# รายงานวิจัย

เรื่อง

**ความเสี่ยงด้านเครดิตและผลการดำเนินงานทางการเงินของธนาคารพาณิชย์ในประเทศไทยระหว่างปี พ.ศ. 2562 - 2566**

**Credit Risk and Financial Performance of Thai Commercial Banks during 2019 to 2023**

โดย

เศรษฐพงศ์ วัฒนพลาชัยกูร

การวิจัยครั้งนี้ได้รับเงินทุนการวิจัยจากมหาวิทยาลัยราชพฤกษ์

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# บทคัดย่อ

การวิจัยนี้สำรวจด้านความเสี่ยงทางเครดิตและประสิทธิภาพทางการเงินของธนาคารพาณิชย์ในประเทศไทยในช่วงระหว่างปี 2562 ถึง 2566 โดยมีวัตถุประสงค์เพื่อศึกษาปัจจัยที่มีผลกระทบต่อความเสี่ยงทางเครดิตของธนาคารพาณิชย์ในประเทศไทย และ ศึกษาผลกระทบจากความเสี่ยงทางเครดิตต่อประสิทธิภาพทางการเงินของธนาคารพาณิชย์ การวิเคราะห์ได้มีการเก็บตัวอย่างที่ประกอบด้วยธนาคารพาณิชย์ 5 รายในประเทศไทยโดยพิจารณาจากยอดสินทรัพย์รวม และ ใช้การวิเคราะห์สมการถดถอยเพื่อศึกษาความสัมพันธ์ระหว่างตัวชี้วัดความเสี่ยงทางเครดิตต่าง ๆ (รวมถึงค่าความค่าความเสี่ยง อัตรากำไรสุทธิ อัตราส่วนสินทรัพย์ที่ไม่ได้ดำเนินงาน อัตราการสำรองสินเชื่อและอัตราส่วนการกู้ยืม) และตัวชี้วัดผลการเงิน การวิจัยมุ่งหวังที่จะให้ข้อมูลที่ครอบคลุมและเข้าใจเกี่ยวกับความสัมพันธ์ระหว่างความเสี่ยงทางเครดิต และ ประสิทธิภาพทางการเงินในธนาคารพาณิชย์ในประเทศไทย เพื่อวางกลยุทธ์การจัดการความเสี่ยงและการตัดสินใจที่มีนัยสำคัญในภาคการเงิน

ผลการวิจัยแสดงถึงความผันผวนในการเผชิญต่อความเสี่ยง ความสามารถในการทำกำไร คุณภาพของสินทรัพย์ การจัดสรรสินเชื่อ และระดับความเป็นหนี้ การวิเคราะห์สมการถดถอยยังเน้นให้ความสำคัญกับผลกระทบที่สำคัญของตัวแปรความเสี่ยงทางเครดิตต่อประสิทธิภาพทางการเงินของธนาคาร โดยเน้นถึงความจำเป็นของกลยุทธ์การจัดการความเสี่ยงที่มีประสิทธิภาพในการเสริมสร้างกำไรและการตัดสินใจเชิงกลยุทธ์สำหรับธนาคารพาณิชย์ในประเทศไทย

**คำสำคัญ:** ความเสี่ยงด้านเครดิต ผลการดำเนินงานทางการเงิน ธนาคารพาณิชย์ไทย

**Research Title:** Credit Risk and Financial Performance of Thai Commercial Banks during 2019 to 2023

**Researcher:** Sethapong Watanapalachaikul

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## Abstract

This research delved into the credit risk and financial performance dynamics of Thai commercial banks spanning the period from 2019 to 2023. The research attempted to explore the factors that contribute to credit risk of Thai commercial banks; and secondly, exploring the impact of credit risk on their financial performance. To fulfill these objectives, an analysis was conducted on a sample consisting of the top five commercial banks in Thailand, chosen based on their total assets and employed multiple regression analysis to probe the relationship between various credit risk indicators (including Value at Risk, Net Interest Margin, Non-Performing Loan Ratio, Loan Loss Provisioning, and Leverage Ratio) and financial performance metrics. Drawing on bank financial reports and Bank of Thailand data, the research aimed to furnish comprehensive insights into the intricate interplay between credit risk and financial performance in Thai commercial banks, thus offering pertinent implications for risk management strategies and strategic decision-making in the banking sector.

The findings unveiled fluctuations in risk exposure, profitability, asset quality, loan provisioning practices, and leverage levels over the study period. Moreover, the regression analysis underscored the significant impact of credit risk variables on bank financial performance, highlighting the imperative of effective risk management practices for bolstering profitability and guiding strategic decision-making in the Thai commercial banking domain.


**Keywords:** Credit Risk, Financial Performance, Thai Commercial Banks

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Sethapong Watanapalachaikul
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# Chapter 1
# Introduction

The intersection of credit risk and the financial performance of commercial banks is a critical area of inquiry, especially against the backdrop of the dynamic economic landscape witnessed from 2019 to 2023. Thai commercial banks, like their global counterparts, operate within an environment marked by intricate financial dynamics, regulatory changes, and economic uncertainties. Understanding the intricate relationship between credit risk and financial performance is pivotal for stakeholders, including policymakers, investors, and banking institutions, as it can influence the stability and resilience of the banking sector.

The years 2019 to 2023 present a particularly intriguing period for studying credit risk and financial performance in Thai commercial banks. The global economy, still grappling with the aftermath of the COVID-19 pandemic, has been subject to various macroeconomic shifts and policy responses. These external factors, coupled with domestic economic conditions and regulatory changes, contribute to a complex landscape that shapes the credit risk exposure and financial outcomes of banks.

This research aims to delve into the multifaceted dimensions of credit risk within the context of Thai commercial banks during the specified period. It seeks to explore how economic conditions, regulatory frameworks, and internal bank strategies interact to influence credit risk profiles. Simultaneously, the study endeavors to analyze the impact of credit risk on the financial performance metrics of these banks. By scrutinizing key financial indicators, such as capital adequacy, asset quality, profitability, and liquidity, the research aims to provide comprehensive insights into how credit risk manifests and its subsequent implications for the overall financial health of Thai commercial banks.

Moreover, the study will consider the effectiveness of risk management practices employed by these banks in mitigating credit risk and sustaining financial stability. The findings of this research are anticipated to contribute not only to the academic understanding of credit risk in the Thai banking sector but also to offer practical implications for regulators, policymakers, and banking professionals navigating the intricacies of financial management in a rapidly evolving economic environment.

The outline structure of this chapter are as follows:

1.1 Background and Problem Statement

1.2 Research Questions

1.3 Research Objectives

1.4 Research Hypothesis

1.5 Research Scope and Limitation

1.6 Definition

1.7 Significance of the Study

**1.1 Background and Problem Statement**

The banking sector in Thailand plays a pivotal role in the country's economic development and stability. Over the years, Thai commercial banks have experienced significant growth and transformation, reflecting the dynamism of the nation's financial landscape. This transformation has been accompanied by both opportunities and challenges, one of the most prominent being the effective management of credit risk.

Credit risk, a fundamental concern for financial institutions, represents the risk that borrowers may default on their financial obligations, such as loans and credit facilities. Managing credit risk is central to the viability and profitability of commercial banks. Understanding and mitigating this risk is imperative for both financial stability and long-term growth in the Thai banking industry. As such, this research aims to explore the intricate relationship between credit risk and the financial performance of Thai commercial banks (Abiola, 2023).

The relevance of this research stems from several factors such as economic significance, rapid transformation, global banking environment and limited Thai-specific research. Economic Significance: Thai banks are integral to the overall health of the Thai economy, channeling funds to various sectors and contributing to economic development. Therefore, their stability and performance are of paramount importance. Rapid Transformation: The Thai banking sector has experienced remarkable growth and transformation in recent years, characterized by technological advancements, increasing competition, and evolving customer demands. These changes have ramifications for credit risk management and financial performance. Global Banking Environment: The international banking environment has been marked by significant regulatory changes, particularly in the post-global financial crisis era. Compliance with international banking standards and regulations is crucial for Thai banks to access international markets. Limited Thai-Specific Research: While there exists a substantial body of research on credit risk and banking performance globally, the specific dynamics of the Thai banking industry have received comparatively less attention. This research seeks to address this gap.

The Thai banking industry has been a significant contributor to the country's economic growth. As the sector continues to evolve, banks face an array of challenges, with credit risk management being a central concern. Credit risk, the risk of borrowers defaulting on their obligations, can have a profound impact on a bank's financial health. Therefore, understanding the relationship between credit risk and financial performance is essential for the stability and sustainability of Thai banks.

Therefore, the Thai banking sector is pivotal for economic development, facing challenges and opportunities amid significant growth and transformation. Effective credit risk management is a central concern, given its impact on the viability and profitability of commercial banks. This research aims to explore the intricate relationship between credit risk and the financial performance of Thai commercial banks. The economic significance of these banks, their rapid transformation, the influence of the global banking environment, and the limited focus on Thai-specific research contribute to the relevance of this study. As Thai banks play a crucial role in Thai economic health, this research seeks to provide valuable insights in a rapidly evolving global landscape with unique challenges.

## 1.2 Research Questions

1.2.1 What are factors contributing to credit risk of commercial banks in Thailand?

1.2.2 How did credit risk impact the financial performance of commercial banks in Thailand?

## 1.3 Research Objectives

1.3.1 To investigate each factor of credit risk of commercial bank's in Thailand.

1.3.2 To examine the impact of credit risk on the financial performance of commercial banks operating in Thailand.

## 1.4 Research Hypothesis

1.4.1 It is expected that during 2019-2023, there were high level of credit risk.

1.4.2 It is expected that credit risk would contribute to low financial stability and profitability of Thai banks and vice versa.

## 1.5 Research Scope and Limitation

This research focuses on the Thai banking sector, encompassing commercial banks, savings banks, and other financial institutions operating in Thailand. The study considers credit risk management practices and their impact on financial performance over a specified time frame. It is important to acknowledge potential limitations of the research as follows.

1. The analysis is based on historical financial data, and thus, the findings may not fully capture the current dynamics of the Thai banking sector.

2. The models assume a linear relationship between variables, which may not always reflect the complex, non-linear nature of financial markets.

3. The dataset relies on the accuracy and completeness of the financial reports provided by Thai commercial banks and Bank of Thailand (BOT).

## 1.6 Definition

Credit Risk, Financial Performance, Thai Commercial Banks

Credit Risk - Credit risk is the probability of a financial loss resulting from a borrower's failure to repay a loan. Essentially, credit risk refers to the risk that a lender may not receive the owed principal and interest, which results in an interruption of cash flows and increased costs for collection. Lenders can mitigate credit risk by analyzing factors about a borrower's creditworthiness, such as their current debt load and income.

Financial Performance - Financial performance is a subjective measure of how well a firm can use assets from its primary mode of business and generate revenues. The term is also used as a general measure of a firm's overall financial health over a given period. Analysts and investors use financial performance to compare similar firms across the same industry or to compare industries or sectors in aggregate.

Thai Commercial Banks – Thai commercial banks are financial institutions that provide services like loans, certificates of deposits, savings bank accounts bank overdrafts, etc. to its customers in Thailand. These institutions make money by lending loans to individuals and earning interest on loans. Various types of loans given by a commercial bank are business loans, car loans, house loans, personal loans, and education loans. They give out these loans from the money deposited by their customers in different types of accounts. They use the deposits as capital for providing loans. Thai commercial banks are essential for the economy of Thailand because they help in creating capital, credit as well as liquidity in the market. These banks are generally physically located in cities but these days there are online banks are growing in numbers.

## 1.7 Significance of the Study

This research has made significant contributions to the field of banking and finance:

1. It has provided empirical evidence of the adverse impact of credit risk on the financial performance of Thai commercial banks, reaffirming the importance of credit risk management.

2. The research has contributed to a better understanding of how credit risk indicators influence key financial performance metrics, which can guide banks, investors, and regulators.

3. The recommendations and future research directions proposed in this paper offer valuable insights for stakeholders and scholars seeking to enhance credit risk management in the Thai banking sector.

# Chapter 2
# Literature Review

This chapter reviewed existing literature relevant to the central themes of this research paper: credit risk and financial performance in the context of Thai commercial banks. It encompassed an overview of credit risk, credit risk elements, and the various financial performance indicators used to evaluate the stability and profitability of banks. This review provided a foundation for understanding the theoretical and empirical aspects that underpin the relationship between credit risk and financial performance in Thai commercial banks. The significance of bank performance within the financial sector cannot be overstated, given its substantial impact on economic stability and growth. Consequently, a thorough understanding of the determinants of bank performance is crucial for various stakeholders, including policymakers, regulators, investors, and analysts.

