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UEH UNIVERSITY

COLLEGE FOR BUSINESS

SCHOOL OF FINANCE

BACHELOR THESIS

THE IMPACT OF BANK FINTECH ON CREDIT RISK OF VIETNAM'S COMMERCIAL BANKS

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PLAGIARISM RESULTS

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LIST OF ABBREVIATIONS

Abbreviation	Meaning
REM	Random Effects Model
FEM	Fixed Effects Model
GMM	Generalized Methods of Moment
VIF	Variance Inflation Factor
e-KYC	Electronic Know Your Customer
NPL	Non-Performing Loans Ratio
EWM	Entropy Weighted Method
CAR	Capital Adequacy Ratio
LLP	Loan Loss Provisions Ratio
CIR	Cost-to-Income Ratio
LDR	Loan-to-Deposit Ratio
ROA	Return On Assets
CPI	Consumer Price Index
GDP	Gross Domestic Product
2SLS	Two-Stage Least Squares
AR(1)	First-order Arellano-Bond test
AR(2)	Second-order Arellano-Bond test

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ABSTRACT

This research aims to discover the relationship between the Fintech innovation within the commercial banks and their risks in Vietnam banking industry. The results indicate that the emerging effect of Fintech not only brings the banking industry a new era of technology but also has a positive influence on managing credit risks among the banks. To extend the research horizon, the researcher also takes on two different types of banks: state-owned and joint stock commercial banks into consideration in term of Fintech innovation's effect on credit risk. Additionally, the study also examines the impact of Fintech development on different bank scales. To summarize, this study contributes to a better understanding of the way Fintech transforms the Vietnamese banking industry, notably in terms of credit risk reduction for commercial banks. These insights play an essential role for the banking sector to establish flexible strategies, capitalize on Fintech's benefits, and manage credit risks proactively.

Keyword: Fintech, Credit risk, Commercial banks

CHAPTER 1. INTRODUCTION

1.1 Research motivation

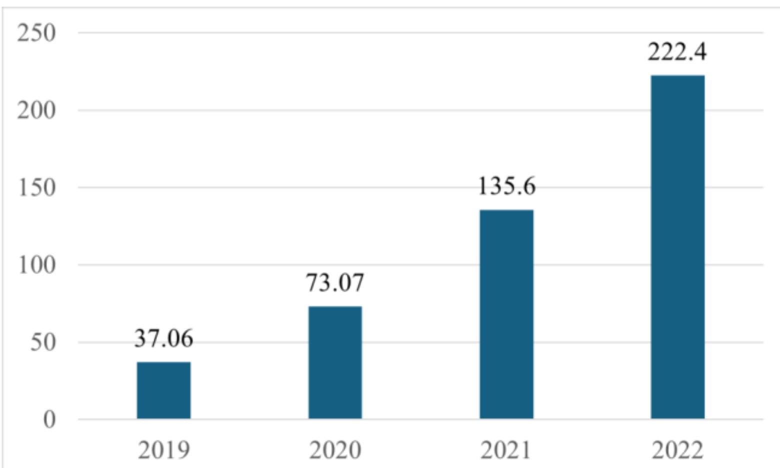
From the first appearance in 1850, financial technology has developed very rapidly in the global in the past two decades (Arner, Barberis, & Buckley, 2015). This is an inevitable trend that many countries, including Vietnam, clearly recognize the opportunities and challenges that this trend brings (Lien, Doan, & Bui, 2020). To seize opportunities in the industry, it is important to have a deep understand about the impact of technology integration in the new era where Fintech shape the industry into a different approach (Murinde, Rizopoulos, & Zachariadis, 2022). With a fast-expanding market for technology businesses enabling digital banking, digital payments, blockchain, and cryptography, Vietnam is one of the most promising and unexplored fintech industries. More than 130 fintech companies operate in Vietnam, catering to hundreds of customers and providing a range of services, including wealth management, blockchain, and digital payments. Vietnam's fintech industry is expanding due to laws, rules, and alluring investment prospects in Asia. In recent years, Fintech has completely transformed several financial services, garnering billions of dollars in international investment and swiftly gaining traction (Mordor Intelligence, 2023). With nearly 10 years of Fintech developing, we need to clearly apprehend how Fintech has been influenced our banking system to add a new perspective into existing literature.

Digital banking and finance play an important part in the world's upcoming Fourth Industrial Revolution. In Vietnam, the fight to survive in the banking industry has intensified (T. Nguyen & Dang, 2018). Technology has helped to remove numerous obstacles, allowing financial institutions and commercial banks to deliver services and more accessible goods to their consumers at a reduced cost (Shetty & K, 2022). Fintech has the potential to enhance the efficiency of banking, particularly in several basic functions such as payments settlements. Advances in credit screening may be made by utilizing big data analysis with the help of Fintech, resulting in better risk management, loan allocation, and capital efficiency (C.-C. Lee, Li, Yu, & Zhao, 2021). However, the rapid growth of Fintech could also pose risks to consumer and investor protection, as well as to financial stability more broadly. Banks and Fintech companies' partnerships can expose the bank and its clients as well as the entire financial sectors to liquidity and credit risks. Such development may lead into change in the market structure of the financial services and have a long-term impact on the financial market and system stability due to a shift in risk-taking behaviour (Ndwiga, 2020). According to Zhao, Goodell, Wang, and Abedin (2023), technological innovation is always a double-edged sword because it also carries potential risks. On the one hand, the development of Fintech in banks has promoted innovation in business operations, while also improving the ability to prevent and control risks. On the other hand, technical risks and operational risks still exist in the process of Fintech development in banks, which can affect credit decisions, causing risks to banks (C.-C. Lee et al., 2021).

According to Vietnam Fintech Market Report proposed by Mordor Intelligence (2023), Vietnam's Fintech is on the rise, supported by government regulations, policies and investment appeal in the Asian region with a significantly high rate of unbanked and underbanked people, combined with growing mobile phone connectivity (150%), Internet penetration (70%) and 3G 4G subscriptions (45%). Therefore, Vietnam remains as an untapped market and a promising land for Fintech investors.

