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EVALUATING THE EFFECTIVENESS OF BASEL III IMPLEMENTATION IN CREDIT RISK MANAGEMENT AT SAI GON THUONG TIN COMMERCIAL JOINT STOCK BANK (SACOMBANK)

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Abstract: In the context that Saigon Thuong Tin Commercial Joint Stock Bank (Sacombank) is gradually completing its ten-year restructuring plan and moving towards risk standardization under Basel III, this study aims to assess the impact of Basel III standards on credit risk management at Sacombank from 2013 to 2024. The research analyzes the theoretical framework of credit risk and the principles of Basel III. The author uses the ARDL regression method to measure the impact of key Basel III factors such as capital adequacy ratio (CAR), profitability ratio (ROAA) and macroeconomic factors on the non-performing loan ratio (NPL) at Sacombank. The findings indicate that Sacombank has made significant progress in controlling credit risk under Basel III. Both CAR and ROAA have a substantial impact on NPLs. The study goes beyond univariate analysis by clarifying the interrelationships among the factors and their influence on credit risk. This study proposes a set of solutions enabling Sacombank to flexibly implement Basel III, thereby enhancing its risk response capacity and promoting the standardization of credit operations in line with international best practices.

Keywords: *Credit risk management, Sacombank, Basel III, ARDL model*

1. Introduction

In the period when Vietnam is promoting financial institutional reform and moving towards deep integration, the banking system plays a central role in leading capital, stabilizing the money market and promoting growth. An efficient credit system not only supports economic development but also facilitates trade and investment. Therefore, building a suitable credit risk management model helps banks improve their competitiveness in today's global context. Basel III has been widely adopted as an international regulatory framework designed to enhance resilience against risks through strengthened capital requirements, liquidity management, and supervision. However, the results of applying Basel III in each country are different depending on the level of completion of the financial system and management capacity, which need to be flexibly adjusted according to the characteristics of the bank.

In Vietnam, the roadmap for Basel implementation was initiated by the State bank of Vietnam (SBV) in 2007. At present, most commercial joint stock banks operate under Basel II, with the goal of achieving comprehensive Basel III compliance by 2030. In that context, Sacombank became a typical bank when it merged with Phuong Nam from 2011-2016 and was assigned to pilot Basel II and then Basel III. The research topic "Evaluating the effectiveness of Basel III application in credit risk management at Sacombank" aims to analyze the current situation and propose solutions to help Sacombank improve its credit control capacity, while contributing to the completion of the credit risk management system of the entire Vietnamese banking industry.

To understand the impact of Basel III on credit risk management, it is necessary to refer to previous studies. Although there are many documents in the world with diverse perspectives, the topic only selects studies with high similarity to ensure practical application in Vietnamese banks.

A notable international study by Fidrmuc and Lind (2020) analyzed 48 quantitative studies to explore the role of the capital adequacy ratio (CAR) in quantitative models. Their findings indicate that increasing capital requirements under Basel III may moderately hinder GDP growth, contingent on the structural characteristics of each country's banking system. These insights offer valuable guidance for

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Sacombank as it navigates challenges in complying with new regulatory standards. Similarly, Boora and Jangra (2019) argue that Basel III transcends mere technical compliance, serving as a catalyst for banks to adopt a proactive and long-term approach to risk management. This perspective aligns well with Sacombank's ongoing restructuring efforts to meet international governance standards. Nguyen and Nguyen (2024) examined data from 21 listed commercial banks in Vietnam from 2017 to 2023 to evaluate the impact of digital transformation and Basel III on the non-performing loan (NPL) ratio. Their results demonstrate that consistent implementation of Basel III significantly reduces credit risk. Additionally, Nguyen's (2020) study of 22 Vietnamese banks from 2010 to 2018 revealed that higher NPL ratios negatively affect bank profitability, underscoring the importance of effective credit risk management through NPL reduction to ensure financial stability. Similarly, Nguyen and Nguyen (2018) investigated the relationship between capital and credit risk in the Vietnamese banking sector from 1999 to 2014, finding that banks with higher capital levels are less prone to default, highlighting the protective role of robust capital reserves against systemic risk.

However, most studies focus on industry-wide impacts or rely on cross-sectional data, with limited research providing in-depth analysis of specific banks, such as Sacombank, that have fully implemented Basel III. Methodologically, this study opts for the Autoregressive Distributed Lag (ARDL) model, which is well-suited for time-series data with a small sample size. This approach enables a clearer examination of both short-term and long-term relationships between Basel III pillars and credit risk, diverging from the commonly used Generalized method of moments (GMM) or Ordinary least squares (OLS) methods.

2. Theoretical framework

2.1 Credit Risk in commercial banking

According to Clause 2, Article 2, and Clause 9, Article 9 of Circular No. 41/2016/TT-NHNN—which provides guiding the calculation of capital safety according to Basel II in Vietnam, is defined as "Credit risk is the risk caused by a customer not performing or not being able to perform part or all of the debt repayment obligation under the contract or agreement with a bank or foreign bank branch."

In addition, the Circular also defines: "Counterpart credit risk is the risk that a counterparty fails to perform or is unable to perform its payment obligations before or when due under transactions under Circular 41". This definition is included to ensure consistency with the research objective of measuring the impact of Basel III on the non-performing loan (NPL) ratio. This definition is academic, can be compared with international standards and covers both customer and financial counterparty aspects, consistent with the nature of Basel on risk measurement and minimum capital requirements.

The Basel Committee on Banking Supervision (BCBS) provides a widely accepted international definition, stating that credit risk is "Credit risk is most simply defined as the possibility that a bank borrower or counterparty will not perform its obligations according to the agreed terms". This is the most widely accepted international standard definition.

2.2 Assessing the impact of Basel III on the level of credit risk of banks

The research model uses NPL as the dependent variable, with independent variables including the Basel group of variables (CAR, INFOR), the group of bank-specific control variables (LN_SIZE, ROAA), the group of macro variables (GDPG, INF), and the dummy variable representing the merger event of Phuong Nam Bank (NHPN).

Most quantitative studies, both in Vietnam and abroad, choose NPL as the dependent variable in credit risk models because it directly reflects the extent of loan losses borne by the bank (Bich, 2024). NPL is compatible with Basel II, Basel III, and Circular No. 11/2021/TT-NHNN issued by the State Bank of Vietnam, making it straightforward to access and measure. Moreover, as banks are required to disclose their NPL ratios under accounting standards and legal regulations, the data is readily available, reliable, and comparable across banks, time periods, and countries.