This chapter endeavors to establish a robust theoretical framework that integrates multiple theoretical perspectives to comprehensively analyze bank performance, with a specific focus on employing multiple regression analysis as a statistical tool. The theoretical constructs examined herein encompass agency theory, financial intermediation theory, efficiency theory, and capital structure theory. Through the lens of these theoretical underpinnings, the chapter aims to illuminate the key factors influencing bank performance and their intricate relationships with various performance metrics. The literature review aims to provide a theoretical foundation for the proposed research and identify gaps in the existing literature.

The outline structure of this chapter are as follows:

2.1 Theoretical Framework

2.2 Review of Related Literature

2.3 Conceptual Framework

## 2.1 Theoretical Framework

The multiple regression model emerges as a powerful statistical tool for scrutinizing the complex relationships between multiple variables. In the context of analyzing bank performance, multiple regression analysis enables researchers to identify significant determinants of performance metrics such as profitability, efficiency, and asset quality. By meticulously examining the impact of various independent variables on bank performance, researchers can quantify the magnitude and direction of these effects, thereby furnishing valuable insights for stakeholders. The utilization of the multiple regression model as a statistical technique had become prevalent across various disciplines, facilitating the analysis of complex relationships between multiple variables. In the context of this study, the multiple regression model served as a valuable tool for investigating the multifaceted determinants of bank performance (Kaya et al., 2013).

### 2.1.1 Theoretical Foundations of Multiple Regression Model

The theoretical foundation of the multiple regression model rested upon principles of linear regression analysis, which aimed to model the relationship between a dependent variable and multiple independent variables. Rooted in statistical theory, the multiple regression model assumed a linear relationship between the variables and sought to estimate the coefficients that best fit the observed data. The model drew upon mathematical concepts such as ordinary least squares (OLS) estimation to minimize the error term and derive unbiased estimates of the regression coefficients.

Mathematically, a linear multiple factor model can be expressed as follows (Kaya et al., 2013):

$$R_{it} = \alpha_i + (\beta_1)_i (F_1)_t + (\beta_2)_i (F_2)_t + . . . + (\beta_n)_i (F_n)_t + \varepsilon_{it}$$

where $R_{it}$ is the return of stock $i$ in period $t$, $\alpha_i$ is the expected value if each factor has a value of zero, $(F_1)_t$ and $(F_2)_t$ are the values of factors 1 and 2 with pervasive influence in period $t$, $(F_n)_t$ is the value of factor $n$, $(\beta_1)_i$ and $(\beta_2)_i$ are the prices of factors 1 and 2 (the risk premium) for stock *i*, $(\beta_n)_i$ is the price of factor n (the risk premium) for stock *i*, and $\varepsilon_{it}$ is the stock specific return.

2.1.2 Methodological Considerations

In the application of the multiple regression model, several methodological considerations warranted attention. These included issues related to model specification, multicollinearity, heteroscedasticity, and autocorrelation. Scholars emphasized the importance of conducting diagnostic tests to assess the validity of model assumptions and ensure the reliability of regression results. Moreover, researchers often employed techniques such as stepwise regression or robust standard errors to address potential challenges and enhance the robustness of regression analyses (Sun et al., 2023).

2.1.3 Empirical Applications in Various Fields

The multiple regression model found widespread application across diverse fields, including economics, finance, psychology, sociology, and public health. In the realm of economics, researchers utilized multiple regression analysis to examine factors influencing economic growth, income inequality, and labor market outcomes. Within the financial domain, studies employed the multiple regression model to investigate determinants of stock returns, corporate profitability, and financial performance metrics. In the social sciences, researchers such as Hodeghatta & Nayak (2023) explored predictors of academic achievement, job satisfaction, and consumer behavior using regression analysis. Moreover, in public health research, multiple regression techniques were applied to study the impact of various interventions on health outcomes and healthcare utilization patterns.

2.1.4 Critique and Limitations

Despite its widespread use, the multiple regression model was not without limitations. Critics highlighted concerns regarding model specification errors, omitted variable bias, and endogeneity issues. Furthermore, the assumption of linearity may not always hold true in practice, leading to potential misspecification of the regression model. Additionally, the interpretation of regression coefficients required caution, as correlation did not imply causation. Scholars emphasized the importance of employing robust regression techniques and conducting sensitivity analyses to address these limitations and enhance the validity of regression results (Ahmed & Elrayah, 2020).

## 2.2 Review of Related Literature

### 2.2.1 Credit Risk in Banking

Credit risk, often referred to as default risk, is the risk that borrowers will fail to meet their financial obligations to lenders, leading to potential financial losses for the lending institutions (Altman & Saunders, 1998). Credit risk can manifest in various forms, including loan defaults, delayed repayments, or the downgrading of credit quality.

Credit risk can be categorized into several types: 1) Default Risk: This is the risk that a borrower will completely fail to meet their financial obligations; 2) Counterparty Risk: This relates to risks associated with the financial health and stability of counterparties in various financial transactions; 3) Concentration Risk: Arising from high exposure to a single borrower or industry, this risk can significantly impact a bank's portfolio; 4) Country Risk: This pertains to the risk associated with lending to borrowers in specific countries, taking into account political, economic, and regulatory factors (Barboza, et al., 2016).

Banking efficiency had been acknowledged as a pivotal strategy for enhancing competitiveness. The primary goal of improving bank performance was to attain excellence in competition for business groups, banks, or countries. One avenue through which competitiveness could be augmented was by enhancing efficiency. Mahjus (2023) conducted an empirical analysis of the impact of credit risk on the cost efficiency of banking in ASEAN, utilizing panel data from banks across 10 ASEAN countries. The measurement of cost efficiency employed stochastic frontier analysis with a fixed effect assumption. The relationship between credit risk and efficiency was examined through a linear regression model, specifically, Feasible Generalized

Least Squares. The overarching finding revealed that banking efficiency in ASEAN consistently surpassed 80%. Notably, a negative association was identified between credit risk and banking efficiency. Particularly, the risk emanating from the loan-to-asset ratio indicator significantly diminished efficiency. The implication was that as banks assumed higher risks, there was a concomitant reduction in the cost-efficiency value of the bank.

Therefore, credit risk involved the potential that borrowers might fail to meet financial obligations, leading to losses for lending institutions. This risk could manifest as loan defaults, delayed repayments, or downgraded credit quality and was categorized into types such as default, counterparty, concentration, and country risk. Concurrently, banking efficiency was crucial for competitiveness. An empirical analysis of credit risk's impact on cost efficiency in ASEAN indicated consistent banking efficiency above 80%, with a negative association between credit risk, particularly from the loan-to-asset ratio indicator, and efficiency. Higher risks correlated with reduced cost-efficiency in banks.

a) COVID-19 Pandemic and Credit Risk

The outbreak of the COVID-19 pandemic brought unprecedented challenges to the global economy, affecting various sectors, including the banking industry. One of the critical dimensions through which the pandemic impacted financial institutions was the assessment and management of credit risk. Wahyuni et al. (2021) explored the existing research on the relationship between COVID-19 and bank credit risk, examining the diverse perspectives regarding to the impact of COVID-19 toward bank credit risk.

b) Macroeconomic Impact of COVID-19 on Credit Risk

The COVID-19 pandemic triggered a severe economic downturn, leading to a rise in credit risk for banks. Anto & Fakhrunnas (2022) investigated the macroeconomic factors influencing credit risk during the pandemic, such as GDP contraction, unemployment rates, and disruptions in supply chains. Studies demonstrated a strong correlation between these macroeconomic indicators and the deterioration of credit quality in bank portfolios.

c) Government Interventions and Credit Risk Mitigation

Governments worldwide implemented various fiscal and monetary measures to counter the economic fallout of the pandemic. Chang & Chen (2015) explored the effectiveness of these interventions in mitigating credit risk for banks. Analysis included the impact of stimulus packages, loan moratoriums, and regulatory adjustments on the stability of financial institutions and their ability to manage credit risk during those unprecedented times.

d) Technological Innovations in Credit Risk Management

The pandemic accelerated the adoption of technology in the banking sector, particularly in credit risk management. Studies delved into the role of artificial intelligence, machine learning, and big data analytics in enhancing banks' ability to assess and monitor credit risk. The integration of digital tools and innovative risk models was explored as a means to adapt to the rapidly changing economic landscape (Ibrahim, 2023; Anto & Fakhrunnas, 2022).

e) Sectoral Analysis of Credit Risk:

Certain sectors, such as hospitality, travel, and entertainment, were disproportionately affected by the pandemic, leading to increased credit risk for banks with exposures in these areas. Some researchers conducted sectoral analyses to understand the differential impact on credit risk across various industries, offering insights into sector-specific risk management strategies employed by financial institutions (Mahjus, 2023; Larcher, 2022).

f) Behavioral Changes in Borrowers

The pandemic induced changes in consumer behavior and business practices, influencing the creditworthiness of borrowers. Researchers such as Anto & Fakhrunnas (2022) and Wahyuni et al. (2021) examined the shifts in payment behavior, debt servicing capacity, and default patterns, providing valuable insights into the evolving nature of credit risk during and post-pandemic.

In conclusion, the literature on COVID-19 and bank credit risk reflected the multidimensional nature of the challenges faced by financial institutions in the wake of the pandemic. Macro-economic factors, government interventions, technological innovations, sectoral dynamics, and behavioral changes collectively contributed to the evolving landscape of credit risk. A nuanced understanding of these factors was crucial for developing effective risk management strategies to ensure the resilience and stability of the banking sector in the face of ongoing uncertainties.

2.2.2 Measurement of Credit Risk

Credit risk is typically quantified through metrics such as: Non-Performing Loan (NPL) Ratio: The percentage of loans that are not generating interest due to being in arrears or default; Loan Loss Provisioning: The amount set aside to cover potential losses from bad loans; Credit Scoring Models: Statistical models that predict the likelihood of borrower default based on various factors.

The efficient measurement of risk of portfolios of financial products were "Value at Risk (VaR)" and "Conditional VaR (cVaR)". By estimating VaR and cVaR for different types of portfolio could demonstrate the effect of reducing risk by diversification that specifically deals with credit risk management (Larcher, 2022).

Various methodologies such as Birbil, et al. (2009) existed to model decision-making under risk, where risk was broadly defined as the impact of variability in random outcomes. One of the primary approaches in the practice of decision-making under risk used mean-risk models, with the classical Markowitz model being a well-known example that employed variance as the risk measure. Honert & Vlok (2014) focused on portfolio optimization models aimed at constructing portfolios with minimal risk while ensuring the achievement of a specified expected return level. Specifically, the quantified risk by employing metrics such as Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR). After comprehensively examining the key characteristics of VaR and CVaR, presented concise proofs for some widely acknowledged results.

a) Value at Risk (VaR) and Conditional Value at Risk (cVaR)

The concept of Value at Risk (VaR) was developed by J.P. Morgan in the late 1980s as a measure of market risk (Altman & Saunders, 1998). Value at Risk (VaR) functioned as a statistical metric within the domain of finance, employed for the quantitative evaluation and estimation of potential financial losses associated with portfolios or investments. This measure delineated an approximation of the maximal conceivable loss over a designated time span, contingent upon a specified confidence level. Several pivotal components and principles contributed to the conceptual framework of Value at Risk:

Time Horizon: VaR computations were conducted over a defined time interval, such as a day, week, or month. The selection of the time horizon was contingent upon the investor's risk appetite, preferences, and the inherent characteristics of the financial instruments under consideration.

Confidence Level: The confidence level denoted the likelihood that the actual losses would not surpass the computed VaR. Commonly employed confidence levels included 95%, 99%, or 99.9%. For instance, in the context of a one-day VaR at a 95% confidence level amounting to $1 million, there existed a 5% probability that the portfolio losses would exceed $1 million within the ensuing day.

Distribution of Returns: VaR presupposed a specific statistical distribution of returns, frequently adopting the normal distribution or alternative distributions such as the t-distribution or historical simulation. This distribution facilitated the modeling of potential fluctuations in the portfolio's value.

The fundamental formula for VaR computation entailed the multiplication of the standard deviation of portfolio returns by the Z-Score corresponding to the chosen confidence level. The formula was articulated as follows:

$$\text{VaR} = \text{Portfolio Value} \times (\text{Asset Volatility} \times \text{Z-Score})$$

Portfolio Value: Denoted the aggregate value of the portfolio or investment in consideration.

Asset Volatility: Signified the standard deviation of the portfolio's returns, portraying the historical or implied volatility of the underlying assets.

Z-Score: The Z-Score, derived from the selected confidence level, conveyed the number of standard deviations from the mean in a normal distribution. For instance, at a 95% confidence level, the Z-Score approximated 1.645.

It was imperative to acknowledge that VaR was not devoid of limitations and assumptions, and it might not comprehensively capture extreme events or tail risks. Consequently, it was frequently utilized in conjunction with additional risk metrics and stress testing methodologies to furnish a more nuanced evaluation of potential portfolio losses (Altman & Saunders, 1998; Birbil, et al., 2009; Barboza, et al., 2016).