Figure 1.1 Increase in Digital Investment in Vietnam

Unit: USD million



Source: Mordor Intelligence

However, Dung (2024) states that with insufficient data and an incomplete technology system in Vietnam, integrating Fintech technology can pose risks related to predictive modelling, personal and financial information security, as well as the possibility of being attacked by fraud and scams. The author believes that risks including systemic risks, financial management, and customer privacy cannot be ignored. Considering the relationship between state ownership and risk-taking behaviour, Ho, Phung, and Nguyen (2021) argue that excessive risk-taking may be encouraged by state ownership as predicted by the double-agency issue theory. They state that state ownership representatives in Vietnamese firms frequently take undue risks to enhance their own interests. W. Zhu and Yang (2016) also discover that ownership by the state is generally linked to greater risks. Banks owned by local governments have the lowest capital adequacy and liquidity ratios, while those under central government control have the highest credit risk. Related to banks' size, big banks may be more likely to take on risk than smaller banks, which would increase their overall systemic risk (Barrell, Davis, Fic, & Karim, 2010). It is noticeable that company size is the primary determinant of typical systemic risk indicators, suggesting a primary worry for "too-big-to-fail" organizations. Smaller banks, nevertheless, might still exposure serious systemic risks (Varotto & Zhao, 2018). Through previous empirical studies proposed by numerous foreign researchers, the researcher realizes that we currently lack quantitative research on the effect of Fintech development on credit risks of banks in Vietnam. Therefore, this research will conduct a detailed analysis of the influence of Fintech innovation on credit risks of Vietnamese commercial banks. To measure Fintech indices, the author analyzes keywords in the annual reports of each bank to identify and specifically evaluate the level of development of Fintech at Vietnamese commercial banks. This study aims to investigate the role of Fintech development to understand whether it is creating benefits or causing risks for commercial banks in Vietnam. By having a deep understanding of these factors, banks can develop better strategies to manage risks and take advantage of technology in business operations. Moreover, the study also aims to enhance the understanding of the financial and technological integration process for commercial banks to thrive and adapt in the increasingly competitive and emerging market in Vietnam.

1.2 Research purpose

There are three main objectives for this research. First, this study aims to investigate the impact of fintech innovation on the credit risk of commercial banks in Vietnam. Fintech applications, such as digital lending, payment platforms, and AI-driven credit assessments, have changed the landscape of risk management, it has the potential of reducing traditional credit risks through better data analytics. However, the rapid development of fintech may pose new forms of risk, such as cyber risks or reliance on unproven algorithms. Second, the research seeks to examine the heterogeneity of fintech's impact on state-owned and joint stock commercial banks. State-owned banks, which often serve a larger base of public and governmental sectors, may face different fintech challenges compared to joint stock banks, which tend to be more agile and willing to adopt digital technologies. This distinction could lead to different outcomes in credit risk management. Third, this study aims to investigate the different impact of fintech development on credit risk of banks with varying sizes. Large banks, with more resources and established infrastructures, may adopt and apply Fintech more effectively than smaller banks. Conversely, smaller banks may be more agile and innovative, thus benefiting disproportionately from fintech solutions compared to larger banks.

1.3 Research question

1. Does Fintech innovation influence Vietnam commercial banks' credit risk?
2. Is the impact of Fintech on credit risk different between state-owned and private commercial banks?
3. Does the impact of Fintech on credit risk differ across commercial banks of different sizes?

1.4 Research scale

The study object includes 24 Vietnam commercial banks, which are listed on the stock exchange and have available annual reports from 2004 to 2023. Secondary data is collected from two sources: macroeconomic data collected from the World Bank or Statista for Vietnam; unstructured text data used to construct the Fintech index and bank-level financial indicators are collected from the banks' annual and financial reports. These reports are downloaded from each bank's official website.

1.5 Research methodology

This research investigates the impact of Fintech development on Vietnamese commercial banks credit risks through Fintech index and non-performing loans ratio with control variables including five bank's financial indices, two macroeconomic factors and two interactive variables. The process of this research was conducted as follows:

(1) Collect data of 24 banks within the period from 2004 to 2023. Proceed on cleaning and checking for missing or impropriate data.

(2) Conduct a summarize of descriptive statistics, Pearson pairwise correlations matrix for each variable to have a general picture of the relationship between each variable.

(3) Perform unit root test to check if the variables are stationary or not and variance inflation factor (VIF) test to check multicollinearity problem.

(4) Perform regression with random (REM) and fixed (FEM) effects model. Conduct heteroscedasticity and autocorrelation test to adjust the model.

(5) Conduct Hausman test to confirm which model is the best fit for the data.

(6) Test for endogeneity with each variable as the instrument variable.

(7) Use difference Generalized Method of Moments (GMM) model to solve the endogeneity problem.

(8) Perform regression with two interactive variables.

(9) Discuss the results, propose suggestions and recommendations.

1.6 Research contribution

This study significantly contributes to both academic literature and practical policymaking in the several ways.

First, the research offers valuable insights into how fintech innovations impact credit risk within Vietnamese commercial banks. While previous research has largely focused on the benefits of fintech in improving operational efficiency or performance, this study shifts the focus to understanding its risk implications, an area that has received limited attention in the context of Vietnam.

Second, by examining the differences between state-owned and joint stock commercial banks, as well as across banks of different sizes, this study highlights how fintech's effects on credit risk are not uniform across the banking sector. This heterogeneity provides deeper insights into the structural differences in how banks manage risks, particularly in emerging economies like Vietnam, where the financial landscape is undergoing rapid digital transformation.

Third, the author believes that the findings will be useful for regulators and policymakers. Understanding how fintech affects credit risk in different types and sizes of banks can guide the creation of more targeted regulatory frameworks, ensuring that the benefits of fintech can be utilized while minimizing risks. Moreover, the research can inform strategies for banks to strengthen their risk management systems in the digital age.

Finally, while fintech research is growing globally, there is limited literature specifically addressing its impact in emerging markets like Vietnam. This study enriches academic literature by providing empirical evidence from a developing economy, offering a model for similar research in other regions. By addressing these gaps, this research will provide a comprehensive understanding of fintech's role in shaping the future of credit risk management in Vietnam's commercial banks.

1.7 Research structure

The research is structured as follows:

Chapter 1: Introduction

In this chapter, the author presents the motivation, purposes, questions, scale, methodology, contribution and structure of this research. This is an overview of the research problem.

Chapter 2: Literature review

This chapter presents the theoretical basis related to credit risk and Fintech and an overview of empirical evidence on the influence of Fintech innovation on banks' credit risk. This chapter introduces related concepts and research works, creating a foundation for a more detailed understanding of the topic.

Chapter 3: Methodology

This chapter identifies the research hypothesis, variables calculating methods, describes the variables and proposes the empirical model used in the research process. This is how the research is designed and the hypotheses set out to address the research problem.

Chapter 4: Result

In this chapter, the author presents and analyzes the results obtained from the study, compares them with the initial hypotheses, and discusses the significance of the results. This is the main part of the research, the important findings and significance of the study will be detailed and analyzed.

Chapter 5: Conclusion

This final chapter will summarize the main points of the study and provide basic conclusions. The author also mentions the issues in the study so that the objective view of the study is provided.

CHAPTER 2. LITERATURE REVIEW

2.1 Concept definition

2.1.1 Fintech

The concept of Fintech (a combination of "finance" and "technology") captures the true meaning of the word, which is the advancement of technology and innovation to promote banking and financial literacy using cutting-edge technologies (Z. Hu, Ding, Li, Chen, & Yang, 2019; I. Lee & Shin, 2018; Thakor, 2020). Fintech also refers to how financial services companies, including those that offer loans, payments, money transfers, and other banking services, interact with technology like cloud computing and mobile internet (Giglio, 2021). Numerous studies have researched the Fintech phenomenon, its concepts, history, and progress.