In this study, non-performing loans (NPLs) are defined as the total value of loans classified under Groups 3, 4, and 5 according to the State Bank of Vietnam's classification criteria, as stipulated in Circular No. 11/2021/TT-NHHN. These are loans assessed as being, or potentially being, irrecoverable on time. The NPL ratio is calculated using the following formula:

$$\text{NPL} = (\text{Total loans in Groups } 3{,}4{,}5)/(\text{Total } customer \text{ loans}) * 100\%$$

2.3 Variables Representing Basel III Implementation

2.3.1 CAR Variable

In theory, the capital adequacy ratio (CAR) and non-performing loan (NPL) ratio exhibit an inverse relationship. Higher equity levels provide banks with greater buffers to absorb unexpected losses, thereby reducing risks associated with credit activities. Empirical studies in Vietnam from 1999 to 2014 support this trend, indicating that banks with higher capital levels are less inclined to engage in risky lending, resulting in lower default rates (Dung, 2018). Conversely, a recent study by Bich (2024) suggests that while CAR is expected to negatively correlate with NPL, the evidence is inconclusive. The impact of CAR on NPL varies depending on factors such as the time period, bank size, risk management strategies, and economic conditions. According to Circular 41/2016/TT-NHNN, the formula for calculating CAR is outlined as follows:

$$\text{CAR} = c/(\text{RWA} + 12{,}5 * (\text{KOR} + \text{KMR}))$$

2.3.2 INFOR variable

INFOR is a dummy variable when Sacombank announces the completion of Basel III, with a value of 1 from the first quarter of 2024 when Sacombank announces that they have completed the Basel III process, and 0 if before the first quarter of 2024.

The study of (Bich, 2024) shows a statistically significant negative correlation between the announcement of Basel III completion and the NPL ratio. This shows that the continuous implementation of Basel III has helped reduce the credit risk level of banks.

2.4 Bank-Specific control vriables

To improve the accuracy of the model, internal and macro factors are incorporated as control variables.

2.4.1 LN_SIZE variable

Large-sized banks are believed to have better risk management capabilities, owing to more comprehensive internal control systems and stronger risk diversification capacity. Therefore, LN_SIZE is expected to be negatively related to NPL.

The study by (Bich, 2024) shows that the LN_SIZE variable has a high VIF coefficient, causing multicollinearity and is therefore eliminated in their regression model. However, other studies still demonstrate the role of size in bank performance. The study by (Hien, 2020) shows that bank size has a significant impact on profitability, and larger banks tend to have better performance.

(LN_SIZE) is the natural logarithm of total assets, which is used to measure the size of the bank.

$$LN_{Size} = Ln\,(Total\ assets)$$

2.4.2 ROAA variable

Return on Average Total Assets (ROAA) is used as a profitability index for banks. The ROAA variable reflects the efficiency of generating profits from the bank's assets. When a bank achieves a high ROAA, it shows that its operations are efficient and its loan portfolio is of good quality. Therefore, ROAA is also expected to have a negative relationship with NPL, i.e., better profitability means lower credit risk. This is consistent with the hypothesis that banks with higher profitability will be more proactive in controlling risks and have “financial space” to handle troubled loans.

$$ROAA = (Net\ income)/(Average\ Total\ Asset)$$

2.5 Macroeconomic factors and merger events

2.5.1 GDPG variable

At the macroeconomic level, GDP growth (GDPG) can have a two-sided effect on NPLs. Economic growth can help customers repay their debts better, thereby reducing NPL. However, in a high growth environment, banks sometimes loosen credit conditions, leading to an increase in potential NPL.

GDP growth is a key macroeconomic indicator affecting both the broader economy and borrowers' repayment ability. Although international theory often suggests that economic growth helps reduce NPL due to improved debt repayment ability, in the context of Vietnam, where credit plays a leading role in growth when GDP increases sharply, banks tend to expand lending excessively, leading to higher potential credit risks.

$$GDPG = \frac{GDP\ this\ year}{GDP\ last\ year} - 1$$

2.5.2 INF variable

The inflation rate can reduce the real income of borrowers, affecting their ability to repay their debts, thereby increasing the NPL ratio. In some cases, inflation helps reduce the real value of debt, supporting borrowers to pay. In general, the impact of INF in Vietnam is not really clear, due to interventions from monetary policy and the role of support institutions such as the State Bank of Vietnam and the Vietnam Asset Management Company (VAMC), to help banks reduce bad debt during periods of high inflation.

$$INF = \frac{CPI_t - CPI_{t-1}}{CPI_t} - 1$$

2.5.3 NHPN variable

The Vietnamese banking system has been continuously restructured and promoted since 2011, including mergers and consolidations of weaker banks to strengthen capital adequacy and compliance with Basel II standards (Hien, 2020).

For Sacombank, the merger of Southern Bank on October 1, 2015 was an important part of the bank's financial restructuring and improvement. This merger has created significant changes in the credit risk portfolio and operating structure of Sacombank, as the bank has to integrate and handle risky assets from the merged bank, while strengthening risk management capacity to approach international standards such as Basel III.

The NHPN variable is a dummy that equals 1 from October 1, 2015, when Southern Bank's name was officially removed, and 0 before that date. Incorporating this variable controls for the one-off spike in NPLs during the transition, thereby preventing distortion in the analysis of Basel III's impact. Initially, NPLs may have risen due to the inherited bad debts, but in the long run, successful restructuring could lead to a reduction in credit risk.

2.6 Model to assess the impact of Basel III on credit risk management

Based on the work of (Bich, 2024), the model was built to test the effectiveness of digital transformation and Basel III implementation on credit risk management of 21 Vietnamese banks, the author built the following model to assess the impact of Basel III on credit risk management at Sacombank in the period 2013 - 2024. However, if only data from Sacombank is available, the number of observations will be less than when using data from many banks, so to make the model more reliable, the author collects data quarterly instead of annually, to quadruple the number of observations and ensure that the analysis will be highly statistically significant.

The research model to evaluate the impact of Basel III on credit risk management at Sacombank (STB) is specified as follows:

NPLt = α + β1CARt + β2INFORt + β3LN_SIZEt + β4ROAAt + β5GDPGt + β6 INFt + β7NHPNt + εt

In which:

NPLt: Credit risk level at time t.

CARTt: Capital adequacy ratio at time t.