Conditional Value at Risk (CVaR), also referred to as Expected Shortfall (ES), represented a risk measure employed within the domain of finance to quantify potential losses in a portfolio or investment beyond a designated confidence level. In contrast to Value at Risk (VaR), which offered an estimate of the maximum potential loss at a specified confidence level, CVaR delved deeper by assessing the expected value of losses occurring beyond the VaR threshold.

In essence, CVaR sought to address the question: "If losses surpass the VaR, what is the average or expected magnitude of those losses?" The following elucidates the key components and characteristics associated with Conditional Value at Risk. VaR used as a starting point, in which CVaR calculation commenced with the determination of VaR, serving as the threshold level at which risk was evaluated. For instance, if VaR was computed at the 95% confidence level, it provided the maximum potential loss not anticipated to be exceeded with a 95% probability over a specified time horizon.

Average of Losses Beyond VaR: Subsequently, CVaR focused on losses occurring beyond the VaR threshold, calculating the average or expected value of these losses. This approach offered a more comprehensive understanding of the downside risk.

The formula for CVaR could be expressed as:

$$CVaR\alpha = 1 - \alpha 1 \int - \infty VaR\alpha x \cdot f(x) dx$$

where:

$CVaR\alpha$ denoted the Conditional Value at Risk at the confidence level

$VaR\alpha$ represented the Value at Risk at the confidence level

$f(x)$ denoted the probability density function of the portfolio's returns, and the integral symbolized an average over the range of losses beyond the VaR threshold.

CVaR offered a more nuanced perspective on the tail risk of a portfolio in comparison to VaR, encompassing not only the probability of extreme events but also the average severity of such events. This attribute rendered CVaR particularly valuable for risk managers and investors seeking a more intricate comprehension of potential losses within the tail of the distribution.

Since the development of Value at Risk (VaR) models, VaR swiftly became the global standard in risk management and forecasting such as in Mata, N. (2021) and Borer, et al. (2023). However, their role during global financial crises raised concerns about the effectiveness of existing tools in managing risk amid extreme events, with some researchers such as Borer, et al. (2023) attributing global financial contagion to VaR practices. A new measure, termed Conditional Value at Risk, was proposed to gauge the responsiveness of a portfolio's VaR to a percentage change in the weight of each investment asset. Using cVaR quarterly data on consolidated international claims, Kim, et al. (2009) tested the new measure with five historical financial crises. Specifically, Value at Risk elasticities were estimated for the portfolios of major banking centers before each crisis, serving as an indicator of an increased risk factor in assets. These estimations were then contrasted with the actual losses observed in the aftermath of the crises, utilizing stock market data. The results demonstrated that the proposed measure performed well in predicting asset losses during several global crises. Based on these findings, the recommendation was made to include conditional Value at Risk as an index to enhance the management of risks in portfolios.

b) Net Interest Margin (NIM)

NIM reflects the difference between a bank's interest income and interest expenses, expressed as a percentage of its interest-earning assets. A wider NIM suggests the bank is effectively managing its interest rate risk and generating income from loans. One indicator of a bank or other financial institution's profitability is its net interest margin. It is used to describe the discrepancy between interest paid and interest received. The financial net interest margin is heavily impacted by interest rates in the economy.

When the bank's net interest margin is positive, it means it is making efficient investments; when it is negative, it suggests making unproductive investments. For a bank, if the non-performing assets (NPAs) are rising, the interest earned would fall and the NIM will decline. The NIM will decrease if there is a greater desire for savings than for loans. In the meantime, a greater NIM would boost the lender's profitability. When investment returns fall short of interest costs, a lender's ability to utilize its assets is demonstrated by a negative net interest margin (NIM). NIM is therefore a crucial marker of a lender's financial stability. Furthermore, it is not possible to compare the NIM of two banks because of differences in asset sizes, customer makeup, priority sector lending, and other aspects of their operations (Harimurti, 2022).

c) Non-Performing Loan (NPL)

Non-Performing Loans (NPLs) literatures delved into various aspects of this crucial element in banking and finance. It examined the definition and measurement of NPLs, highlighting the metrics and thresholds used for classification. Researchers investigated the root causes of NPLs, encompassing macroeconomic and microeconomic factors, and explored the consequences on financial institutions and the broader economy. Khairi et al. (2021) research focused on risk management practices to prevent and address NPLs, including credit risk assessment and resolution strategies like loan workouts and asset sales. The review delved into the role of regulatory frameworks, analyzing the impact of policies such as provisioning requirements on NPL management. Comparative analyses across regions and economies shed light on variations in NPL trends, considering cultural, economic, and regulatory influences. Recent literature explored emerging trends and innovations in NPL management, including the use of technology and data analytics (Khairi et al., 2021).

In conclusion, the literature review synthesized a comprehensive understanding of NPLs, providing insights into their complexities, causes, consequences, and strategies employed by financial institutions. Future research may further explore the evolving landscape of NPLs in the context of technological advancements and global economic dynamics.

d) Loan Loss Provisioning (LLP)

The literature review on Loan Loss Provisioning (LLP) explored the multifaceted aspects of this critical component in financial institutions' risk management strategies. It examined the definition and various methods of calculating LLP, including incurred loss models and forward-looking Expected Credit Loss (ECL) models. Ozili (2023) investigated the determinants influencing LLP, such as economic conditions, industry-specific risks, and borrower characteristics. The impact of LLP on the financial health and performance of banks was analyzed, focusing on key indicators like profitability and capital adequacy (Martens & Bui, 2022).

The pro-cyclicality of LLP, particularly its tendency to increase during economic downturns, was a subject of exploration. The literature delved into the regulatory frameworks shaping LLP practices, aiming for consistency and transparency in financial reporting. Comparative analyses provided insights into variations in LLP practices across regions and financial institutions. Researchers evaluated the effectiveness of different LLP models, including historical loss experience models and forward-looking approaches, considering their strengths and limitations.

Recent literature such as Ozili (2023) and Martens & Bui (2022) highlighted emerging trends and innovations in LLP, including the integration of technology and data analytics for more sophisticated credit risk assessment and provisioning.

In conclusion, the literature review synthesized a comprehensive understanding of Loan Loss Provisioning, shedding light on its definition, determinants, impact, regulatory frameworks, and emerging trends. Future research may explore evolving LLP practices in the context of technological advancements and dynamic economic conditions.

e) Leverage Ratio (LEV)

Avgouleas (2015) explored various dimensions of this fundamental measure in financial institutions' capital adequacy. It examined different calculation methodologies, including the standardized method and supplementary leverage ratio (SLR) within the Basel III framework. Researchers investigated the determinants of the Leverage Ratio, considering factors such as the composition of a bank's balance sheet, risk-taking behavior, and the regulatory environment. The review delved into the regulatory implications of the Leverage Ratio, emphasizing its role in ensuring financial stability and regulating risk-taking by financial institutions.

Studies such as Hessou & Lai (2021) explored the impact of the Leverage Ratio on risk management practices within financial institutions, analyzing its influence on risk-taking behavior, capital allocation strategies, and overall risk culture. Comparative analyses provided insights into variations in Leverage Ratios across different institutions, regions, and regulatory environments. The literature review addressed the ongoing debate on the effectiveness of the Leverage Ratio as a regulatory tool. Scholars explored its strengths in promoting simplicity and comparability, as well as its limitations, including potential distortions and a one-size-fits-all approach.

Hessou & Lai (2021) also investigated the role of the Leverage Ratio in enhancing market discipline, examining how market participants use it to assess a bank's risk profile and make informed investment decisions. Recent literature focused on emerging trends and innovations in Leverage Ratio measurement, considering advancements in data analytics and technology for more accurate and timely reporting.

In conclusion, the literature review synthesized a comprehensive understanding of the Leverage Ratio, covering its definition, determinants, regulatory implications, impact on risk management, effectiveness, and emerging trends. Future research may explore evolving Leverage Ratio practices in the context of ongoing regulatory developments and technological advancements.

2.2.3 Financial Performance Indicators

a) Return on Assets (ROA)

ROA is a crucial indicator that measures a bank's ability to generate profit from its total assets. It is calculated as the net income divided by the total assets. A higher ROA suggests efficient asset utilization and overall profitability. A profitability ratio called return on assets shows how much money a business can make from its assets. Stated differently, return on assets (ROA) quantifies the effectiveness of a company's management in generating profits from the assets or financial resources listed on its balance sheet.

The higher the number, which represents ROA as a percentage, the more effectively a company's management manages its balance sheet to produce profits. Because a company's asset total might change over time as a result of the acquisition or sale of cars, land, or equipment, as well as inventory adjustments or seasonal variations in sales, average total assets is used to calculate return on assets (ROA). Because of this, computing the average total assets throughout the relevant time yields more accurate results than computing the total assets for a single period. The balance sheet shows all of a company's assets (Cooper, et al., 2009).

b) Return on Equity (ROE)

ROE represents the profitability of a bank in relation to its shareholders' equity. It is calculated as the net income divided by shareholders' equity. A higher ROE indicates greater returns for the shareholders. Because it combines the balance sheet and the income statement, where net income or profit is compared to shareholders' equity, return on equity is a two-part ratio in its calculation. ROE illustrates the firm's capacity to generate profits from equity investments and represents the overall return on equity capital. Stated differently, it quantifies the earnings generated for every dollar invested by stockholders.

A straightforward tool for assessing investment returns is provided by ROE. One can identify a company's competitive edge by comparing its return on equity (ROE) to the industry average. ROE may also provide light on how management of the company is utilizing equity capital to expand the company.

With ROE, a corporation may assess how well they're using the firm's equity and investors can determine if they're getting a decent return on their investment. ROE needs to be compared to both the industry average and the company's historical ROE. For evaluation reasons, a more thorough and comprehensive image of the organization can be obtained by looking at other financial ratios. A business should be able to provide investors with a return on equity (ROE) that is higher than that of a lower risk investment. An organization may be more successful at making money internally if its ROE is high. It does not, however, adequately convey the risk connected to that return. A business may use debt extensively in order to increase net profit, thereby boosting the ROE higher (Ichsani, et al., 2015).

2.2.4 Credit Risk and Financial Performance

The relationship between credit risk and financial performance in the banking sector has been a subject of extensive research. Several key findings emerge such as Negative Impact on Profitability: A strong body of research (Demirgüç-Kunt & Huizinga, 1999; Altman & Saunders, 1998) indicates that higher credit risk is associated with reduced bank profitability. Increased default rates and the need for higher loan loss provisions directly impact a bank's bottom line.

Stability and Resilience: Effective credit risk management practices enhance the stability and resilience of banks, especially during economic downturns. A well-structured credit risk management framework can help banks weather financial crises with minimal impact on their operations (Akhigbe et al., 2012).

Regulatory Compliance: The global banking environment has witnessed significant regulatory changes post-global financial crisis. Compliance with international banking standards and regulations is critical for Thai banks, as it influences their access to international markets.

a) Merton's Structural Model

Merton's Structural Model, also known as the Merton model or the Merton approach, was a financial model developed by economist and Nobel laureate Robert C. Merton in 1974. The model provided a framework for understanding and estimating the credit risk of a corporation by considering the relationship between its assets and liabilities. It was particularly applied to assess the risk of default on corporate debt. The model made assumptions about a firm's value being a function of its assets and having a single class of debt. It conceptualized corporate debt as a financial option, specifically likening it to a call option on the firm's assets. Debt holders had the right, but not the obligation, to claim the assets if the value of the firm's assets fell below a certain threshold (Siu et al., 2008).

The probability of default was calculated based on the likelihood that the firm's assets would fall below the face value of its debt, often using the Black-Scholes option pricing model. The model considered factors such as volatility of the firm's assets, debt maturity, debt level, and the strike price (face value of debt) in influencing the probability of default. While the Merton model provided a theoretical foundation for understanding the relationship between a firm's financial structure and its probability of default, it made simplifying assumptions that may not have always reflected real-world complexities. For instance, it assumed continuous asset value processes and constant volatility, which may not have held true in all cases. Despite its limitations, Merton's Structural Model laid the groundwork for subsequent advancements in credit risk modeling and remained a significant contribution to the field of finance during its active use (Siu et al., 2008; Jarrow et al, 2023).

b) Credit Migration Models

Credit Migration Models (CMM) were statistical models widely used in finance to analyze and predict changes in the credit quality of borrowers over time. These models were particularly valuable for assessing the probability of migration between different credit rating categories, providing insights into how the creditworthiness of entities evolved. The primary objective of Credit Migration Models was to quantify and understand the transitions or changes in credit ratings for a given set of borrowers over a specified period. These models operated on the assumption that credit ratings were dynamic and subject to change, and they aimed to capture and predict these changes systematically (D'Rosario & Hsieh, 2020).