The phrase Fintech has appeared since the 1800s. Its development can be divided into three stages: Fintech 1.0 occurred from 1866 to 1967, Fintech 2.0 developed from 1967 to 2008, Fintech 3.0 is from 2008 to now for developed countries and additionally 3.5 for developing countries (Anh, Zettinig, & Mumford, 2018; Buckley, Arner, & Barberis, 2016; Giglio, 2021). According to Buckley et al. (2016), the detailed innovation of Fintech for each stage is described as follows.

Fintech 1.0 mentioned the process of development from analog to digital. In the late 19th century and the early 20th century, the financial services industry remained mostly analogue, although it was heavily interlinked with technology. Thanks to several important technologies such as telegraph, railroad and steamship, there was a worldwide telex network in existence, which served as the communications backbone for the development of the next fintech stage. Fintech 2.0 marked the digitalization of traditional financial services, beginning with the development of electronic payment systems. International interbank networks such as SWIFT and regulatory frameworks by the Basel Committee also emerged during this period. Major market crises innovated regulatory changes to control technological risks. In the mid-1990s, the rise of online consumer banking set the stage for widespread e-banking, which also created new credit risks and regulatory challenges. These advancements laid the groundwork for Fintech 3.0. Fintech 3.0 in developed countries emerged around the 2007-2008 global financial crisis (GFC), which damaged trust in traditional banks. Technological advances, including smartphones and APIs, facilitated the rise of fintech, with consumers increasingly relying on tech companies for financial services, such as peer-to-peer (P2P) lending, often outside clear regulatory frameworks. Post-crisis regulations imposed higher compliance costs on banks, shifting the market toward fintech startups. The fintech industry now spans five key areas: finance and investment, internal financial operations, payments and infrastructure, data security, and consumer interfaces, where tech companies compete with traditional banks by leveraging existing customer bases and tech platforms. This shift represents a change in who provides financial services and at what speed, particularly in emerging markets. Additionally, there are several strong underlying reasons that support Fintech 3.5 among the developing countries. First, these countries have youthful, tech-savvy populations with mobile devices with rapidly expanding middle class. Second, inefficient financial and capital markets give an increase in opportunities for unofficial alternatives. Third, a lack of physical banking infrastructure is a wonderful reason for fintech to innovate in emerging areas. Fourth, people in these areas have a behavioral tendency toward convenience over trust. Finally, developing countries pose unexplored market opportunities with looser regulations regarding data protection and competition. In the future, Fintech will mark new technological innovations and expanded business models, providing smarter and more flexible financial solutions for consumers and businesses. However, it also poses challenges in terms of security, privacy, and risks associated with the process of building and innovating (Dung, 2024).

Fintech is still relatively young in developing countries like Vietnam, but it has the potential to provide ground-breaking innovations in the future. Fintech has drawn a lot of interest from researchers, policy makers, especially the authorities in the banking industry of Vietnam. Fintech is a topic that is frequently discussed in conferences and forums (Lien et al., 2020). Vietnam's finance industry is changing quickly as Fintech firms and traditional banks compete for the country's massive digital user base. This explains why the development of digital transformation and digital banking was supported by the banking industry's electronic Know Your Customer (e-KYC) circular (Acclime Vietnam, 2023). Up to 2018, in Vietnam, there have been over 41 commercial banks providing mobile payment services with the number and value of transactions continuously increasing rapidly (T. N. L. Dang, 2018). In the era of Industrial Revolution 4.0, where everything is connected and shared on the cloud, fintech is a denial trend. By introducing new business models and redefining industries, the

Internet of Things, big data, cloud computing, artificial intelligence, and augmented reality will transform the world. The swift pace of change compels Vietnamese regulators and intuitions to consider their basic operations and monitoring systems in detail to either adapt or risk being left behind in the mainstream. Similar to online and mobile banking, online payment systems, and other technologies, there are always advantages and disadvantages to new technology, but the trend is unstoppable (T. T. D. Nguyen & Ngo, 2018).

2.1.2 Credit risk

In banking business, credit granting activities are the main profit-generating activities for banks but also pose huge risks, accounting for 70% of the bank's total operational risks (Arunkumar & Gowdara, 2006). Banking business is roughly understood as a risky business, pursuing profits with acceptable risks is the nature of banking. There are many ways to approach the concept of credit risk. According to the State Bank of Vietnam, credit risk in banking activities is the possibility of loss to the bank due to customers not performing or not being able to perform their obligations according to commitments (The State Bank of Vietnam, 2005). Similarly, credit risk is known as the risk that arises in case the borrower is unable to repay debt on time due to insolvency or intentional violation of agreed terms (Baesens, Van Gestel, & Thomas, 2009). At the same time, the research about bank size, credit risk and bank performance among the commercial banks in Vietnam also consider credit value as an important indicator for the financial health of banks (Thi Thanh Tran & Phan, 2020). Adeyemi (2011) found that commercial banks that have high non-performing loans ratios have a negative impact on the industry. The more credit risk a bank faces, the higher the likelihood that that bank will face a financial crisis. Although banks can gain high profitability from this high level of risk, there is a possibility that credit risk can lead to a high level of default risk, which then will harm the bank financial performance (Tam Dang & Linh, 2020). Therefore, banks need to have an effective method to manage and limit credit risks. Effective credit risk management not only helps banks improve the sustainability and profitability of their operations but also contributes to effective capital allocation and economic stability (Psillaki, Tsolas, & Margaritis, 2010).

Bank credit risk can be assessed through the non-performing ratio, which is the ratio of total non-performing loan divided by total outstanding loans (Tam Dang & Linh, 2020; Thi Dang, Pham, Nguyen, & Dao, 2024; Ha & Nguyen Vinh, 2022; V. Nguyen, Pham, Doan,

Doan, & Ho, 2023; Thi Thanh Tran & Phan, 2020; Wu, Jin, Yang, & Qi, 2023). Some other studies measure credit risk through the ratio of credit risk provisions divided by the total assets of the bank (Laeven & Majnoni, 2003; Zribi & Boujelbène, 2011). These researchers suggests that outstanding loans account for the majority of total assets, so the value of total assets can be used directly to calculate risk. Sobarsyah et al. (2020) combine the above two methods to calculate credit risk. This measurement criterion considers the issue of provisioning for possible losses for each specific debt; therefore, it may reflect credit risk more accurately. If we compare the value of bad debt in different debt groups (groups 3, 4 and 5) with the total outstanding debt from groups 1 to 5, it will not reflect the true nature of credit risk. The State Bank of Vietnam considers bad debt as debt in groups 3, 4 and 5, but stipulates that debt from group 2 onwards must have risk provisions (The State Bank of Vietnam, 2005). After considering several methods, in this study, the author decides to use non-performing loans ratio as an indicator for credit risk among the commercial banks in Vietnam.

2.2 Theoretical framework

2.2.1 Theory of Financial Intermediation

The work of Gurley and Shaw (1960) served as the foundation for the development of the theory around financial intermediation, which began in the 1960s of the 20th century. The agency theory and the notion of informational asymmetry is the foundation for the financial intermediation theory. It explains how financial institutions serve as intermediaries between borrowers and lenders, facilitating the flow of funds in the economy. Banks play a critical role in credit allocation, risk management, liquidity provision, and reducing information asymmetry between savers and borrowers (Allen & Carletti, 2012). In theory, the following elements account for the presence of financial intermediaries: high transaction costs, a lack of timely information, and regulatory approaches. The idea concerning informational asymmetry is what makes the financial intermediation studies distinct. However, there have been notable adjustments. Intermediation has grown even though transaction costs and asymmetric information have decreased (Allen & Santomero, 1997).