INFORt: Dummy variable representing the status of Basel III completion announcement at time t

LN_SIZEt: Bank size at time t

ROAAt: Bank profitability at time t

GDPGt: GDP growth rate at time t

INFt: Inflation rate at time t

NHPNt: Dummy variable for the event of Phuong Nam Bank merging with Sacombank at time t

εt: Model error.

3. Data and methodology

In this study, instead of using the traditional OLS regression method like many previous studies, the authors chose the ARDL model as the main tool for analysis. The reason is that ARDL is more suitable for small-sized time series data and does not require all variables to share the same order of integration. This is also a method that helps to simultaneously detect short-term and long-term relationships between financial indicators related to Basel III and the level of credit risk within the bank.

In the context of Sacombank's limited data, the ARDL method has the advantage of being able to operate well even when the variables have different lags or stationary levels, as long as they do not exceed level I(1). This is very necessary in banking research, where economic and financial indicators often react slowly to policies. Another notable point is that ARDL is capable of automatically determining the optimal lag for each variable in the model. For example, the impact of the CAR ratio on bad debt does not occur immediately but takes several quarters to be clearly reflected. By capturing these lagged effects, the ARDL framework provides a more accurate representation of the temporal dynamics inherent in lending activities and financial management.

Capital adequacy ratio (CAR) data are published at annual frequency before 2020, and semi-annual frequency after 2020, so to match the quarterly frequency of the dependent variable (NPL), the CAR data were converted into quarterly observations through interpolation. In practice, this involved repeating the annual or semi-annual CAR value for each corresponding quarter in the reporting period. For instance, if CAR was X% at the end of year YYYY, this same value was assigned to all four quarters of that year. Similarly, for semi-annual data, the first-half CAR figure was applied to Q1 and Q2, while the second-half value was applied to Q3 and Q4. Although this method can reduce the volatility of the CAR variable in the short run, in terms of econometrics, this is a common approach when dealing with nonuniform frequency data, to ensure the ability to deploy the ARDL model and analyze the relationship between variables.

3.1 ADF stationarity test for the 6-variable model

Before running time-series regressions, it is essential to verify the stationarity of variables to avoid the problem of spurious regression. Therefore, this study applies the Augmented Dickey-Fuller (ADF) unit root test to examine whether each variable is stationary. The test results provide the basis for determining the order of integration of the variables before proceeding to model estimation.

Table 1. ADF stationarity test

Independent variable	Type of test	ORIGINAL LEVEL I(0)							ORIGINAL LEVEL I(1)							Conclusion
		ADF Statistic	P-value	1% CV	5% CV	10% CV	Conclusion by ADF stas	Conclusion by P-value	ADF Statistic	P-value	1% CV	5% CV	10% CV	Conclusion by ADF stas	Conclusion by P-value	
NPL	Intercept	-2,6630	0,0885	-3,5880	-2,9290	-2,6030	Reject H0 (10%)	Reject H0 (10%)	-3,8209	0,0053	-3,5847	-2,9281	-2,6022	Reject H0 (1%)	Reject H0 (1%)	STOP LEVEL 1
	Trend	-2,7865	0,2097	-4,1809	-3,5100	-3,1800	Fail to reject H₀	Fail to reject H₀	-3,7747	0,0273	-4,1756	-3,5131	-3,1869	Reject H0 (5%)	Reject H0 (5%)	STOP LEVEL 1
CAR	Intercept	-2,3471	0,1621	-3,5777	-2,9251	-2,6006	Fail to reject H₀	Fail to reject H₀	-6,5428	0,0000	-3,5847	-2,9281	-2,6022	Reject H0 (1%)	Reject H0 (1%)	STOP LEVEL 1
	Trend	-2,4400	0,3537	-4,1657	-3,5085	-3,1842	Fail to reject H₀	Fail to reject H₀	-6,4660	0,0000	-4,1756	-3,5100	-3,1800	Reject H0 (1%)	Reject H0 (1%)	STOP LEVEL 1
ROAA	Intercept	-1,6428	0,4530	-3,5812	-2,9266	-2,6014	Fail to reject H₀	Fail to reject H₀	-5,9984	0,0000	-3,5885	-2,9297	-2,6031	Reject H0 (1%)	Reject H0 (1%)	STOP LEVEL 1
	Trend	-2,9139	0,1676	-4,1658	-3,5085	-3,1842	Fail to reject H₀	Fail to reject H₀	-6,8673	0,0000	-4,1809	-3,5155	-3,1883	Reject H0 (1%)	Reject H0 (1%)	STOP LEVEL 1
GDP	Intercept	-5,2421	0,0001	-3,5777	-2,9252	-2,6007	Reject H0 (1%)	Reject H0 (1%)								STOP LEVEL 0
	Trend	-5,1945	0,0005	-4,1658	-3,5085	-3,1842	Reject H0 (1%)	Reject H0 (1%)								STOP LEVEL 0
INF	Intercept	-2,9538	0,0486	-3,6156	-2,9411	-2,6091	Reject H0 (5%)	Reject H0 (5%)								STOP LEVEL 0
	Trend	-2,9736	0,1526	-4,2191	-3,5331	-3,1983	Do not reject H0	Do not reject H0	-4,5126	0,0046	-4,5212	-3,5298	-3,1964	Reject H0 (5%)	Reject H0 (5%)	STOP LEVEL 1

The unit root test results show that the variables NPL (dependent variable), CAR, LN_SIZE, ROAA, INF are all integrated to order 1, while the GDPG variable is integrated to order 0 with a statistical significance level of 1%.

3.2 ARDL test of the 6-variable empirical model

3.2.1 Criteria for selecting the optimal lag AIC for the 6-variable model

After considering the stationarity of the variables, the search for the optimal lag for the model is carried out based on the Akaike Information Criterion (AIC) to determine the correct data structure and give the most accurate estimation results. The estimation results presented in Table 3.2 show that:

Table 2. Testing the optimal lag of the 6-variable model

Independent Variable	Estimated Coefficient	P-value	Statistically significant
NPL(-1)	0,7857	0,0000	Not statistically significant
CAR	-0,0461	0,7825	Not statistically significant
CAR(-1)	0,1540	0,4408	Statistically significant
CAR(-2)	-0,3708	0,0184	Not statistically significant
INFOR	0,2644	0,5258	Statistically significant
ROAA	-3,3796	0,0067	Not statistically significant
GDPG	0,0025	0,9455	Not statistically significant
INF	0,0888	0,2192	Not statistically significant
NHPN	-1,2195	0,1693	Not statistically significant
NHPN(-1)	1,1643	0,1365	Statistically significant
C	3,559562	0,0133	Statistically significant

The optimal lag order in the ARDL model is selected based on Table 2 showing that the optimal lag of the ARDL model is (1, 2, 0, 0, 0, 0, 1), R-squared = 0,83 and F test (Prob = 0,000) shows that the model is capable of explaining more than 82% of the fluctuations in NPL. In addition, the statistical value of F is 17,08217 (p < 0,01) confirming that the model has overall statistical significance.