Credit Migration Models often utilized a transitions matrix to represent the probabilities of moving between different credit rating categories over time. This matrix encapsulated the likelihood of a borrower with a specific credit rating at the beginning of a period transitioning to various credit ratings by the end of that period. These models were designed for different time horizons, such as monthly, quarterly, or annually, depending on the data and the specific needs of the analysis. They required historical data on credit ratings for a set of borrowers, including information on the initial credit rating, subsequent credit ratings, and the time intervals between these ratings (Albanese & Chen, 2006).

Credit Migration Models typically employed the Markov chain framework to model the transitions between credit rating states. The Markov chain assumed that future states depended only on the current state and were independent of the sequence of events that preceded them. Estimation techniques, including maximum likelihood estimation (MLE), were commonly used to estimate the parameters of the

Credit Migration Model, allowing for the derivation of transition probabilities between different credit rating states. These models found application in various financial institutions, aiding in the assessment of credit risk over time. They were valuable for stress testing and scenario analysis, enabling users to understand how changes in economic conditions might impact the credit quality of a portfolio (D'Rosario & Hsieh, 2020). According to Albanese & Chen (2006), while Credit Migration Models provided valuable insights, they were not without limitations. They assumed that credit transitions were independent of previous events and might not have fully captured sudden, unforeseen events that could impact credit ratings. As with any statistical model, their reliability depended on the quality of historical data and the appropriateness of underlying assumptions.

2.2.5 Thai Commercial Banks

While there was a substantial body of literature examining credit risk and financial performance in the global banking context, the specific dynamics of Thai commercial banks received comparatively less attention. It was essential to consider the unique characteristics of the Thai banking sector, including regulatory requirements, economic conditions, and cultural factors, which might have influenced the relationship between credit risk and financial performance in this specific context. For a banking institution, credit risk management was crucial. There were studies that looked into how macroeconomic and bank-specific factors might have affected the credit risk of commercial banks in Thailand (Siew Pei, 2019).

The financial sector in Thailand was characterized by the presence of a notable array of commercial banking institutions. As of January 2024, some of the principal commercial banks operating within the Thai financial market included Thai commercial banks were banks that were registered in Thailand. There were 13 commercial banks, including Bangkok Bank, Krung Thai Bank, Siam Commercial Bank, Kasikorn Bank, Thai Military Bank, Krungsri Ayudhya Bank, TISCO Bank, Kiatnakin Phatra Bank, UOB Thailand, Standard Chartered (Thai), ICBC (Thai), CIMB Thai Bank, and Land

and Houses Bank. The hierarchy of Thai commercial banks, concerning their size, was contingent upon various financial metrics, and the precise ranking could undergo fluctuations over time. While real-time data was imperative for an accurate assessment, a retrospective overview, as of January 2024, revealed certain stalwart institutions based on total assets, a pivotal indicator of a bank's magnitude.

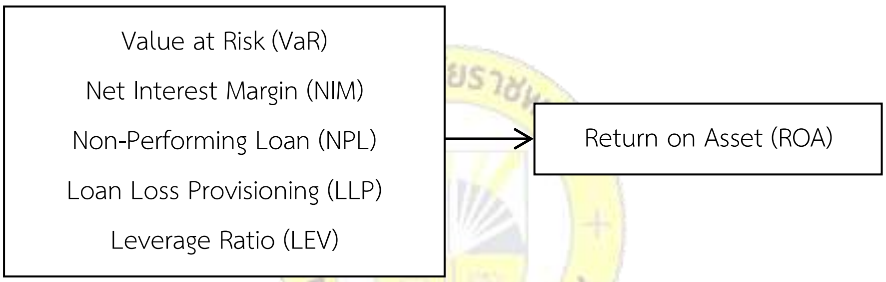
Table 2.1 presented the hierarchical arrangement of major Thai commercial banks by total assets.

**Table 2.1** Top Thai Commercial Banks Ranked by Total Asset, 2023

| Rank | Name | Total Asset as of June 2023 (Million Baht) |
|---|---|---|
| 1 | Bangkok Bank (BBL) | 4,514,484 |
| 2 | Kasikornbank (KBANK) | 4,266,004 |
| 3 | Siam Commercial Bank (SCB) | 2,963,746 |
| 4 | Krung Thai Bank (KTB) | 2,827,332 |
| 5 | Bank of Ayudhya (BAY) | 2,759,717 |

Source: Banks Annual Report, 2023

## 2.3 Conceptual Framework



# Chapter 3
# Methodology

This research is an empirical research that attempts to evaluate commercial banks' financial performance in Thailand toward credit risk by utilizing multiple regression model. The methodology includes data collection, data preprocessing, variable selection, model development, and model evaluation.

The outline structure of this chapter are as follows:

3.1 Population and Sampling

3.2 Model Development

3.3 Model Evaluation

3.4 Data Collection

3.5 Data Analysis

3.6 Statistical Testing

## 3.1 Population and Sampling

The population of this research was Thai Commercial Banks, which were banks that registered in Thailand. As of June 2023, there were 13 commercial banks, including Bangkok Bank, Krung Thai Bank, Siam Commercial Bank, Kasikorn Bank, Thai Military Bank, Krungsri Ayudhya Bank, TISCO Bank, Kiatnakin Phatra Bank, UOB Thailand, Standard Chartered (Thai), ICBC (Thai), CIMB Thai Bank, and Land and Houses Bank.

In the conducted research, the sampling method employed focused on selecting the top five commercial banks in Thailand based on their total assets. This approach ensured that the selected banks represented a significant portion of the banking sector in the country and provided a comprehensive overview of the industry's landscape, which were Bangkok Bank (BBL), Kasikornbank (KBANK), Siam Commercial Bank (SCB), Krung Thai Bank (KTB) and Bank of Ayudhya (BAY) (see Table 2.1, for details).

## 3.2 Model Development

This research employed multiple regression analysis to examine the relationship between credit risk variables (see Table 3.1) and financial performance. Multiple regression models were well-suited for understanding how multiple variables influence a dependent variable simultaneously to analyze the time series data. It also used Ordinary Least Square (OLS) multiple regressions to determine the effect of the independent variables on the dependent variable.

**Table 3.1** Reasons for Variables Inclusion in the Model Analysis

| Variables | |
|---|---|
| VaR | Crucial for banking as it quantifies potential losses due to market movements, ensuring regulatory compliance, facilitating risk management, optimizing capital allocation, and informing decision-making processes. |
| NIM | It represents the difference between interest income earned from loans and investments and interest expenses paid on deposits and borrowings, directly impacting profitability and serving as a key performance indicator for assessing a bank's financial health and efficiency. |
| NPL | Critical for banking as it indicates the portion of loans where borrowers have failed to make scheduled payments, serving as a key metric for assessing credit risk, profitability, and the overall health of a bank's loan portfolio. |
| LLP | It involves setting aside funds to cover potential losses from non-performing loans, ensuring financial stability, regulatory compliance, and accurate financial reporting while safeguarding against adverse economic conditions and mitigating credit risk. |
| LEV | Crucial for banking as it provides a measure of a bank's capital adequacy by comparing its Tier 1 capital to its total assets, serving as a safeguard against excessive risk-taking and ensuring financial stability. |

The following equations were estimated to measure the bank financial performance by using independent variables in Table 3.1:

$$ROA_{it} = \alpha+\beta_1 VaR_{it}+\beta_2 NIM_{it}+\beta_3 NPL_{it}+\beta_4 LLP_{it}+\beta_5 LEV_{it}+\varepsilon_{it}$$

The results of multiple regression model showed the relationship between independent variables and Return on Asset of Thai commercial banks.

### 3.3 Model Evaluation

The evaluation of a multiple regression model involved assessing its overall fit, the significance of individual predictors, and the model's ability to make accurate predictions. The p-values associated with each coefficient were examined to determine their statistical significance, with a lower p-value indicating a likely contribution to the model. The magnitude and direction of each coefficient were evaluated to understand the strength and nature of the relationships between predictors and the response variable.

The statistical tests of Parameter estimates were conducted using their Adjusted $R^2$, Standard Error, and at 5% level of significance. R-squared were calculated to measure the proportion of the variance in the dependent variable explained by the independent variables.

### 3.4 Data Collection

This research had collected secondary data of top 5 banks ranked by total asset for the time period 2019-2023, from published financial reports and data from BOT. This research utilized a comprehensive dataset containing financial data for Thai commercial banks. The dataset was collected for a specific time frame during 2019 to 2023 using quarterly released data of top 5 commercial banks (by total asset) of Thailand, see Table 2.1 for ranking.

The primary sources of data for this study include: Bank Financial Statements: Financial reports and statements of Thai commercial banks were collected from regulatory bodies and the banks themselves. These reports provide information on various financial indicators and credit risk metrics. The Bank of Thailand is the central regulatory authority overseeing the Thai banking sector. Data related to regulatory compliance and some independent variables were obtained from the BOT.

The Bank of Thailand provided comprehensive financial information relevant to the commercial banking sector. This included data on the performance of commercial banks, such as balance sheets, profitability, capital adequacy ratios, and asset quality. Additionally, regulatory reports from commercial banks were collected by BOT, aiding in regulatory oversight and supervision. Overall, the Bank of Thailand served as a crucial source of financial insights for stakeholders within the commercial banking industry.

### 3.5 Data Analysis

The data analysis of this research draws primarily from two key sources: Bank Financial Statements and data provided by the Bank of Thailand (BOT).

Bank Financial Statements: Financial reports and statements of Thai commercial banks were collected from regulatory bodies and the banks themselves. These reports offer insights into various financial indicators and credit risk metrics, providing valuable data for analysis.

Bank of Thailand (BOT) Data: As the central regulatory authority overseeing the Thai banking sector, the BOT provided comprehensive financial information relevant to commercial banks. This included data on bank performance metrics such as balance sheets, profitability, capital adequacy ratios, and asset quality. Additionally, regulatory reports from commercial banks were collected by the BOT, contributing to regulatory oversight and supervision.

By leveraging data from these sources, the analysis aims to gain a comprehensive understanding of the performance and regulatory compliance of commercial banks in Thailand. The data provided by the BOT serves as a crucial foundation for the research, offering valuable insights into the financial health and stability of the commercial banking sector.

The variables, explanation and formula are defined in Table 3.2. Independent variables includes:

1) Value at Risk (VaR), which represented a risk measure employed within the domain of finance to quantify potential losses in a portfolio or investment.

2) Net Interest Margin (NIM), which reflected the difference between a bank's interest income and interest expenses, expressed as a percentage of its interest-earning assets.
3) Non-Performing Loan (NPL) Ratio, which was a key credit risk indicator representing the percentage of non-performing loans relative to the total loan portfolio.
4) Loan Loss Provisioning (LLP), which was the amount set aside to cover potential losses from bad loans.
5) Leverage Ratio (LEV), which was a financial metric that measures the proportion of a financial institution's capital to its total assets. It is designed to provide a simple, non-risk-weighted measure of a bank's capital adequacy and acts as a safeguard against excessive leverage.

**Table 3.2** Definition of Variables & Formulas

| Variables | Explanation | Formula |
|---|---|---|
| VaR | Value at Risk | Portfolio Value × (Asset Volatility × Z-Score) |
| NIM | Net Interest Margin | $\left(\frac{\text{Net Interest Income}}{\text{Average Earning Assets}}\right) \times 100$ |
| NPL | Non-Performing Loan | $\left(\frac{\text{Total Non-Performing Loans}}{\text{Total Gross Loans}}\right) \times 100$ |
| LLP | Loan Loss Provisioning | Bad Debt Expense – Recoveries on Previously Written -off Loans + Beginning Allowance for Loan Losses – Ending Allowance for Loan Losses |
| LEV | Leverage Ratio (LEV) | Tier 1 capital / Total Leverage Ratio Exposure Measure |

## 3.6 Statistical Testing

Statistical analysis and regression modeling were conducted using MS Excel, which allowed for the computation of regression coefficients, significance levels, and other statistical measures required for the analysis. R square, Standard errors, t statistics, and p-values were used to test the model.

# Chapter 4
# Empirical Results

This chapter aimed to explore the relationship between credit risk and financial performance within the context of Thai commercial banks from 2019 to 2023. By examining credit risk indicators such as Value at Risk (VaR), Net Interest Margin (NIM), Non-Performing Loan (NPL), Loan Loss Provisioning (LLP), and Leverage Ratio (LEV), this research sought to provide insights into how credit risk management practices influenced the profitability, stability, and overall performance of Thai commercial banks during this period. This chapter structured as follows:

4.1 Credit Risk Results

4.2 Financial Performance Results

## 4.1 Credit Risk Results

### 4.1.1 Value at Risk (VaR)

Table 4.1 depicted the Value at Risk (VaR) for the top five banks in terms of asset value, measured in million Baht. The VaR represented the estimated maximum potential loss each bank's portfolio could have incurred over a given period, calculated at a 95% confidence level.