Fintech transforms the traditional functions of financial intermediation (Harsono & Suprapti, 2024). Traditionally, banks mitigate the information asymmetry problems through credit checks, relationship banking, and risk assessments based on historical data and personal relationships (Mayowa, 2020). Fintech innovations, particularly through data analytics and

AI-driven credit scoring, aim to reduce information asymmetry more efficiently by leveraging alternative data sources such as social media activity, transaction history, and behavioural data (Djeundje, Crook, Calabrese, & Hamid, 2021; Nicola, 2024). However, while fintech tools can enhance credit assessments by incorporating more diverse and real-time data, Fintech often rely on algorithmic models that may lack the depth of understanding found in traditional banking relationships (Khan, Khan, & Ghafoor, 2023). As a result, banks adopting fintech solutions may face model risk, where these automated tools fail to fully capture the credit risk associated with certain borrowers, potentially increasing the bank's exposure to default risk (Agorbia-Atta, Abikoye, Adelusi, Umeorah, & Adelaja, 2024).

2.2.2 Theory of Dynamic Capabilities

Dynamic Capabilities Theory, proposed by Teece, Pisano, and Shuen (1997), states that an organization's ability to achieve competitive advantage in rapidly changing environments depends on its ability to integrate, build, and reconfigure internal and external resources. In the banking industry, Cristina and Carmen (2020) states that capabilities such as detection, absorption, integration, and innovation enable banks to develop the managerial skills necessary to reduce expenses, boost productivity, and gain a competitive edge when examining the experiences banks have had using AI from the theory of dynamic capabilities. Banks that can sense technological trends, seize fintech opportunities, and transform their operations accordingly will be better positioned to manage credit risk. Banks with strong dynamic capabilities are better able to respond to the rapid pace of fintech innovation. Abdurrahman, Gustomo, and Prasetio (2024) have shown that a key element of innovation and the process of digital transformation is dynamic capacities. Acknowledging digital transformation as a project involving both technological and non-technological components requires talents that complement this perspective. They can integrate advanced risk assessment tools and restructure their credit risk management processes to minimize exposure to defaults and bad loans. Those that lack dynamic capabilities may struggle to adapt, facing higher credit risk as they lag fintech-driven improvements.

2.3 Empirical evidence

2.3.1 Domestic research

Dung (2024) assesses the impact of Fintech development on credit risk in Vietnam's commercial banks, revealing that Fintech not only creates new opportunities but also reduces credit risk and enhances risk control efficiency in the master thesis. The researcher collects a dataset consisting of 27 commercial banks from 2004 to 2022 computes the Fintech index using Entropy Weighted Method (EWM) on Fintech lexicons frequency in banks' annual reports. The findings highlight that state-owned banks respond more strongly to Fintech's impact than private banks, and larger banks experience a greater effect compared to smaller ones. Overall, the study underscores Fintech's role in transforming Vietnam's banking sector by lowering credit risk and guiding banks to develop flexible strategies for leveraging Fintech and managing risks proactively. It is explained that the application of advanced technologies such as Big Data and Machine Learning to risk prevention and control models not only improves prevention efficiency but also controls risks accurately. In addition to attracting many customers at low marginal costs thanks to digital technology services, the risk management system that Fintech development brings also helps to monitor changes in credit risk quickly and promptly, minimizing the risk of borrower default.

2.3.2 Foreign research

Wu et al. (2023) explores the link between bank FinTech and commercial bank micro-risks, such as credit, liquidity, and bankruptcy with the system Generalized Method of Moments (GMM) model. To address the limitations of existing bank FinTech metrics, their research uses text mining to create a Fintech index that includes 148 commercial banks' annual financial reports from 2007 to 2019 in China. In addition, they also explore the diversity of ownership and influence channels. Their findings conclude that bank Fintech innovation increases bank credit and liquidity risks while decreasing insolvency risk; bank FinTech in state-owned commercial banks allows for effective credit risk control, whereas joint-stock commercial banks increase liquidity risk while decreasing insolvency risk; the technological application of bank Fintech raises the credit and liquidity risk of commercial banks while decreasing their insolvency risk and the innovation of business mostly increases the liquidity risk. The explanation for these results is primarily because joint stock commercial banks in China are more profit-driven than state-owned banks and can operate on a larger scale than smaller banks, state-owned banks are not very flexible in their technology development because of their size and policy responsibilities. Digital technology applications in banks can efficiently optimize cost within banks' operation but rely heavily on credit and security data. Banks in China can enhance the stability and reduce insolvency banks due to the efficiency in managing cost, however, face a contemporary problem of inaccurate and insufficient data which consequently results in an increase in credit and liquidity risks.

The study of Ndwiga (2020) examines the relationship of market power, which was measured by Lerner index, and the stability of the banks in two periods: before (from 2003 to 2009) and after (from 2010 to 2017) the Fintech innovations. Additionally, the author also analyzes the effect of market power changes on the banking industry's risk-taking behavior calculated by non-performing loans ratio. The study's findings show that the introduction of mobile banking has impacted banks' market power, which then raised their credit risk. This could be explained by the fact that, in comparison to traditional financial services, digital financial products have fewer restrictions and are therefore easier for borrowers to get. Furthermore, compared to traditional financial services, this product's accessibility is increased by the borrower because it involves small sums of money that are advanced by the bank to the borrower. Moreover, commercial banks are likely to attempt to compete for the same market niche through the proliferation of digital credit to maintain their respective market strength, given the entry of Fintech and the resulting heightened market rivalry. As a result, there's a chance that the reliability of these digital credits could be questioned, which could lead to loan defaults and credit risk.

Beck, Chen, Lin, and Song (2016) investigate the influence of Fintech innovation on bank growth and fragility as well as economic growth based on the dataset of 32 countries in the period from 1996 to 2010 by using Ordinary Least Squares (OLS) regression model. In summary, their research implies that the provision of positive credit and risk diversification services to businesses and consumers is facilitated by financial innovation, which is linked to banks taking more aggressive risks and growing faster. This improves capital allocation efficiency of banks and thus enhances economic growth. The drawback of taking on more risk is that it makes banks much more vulnerable to losses during a banking crisis and considerably more volatile in terms of profits.

Another research shows that the relationship between Fintech inputs and non-performing loans risk is significantly negative. Wang, Mao, Wu, and Luo (2023) analyzes micro-survey data from 432 commercial bank branches in Beijing city located in China within the period from 2005 to 2022 to investigate the risk reduction effect of Fintech on bank non-performing loans by using Ordinary Least Squares regressions (OLS) econometric model. The research focuses on how fintech technologies help banks to have a better evaluation of the default risks, enables more precise loan pricing and reduces the chance of defaults, thus lowering the number of non-performing loans. Due to a reduction in the number of non-performing loans, Fintech inputs indirectly boost bank performance, lower NPLs lead to better bank performance, reflected in metrics like return on assets (ROA) and net interest margin (NIM). The study takes into consideration a variety of control variables, including banks' branch size, loan structure, the competitive environment, and macroeconomic indicators such as GDP and central bank lending rates. These factors assist in contextualizing the impact of fintech inputs on NPL reduction and the boost of performance.