However, when considering each variable in the model separately, only three variables give clear statistical significance. First, the variable NPL(-1) has a positive coefficient (0,7857) and p-value = 0 < 0,01, reflecting that the current NPL is strongly influenced by its own value in the past. Second, the ROAA variable has a negative coefficient (-3,3796) and p = 0,0067, which is statistically significant at the 1% level, consistent with the theory that higher profitability will help banks reduce their NPL ratio. Finally, the CAR(-2) variable is significant at the 5% level with a negative coefficient (-0,3708), indicating that after two quarters, the capital adequacy ratio begins to play a role in reducing credit risk.

In contrast, variables such as CAR (current and 1-quarter lagged), INFOR, GDPG, INF and NHPN are not individually statistically significant with p-value > 0,1. This shows that these variables do not contribute significantly to explaining the behavior of NPL in the real context at Sacombank.
Bound test determines long-run relationship for 6-variable model

3.2.2 Bound test determines long-run relationship for 6-variable model

Bound test determines cointegration between variables, that is, find long-run relationship between variables. The estimation results presented in Table 3 show that:

Table 3. Bound test determines long-run relationship for 6-variable model

Equation	**Lag**	**F-statistic**	**P-value**
NPL = f(CAR, ROAA, GDP, INF, INFOR, NHPN)	(1, 2, 0, 0, 0, 0, 1)	2,2786	
Critical value	**10%**	**5%**	**1%**
Lower bound I(0)	1,99	2,27	2,88
Upper bound I(1)	2,94	3,28	3,99

The result of Bound Test with F = 2,278643 shows that the value lies between the two boundaries I(0) and I(1) at the 5% significance level, indicating that there is no strong statistical evidence of a long-run cointegration relationship between the variables.

3.2.3 Estimation of short-run coefficients conditional error correction regression for the 6-variable model

After verifying the existence of long-run and short-run relationships between the variables from the ARDL constraint test, the study finds the short-run parameters of the variables.

Table 4. Test of short-run coefficient estimates conditional error correction regression for the 6-variable model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3,559562	1,364817	2,608088	0,0133
NPL(-1)*	-0,214253	0,102091	-2,098643	0,0431
CAR(-1)	-0,262883	0,139851	-1,879740	0,0685
INFOR**	0,264431	0,412603	0,640886	0,5258
ROAA**	-3,379639	1,171559	-2,884737	0,0067
GDP**	0,002523	0,036644	0,068863	0,9455
INF**	0,088772	0,070952	1,251146	0,2192
NHPN(-1)	-0,055268	0,278506	-0,198445	0,8438
D(CAR)	-0,046177	0,166015	-0,278147	0,7825
D(CAR(-1))	0,370753	0,149907	2,473211	0,0184
D(NHPN)	-1,219528	0,868926	-1,403488	0,1693

In the ECM model, the factor to determine the long-term relationship and the adjustment speed is the error correction term coefficient (ECM). In this case, ECM (NPL(-1) = -0,21) has a probability value of 0,0431, which is statistically significant at the 5% level and carries a negative sign as theoretically expected. So the system exists in a long-term equilibrium relationship and is adjusting at an adjustment speed of −21%, meaning that if it deviates from equilibrium, it will adjust 21% of the deviation each quarter.

However, to ensure that the model focuses on the variables that really affect NPL, assessing each independent variable is a key step. We see that CAR has a negative regression coefficient and is nearly statistically significant at the 10% level, indicating a positive relationship between capital adequacy and credit stability, although this impact is still limited in terms of quantity. Return on Average Assets (ROAA) presents a negative and highly significant coefficient at the 1% level, implying that higher financial performance contributes to reducing the non-performing loan ratio. This finding aligns with financial theory and previous empirical research. On the other hand, macroeconomic indicators and dummy variables—namely GDP growth (GDPG), inflation rate (INF), Basel III announcement dummy (INFOR), and Phuong Nam merger dummy (NHPN)—show no statistical significance in the model, indicating that these factors do not play a notable role in explaining NPL fluctuations in the case of Sacombank.

From a short-run perspective, only the lagged CAR variable by one quarter (D(CAR(-1))) achieves statistical significance at the 5% level, suggesting that higher capital levels in the previous period can help control current non-performing loans.

3.2.4 Remarks on the six-variable model:

The objective of the model is to comprehensively examine Basel III elements that may affect credit risk management at Sacombank, as measured by the NPL ratio. To achieve this, the author adopted a cautious approach by selecting an ARDL model with six theoretically grounded variables reflecting both Basel III components and Sacombank-specific characteristics. However, after the estimation process, 4 out of 6 independent variables do not reach statistical significance in both the short-term and the general. Moreover, the Bound Test shows that there is no long-term cointegration relationship.

From the above analysis, it can be seen that ROAA and CAR are two key variables that have a substantial impact on NPLs, while variables such as INFOR, GDPG, INF or NHPN, although they may have economic theoretical significance, do not play a clear explanatory role in the case of Sacombank. This reflects that the original model was "noisy" by the inclusion of unnecessary variables. Incorporating all six variables into an ARDL framework under limited data conditions (48 observations) created an over-parameterization issue, reducing result reliability and obscuring the core relationship between NPL and other critical financial factors.

The author chose to remove the statistically insignificant variables INFOR, GDPG, INF and NHPN from the regression model. To check whether the problem was resolved, the author reran all ARDL tests. The test results also show that the coefficients of the remaining independent variables are all statistically significant within the 5% significance threshold. This means that after removing the unwanted variable, the data set can now be accepted for use and is presented in the next section as follows.

3.3 ARDL test of the 2-variable lean empirical model

3.3.1 Criteria for selecting the optimal lag AIC for the 2-variable model

The optimal lag for the 2-independent variable model CAR and ROAA is presented in Table 5 showing that the optimal lag should be (1,2,0).