Each row of the table corresponded to a specific quarter, commencing from Q1/2019 and progressing sequentially until Q4/2023. Within each row, the respective VaR values for each bank were listed under their corresponding columns. The banks included in the analysis were Bangkok Bank (BBL), Kasikornbank (KBANK), Siam Commercial Bank (SCB), Krung Thai Bank (KTB), and Bank of Ayudhya (BAY). For instance, in Q1/2019, Bangkok Bank's portfolio had a VaR of 15.602057 billion baht, Kasikornbank's portfolio had a VaR of 14.874230 billion baht, and so forth.

**Table 4.1** Value at Risk of Top 5 Commercial Banks in Thailand (by Asset), at a 95% confidence level (Value in billion)

| | BBL | KBANK | SCB | KTB | BAY |
|---|---|---|---|---|---|
| **Q1/2019** | 15.602057 | 14.874230 | 10.240658 | 9.958830 | 9.610824 |
| **Q2/2019** | 15.444050 | 14.723594 | 10.136948 | 9.857974 | 9.513492 |
| **Q3/2019** | 16.003846 | 15.257276 | 10.504379 | 10.215293 | 9.858325 |
| **Q4/2019** | 16.495925 | 15.726400 | 10.827363 | 10.529388 | 10.161444 |
| **Q1/2020** | 17.051206 | 16.255778 | 11.191831 | 10.883826 | 10.503496 |
| **Q2/2020** | 16.094135 | 15.343354 | 10.563642 | 10.272926 | 9.913943 |
| **Q3/2020** | 17.430423 | 16.617304 | 11.440736 | 11.125881 | 10.737092 |
| **Q4/2020** | 18.008277 | 17.168202 | 11.820019 | 11.494726 | 11.093049 |
| **Q1/2021** | 17.502654 | 16.686166 | 11.488146 | 11.171987 | 10.781587 |
| **Q2/2021** | 18.062450 | 17.219848 | 11.855577 | 11.529306 | 11.126420 |
| **Q3/2021** | 18.518413 | 17.654541 | 12.154856 | 11.820348 | 11.407291 |
| **Q4/2021** | 18.559044 | 17.693276 | 12.181524 | 11.846282 | 11.432320 |
| **Q1/2022** | 18.500355 | 17.637325 | 12.143003 | 11.808822 | 11.396168 |
| **Q2/2022** | 19.516114 | 18.605700 | 12.809713 | 12.457183 | 12.021872 |
| **Q3/2022** | 19.114325 | 18.222654 | 12.545992 | 12.200720 | 11.774371 |
| **Q4/2022** | 20.107512 | 19.169509 | 13.197886 | 12.834673 | 12.386172 |
| **Q1/2023** | 19.511600 | 18.601396 | 12.806749 | 12.454301 | 12.019092 |
| **Q2/2023** | 20.419011 | 19.466477 | 13.402343 | 13.033504 | 12.578054 |
| **Q3/2023** | 20.464156 | 19.509516 | 13.431975 | 13.062320 | 12.605863 |
| **Q4/2023** | 21.014923 | 20.034590 | 13.793479 | 13.413876 | 12.945134 |

**Source:** Author's calculation

Figure 4.1, provided series of data depicted a trend spanning multiple quarters of average VaR of commercial bank during 2019-2024, with each period accompanied by a corresponding numerical value. The trend was characterized by an observable pattern of increase over time. From Q1/2019 to Q4/2023, the values exhibited a gradual upward trajectory. Beginning at 12.06, there was a consistent progression with occasional fluctuations observed in certain quarters. The values generally rose from one quarter to the next, reaching a peak of 16.24 by Q4/2023. This upward trend suggested a continuous growth in VaR or increase in the variable being measured over the specified period.

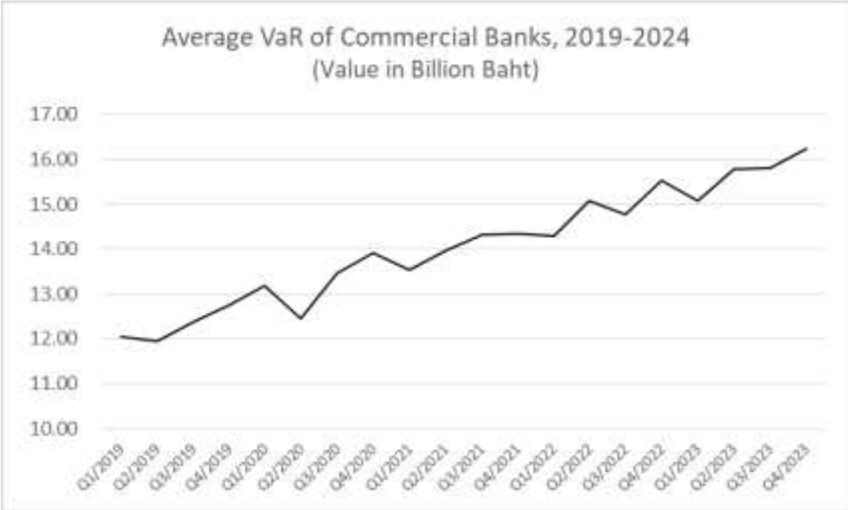



**Figure 4.1** Average VaR of Thai Commercial Banks, 2019-2024

**Source:** Author's calculation

| | VaR |
|---|---|
| Q1/2019 | 1 |
| Q2/2019 | -1.01 |
| Q3/2019 | 3.62 |
| Q4/2019 | 3.07 |
| Q1/2020 | 3.37 |
| Q2/2020 | -5.61 |
| Q3/2020 | 8.30 |
| Q4/2020 | 3.32 |
| Q1/2021 | -2.81 |
| Q2/2021 | 3.20 |
| Q3/2021 | 2.52 |
| Q4/2021 | 0.22 |
| Q1/2022 | -0.32 |
| Q2/2022 | 5.49 |
| Q3/2022 | -2.06 |
| Q4/2022 | 5.20 |
| Q1/2023 | -2.96 |
| Q2/2023 | 4.65 |
| Q3/2023 | 0.22 |
| Q4/2023 | 2.69 |

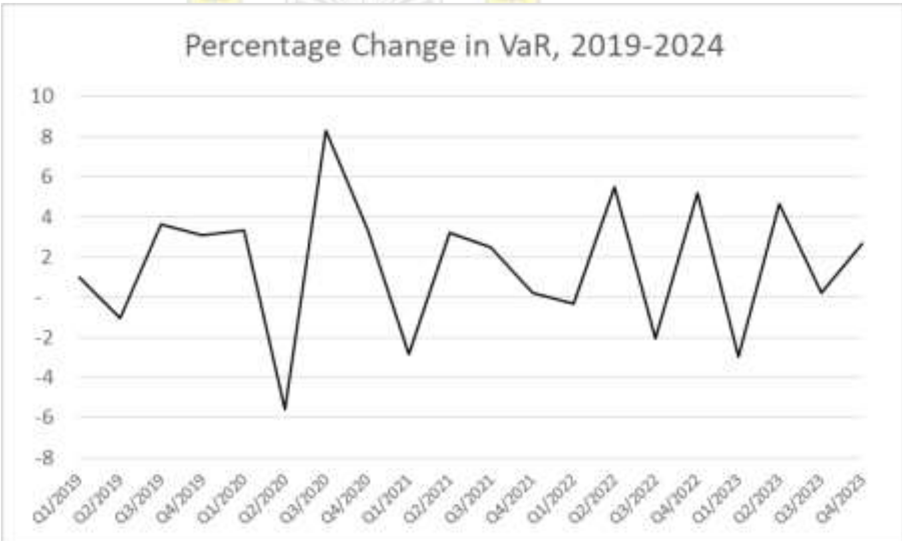



**Figure 4.2** Percentage Change in VaR of Thai Commercial Banks, 2019-2024

**Source:** Author's calculation

According to Figure 4.1 and Figure 4.2, the fifth percentile return was determined to be the value at the index (0.05 * 19), resulting in 18.95. Given that this value is not a whole number, it was necessary to compute the average of the returns at indices 18 and 19.

At index 18, corresponding to Q1/2023, the return of major commercial banks in Thailand was recorded as -2.96, while at index 19, representing Q2/2023, the return stood at 4.65. By averaging these two returns, a value of 1.345 was obtained.

Consequently, the five-year 95% VaR was approximately 13.45. This indicates that with 95% confidence, the maximum loss over a five-year period would have been 13.45% of the initial investment.

4.1.2 Net Interest Margin (NIM)

The Table 4.2 presented the Net Interest Margin (NIM) data for the top 5 Thai commercial banks, ranked by asset value, over the period from 2019 to 2024. NIM serves as a crucial financial metric, indicating the profitability of a bank's lending operations by assessing the difference between interest income generated from loans and interest expenses incurred from deposits and other funding sources, relative to the bank's average interest-earning assets. Each row of the table represented a specific quarter within the designated years, while each column corresponded to one of the top 5 banks: BBL, KBANK, SCB, KTB and BAY. Key observations drawn from Table 4.2 included:

a) Variability in NIM values across quarters and banks: The NIM values fluctuated over time for each bank, with some quarters exhibiting higher NIM values compared to others.
b) Differences in NIM values among the banks provided insights into their relative profitability and efficiency in managing interest income and expenses.
c) Trends over time: Patterns or trends in NIM values across quarters and years were indicative of changes in the banks' lending strategies, interest rate environments, or overall financial performance.

**Table 4.2** Net Interest Margin of Top 5 Commercial Banks in Thailand (by Asset), 2019-2024

| | BBL | KBANK | SCB | KTB | BAY |
|---|---|---|---|---|---|
| Q1/2019 | 2.90 | 2.87 | 2.85 | 2.78 | 2.82 |
| Q2/2019 | 2.88 | 2.85 | 2.83 | 2.76 | 2.80 |
| Q3/2019 | 2.84 | 2.81 | 2.79 | 2.72 | 2.76 |
| Q4/2019 | 2.78 | 2.76 | 2.74 | 2.68 | 2.71 |
| Q1/2020 | 2.76 | 2.74 | 2.72 | 2.66 | 2.69 |
| Q2/2020 | 2.73 | 2.71 | 2.69 | 2.63 | 2.66 |
| Q3/2020 | 2.70 | 2.68 | 2.66 | 2.60 | 2.63 |
| Q4/2020 | 2.68 | 2.66 | 2.64 | 2.58 | 2.61 |
| Q1/2021 | 2.65 | 2.63 | 2.61 | 2.55 | 2.58 |
| Q2/2021 | 2.60 | 2.58 | 2.56 | 2.50 | 2.53 |
| Q3/2021 | 2.55 | 2.53 | 2.51 | 2.45 | 2.48 |
| Q4/2021 | 2.51 | 2.48 | 2.47 | 2.41 | 2.44 |
| Q1/2022 | 2.55 | 2.53 | 2.51 | 2.45 | 2.48 |
| Q2/2022 | 2.57 | 2.55 | 2.53 | 2.47 | 2.50 |
| Q3/2022 | 2.62 | 2.60 | 2.58 | 2.52 | 2.55 |
| Q4/2022 | 2.67 | 2.65 | 2.63 | 2.57 | 2.60 |
| Q1/2023 | 2.83 | 2.80 | 2.78 | 2.71 | 2.75 |
| Q2/2023 | 3.01 | 2.98 | 2.96 | 2.89 | 2.93 |
| Q3/2023 | 3.17 | 3.14 | 3.12 | 3.05 | 3.09 |
| Q4/2023 | 3.27 | 3.24 | 3.22 | 3.15 | 3.18 |

**Source:** Author's calculation

According to Figure 4.3, the trend in the Net Interest Margin (NIM) values over the specified period reflected a fluctuating pattern. Initially, in Q1/2019, the NIM stood at 2.84. This was followed by a slight decrease to 2.82 in Q2/2019 and a further decline to 2.78 in Q3/2019. By Q4/2019, the NIM experienced a more pronounced decrease, reaching 2.73. The declining trend continued into the first two quarters of 2020, with NIM values of 2.71 in Q1/2020 and 2.68 in Q2/2020. This trend persisted throughout the year, with slight decreases observed in Q3/2020 (2.65) and Q4/2020 (2.63).

In the subsequent quarters, from Q1/2021 to Q4/2021, the NIM values continued to decrease gradually, reaching 2.46 by the end of Q4/2021. However, there was a slight uptick in Q1/2022, with the NIM rising to 2.5, followed by a further increase to 2.52 in Q2/2022 and 2.57 in Q3/2022. The trend shifted notably in Q1/2023, with a significant increase in the NIM to 2.77, followed by a substantial rise to 2.95 in Q2/2023 and further to 3.11 in Q3/2023. This upward trajectory continued into Q4/2023, with the NIM reaching its peak value of 3.21. Overall, the trend in the NIM values indicated fluctuations over time, with periods of decline followed by periods of increase. This pattern may have reflected changes in interest rates, lending practices, market conditions, or other factors influencing the profitability of banking operations during the specified period.