The study by Guo and Zhang (2023) focuses on investigating the impact of Fintech on the liquidity creation of Chinese commercial banks from 2008 to 2019. To measure the level of Fintech development, the study constructs a Fintech index using entropy weight method to compute the weight of each keyword in the annual reports according to the Fintech lexicons. The results of the study indicate a positive relationship between Fintech development and bank liquidity. They conclude that banks with Fintech development tend to have higher liquidity. This relationship is explained through several factors such as deposit flow, risk management, and cost efficiency when applying Fintech. For state-owned and unlisted banks, the impact of Fintech becomes less strong than that of non-state-owned banks. It is concluded that the impact of Fintech is uneven among banks, with differences between state-owned and unlisted banks and the remaining banks. The reason for this is that unlisted banks often have fewer market resources, poorer internal governance structures, less capacity for risk management, and lower cost efficiency than listed banks. Since they are subject to less market discipline and have less access to capital markets, Fintech's deposit financing and management techniques will thus result in a greater improvement in the production of liquidity in unlisted banks.

Banna, Kabir Hassan, and Rashid (2021) examine the relationship between banks' risk-taking and fintech-based financial inclusion (FFI) by analyzing data from 534 banks across 24 OIC nations within the period from 2011 to 2019. The bank risk-taking is calculated by z-score, which indicates the default risk as well as bank stability. The authors take the number of the number of mobile money agent and non-branch commercial bank agent outlets, point of sales (POS) terminals, mobile money accounts, and mobile and internet banking transactions into account for the FFI index then use principal components analysis (PCA) to construct an inclusive index of FFI. The findings suggest that banks' tendency for taking risks is regulated to a greater extent by FFI. In the post-industrial revolution 4.0 (IR4.0) period, the relationship became stronger.

2.4 Literature review gaps

Despite the growing global interest in the impact of fintech on the banking industry, there is a significant gap in the literature regarding quantitative research on how fintech affects credit risk in Vietnam's commercial banks. While numerous international studies have examined the role of fintech in reshaping credit risk management, particularly in developed economies, these studies often focus on markets with advanced fintech ecosystems, such as China. In these regions, researchers have quantitatively analyzed fintech's influence on credit risk using large datasets, sophisticated risk models, and advanced econometric techniques. This has provided valuable insights into how financial technology can mitigate credit risks under different market conditions.

In contrast, the body of research in Vietnam remains limited, particularly in terms of empirical, data-driven studies that analyze the specific relationship between fintech and credit risk in the country's banking sector. Most of the existing studies in Vietnam focus on the general adoption of fintech, its regulatory challenges, or its potential benefits, but do not quantitatively assess its direct impact on credit risk at the bank level. Additionally, while some qualitative research touches on the potential of fintech in Vietnam's financial landscape, there is a noticeable lack of empirical evidence that measures fintech's influence on credit risk for state-owned versus private banks or large versus small-scale banks.

This gap highlights the need for quantitative studies that use local data from Vietnam's banking sector to assess fintech's impact on credit risk. Given the rapid development of fintech in Vietnam and its increasing integration into banking operations, such research is crucial to understanding how fintech is transforming credit risk management in Vietnam's unique economic and regulatory environment. Addressing this gap will provide more region-specific insights and enable banks and regulators to make informed decisions about fintech adoption and risk management strategies.

2.5 Hypothesis

In this part, the researcher constructs three testable hypotheses about the relationship between bank FinTech and credit risk. The impact of bank Fintech on non-performing loans ratios is examined first. Then we look at how bank characteristics, specifically banks' size and bank's types of ownership, play a significant role in the relationship between bank Fintech and liquidity creation.

Studies on Fintech unanimously confirm that Fintech development reduces credit risk of commercial banks. According to Guo and Zhang (2023), Fintech not only improves liquidity creation among banks but also reduces liquidity risk in the banking system. Along with that, the study of (D. Hu, Zhao, & Yang, 2024) shows the significantly positive impact of Fintech in reducing the risk-taking of commercial banks. Thus, using Fintech helps banks improve risk management based on the capabilities including increasing liquidity, enhancing credit control and optimizing transaction processes. This means that the innovation of Fintech can reduce credit risk and plays an important role in ensuring stability and safety in bank operations. Therefore, hypothesis 1 can be formulated as follows:

H1: Fintech innovation can reduce bank credit risk.

Based on the financial data compiled by the researcher, in 2023, state-owned commercial banks which own more than 50% of the state capital include BIDV, Vietcombank, Vietinbank, especially Agribank which is a 100% state-owned bank. They account for approximately 45% of total assets of all commercial banks in the market and have a direct impact on the entire banking system. Therefore, this research also raises the question of whether there is a difference between state-owned commercial banks and private commercial banks in the development of Fintech affecting credit risks. Guo and Zhang (2023) conclude in their research that by looking at the heterogeneous and nonlinear link between bank FinTech and liquidity generation, the positive influence of bank FinTech on liquidity creation is more prominent for non-state-owned banks. Another research shows that banks with government ownership concentration has a considerable negative impact on credit risk, however, private commercial banks has a positive influence in China (Liu, Brahma, & Boateng, 2020). According to the conclusions of T. B. D. Pham and Pham (2021) study, increasing equity capital in foreign-owned banks has a greater impact on reducing credit risk than other banks and also when Vietnam's state-owned commercial banks increase their equity, their credit risk will rises. Based on this, the researcher proposes the second hypothesis:

H2: Fintech innovation has a heterogeneous impact on credit risk of banks with different ownership.

At the same time, many studies have indicated that the influence of Fintech development on commercial banks' credit risk is not uniform across banks of different sizes. A research conducted on China commercial banks discovers that further investigation reveals that the negative effects of bank FinTech on credit risk are relatively minor among major banks, state-owned banks and publicly traded banks (Cheng & Qu, 2020). Furthermore, Rogers Ondiba (2023) states that Fintech's impact varies depending on bank size. Large banks seem to be more responsive to changes in Fintech development than small and medium-sized banks. For this purpose, the researcher proposes the last hypothesis:

H3: Fintech innovation has a heterogeneous impact on credit risk of banks with different size.

CHAPTER 3. METHODOLOGY

3.1 Data collection

The data of 24 banks across the period from 2004 to 2023 is collected based on the annual report of each bank. Because Vietnam commercial banks publish the annual reports in variety of file format such as pdf, picture or word file, the author mainly chooses the banks that has pdf or word file that is text extractable to accurately construct the Fintech index. The period that has been chosen covers many important events for Vietnam banking industry, in which the most important milestone is that Fintech started to gain tension in the Vietnamese banking industry because of rising investments in fintech firms, digital banking, and mobile payments in 2016. However, since not all the banks have full reports within this period, through the process of cleaning the data, we have an unbalanced panel data set with a total 430 observations.

