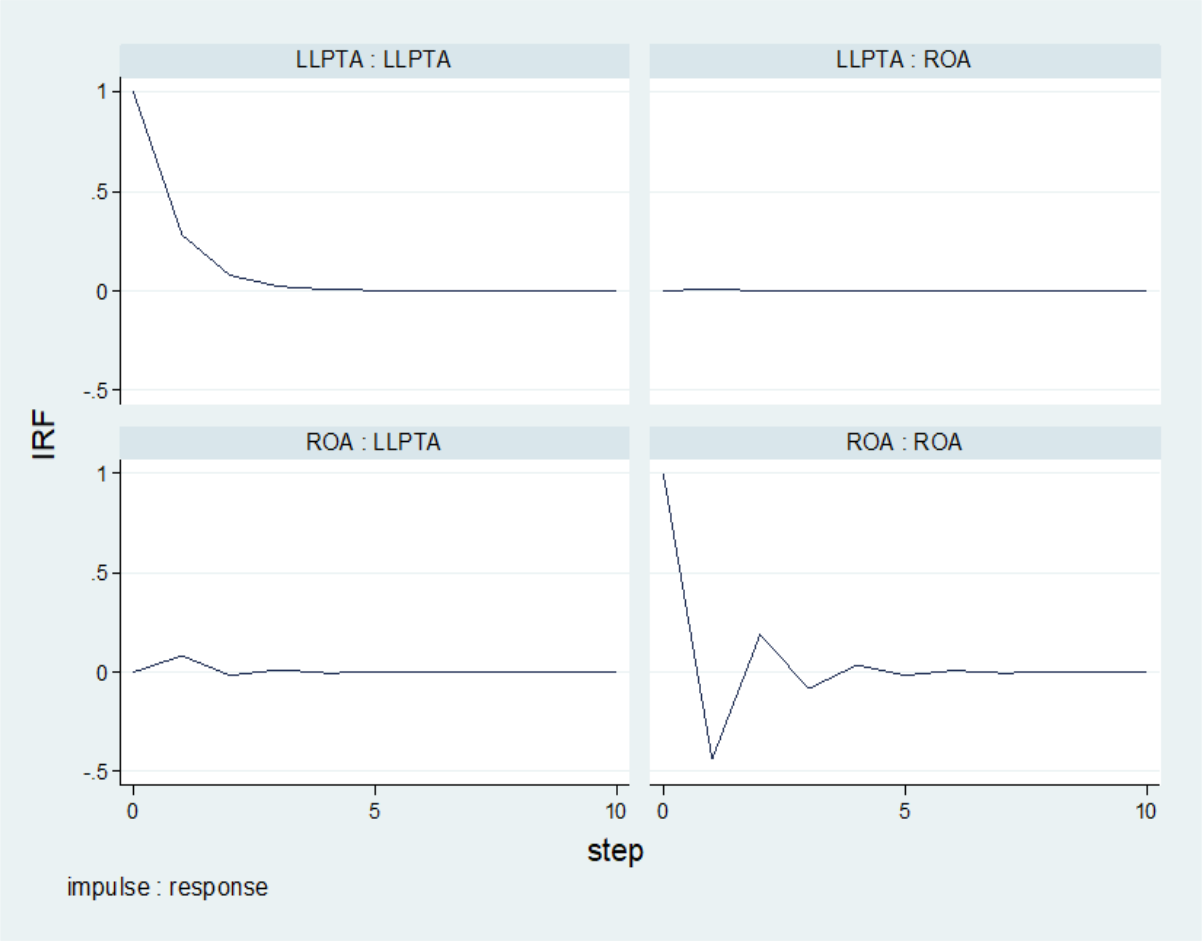

Figure 3.
(a) Impulse–response functions for a one lag VAR of ROA and LLP.