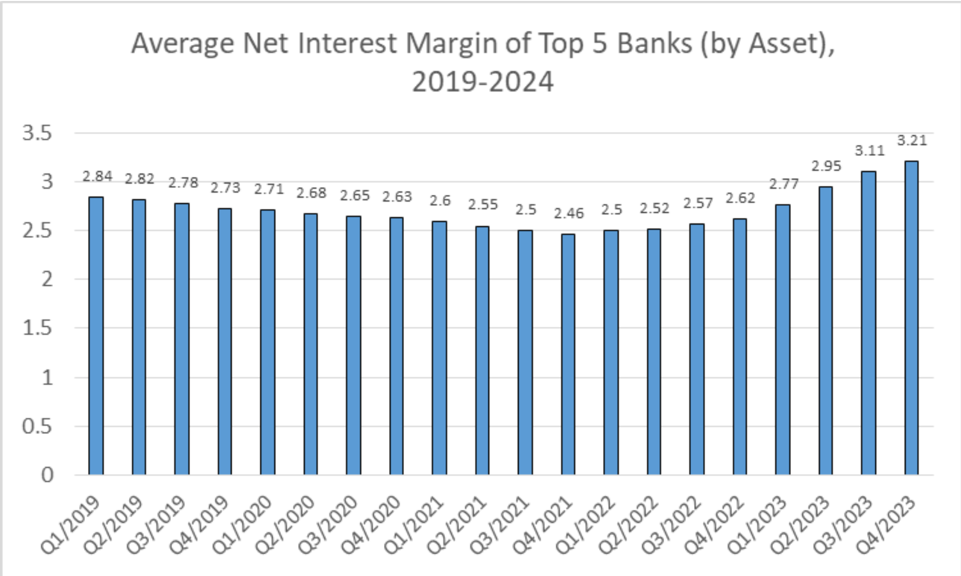



**Figure 4.3** Average Net Interest Margin of Top 5 Commercial Banks in Thailand (by Asset), 2019-2024

**Source:** Author’s calculation

### 4.1.3 Non-Performing Loan (NPL)

**Table 4.3** Non-Performing Loan of Top 5 Commercial Banks in Thailand (by Asset), 2019-2024 (value in million)

| | BBL | KBANK | SCB | KTB | BAY |
|---|---|---|---|---|---|
| **Q1/2019** | 12,029 | 11,468 | 7,895 | 7,678 | 7,410 |
| **Q2/2019** | 12,252 | 11,681 | 8,042 | 7,821 | 7,547 |
| **Q3/2019** | 13,412 | 12,786 | 8,803 | 8,561 | 8,262 |
| **Q4/2019** | 14,285 | 13,619 | 9,376 | 9,118 | 8,799 |
| **Q1/2020** | 14,480 | 13,805 | 9,504 | 9,243 | 8,920 |
| **Q2/2020** | 13,487 | 12,858 | 8,853 | 8,609 | 8,308 |
| **Q3/2020** | 15,581 | 14,854 | 10,227 | 9,945 | 9,598 |
| **Q4/2020** | 16,601 | 15,826 | 10,896 | 10,596 | 10,226 |
| **Q1/2021** | 17,015 | 16,221 | 11,168 | 10,860 | 10,481 |
| **Q2/2021** | 17,256 | 16,451 | 11,326 | 11,015 | 10,630 |
| **Q3/2021** | 17,588 | 16,768 | 11,544 | 11,227 | 10,834 |
| **Q4/2021** | 16,797 | 16,014 | 11,025 | 10,722 | 10,347 |
| **Q1/2022** | 16,331 | 15,569 | 10,719 | 10,424 | 10,060 |
| **Q2/2022** | 17,336 | 16,528 | 11,379 | 11,066 | 10,679 |
| **Q3/2022** | 15,912 | 15,169 | 10,444 | 10,156 | 9,802 |
| **Q4/2022** | 14,941 | 14,244 | 9,807 | 9,537 | 9,204 |
| **Q1/2023** | 15,697 | 14,965 | 10,303 | 10,020 | 9,669 |
| **Q2/2023** | 16,655 | 15,879 | 10,932 | 10,631 | 10,260 |
| **Q3/2023** | 15,892 | 15,151 | 10,431 | 10,144 | 9,789 |
| **Q4/2023** | 15,850 | 15,111 | 10,403 | 10,117 | 9,764 |

**Source:** Bank of Thailand (2023)

The presented Table 4.3 delineated the Non-Performing Loan (NPL) data for the top 5 commercial banks in Thailand across various quarters spanning from 2019 to 2023. Non-Performing Loans denote loans where borrowers failed to meet scheduled payments for a specified period, indicating potential credit risk for the banks. Upon scrutinizing the trend in NPL values, several noteworthy observations emerged:

Initial Increase and Fluctuations: From Q1/2019 to Q4/2019, a general trend of increasing NPL values transpired across all banks, suggesting a period marked by deteriorating loan quality and potentially heightened credit risk in the banking sector. However, within this timeframe, fluctuations in NPL values for individual banks were observed, indicating variations in their loan portfolios and risk exposures.

Peak and Subsequent Decline: By Q1/2021, NPL values had peaked for most banks, indicating the highest level of non-performing loans within the observed period. Nonetheless, from Q1/2021 to Q4/2022, a general trend of decline in NPL values across most banks was observed. This suggests concerted efforts by banks to address non-performing loans, improve loan quality, and manage credit risk more effectively.

Stabilization and Fluctuations: From Q1/2023 to Q4/2023, NPL values appeared to stabilize or experience minor fluctuations across banks. This stabilization may indicate a more stable credit environment or the successful implementation of strategies by banks to mitigate non-performing loans.

In conclusion, the trend in NPL values reflects the dynamics of credit risk management within the banking sector. The initial increase followed by a subsequent decline suggests a cyclical pattern influenced by factors such as economic conditions, lending practices, and regulatory interventions. The stabilization or fluctuations in NPL values in later periods may indicate the efficacy of banks' risk management endeavors in upholding loan quality and financial stability.

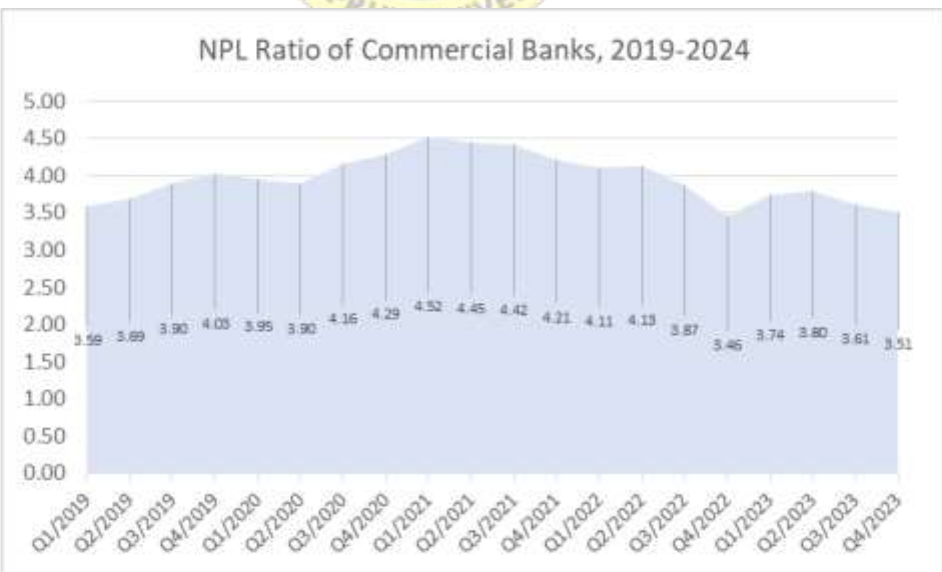



**Figure 4.4** Non-Performing Loan Ratio of Top 5 Commercial Banks in Thailand (by Asset), 2019-2024

**Source:** Author’s calculation

Figure 4.4 provided NPL ratio level across various quarters from 2019 to 2023. It depicted fluctuations in NPL ratio levels, indicating changes in the proportion of non-performing loans within the total loan portfolio of the banks. From Q1/2019 to Q4/2019, there was a slight increase in the NPL ratio level, with some fluctuation but a general upward trend. By Q1/2021, the NPL ratio level reached its peak, indicating the highest proportion of non-performing loans during the observed period. However, from Q1/2021 to Q4/2022, a noticeable decline in the NPL ratio level occurred, reflecting efforts by banks to address non-performing loans and enhance asset quality. From Q1/2023 to Q4/2023, the NPL ratio level stabilized around 3.5% to 3.8%, with minor fluctuations. This stabilization suggested potential improvements in credit risk management practices by banks or a more stable economic environment.

Overall, the trend in NPL ratio level portrayed the dynamics of credit risk within the banking sector, influenced by factors such as economic conditions and banks' risk management strategies. The peak and subsequent decline in NPL ratio levels underscored the importance of proactive measures by banks to mitigate credit risk and maintain financial stability.

4.1.4 Loan Loss Provisioning (LLP)

Table 4.4 depicted Loan Loss Provisioning (LLP) of the top 5 commercial banks in Thailand from 2019 to 2023, categorized by quarters. Loan Loss Provisioning refers to the amount of money set aside by banks to cover potential losses from non-performing loans or other impaired assets.

Follows were the results of the table. In Q1/2019, the LLP for all banks ranged from approximately 16,300 million to 26,464 million. From Q1/2019 to Q4/2019, there was a general upward trend in LLP across all banks, indicating an increase in provisions for potential loan losses. In Q2/2020, there was a significant increase in LLP across all banks compared to the previous quarter, suggesting heightened concerns about credit quality due to economic challenges, possibly related to the COVID-19 pandemic. From Q3/2020 to Q2/2021, LLP continued to increase steadily, reflecting ongoing efforts by banks to prudently manage risks amid economic uncertainties. In Q3/2021, there was a notable peak in LLP for most banks, potentially reflecting increased provisioning as a precautionary measure against potential loan defaults or economic downturns. From Q4/2021 to Q4/2022, there was a gradual decline in LLP, indicating improving credit quality or reduced concerns about loan losses. In Q1/2023, there was a slight increase in LLP compared to the previous quarter, possibly indicating renewed caution amid economic fluctuations.

**Table 4.4** Loan Loss Provisioning of Top 5 Commercial Banks in Thailand (by Asset), 2019-2024 (value in million)

| | BBL | KBANK | SCB | KTB | BAY |
|---|---|---|---|---|---|
| Q1/2019 | 26,464 | 25,229 | 17,370 | 16,892 | 16,302 |
| Q2/2019 | 26,955 | 25,698 | 17,692 | 17,206 | 16,604 |
| Q3/2019 | 29,506 | 28,129 | 19,367 | 18,834 | 18,176 |
| Q4/2019 | 31,427 | 29,961 | 20,627 | 20,060 | 19,359 |
| Q1/2020 | 31,856 | 30,370 | 20,909 | 20,334 | 19,623 |
| Q2/2020 | 29,672 | 28,288 | 19,476 | 18,940 | 18,278 |
| Q3/2020 | 34,278 | 32,679 | 22,499 | 21,880 | 21,115 |
| Q4/2020 | 36,521 | 34,818 | 23,971 | 23,312 | 22,497 |
| Q1/2021 | 37,432 | 35,686 | 24,569 | 23,893 | 23,058 |
| Q2/2021 | 37,963 | 36,192 | 24,918 | 24,232 | 23,385 |
| Q3/2021 | 38,694 | 36,889 | 25,397 | 24,699 | 23,835 |
| Q4/2021 | 36,954 | 35,230 | 24,255 | 23,588 | 22,764 |
| Q1/2022 | 35,928 | 34,252 | 23,582 | 22,933 | 22,131 |
| Q2/2022 | 38,140 | 36,361 | 25,034 | 24,345 | 23,494 |
| Q3/2022 | 35,006 | 33,373 | 22,976 | 22,344 | 21,563 |
| Q4/2022 | 32,870 | 31,337 | 21,575 | 20,981 | 20,248 |
| Q1/2023 | 34,534 | 32,923 | 22,667 | 22,043 | 21,273 |
| Q2/2023 | 36,642 | 34,933 | 24,051 | 23,389 | 22,571 |
| Q3/2023 | 34,962 | 33,331 | 22,948 | 22,317 | 21,537 |
| Q4/2023 | 34,870 | 33,243 | 22,888 | 22,258 | 21,480 |

**Source:** Author’s calculation

Overall, the fluctuations in LLP over the quarters reflected the dynamic nature of banking operations and their responses to changing economic conditions, regulatory requirements, and risk management practices.