Table 5. Criteria for selecting the optimal lag AIC for the 2-variable model

Independent Variable	Estimated Coefficient	P-value	Statistically significant
NPL(-1)	0,862739	0,0000	Statistically significant
CAR	-0,075359	0,6441	Not statistically significant
CAR(-1)	0,196714	0,3112	Not statistically significant
CAR(-2)	-0,360583	0,0168	Statistically significant
ROAA	-1,876580	0,0133	Statistically significant
C	3,096105	0,0162	Statistically significant

The estimation results of this general model indicate that all included variables have statistically significant relationships, and the model demonstrates a high explanatory power. This is reflected in the R^2 value of 0,8089 and the Adjusted R^2 of 0,7850, meaning that approximately 80,89% of the variation in NPL can be explained by the variables in the model. Furthermore, the F-statistic value of 33,86017 with $p = 0$ confirms that the model is statistically significant as a whole.

Looking at each variable individually, NPL(-1) has a positive coefficient of 0,862739 with p = 0,000, suggesting a strong dependence of the current NPL on its past values, which reflects the dynamic nature of non-performing loan behavior in the bank, ROAA carries a negative coefficient (-1,876580) with p = 0,0133, significant at the 5% level. This supports the theoretical expectation that higher profitability contributes to reducing the NPL ratio. Notably, CAR(-2) has a negative coefficient (-0,360583) with p = 0,0168, also significant at the 5% level, indicating that after about two quarters, an increase in capital adequacy helps improve credit risk control. In contrast, CAR and CAR(-1) do not show strong statistical significance, implying that higher capital in the current quarter or one quarter before may not have an immediate impact on risk control. Nevertheless, the model still maintains overall robustness.

3.3.2 Bound test for long-run relationship in the two-variable model

The results of the Bound Test show an F-statistic value of 3,577070, which lies between the I(0) and I(1) critical bounds at the 5% significance level. This means there is no clear statistical evidence of a long-run cointegration relationship between the variables.Table 3.6 Bound test to determine long-run relationship for 2-variable model.

Table 6. Bound test to determine long-run relationship for 2-variable model

Equation	**Lag**	**F-statistic**	**P-value**
NPL = f(CAR, ROAA)	(1, 2, 0)	3,577070	—
Critical value	**10%**	**5%**	**1%**
Lower bound I(0)	2,63	3,1	4,13
Upper bound I(1)	3,35	3,87	5

Therefore, the study focuses on analyzing the overall and short-term impacts of explanatory variables on NPL, which still holds practical significance for banking policy and management.

3.3.3 Estimation of short-term coefficients conditional error correction regression for 2-variable model

Table 7 Test of short-term coefficient estimates Conditional Error Correction Regression for 2-variable model

Table 7. Test of short-term coefficient estimates conditional error correction regression for 2-variable model

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	3,096105	1,232731	2,511583	0,0162
NPL(-1)*	-0,137261	0,091136	-1,506112	0,1399
CAR(-1)	-0,239227	0,127766	-1,872391	0,0685
ROAA**	-1,876580	0,724179	-2,591319	0,0133
D(CAR)	-0,075359	0,161874	-0,465539	0,6441
D(CAR(-1))	0,360583	0,144509	2,495227	0,0168

The variable NPL(-1) is not simply a lagged variable of the non-performing loan ratio (NPL) as in the original model. In fact, it represents the Error Correction Term (ECT), a component that reflects the speed of adjustment of deviations from the long-run equilibrium. Although not named "ECT", in essence, EViews automatically represents ECT as a lagged variable of the main dependent variable when running the conditional short-run table. This is completely consistent with the structure of the ARDL model, in which long-run information is "compressed" into an adjustment component to measure the ability of the system to recover to equilibrium after a shock. Its role is to represent the speed at which the system returns to equilibrium after a shock. This interpretation is confirmed by the software's own note: "p-value incompatible with t-Bounds distribution," meaning that the p-value should not be used to assess the cointegration relationship, as it does not follow the standard Bounds distribution. Instead, the analyst should focus on the coefficient and t-statistic of NPL(-1) itself to evaluate the presence of long-run adjustment.

The first-difference variable D(CAR(-1)) has a positive coefficient with p = 0,0168, significant at the 5% level. This implies that recent past changes in CAR have an immediate positive effect on NPL in the short term, possibly because capital adjustments have not yet translated into improved credit quality. Meanwhile, D(CAR) and CAR(-1) are not statistically significant, suggesting that changes in CAR in the current quarter or one quarter earlier do not have a clear short-term impact on NPL.

ROAA continues to play an important role, with a negative coefficient and p = 0,0133, significant at the 5% level. This reflects that higher profitability can immediately improve credit quality.

3.3.4 Granger causality test for the two-variable model

The Granger causality test is used to determine whether one time series can predict another time series. If the test results show that an independent variable is not statistically significant in predicting the dependent variable (i.e. there is no Granger effect), this means that the independent variable does not improve the predictive ability of the model. However, this does not necessarily mean that the variable is worthless.

Table 8. Granger causality test between CAR and NPL for 2-variable models

Null Hypothesis	F-Statistic	Prob
NPL does not Granger Cause CAR	6,15554	0,0046
CAR does not Granger Cause NPL	2,95101	0,0635

The Granger test results show that there is a two-way causality relationship between the non-performing loan ratio (NPL) and the capital adequacy ratio (CAR). Specifically, NPL significantly affects CAR at the 1% significance level. This means that when the level of non-performing loans increases, the bank responds by raising its CAR to safeguard capital. This behavior indicates that Sacombank actively adjusts its capital in line with risk exposure rather than reacting passively, a response that aligns well with the principles of Basel III.

In the opposite direction, CAR also influences NPL at the 10% significance level, suggesting that capital adequacy plays a role in controlling credit risk. However, under the Granger test, this impact appears relatively weak in the short term.

Table 9. Granger causality test between ROAA and NPL for the 2-variable model

Null Hypothesis	F-Statistic	Prob.
NPL does not Granger Cause ROAA	0,02843	0,9720
ROAA does not Granger Cause NPL	1,23886	0,3003

In contrast to the above results, the Granger Causality test between ROAA and NPL does not show any significant causal relationship in both directions. Specifically, the p-value is > 0,3, indicating that there is no evidence to conclude that return on total assets (ROAA) affects the bad debt ratio, or vice versa in the short run. This is because Granger does not measure the strength of the impact, but only tests the short-term predictive ability. A variable may not be predictive (Granger is not significant), but still has a clear causal effect in the regression models.