3.2 Empirical model

3.2.1 Models that show the impact of Fintech innovation on bank credit risk

The empirical model proposed in this paper follows the model developed by Guo and Zhang (2023) and also take reference from the study of Dung (2024). The model showing the relationship between Fintech innovation and bank credit risk is built as the following basic regression model:

$$\boldsymbol{NPL_{it} = \beta_0 + \beta_1\, FIN_{it} + \beta_2\, Controls_{it} + \varepsilon_{it}}$$

In which, i = 1, 2..., N represents the banks and t = 1, 2..., T corresponds to the years.

NPL_{it} is the non-performing loans ratio of bank i in year t.

FIN_{it} describes the development of finance technology, obtaining through Fintech index by text mining bank i's annual report in year t.

$Controls_{it}$ is a vector of control variables, including CAR_{it}, LLP_{it}, CIR_{it}, LDR_{it}, ROA_{it}, GDP_{it}, CPI_{it}.

ε_{it} is the error term.

3.2.2 Models that show the impact of Fintech innovation on bank credit risk with state-owned variable

$$\boldsymbol{NPL_{it} = \beta_0 + \beta_1 FIN_{it} + \beta_2 FIN_{it} \cdot OWN + OWN + \beta_3\, Controls_{it} + \varepsilon_{it}}$$

In which, i = 1, 2..., N represents the banks and t = 1, 2..., T corresponds to the years.

NPL_{it} is the non-performing loans ratio of bank i in year t.

FIN_{it} describes the development of finance technology, obtaining through Fintech index by text mining bank i's annual report in year t.

OWN is the variable that shows the bank's ownership, divides into 2 types: state-owned bank and private bank

$Controls_{it}$ is a vector of control variables, including CAR_{it}, LLP_{it}, CIR_{it}, LDR_{it}, ROA_{it}, GDP_{it}, CPI_{it}.

ε_{it} is the error term.

3.2.3 Models that show the impact of Fintech innovation on bank credit risk with bank's size variable

$$\boldsymbol{NPL_{it} = \beta_0 + \beta_1 FIN_{it} + \beta_2 FIN_{it} \cdot SIZE + SIZE + \beta_3\, Controls_{it} + \varepsilon_{it}}$$

In which, i = 1, 2..., N represents the banks and t = 1, 2..., T corresponds to the years.

NPL_{it} is the non-performing loans ratio of bank i in year t.

FIN_{it} describes the development of finance technology, obtaining through Fintech index by text mining bank i's annual report in year t.

SIZE is the variable that shows the bank's size, divides into 2 types: big bank and small bank based on bank's total assets.

$Controls_{it}$ is a vector of control variables, including CAR_{it}, LLP_{it}, CIR_{it}, LDR_{it}, ROA_{it}, GDP_{it}, CPI_{it}.

ε_{it} is the error term.

3.3 Measurement

3.3.1 Dependent variable

Referring to the research articles of authors Cheng and Qu (2020); Wu et al. (2023); Wang et al. (2023) on the impact of Fintech on the risks of commercial banks, the non-performing loans ratio (NPL) was used to measure the level of credit risk of the bank. In addition, commercial banks in Vietnam also apply the criteria for classifying loans by five levels to determine bad debts which including subordinated, doubtful and loss loans. The higher the NPL ratio, the higher the credit risk that the bank must bear, that's the reason why NPL ratio can reflect the safety level of bank credit assets and the level of credit risk of the bank. Therefore, in this research, non-performing loans ratio is used to measure the credit risk of the bank.

$$NPL = \frac{Total\ non - performing\ loans}{Total\ loans}$$

3.3.2 Independent variable

According to Wang et al. (2023), there is no standard statistical metric for Fintech inputs, which mostly include personnel, software, and technology. Therefore, the author decided to capture the variable by calculating the total number of IT staff, IT software inputs and hardware inputs. On the other hand, Cheng and Qu (2020); Guo and Zhang (2023); Rogers Ondiba (2023); Wu et al. (2023) use text mining techniques to establish a Fintech index for each bank using its annual report. Specifically, this research will refer to the textual analysis of banks' annual reports according to Guo and Zhang (2023) to construct bank Fintech indices for Vietnam commercial banks. There are several reasons for this selection. Firstly, like China, Vietnam commercial banks often do not reveal Fintech expenses in financial statements, but instead provide textual information about finance technology they applied in annual reports. Secondly, according to the text mining hypothesis propose by Feldman and Dagan (1995), enormous amounts of unstructured data can contain a range of varied information that researchers can utilized on to find out useful knowledge. Based on previous research, the researcher believes that the frequency of Fintech-related phrases in bank annual reports is a reliable indicator of the industry's advancement in this aspect. The researcher uses natural language processing, including word segmentation and frequency statistics, to create bank Fintech indices (FIN). It takes several steps as follows; all these steps require Google Colab software to operate.

First, the author manually collected the annual reports of each bank from 2004 to 2023 and used Google Colab software to extract them into text files. Next, the raw text from annual reports of the banks was iterated one by one to count Fintech keywords and the total words that the text file contains. Table 3.1 describes the Fintech keywords that are required to calculate the frequency in Vietnamese which the author take reference from the study of Guo and Zhang (2023). After considering the characteristics of the banks' annual reports, the author decided to adjust the keywords to have a better fit for Vietnam commercial banks because an English word can translate into many words in Vietnamese. The table reports 37 Fintech keywords.

Table 3.1 Fintech keywords used in the research

Artificial Intelligence Technology	**Blockchain Technology**	**Cloud Computing Technology**	**Big Data Technology**
Trí tuệ nhân tạo	Blockchain	Điện toán đám mây	Dữ liệu lớn
Nhận diện khuôn mặt	Chuỗi khối liên minh	Dịch vụ đám mây	Dòng dữ liệu
Nhận diện giọng nói	Sổ giao dịch điện tử	Nền tảng đám mây	Khai phá dữ liệu
Nhận diện dấu vân tay	Mã hóa dữ liệu	Kiến trúc đám mây	Trực quan hóa dữ liệu
			Dữ liệu trực quan

Payment Settlement Innovation	**Resource Allocation Innovation**	**Risk Management Innovation**	**Channel Construction Innovation**
Thanh toán trực tuyến	Vay trực tuyến	Chân dung khách hàng	Ngân hàng trực tuyến
Thanh toán di động	Nền tảng cho vay	Mô hình dự báo	Ngân hàng điện tử
QR code	Tích hợp tín dụng	Đánh giá tín dụng	Ngân hàng di động
Ví điện tử	Tài chính trực tuyến	Chống gian lận	Internet banking
Thanh toán qua			Ứng dụng ngân hàng
			Ứng dụng điện tử
			Ngân hàng số

Source: The author take reference from Guo and Zhang (2023)

Second, after having the full word count results and total number of words in the reports, the author divided the number of keywords by the total number of words to get the frequency of the word and the last step is performing the entropy weighted method (EWM) to get the Fintech indices. The entropy weighted method has 4 steps:

(1) Normalize the keyword frequency data so that they are comparable across banks and years by using the Min-Max scaler. The normalized value is calculated as:

$$Y_{ijt} = \frac{X_{ijt} - \min(X_j)}{\max(X_j) - \min(X_j)}$$

In which $i = 1, 2\ldots, N$ represents banks, $j = 1, 2\ldots, K$ implicates keywords and $t = 1, 2\ldots, T$ shows year. X_{ijt} is the original frequencies and Y_{ijt} is the normalized frequencies of keyword j of bank i in year t.