| | |
|---|---|
| Q1/2019 | 1 |
| Q2/2019 | 1.86 |
| Q3/2019 | 9.46 |
| Q4/2019 | 6.51 |
| Q1/2020 | 1.37 |
| Q2/2020 | -6.85 |
| Q3/2020 | 15.52 |
| Q4/2020 | 6.54 |
| Q1/2021 | 2.49 |
| Q2/2021 | 1.42 |
| Q3/2021 | 1.92 |
| Q4/2021 | -4.50 |
| Q1/2022 | -2.78 |
| Q2/2022 | 6.16 |
| Q3/2022 | -8.22 |
| Q4/2022 | -6.10 |
| Q1/2023 | 5.06 |
| Q2/2023 | 6.10 |
| Q3/2023 | -4.58 |
| Q4/2023 | -0.26 |

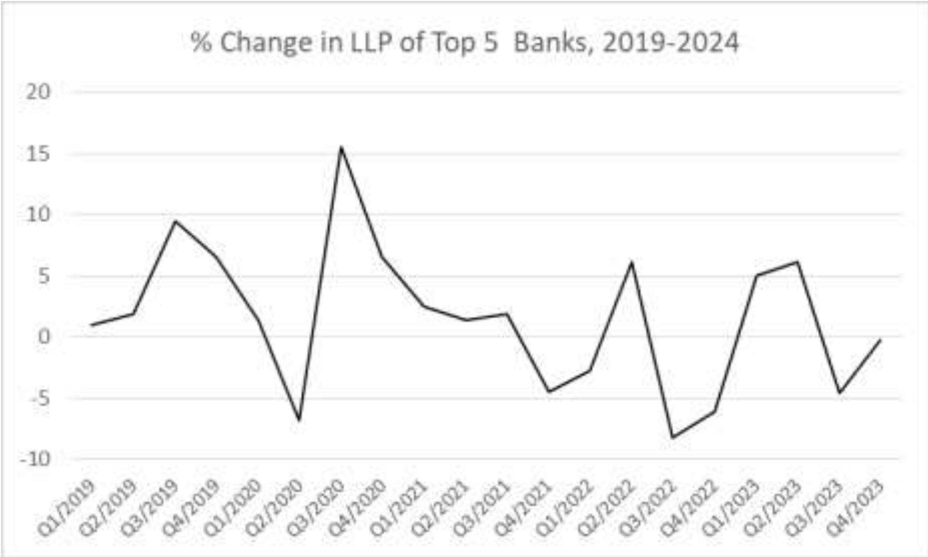



**Figure 4.5** Percentage Change in Loan Loss Provisioning of Top 5 Commercial Banks in Thailand (by Asset), 2019-2024

**Source:** Author's calculation

Figure 4.5 presented figure delineates the percentage change in loan loss provisioning across an undisclosed sequence of periods, ostensibly quarters, spanning from Q1/2019 to Q4/2023. From Q1/2019 to Q2/2019, a moderate increase of 1.86% in loan loss provisioning was observed. Subsequently, between Q2/2019 and Q3/2019, there occurred a substantial surge of 9.46% in loan loss provisioning. The momentum persisted into the subsequent period (Q3/2019 to Q4/2019), where a further increase of 6.51% was noted. The trend shifted marginally in Q1/2020, witnessing a modest increase of 1.37% in loan loss provisioning. However, a notable decline of 6.85% in loan loss provisioning transpired from Q1/2020 to Q2/2020. Transitioning to Q3/2020, a significant upswing of 15.52% was evident in loan loss provisioning. This trajectory continued into Q4/2020, witnessing a further increase of 6.54% in loan loss provisioning. From Q4/2020 to Q1/2021, a modest rise of 2.49% in loan loss provisioning was observed. The following period (Q1/2021 to Q2/2021) saw a slight increase of 1.42% in loan loss provisioning. Continuing the upward trend, Q2/2021 to Q3/2021 experienced another modest increase of 1.92% in loan loss provisioning. However, a downturn ensued in Q4/2021, reflecting a decrease of 4.50% in loan loss provisioning. This trend persisted into Q1/2022, with a further decrease of 2.78% in loan loss provisioning. Thereafter, Q1/2022 to Q2/2022 exhibited a notable increase of 6.16% in loan loss provisioning. Contrarily, from Q2/2022 to Q3/2022, a significant decrease of 8.22% in loan loss provisioning was recorded. Continuing this decline, Q3/2022 to Q4/2022 saw a further decrease of 6.10% in loan loss provisioning. Nevertheless, Q4/2022 to Q1/2023 witnessed a modest increase of 5.06% in loan loss provisioning. This upward trajectory persisted into Q2/2023, where another increase of 6.10% in loan loss provisioning was noted. Conversely, a downturn followed in Q3/2023, marked by a decrease of 4.58% in loan loss provisioning. Finally, from Q3/2023 to Q4/2023, a marginal decrease of 0.26% in loan loss provisioning was observed.

In summary, these fluctuations in loan loss provisioning percentages depict varying degrees of risk management and financial performance across the observed periods. Increases may indicate anticipation of higher credit losses or a proactive approach to risk management, while decreases could imply improved credit quality or adjustments in provisioning practices.

4.1.5 Leverage Ratio (LEV)

Table 4.5 delineated the leverage ratios of five prominent commercial banks in Thailand throughout various quarters from Q1/2019 to Q4/2023. Here's a summary of the findings:

1) Bangkok Bank (BBL)

The leverage ratio fluctuated between 26.65 and 38.96 over the observed period. Generally, the bank maintained a moderate level of leverage, with occasional fluctuations. There was a slight increase in leverage noted in the latter half of the study period.

2) Kasikornbank (KBANK)

KBANK exhibited a leverage ratio ranging from 30.48 to 44.57. Similar to BBL, the bank sustained a moderate level of leverage across the timeframe. The ratio displayed fluctuations but generally trended upwards.

**Table 4.5** Leverage Ratio of Top 5 Commercial Banks in Thailand (by Asset), 2019-2024 (in percentage)

| | BBL | KBANK | SCB | KTB | BAY |
|---|---|---|---|---|---|
| Q1/2019 | 26.65 | 30.48 | 36.36 | 44.67 | 36.47 |
| Q2/2019 | 27.14 | 31.05 | 37.03 | 45.50 | 37.15 |
| Q3/2019 | 29.71 | 33.99 | 40.54 | 49.80 | 40.66 |
| Q4/2019 | 31.64 | 36.20 | 43.18 | 53.05 | 43.31 |
| Q1/2020 | 32.07 | 36.69 | 43.77 | 53.77 | 43.90 |
| Q2/2020 | 29.88 | 34.18 | 40.77 | 50.08 | 40.89 |
| Q3/2020 | 34.51 | 39.48 | 47.10 | 57.86 | 47.24 |
| Q4/2020 | 36.77 | 42.07 | 50.18 | 61.65 | 50.33 |
| Q1/2021 | 37.69 | 43.12 | 51.43 | 63.18 | 51.59 |
| Q2/2021 | 38.22 | 43.73 | 52.16 | 64.08 | 52.32 |
| Q3/2021 | 38.96 | 44.57 | 53.16 | 65.31 | 53.33 |
| Q4/2021 | 37.21 | 42.57 | 50.77 | 62.38 | 50.93 |
| Q1/2022 | 36.17 | 41.38 | 49.36 | 60.64 | 49.51 |
| Q2/2022 | 38.40 | 43.93 | 52.40 | 64.38 | 52.56 |
| Q3/2022 | 35.25 | 40.32 | 48.10 | 59.09 | 48.24 |
| Q4/2022 | 33.10 | 37.86 | 45.16 | 55.48 | 45.30 |
| Q1/2023 | 34.77 | 39.78 | 47.45 | 58.29 | 47.59 |
| Q2/2023 | 36.89 | 42.21 | 50.34 | 61.85 | 50.50 |
| Q3/2023 | 35.20 | 40.27 | 48.04 | 59.01 | 48.18 |
| Q4/2023 | 35.11 | 40.17 | 47.91 | 58.86 | 48.06 |

**Source:** Author’s calculation

3) Siam Commercial Bank (SCB)

SCB demonstrated a comparatively higher leverage ratio, spanning from 36.36 to 53.16. Throughout the period, SCB's leverage ratio consistently exceeded that of its counterparts. An upward trajectory in leverage was observed over time.

4) Krung Thai Bank (KTB)

KTB initiated the observation period with a higher leverage ratio of 44.67 in Q1/2019, peaking at 65.31 in Q3/2021 before experiencing a marginal decline.
The bank consistently maintained the highest leverage ratio among the sampled institutions. Notably, there was an observable surge in leverage from 2019 to 2021, followed by a slight decrease in subsequent quarters.

5) Bank of Ayudhya (BAY)

BAY's leverage ratio ranged from 36.47 to 53.33. Similar to BBL and KBANK, BAY upheld a moderate level of leverage. The ratio exhibited fluctuations but generally trended upwards over time.

These findings provide insights into the capital structures and risk profiles of the banks examined. SCB and KTB tended to exhibit higher leverage ratios, indicating a relatively greater dependence on debt financing compared to BBL, KBANK, and BAY.

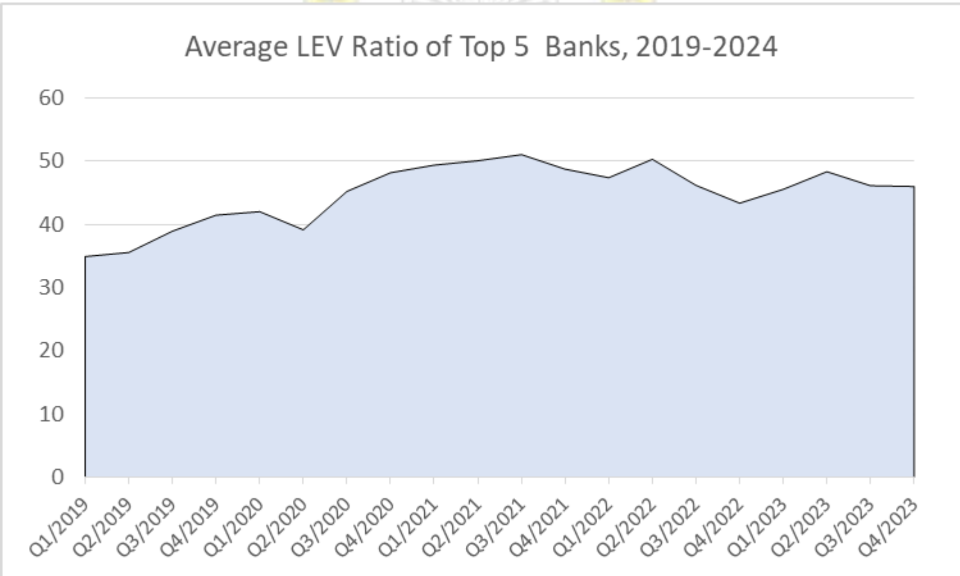



**Figure 4.6** Average Leverage Ratio of Top 5 Commercial Banks in Thailand (by Asset), 2019-2024

**Source:** Author’s calculation

Figure 4.6 showed the results of leverage ratio observed across consecutive quarters spanning from Q1/2019 to Q4/2023. Initially, it stood at 34.93 in Q1/2019, with the leverage ratio exhibiting a consistent upward trajectory, reaching 41.48 by Q4/2019. Throughout the subsequent year, this trend continued, with the ratio steadily increasing to 48.20 in Q4/2020. Notably, a minor decline was noted in Q2/2020, followed by a substantial surge to 45.24 in Q3/2020. The ascending pattern persisted into 2021, culminating in the highest recorded ratio of 51.07 in Q3/2021. However, a reversal occurred in Q4/2021, leading to a decrease to 48.77, which further declined to 43.38 by Q4/2022. Although a modest recovery was observed in Q1/2023, with the ratio rising to 45.58, subsequent quarters saw relatively stable levels, culminating at 46.02 in Q4/2023. These fluctuations in the leverage ratio reflected dynamic shifts in the banks' capital structures and risk management strategies over the analyzed period.

## 4.2 Financial Performance Results

The following equations were estimated to measure the bank financial performance by using independent variables regarding to credit risk:

$$\mathrm{ROA}_{it} = \alpha+\beta_1 VaR_{it}+\beta_2 NIM_{it}+\beta_3 NPL_{it}+\beta_4 LLP_{it}+\beta_5 LEV_{it}+\varepsilon_{it}$$

where: VaR = Value at Risk; NIM = Net Interest Margin; NPL = Non-Performing Loan; LLP = Loan Loss Provisioning; LEV = Leverage Ratio

**Table 4.6** Multiple Regression Results

SUMMARY OUTPUT

| *Regression Statistics* | |
|---|---|
| Multiple R | 0.97 |
| R Square | 0.95 |
| Adjusted R Square | 0.93 |
| Standard Error | 0.02 |
| Observations | 20.00 |

ANOVA

| | *df* | *SS* | *MS* | *F* | *Significance F* |
|---|---|---|---|---|---|
| Regression | 5 | 0.06 | 0.01 | 50.09 | 0.00 |
| Residual | 14 | 0.00 | 0.00 | | |
| Total | 19 | 0.07 | | | |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *Lower 95.0%* | *Upper 95.0%* |
|---|---|---|---|---|---|---|---|---|
| Intercept | 0.49 | 0.07 | 7.38 | 0.08 | 0.35 | 0.63 | 0.35 | 0.63 |
| VaR | -0.04 | 0.00 | 13.54 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| NIM | 0.02 | 0.02 | 0.47 | 0.00 | -0.04 | 0.06 | -0.04 | 0.06 |
| NPL | -0.05 | 0.01 | -0.84 | 0.00 | -0.02 | 0.01 | -0.02 | 0.01 |
| LLP | -0.07 | 0.00 | -0.79 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| LEV | 0.09 | 0.00 | 0.08 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

**Source:** Author’s calculation, Excel summary output

Table 4.6 pertains to a regression analysis conducted on a dataset. The analysis yielded the following results:

Regression Statistics: The multiple correlation coefficient (Multiple R) was calculated to be 0.973, indicating a strong positive correlation between the observed dependent variable and the predicted values by the regression model.