3.3.5 Wald test for 2-variable models

The Wald test will evaluate the separate statistical significance of each coefficient in the ARDL model.

Table 10. Wald test for 2-variable models

No.	Variable	C(1) = 0	C(2) = 0	C(3) = 0	C(4) = 0
1	Coefficient	0,862739	–0,0754	0,1967	–0,3606
2	P-VALUE	0,0000	0,6441	0, 3112	0,0168

In the Wald test, the coefficients C(1) and C(4) correspond to the lagged value of NPL and the ROAA variable in the ARDL(1,2,0) model, respectively. The results show that both coefficients are statistically significant, with p-values of 0,0000 for C(1) and approximately

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0,0168–0,0126 for C(4), all within the 5% significance level. This indicates that NPL exhibits strong autoregressive behavior, accurately reflecting the dynamic nature of non-performing loans in the banking sector, which are often influenced by their own historical trends. Furthermore, ROAA has a negative effect on NPL, suggesting that higher profitability helps banks better control credit risk. The statistical significance of these coefficients supports the decision to retain them in the model, both from an economic and statistical standpoint. In contrast, the coefficients C(2) and C(3), representing CAR(-1) and CAR(-2), are not statistically significant according to the Wald test, with p-values of 0,6441 and 0,3050, respectively. This implies that, when considered individually, CAR at each specific lag does not exert a notable impact on NPL in the current model. This reflects the banking practice: the impact of capital adequacy ratio is often lagged and cumulative, not manifested immediately in a single lag level. Therefore, CAR may not be "prominent" in Wald, but still plays an important role in the bigger picture.

3.3.6 Diagnostic tests for the 2-variable model

The author conducts model assumptions testing, including: checks for the normal distribution of residuals, serial correlation, heteroskedasticity, and multicollinearity.

Table 11. Diagnostic tests for the 2-variable model

No	**Test**	**Testing method**	**Statistical value**	**Probability**	**Conclusion**
1	Normal Distribution	JB	117,8301	0,00000	Non-normal distribution
2	Jarque-Bera Serial Correlation	F(2,38)	1,37568	0,26500	No autocorrelation
		Chi-Square(2)	3,10572	0,21160	No autocorrelation
3	Breusch Godfrey LM	F(5,40)	1,67168	0,16370	Residuals have constant variance
		Chi-Square(5)	7,95075	0,15900	Residuals have constant variance
4	Heteroscedasticity – Breusch-Pagan-Godfrey	NPL(-1)	0,00831	1,73915	No multicollinearity
		CAR	0,02620	3,22818	No multicollinearity
		CAR(-1)	0,03678	4,53126	Potential signs
		CAR(-2)	0,02088	2,59496	No multicollinearity
		ROAA	0,52444	1,17110	No multicollinearity
		C	1,51963	NA	No comments

The results show that the model is completely suitable and statistically reliable, and can be used to draw economic and financial conclusions about the impact of Basel III on risk management at Sacombank.

The model shows no signs of serial correlation (p = 0,265 > 0,05) and no significant heteroskedasticity (p = 0,16370 and 0,15900). This indicates that the residuals are stable and independent over time, an essential condition for dynamic models such as ARDL.

Regarding multicollinearity, all variance inflation factor (VIF) values are below 5, with only CAR(-1) recording a VIF of 4,53, close to the cautionary threshold. However, in the context of analyzing financial data with logical lags according to banking policies, this value is still within acceptable limits. In particular, the ROAA variable has a very low VIF, indicating good independence from the remaining variables. This confirms that the model does not have serious problems with multicollinearity, does not distort the regression coefficient, thereby improving the accuracy in analyzing the relationship between capital (CAR), profit (ROAA) and credit risk (NPL).

A unique point is that the normal distribution of the residuals has p = 0,000. This is a common phenomenon in limited financial datasets, and given that the ARDL method is semi-parametric in nature, it does not significantly undermine the reliability of the estimates.

In summary, all diagnostic tests support the model's validity, allowing the ARDL results to be used for empirical economic conclusions on the influence of Basel III on Sacombank's credit risk over the 2013–2024 period.

3.3.7 Testing the stability of coefficients and CUSUM and CUSUM of Squares for the 2-variable model

Due to the change in the banking structure in the merger of Phuong Nam Bank, the study conducted a stability test through two popular tools, CUSUM (Cumulative Sum) and CUSUMSQ (Cumulative Sum of Squares), which help assess the stability of the model coefficients in both the short and long run by using the residuals of the ECM model. If the test line remain entirely within the 5% significance boundaries, it can be concluded that the coefficients have not experienced significant variation over time.

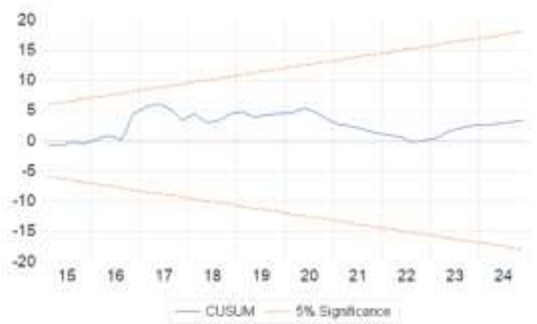

Figure 1 CUSUM Test

Figure 2. CUSUMSQ Test

The CUSUM chart reveals that the test line (blue) remains entirely within the 5% significance boundaries (red lines), confirming that the model maintained stability throughout the study period.

In contrast, the CUSUM of Squares chart, which is used to check whether the coefficients change abruptly, shows that there is a small segment outside the upper limit during the period from about 2017 to 2020. However, this overshoot was short-lived, with the statistic quickly returning to the stability zone. Since CUSUMSQ is particularly sensitive to policy shocks or unusual macroeconomic events, these fluctuations are likely the result of external factors such as macroeconomic volatility or regulatory changes, rather than any inherent flaw in the overall model (Muhammad Nasrullah et al., 2021).

4. Discussion of results

The study's model was constructed with variables selected on the basis of Basel III credit risk management theory and prior empirical research. Six initial variables were included—CAR, INFOR, and the control variables ROAA, GDPG, INF, and NHPN. According to the ADF test results, all variables met the stationarity requirement at either I(0) or I(1), qualifying them for ARDL methodology.