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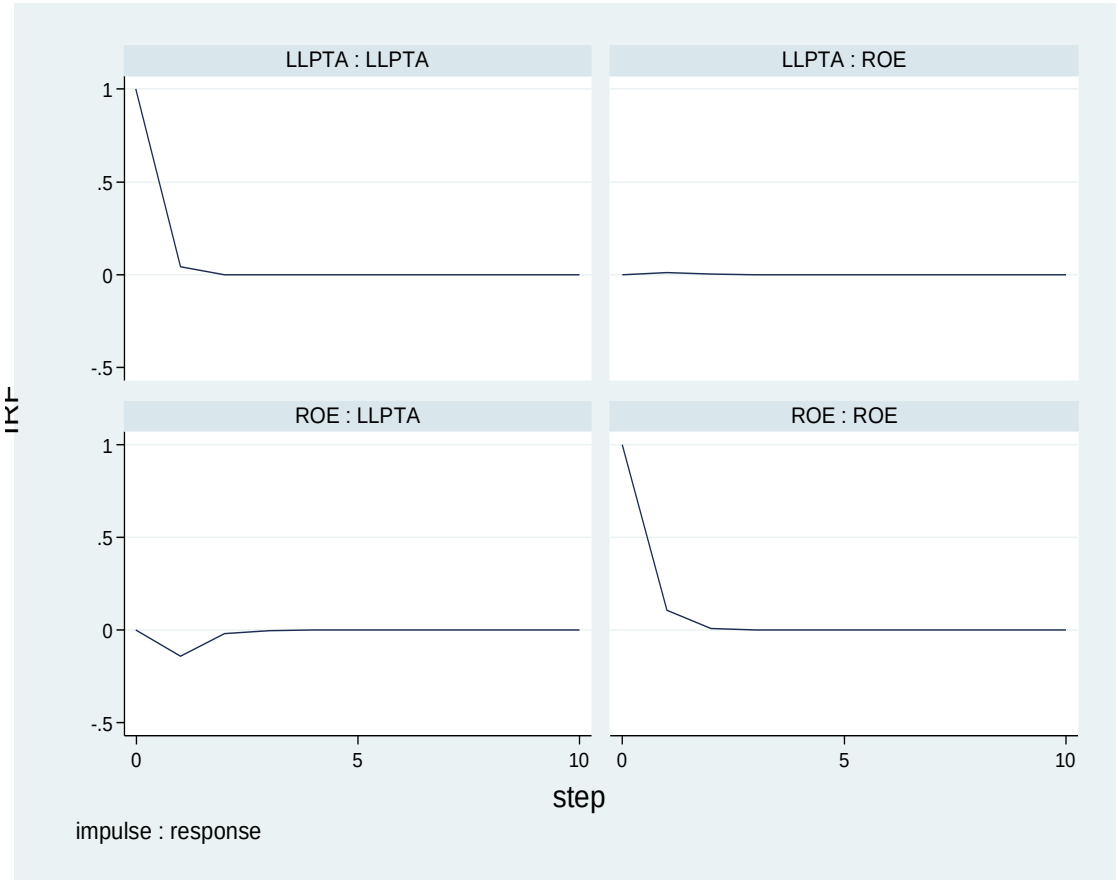

Figure 3.
(b) Impulse–response functions for a lag VAR of ROE and LLP.

The results of Table 6 analysis of variance are shown in detail: The change in profitability, ROA, and ROE is explained by the LLP at 0% for the first period, respectively, and about 0.008% and 0.001% for subsequent periods. In the opposite direction, the change in LLP is explained by the change in profitability by ROA at only 0.001% in all stages; while the profitability by ROE in the first stage is 0.001% and increases to 0.003% in the following stages.

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Table 6.
Forecast variance decomposition for impulse variable: ROA and LLP; ROE and LLP.

Response variable and Forecast horizon	Model (1): ROA and LLP		Response variable and Forecast horizon	Model (2): ROE and LLP	
	Impulse variable			Impulse variable	
	ROA	LLPTA		ROE	LLPTA
ROA			ROE		
0	0	0	0	0	0
1	1	0	1	1	0
2	0.992	0.008	2	0.999	0.001
3	0.992	0.008	3	0.999	0.001
4	0.992	0.008	4	0.999	0.001
5	0.992	0.008	5	0.999	0.001
6	0.992	0.008	6	0.999	0.001
7	0.992	0.008	7	0.999	0.001
8	0.992	0.008	8	0.999	0.001
9	0.992	0.008	9	0.999	0.001
10	0.992	0.008	10	0.999	0.001
LLPTA			LLPTA		
0	0	0	0	0	0
1	0.001	0.999	1	0.001	0.999
2	0.001	0.999	2	0.003	0.997
3	0.001	0.999	3	0.003	0.997
4	0.001	0.999	4	0.003	0.997
5	0.001	0.999	5	0.003	0.997
6	0.001	0.999	6	0.003	0.997
7	0.001	0.999	7	0.003	0.997
8	0.001	0.999	8	0.003	0.997
9	0.001	0.999	9	0.003	0.997
10	0.001	0.999	10	0.003	0.997

5. Conclucion

The article examines the causal relationship between profitability and credit risk of Southeast Asian commercial banks. The author measures profitability using the net return on total assets ratio (ROA) and the net return on equity ratio (ROE). Bank credit risk is assessed by the loan loss provision to total assets (LLP). The study employs the PVAR method to estimate this cause-and-effect relationship. The author selects a lag of 1 for the research model. The results indicate a positive causal relationship between profitability (ROA) and credit risk. Conversely, profitability (ROE) and credit risk do not exhibit a causal relationship. Specifically, there is only a negative impact of profitability (ROE) on credit risk, but the research findings did not provide conclusive evidence of this relationship.

IRFs and FEVD indicate that the causal relationship between profitability and credit risk is quite close for ASEAN commercial banks. The shock to credit risk will cause profitability to decrease and then increase slightly in the first stage, after which it will not be affected in subsequent stages. Similarly, when there is a shock to profitability, such as ROA and ROE, credit risk remains unaffected across all periods.

In addition to providing empirical evidence for the causal relationship between profitability and credit risk of Southeast Asian commercial banks, the article has some policy implications for bank administrators. Firstly, control costs effectively, closely monitor the lending stage; pay attention to the profitability of risky assets, thereby implementing appropriate lending policies to improve profits while ensuring safety. Second, consider reducing costs (supervisory costs, borrower screening, appraisal costs, etc.) to achieve short-term profitability with future credit risks. Third, bank administrators should continue to promote financial soundness and identify potential credit risks within banks.

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Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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