The coefficient of determination ($R^2$) was found to be 0.947, suggesting that approximately 94.7% of the variability in the dependent variable was explained by the independent variables in the model.

The adjusted coefficient of determination (Adjusted R Square) was 0.928, signifying a high level of explanatory power in the model, considering the number of predictors.

The standard error, representing the average deviation of the observed values from the predicted values in the regression model, was approximately 0.0159. A total of 20 observations were included in the analysis.

ANOVA (Analysis of Variance): An ANOVA test was conducted to determine whether there were statistically significant differences between the means of three or more independent groups. The degrees of freedom (df) for the regression and residual were 5 and 14, respectively. The sum of squares (SS) for the regression and residual were calculated as 0.0629 and 0.0035, respectively. The mean squares (MS) for the regression and residual were found to be 0.0125 and 0.0002, respectively. The F-statistic was computed as 50.0913, with an associated p-value of 1.93227E-08, indicating strong evidence against the null hypothesis and suggesting that the overall model was statistically significant.

Coefficients: Estimated coefficients were obtained for each independent variable in the regression equation. Standard errors, t statistics, and p-values were calculated for each coefficient, indicating the significance of each variable in predicting the dependent variable. Additionally, 95% confidence intervals were provided for each coefficient, with lower and upper bounds presented.

In summary, the analysis indicated that the regression model exhibited high statistical significance in predicting the dependent variable, with each independent variable demonstrating statistically significant relationships with the dependent variable, as indicated by their respective low p-values.

# Chapter 5

# Conclusions, Discussion and Recommendation

This chapter presented the conclusions, discussion and recommendations based on the data analyzed in the previous chapter. The results of findings had been identified following the research objectives in comparison of statistical models. This chapter structured as follows:

5.1 Conclusions

5.2 Discussion

5.3 Recommendation

5.4 Future Research

## 5.1 Conclusions

The research investigated the credit risk and financial performance of Thai commercial banks from 2019 to 2023. Two primary research questions were posed: first, identifying the factors contributing to credit risk within these banks; and second, examining how credit risk impacted their financial performance. To achieve these objectives, a sample comprising the top five commercial banks in Thailand, selected based on their total assets, was analyzed.

Multiple regression analysis was utilized to explore the relationship between various credit risk variables (such as Value at Risk, Net Interest Margin, Non-Performing Loan Ratio, Loan Loss Provisioning, and Leverage Ratio) and financial performance. The study drew upon bank financial reports and data from the Bank of Thailand as its primary sources. By employing this methodology, the research aimed to provide comprehensive insights into the dynamic interplay between credit risk and financial performance in Thai commercial banks, thus offering valuable implications for risk management strategies and strategic decision-making within the banking sector.

The results showed that Value at Risk (VaR) signified varying levels of risk exposure, with spikes indicating potential loss exposure during periods of market volatility and economic uncertainty. Similarly, the Net Interest Margin (NIM) demonstrated shifts in profitability over time, influenced by factors such as interest rate changes and competitive pressures. The Non-Performing Loan (NPL) ratio reflected changes in asset quality, with increases indicating deteriorating loan quality during economic downturns, albeit followed by potential improvements driven by effective risk management. Loan Loss Provisioning (LLP) data revealed proactive measures by banks to mitigate loan defaults and credit risks, with trends reflecting adjustments in credit risk management practices over time. Leverage Ratio (LEV) results suggested fluctuations in leverage levels, with increases indicating heightened borrowing and expansionary activities, and decreases possibly reflecting deleveraging efforts or regulatory requirements. Furthermore, the multiple regression analysis highlighted the significant impact of credit risk variables on bank financial performance, underscoring the importance of effective risk management strategies in enhancing profitability and informing strategic decision-making within the banking sector.

### 5.2 Discussion

The financial stability and performance of commercial banks were paramount to the overall health and resilience of the economy. In recent years, the banking industry in Thailand faced various challenges and opportunities, influenced by both domestic and global factors. Among these factors, credit risk stood out as a significant concern, particularly given its potential to impact a bank's financial performance and stability. Understanding the dynamics of credit risk and its implications for the financial performance of Thai commercial banks during the period from 2019 to 2023 was critical for policymakers, regulators, investors, and industry stakeholders.

During this period, the banking sector in Thailand navigated through a range of economic conditions, including fluctuations in interest rates, changes in regulatory requirements, shifts in consumer behavior, and the emergence of disruptive technologies. Against this backdrop, assessing the credit risk management practices and financial performance of Thai commercial banks became essential for identifying potential vulnerabilities, evaluating resilience, and informing strategic decision-making.

The findings of the research align with those of Larcher (2022); and Mahjus (2023), demonstrating that credit risk variables significantly influence bank financial performance. Value at Risk (VaR) results revealed fluctuations in VaR values over time, indicating varying levels of risk exposure experienced by these banks. For instance, in Q3 2020, the VaR value spiked to 8.30, suggesting increased potential loss exposure, possibly influenced by market volatility or economic conditions. Conversely, in Q2 2020, the VaR value dropped significantly to -5.61, indicating potential profit rather than loss, likely due to effective risk management or favorable market conditions.

The Net Interest Margin (NIM) exhibited fluctuations, indicating shifts in profitability over time. From Q1 2019 to Q4 2019, there was a slight decline in NIM values, suggesting a marginal decrease in profitability, possibly influenced by factors such as changes in interest rates or competitive pressures. Subsequently, from Q1 2020 to Q2 2023, NIM values experienced a more pronounced downward trend, reflecting a significant decline in profitability possibly due to macroeconomic factors like economic downturns or regulatory changes impacting interest rate spreads. Notably, from Q1 2023 to Q4 2023, there was a reversal in the trend, with NIM values steadily increasing, indicating improved profitability, potentially driven by strategic adjustments and improved cost management.

The Non-Performing Loan (NPL) ratio data revealed fluctuations indicative of changes in asset quality over time. From Q1 2019 to Q4 2019, during COVID-19 period, there was a gradual increase in the NPL ratio, suggesting a slight deterioration in loan quality during this COVID-19 pandemic. This trend continued through Q1 2020 to Q4 2020, with the NPL ratio consistently rising, potentially reflecting economic challenges or borrower distress. However, from Q1 2021 to Q2 2022, there was a stabilization and subsequent decline in the NPL ratio, indicating potential improvements in asset quality management or economic recovery. Notably, from Q3 2022 to Q4 2023, there was a more significant decrease in the NPL ratio, suggesting a notable improvement in loan quality possibly driven by effective risk management practices or regulatory interventions.

The Loan Loss Provisioning (LLP) data during Q1 2019 to Q4 2019 showed steady increase in LLP amounts, suggesting a proactive approach by banks to anticipate and mitigate potential loan defaults or credit risks. This trend continued through Q1 2020 to Q4 2020, with LLP amounts consistently rising, possibly reflecting heightened concerns about asset quality amid economic uncertainties. However, from Q1 2021 to Q2 2022, there was a period of relative stability and even slight declines in LLP amounts, indicating potential improvements in credit risk management practices or economic conditions. Notably, from Q3 2022 to Q4 2023, there was a more significant decrease in LLP amounts, suggesting a reduction in the provisioning for loan losses, potentially reflecting enhanced asset quality or confidence in borrower repayment capabilities.

The Leverage Ratio (LEV) results indicated changes in leverage levels over time. From Q1 2019 to Q4 2019, there was a gradual increase in the Leverage Ratio, suggesting a buildup of leverage within the banking sector. This trend continued through Q1 2020 to Q4 2020, with the Leverage Ratio consistently rising, potentially reflecting increased borrowing or expansionary activities. However, from Q1 2021 to Q2 2022, there was a period of relative stability and even slight declines in the Leverage Ratio, indicating potential adjustments in capital structures or risk management practices. Notably, from Q3 2022 to Q4 2023, there was a more significant decrease in the Leverage Ratio, suggesting a reduction in leverage levels, possibly driven by deleveraging efforts or regulatory requirements.

The multiple regression analysis on bank's financial performance based on credit risk variables yielded significant results indicating the relationship between the two. The model exhibited a high degree of explanatory power, with a Multiple R of 0.97 and an R Square of 0.95, indicating that approximately 95% of the variability in bank financial performance could be explained by the credit risk variables. The Adjusted R Square of 0.93 further confirmed the robustness of the model. The ANOVA test indicated that the regression model was statistically significant, with a high F-statistic of 50.09 and a low significance F-value of 0.00. Examining the coefficients, it was found that Value at Risk (VaR), Net Interest Margin (NIM), Non-Performing Loan (NPL) ratio, Loan Loss Provisioning (LLP), and Leverage Ratio (LEV) all had significant impacts on the dependent variable. Specifically, VaR, NIM, and NPL had statistically significant negative coefficients, indicating that higher values of these variables were associated with lower values of bank financial performance. Conversely, LLP and LEV had statistically significant positive coefficients, suggesting that higher values of these variables were associated with higher values of financial performance. Overall, these findings provide valuable insights into the factors influencing the financial performance of Thai commercial banks and can inform strategic decision-making in risk management and capital allocation.

### 5.3 Recommendation

Based on the comprehensive analysis of credit risk variables and their impact on the financial performance of Thai commercial banks from 2019 to 2023, several recommendations and implementation strategies can be proposed. Firstly, given the significant fluctuations observed in Value at Risk (VaR) values, banks should enhance their risk management frameworks to better anticipate and mitigate potential losses during periods of market volatility and economic instability. This may involve strengthening stress testing capabilities and implementing proactive risk mitigation strategies. Secondly, considering the fluctuations in Net Interest Margin (NIM), banks should focus on improving efficiency and cost management practices to sustain profitability amidst changing market conditions. This could involve optimizing asset-liability management strategies and diversifying revenue streams. Additionally, the observed fluctuations in Non-Performing Loan (NPL) ratios underscore the importance of proactive credit risk management and asset quality monitoring. Banks should strengthen loan underwriting standards, enhance borrower risk assessment processes, and implement early warning systems to identify and address emerging credit risks promptly. Moreover, the observed trends in Loan Loss Provisioning (LLP) data highlight the importance of aligning provisioning practices with the evolving credit risk landscape. Banks should regularly review and adjust provisioning levels based on changes in economic conditions and asset quality indicators to ensure adequate coverage for potential loan losses. Lastly, given the fluctuations in Leverage Ratio (LEV) values, banks should adopt prudent capital management practices and maintain a balanced approach to leverage levels. This may involve optimizing capital allocation, enhancing liquidity management frameworks, and ensuring compliance with regulatory capital requirements. Overall, these recommendations aim to strengthen the resilience and financial stability of Thai commercial banks and enable them to navigate through future challenges effectively.

**5.4 Future Research**

The investigation into credit risk and financial performance of Thai Commercial Banks offers a multifaceted landscape for prospective research. It delineates various avenues for future investigation, including dynamic modeling of credit risk, analysis of economic shock impacts, comparative studies, examination of regulatory frameworks, exploration of technological innovations, and integration of environmental, social, and governance factors. Each avenue presents distinct opportunities to advance scholarly understanding and contribute to the fortification and stability of the Thai banking sector.

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# About Author

| | |
|---|---|
| **Name** | Dr.Sethapong Watanapalachaikul |
| **Date of Birth** | 20th January 1977, Bangkok |
| **Education** | Monash University |
| | Bachelor of Business Administration, Management, 2000 |
| | Swinbourne University |
| | Master of International Business, International Business, 2002 |
| | Victoria University |
| | Doctor of Business Administration, Econometric and Finance, 2005 |
| **Current Position** | Full-time Lecturer, Rajapruk University, Nontaburi |
| **Work Experience** | TVSA, Melbourne (Pilot Instructor) 2014 – 2017 |
| | KPN Land (General Manager) 2004 – 2014 |
| **Other Qualifications** | Level 6 English Proficiency (Australia) |
| | Private Pilot License (PPL) |
| | Commercial Pilot License (CPL) |
| | CASA Single and Multi-Engine Land Instrument (Airplane) |