Choosing this set of six variables was a cautious strategy to avoid omitting potentially significant drivers and to ensure a strong theoretical foundation. However, incorporating all six into an ARDL framework with only 48 observations introduced the problem of excessive parameters, which diluted the reliability of coefficient estimates for certain variables. Based on the AIC criterion, the optimal lag structure identified was ARDL(1, 2, 0, 0, 0, 0, 1). The Bound Test results indicated no long-run cointegration, implying that Basel III's influence at Sacombank was primarily manifested in the short term.

Subsequent diagnostic checks revealed that only CAR and ROAA consistently demonstrated statistical significance and stability across all model specifications. The remaining four variables—INFOR, GDPG, INF, and State Bank failed to achieve significance at any level, either in the general or short-run equations. Retaining them did not improve explanatory power but rather masked the true effects of the key drivers, adding noise to the model.

Refining the model to include only CAR and ROAA addressed these limitations effectively, resulting in a more robust specification that overcame the sample size constraint for CAR while improving reliability and interpretability. Removing the four insignificant variables not only enhanced statistical significance but also improved compliance with econometric assumptions. Notably, CAR(-2)'s p-value dropped from 0,0184 to 0,0168, while ROAA consistently remained below 0,05. This confirmed that the exclusion of irrelevant variables increased both stability and precision. The Bound Test results also improved substantially, with the long-run F-statistic rising from 2,28 to 3,57, reinforcing the validity of the simplified model. In particular, the NPL(-1) variable plays the same role as ECT (error correction coefficient), although it is not statistically significant (p = 0,139), but has the expected negative sign, confirming the adjustment momentum towards balance, thereby ensuring theoretical validity. This reflects the practical characteristics at Sacombank: although Basel III has just been implemented, the credit risk adjustment response mechanism is still taking place in a positive and stable direction.

A closer look at specific tests for the two-variable model showed that CAR exhibited a causal relationship with NPL (Granger causality test), while ROAA's significance emerged clearly through the Wald test. This complementarity strengthens the theoretical and empirical basis of the current specification. The impact of ROAA tends to have a clearer and more immediate effect on bad loans, as banks with stronger profitability generally face lower credit risk. By contrast, CAR adjustments are slower and more regulatory in nature, while ROAA reflects operational performance, which has a stronger impact on credit quality over the same period.

All diagnostic checks including normality, heteroskedasticity, autocorrelation, and multicollinearity produced satisfactory results. Only the CUSUM of Squares test shows a small period (2017 – 2020) slightly exceeding the stability limit.

However, if the overall trend of the test line remains stable and the periods exceeding the limit are not prolonged or reversible, the model remains reliable. This is especially true in the context of Sacombank undergoing a strong restructuring and recovery period after 2017, which may affect the model's sensitivity without losing its scientific value. From the theoretical basis to the tests, the two-variable model CAR and ROAA is completely reasonable. Not only does it show clear statistical significance, these two variables also represent the true focus of Basel III credit risk management (CAR belongs to the capital pillar, ROAA reflects internal financial efficiency). CAR and ROAA both explain the dependent variable well, satisfy most of the model assumptions, and ensure a clear relationship.

However, in the context of studying a single bank (Sacombank), some theoretical variables that are true in the industry-wide study do not have a clear impact in the local data. Therefore, the 2-variable reduced model is not against the theory, but reflects the specificity and practice.

Evolution of CAR with NPL in the 2-variable model

CAR acts as a risk-absorbing capital buffer, providing a direct and stable impact on reducing NPL, reflecting that a bank that is healthy in terms of profits will be better able to manage and handle bad debts.

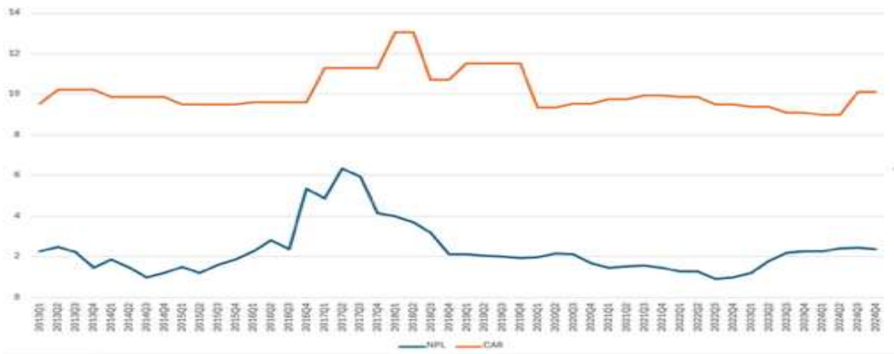

Figure 3. Analysis of CAR and NPL in the 2-variable model

Theoretically, CAR is expected to have an inverse relationship with NPL. The results from the ARDL model have shown a complex and lagged relationship between CAR and NPL. Meanwhile, CAR although showing a certain lag (2 quarters) in the impact of reducing NPL, still shows the role of capital consolidation as a strategic measure that takes time to be effective in improving credit quality. The two-way causal relationship between NPL and CAR also shows that NPL is not only affected by capital but also a factor that has a reverse impact on the bank's capital adjustment decision. For Sacombank, building a healthy loan portfolio requires more than regulatory compliance, it depends critically on the bank’s intrinsic ability to generate sustainable profits and maintain a robust capital base.

For most of the period from 2013 to 2024, Sacombank's CAR remained above 9%, in compliance with the regulations of the State Bank of Vietnam (Circular 22/2019/TT, 2019). Only the CAR in the first and second quarters of 2024 is 8,99%, slightly lower than the required consolidation level of 9%, but still higher than the 8% limit allowed by Basel III. Compliance with and improvement of CAR according to Basel standards encourages banks to improve their risk management capacity, including credit risk.

In the short term, banks are forced to increase CAR when credit risk is present and NPLs are increasing. Therefore, the increase in CAR in the short term may be a sign that banks are trying to cope with the wave of bad debts, and the capital adjustment effect has not yet penetrated into credit quality to reduce NPLs immediately.

The reduction in CAR occurs in a "slow but sure" way, the increase in the equity capital ratio does not immediately show its effectiveness in improving credit quality, but usually takes a period of 2 quarters to take effect. In other words, capital consolidation is like a strategic defense plan, not immediately solving the current situation but playing an important role in preventing risks and improving the ability to respond in the future.

It is worth noting that the relationship between these two variables is not simply one-way. Many evidences show that the current bad debt situation can also affect the decision on capital scale in reverse, the causal direction from NPL to CAR, also shows that NPL is not only affected by capital but also a factor that affects the bank's capital adjustment decision, when the bank is forced to increase its reserve capital or restructure its balance sheet to ensure financial safety ratios.