(2) Calculate entropy for each keyword to measure the uncertainty or information diversity in the keyword frequencies. The entropy for each keyword is calculated as:

$$E_j = -\frac{1}{\ln(NT)} \sum_{t=1}^{T} \sum_{i=1}^{N} P_{ijt} \ln P_{ijt}$$

In which the P_{ijt} is calculated as the below formula:

$$P_{ijt} = \frac{Y_{ijt}}{\sum_{t=1}^{T} \sum_{i=1}^{N} Y_{ijt}}$$

The entropy value E_j ranges from 0 to 1. The higher the E_j, the greater the differentiation degree of index j, and more information may be extracted.

(3) The calculation of the entropy weight is defined as below:

$$W_j = \frac{1 - E_j}{\sum_{j=1}^{K} (1 - E_j)}$$

The Entropy Weighted Method (EWM) is a method used to determine the maximum criteria, including many factors necessary for evaluating the price and evaluating the quantity in accordance with their importance. The higher the degree of dispersion, the higher the degree of differentiation, results in more extractable information (Y. Zhu, Tian, & Yan, 2020).

(4) Lastly, the Fintech indices is determined with normalized frequencies Y_{ijt} and the entropy weight W_j as the formula below:

$$FIN_{it} = \sum_{j=1}^{K} W_j Y_{ijt}$$

In which FIN_{it} is the Fintech indices of bank i in year t.

3.3.3 Control variables

In this study, the author examines control factors from both the bank and macro-level viewpoints. The control variables used in this work are based on an overview of research on macro factors influencing credit risk. According to banks' operation rationale and prior research, the researcher selects seven variables that can affect non-performing loans ratio within the banks. These variables can be divided into 2 groups: bank level variables and macro level variables. The first category includes capital adequacy ratio (CAR), loan loss provision ratio (LLP), cost-to-income ratio (CIR), loan-to-deposit ratio (LDR) and finally return on assets (ROA). The second category have only two variables: the growth of GDP of Vietnam annually (GDP) and inflation (CPI).

3.3.3.1 Capital adequacy ratio (CAR)

Commercial banks are becoming increasingly worldwide because of the banking industry's growth. Consequently, it is essential for financial regulators to maintain the stability of the banking sector. A metric used to assess a bank's solvency is the capital adequacy ratio, as it compares the amount of capital to the risk-weighted assets the bank have to be able to meet its obligation (Luong & Nguyen, 2021). Research investigates the determinants of non-performing ratio conducted by Vatansever and Hepsen (2015) have shown empirical evidence of the impact of capital adequacy ratio (CAR) on non-performing loans ratio. The findings suggest that CAR ratio can have a positive impact on NPL ratio, which means if the bank cannot manage their capital efficiently, it will pose a potential credit risk to the bank. Recognizing the possible influence that CAR may have on NPL, the dependent variable, the author includes CAR as a control variable. The formula of CAR is shown as below:

$$CAR = \frac{Tier\ 1\ capital + Tier\ 2\ capital}{Risk - weighted\ assets}$$

3.3.3.2 Loan loss provisions ratio (LLP)

The most important estimation in banks is provisions for loan losses since lending risk is the primary cause of these provisions. Lending risk is frequently considered when determining the level of provision rate estimates (D. T. T. Nguyen, 2022). Since banks are crucial to the economy's ability to provide credit, it is important to comprehend the variables that affect their capacity for credit loss. Making unnecessary provisions might limit a bank's ability to lend money and hinder its expansion and profitability (Ng, Saffar, & Zhang, 2020). High non-performing loans ratio might require banks to raise their provisions for loan losses, which can result in the limitation of the amount of loans that can be offered by banks (Do, Ngo, & Phung, 2020). Loan loss provisions ratio is calculated as follows:

$$LLP = \frac{Total\ loan\ loss\ provisions}{Total\ loans}$$

3.3.3.3 Cost-to-income ratio (CIR)

The Cost-to-income Ratio (CIR) is a key financial metric used to assess a bank's operational efficiency by comparing its operating costs to its operating income. Cost-to-income ratio can have a significant impact on the bank's performance in Vietnam, therefore, this is one of the elements that the bank should consider to maintain a sufficient capital level and effectively perform (Dao, 2020). A paper conducted in 80 countries within the period from 1999 to 2019 examine the evolution of the non-performing loans ratio suggest that a high non-performing loans ratio is significantly associated with an increase of the bank-cost-to-income ratio (Ferreira, 2022). Therefore, CIR is considered as a control variable with the following formula:

$$CIR = \frac{Total\ operating\ expenses}{Total\ operating\ income}$$

3.3.3.4 Loan-to-deposit ratio (LDR)

The Loan-to-deposit ratio (LDR) is an important measure of a bank's liquidity and lending practices, comparing the total amount of loans issued by the bank to the total amount of deposits it holds. Loan is one of the most important asset of a bank, accounting for the highest proportion and earning the largest revenue on the financial statements of any bank (Tran, Nguyen, & Long, 2019). H. N. Pham (2021) states that loan-to-deposit ratio have a negative influence on credit risk, which means that if banks lend more on deposits, it can mitigate credit risk. Banks reduce their liquidity reserves and allocate their funds to more secure assets, resulting in a decline in credit risk. Loan-to-deposit ratio can be calculated as:

$$LDR = \frac{Total\ loans}{Total\ deposits}$$

3.3.3.5 Return on assets (ROA)

Long, Yen, and Long (2020) in their research suggest that ROA is considered as a source of life to enhance the reputation and value of the bank. After investigating the determinants of non-performing loans on 20 banks within 10 years (from 1008 to 2017), their findings state that ROA has a negative relationship with non-performing loans ratio. A comprehensive restructuring of the banking system is necessary for bank reform, product diversification, liquidity assurance, control quality improvement, credit operations management, and bad debt resolution. The formula for ROA is calculated as below:

$$ROA = \frac{After - tax\ net\ income}{Total\ assets}$$

3.3.3.6 GDP growth by year (GDP)

The GDP variable indicates the GDP growth annually, which is collected from World Bank. Hà, Triển, and Diệp (2014) investigate on the impact of several macroeconomic factors on the non-performing loans ratio within the Vietnamese commercial banks by using panel regression models from 2008 to 2013. Their findings imply that GDP growth rate have a significantly negative relationship with non-performing loans ratio which suggest that an improvement in Vietnam economic growth can result in a lower credit risk for commercial banks. A study conducted in Italy, Greece and Spain for 85 commercial banks in the period from 2004 to 2008 concludes the same result, which is the non-performing loans have a negative correlation with the rate of GDP growth (Messai & Jouini, 2013). For this reason, the author decided to choose GDP growth as a control variable for non-performing loans ratio.