Evolution of ROAA and NPL in the 2-variable model

In essence, ROAA reflects the profitability of average total assets, while NPL shows the credit quality and risk level of the loan portfolio. The underlying theory predicts an inverse relationship: When a bank operates effectively, achieving a high ROAA shows good profitability, which means that the bank has better risk management and control capacity, as well as the ability to make adequate provisions to cover impaired loans. This helps limit the increase in bad debt and reduce the NPL ratio. Conversely, increasing bad debt will erode profits, pulling ROAA down.

The test results from the ARDL model show that better ROAA performance helps reduce the NPL ratio significantly. This impact is assessed as clear and stable, reflecting a significant immediate impact on credit risk.

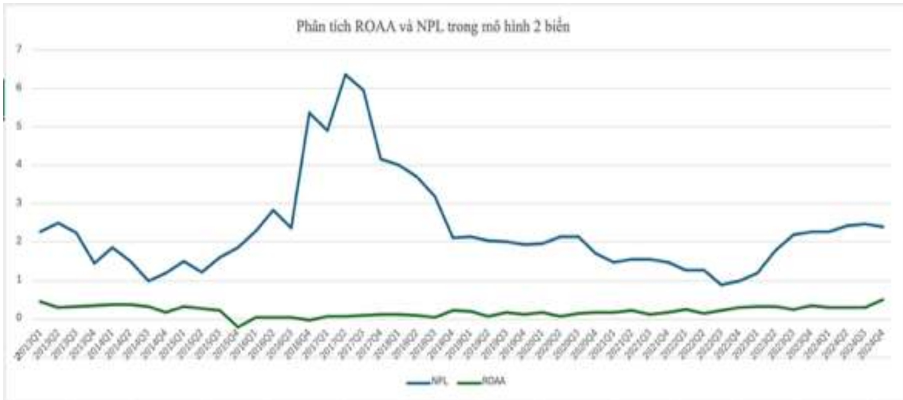

Figure 4. Analysis of ROAA and NPL in the 2-variable model

During the period from Q1.2013 to Q4.2024, ROAA and NPL at Sacombank clearly showed inverse relationships. The challenging post-merger period saw a sharp surge in NPLs and a severe decline in ROAA. In contrast, decisive efforts in bad debt resolution and restructuring during 2018–2022 helped ROAA recover strongly in parallel with the reduction of NPL. Even in the recent challenging macroeconomic period (2023-2024), the fulfillment of financial obligations related to bad debt and effective governance helped Sacombank maintain high ROAA, creating a solid foundation for controlling NPL.

The results from ARDL model, combined with the Wald test simultaneously confirmed: ROAA has a negative and statistically significant impact on NPL. Although the Granger causality test did not detect a short-term directional relationship, this does not diminish ROAA's stable and structural role in safeguarding credit quality.

5. Conclusion

The refined ARDL model has provided a deeper and more consistent insight into the mutual roles of CAR and ROAA on NPLs, avoiding contradictory findings. Despite their separate roles, ROAA and CAR can still support each other in managing NPLs.

ROAA as an initial “prevention”: When a bank has a high ROAA, it is often accompanied by good internal control systems and stable loan portfolio quality. This helps prevent the increase of NPLs at the root, creating a solid business foundation, minimizing credit risks before they become serious.

CAR is a strategic “defense” when there is a potential risk of new bad debts, banks adjust capital to strengthen their financial response capacity, creating a significant capital buffer to overcome the crisis. In practice, rising NPLs may prompt banks to raise CAR to safeguard balance sheet health. This reactive cycle between NPL and CAR means that higher NPLs can trigger capital increases, enabling banks to maintain market confidence and avoid systemic shocks.

During the research period, Sacombank complied with CAR and NPL requirements according to the Circulars of the State Bank. The relationship between CAR and NPL is more complicated than one-way, sometimes showing a desirable inverse relationship, but also showing a positive relationship, when banks proactively or are required to increase capital to cope with declining asset quality. Sacombank has also invested significantly in its management data system, but for complex quantitative analysis models, the data still lacks continuity, especially full quarterly CAR information. The current model has been scientifically adjusted, showing a clear relationship between CAR(-2), ROAA and NPL, explaining most of the variation in NPL (Adjusted $R^2 = 0,78$). However, if full CAR data is added, the number of observations will increase, helping to make parameter estimates more accurate and clarify the long-term relationship. Likewise, additional data on macroeconomic variables such as GDP growth, inflation, and other factors could uncover new lags or linkages currently undetected due to data limitations.

The author recommends strategic directions and measures to enhance Sacombank’s business capacity and credit risk management for 2025–2030. The strategic orientation focuses on affirming the position of a regional bank, promoting comprehensive digitalization to form a digital financial ecosystem, strengthening internal strength and developing human resources, along with completing the restructuring project and optimizing shareholder benefits by resolving the issue of frozen shares.

For credit risk governance, Sacombank should transition toward a proactive risk, preventing risks early right from the loan approval stage. This includes enhancing the effectiveness of the internal control system (three-line protection model), applying modern technology to risk monitoring (the "24/7 Eye" system, real-time data warehouse, completing IFRS 9), and persistently resolving bad debts and unrecovered assets.

Specific measures to enhance credit risk management include strengthening the capital management framework and capital allocation in line with Basel III—particularly by improving the quality of Common Equity Tier 1 (CET1) capital, optimizing operational efficiency through the ROAA indicator, and reshaping the implementation roadmap for Basel III Pillars 2 and 3. Banks also need to learn from statistically insignificant macro factors by building an early warning system. Other solutions include continuously improving credit policies, developing a high-quality risk team, enhancing the integration of ESG factors, and cooperating and providing transparent information to stakeholders.

Finally, the study suggests complementary policies, such as advising the State Bank of Vietnam (SBV) to design a suitable Basel III adoption roadmap, strengthen supervisory oversight and technical support, and accelerate procedures to resolve the issue of frozen equity capital. In addition, it is recommended to foster collaboration with credit rating agencies, industry associations, Fintech companies, and clients to establish a safe and sustainable credit ecosystem.

The adoption of Basel III is already showing positive results in credit risk management at Sacombank. Overall, the combination of theoretical analysis, quantitative modeling, and practical implementation demonstrates that this regulatory framework not only improves the bank's resilience to risks but also facilitates deeper integration of Sacombank into the global financial market.

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