3.3.3.7 Inflation (CPI)

Inflation refers to the general rise in prices of goods and services over time, leading to a decrease in the purchasing power of money. A common measure of inflation is the Consumer Price Index (CPI), which tracks the average change in prices paid by consumers for a selected basket of goods and services. A research conducted in Kenya by Mwaurah

(2013) on 43 commercial banks within the period from 2003 to 2012 examines the various internal and external determinants of credit risk. The findings conclude that an increase in inflation, which is calculated by the percentage increase in consumer goods price, can result in a decline in credit risk. Therefore, the author must include CPI variable in the control variable as it can negatively affect the dependent variable.

3.3.4 Interactive variables

Additionally, two interactive variables which are classification of types of banks and sizes are also included based on the hypotheses that has been proposed in the previous section.

3.3.4.1 Types of ownership (OWN)

As for the interactive variable, the author constructs a dummy variable named OWN to indicate the ownership of commercial banks in Vietnam. As far as the research is concerned, in Vietnam there are 4 types of ownership which are SOCBs (State-owned commercial banks), JSCBs (Joint stock commercial banks), FOCBs (Wholly foreign-owned banks) and PB (Policy banks) (Le, Ho, Ngo, Nguyen, & Tran, 2022). Considering the sizes and number of banks of each type, the author decides to choose only two kinds of ownerships, which are state-owned and joint stock commercial banks to ensure that the research's results are solid and reliable. Therefore, the OWN variable will be 1 if the bank's ownership is state-owned and 0 if the bank's ownership is joint stock.

3.3.4.2 Banks' size classification (SIZE)

To determine whether the bank is large or small, the author take reference from the master thesis of Dung (2024). The bank is considered large when its total assets exceed the mean value of total assets in the entire dataset and conversely, when a bank's total assets value is not larger than the mean value, it is considered as small banks. Therefore, the SIZE variable is 1 for the large bank and 0 for the small bank. Table 3.2 shows the summary of variables.

Table 3.2 Summary of variables

Index	Description	Expectation	References
NPL	Total non-performing loans / Total loans		Cheng and Qu (2020); Wu et al. (2023); Wang et al. (2023)
FIN	Obtain through annual reports by using Google Colab for crawling data and text mining. Use entropy weight method to calculate the weight of each keyword in the annual reports	–	Guo and Zhang (2023); Dung (2024)
CAR	(Tier 1 Capital + Tier 2 Capital) / Risk – weighted assets	+	Luong and Nguyen (2021)
LLP	Total loan loss provisions / Total loans	+	Do et al. (2020)
CIR	Total operating expenses / Total operating income	+	Ferreira (2022)
LDR	Total loans / Total deposits	–	H. N. Pham (2021)
ROA	After-tax net income / Total assets	–	Long et al. (2020)
GDP	GDP growth by year, data is collected from World Bank	–	Messai and Jouini (2013)
CPI	Data is collected from Statista	–	Mwaurah (2013)
OWN	1 if owned by state, otherwise 0		Dung (2024)
SIZE	Take the logarithm of banks' total assets then classification as 1 if the figure is higher than the median of the dataset, otherwise 0.		Dung (2024)

Source: Compiled by the author

3.4 Data analysis

To analyse the influence of Fintech innovation on credit risk of Vietnamese commercial banks from 2004 to 2023, the author collects secondary data from the financial statements and annual reports of 24 commercial banks in Vietnam and uses the quantitative research method of panel data with regression models on Stata statistical software. In this study, the author first uses two models: fixed effects model (FEM) and the random effects model (REM). At the same time, the Hausman test is used to select the appropriate estimation model. To account for heterogeneity and autocorrelation problem, standard errors are clustered at the bank level. Moreover, to further control the endogeneity problem, the author applies a two-step difference GMM model proposed by Arellano and Bond (1991).

3.5 Process

Step 1: Report descriptive statistics

In the first step, the author reports the descriptive statistics of each variable. This step is important as they help to visualize data more efficiently, allow the data to be presented in a meaningful and understandable way. Through descriptive statistics tables, researcher can have an overview of the research data set, measures of central tendency, frequency distribution, standard deviation, and the sum of observations of each variable in the research sample to analyse the trends that the data is showing, adding more insights into the research.

Step 2: Perform unit root test

Performing a unit root test is significantly essential in panel data analysis to determine the stationarity of a variable. A variable with a unit root is non-stationary, which can lead to unreliable and misleading results in regression analysis. This research employs an unbalanced panel data; thus, the researcher decides to use Fisher type unit root test, based on the Philips – Perron tests, which works well with this type of dataset. This test involves 2 hypotheses:

- Null hypothesis H_0: All panels contain unit roots.
- Alternative hypothesis H_a: At least one panel is stationary.

The test produces four test statistics, including inverse chi-squared (P), inverse normal (Z), inverse logit t (L), and modified inverse chi-squared (Pm). If the p-value of these test statistics is smaller than the significant level (in this case 5%), the null hypothesis is rejected, meaning that at least one panel is stationary. If the p-value is greater than the significant level, the null hypothesis cannot be rejected, implying that all panels likely contain unit roots, the variable is non-stationary.

Step 3: Analyse Pearson pairwise correlation matrix

In linear regression, it is important to consider the multicollinearity problems between independent variables with another variable in the model since it can produce a false regression result. To avoid this issue, the researcher examines whether if there is the multicollinearity issue through the Pearson pairwise correlation matrix. This matrix provides the correlation between all the variables with each other, which is a massively useful tool to summarize the relationship between each variable. To address the problem, the researcher observes if the coefficient value is higher than 0.7, indicating there is a high correlation between pairs of variables, it can imply that there is a potential problem of multicollinearity within the model.

Step 4: Perform multicollinearity test

To ensure the multicollinearity problem of the model, a variance inflation factor (VIF) test is performed. If the VIF values are high, it suggests that multicollinearity may be inflating the variance of regression coefficients, resulting in an unreliable, unstable and insignificant estimates. The VIF test is interpreted as follows:

- VIF = 1: There is no correlation between the variable and the others, meaning that there is no multicollinearity problem.
- $1 < VIF \leq 5$: There is a low correlation between the variable and the others, but it is not severe enough to be a major problem.
- VIF > 5: This value indicates a moderate to high multicollinearity problem.

Step 5: Estimate and select between FEM and REM

In this study, with panel data, the author estimates the regression models along with tests to choose the most optimal model among the two models FEM and REM.

The fixed effects model (FEM) is a panel data regression method used to control for unobserved, time-invariant characteristics that may be correlated with the independent variables. By focusing on within-entity variation over time, the FEM helps prevent omitted variable bias and isolates the effect of time-varying explanatory variables on the dependent variable. It eliminates the influence of factors that do not change over time, such as cultural or structural characteristics, but cannot estimate the effect of these time-invariant variables.

The random effects model (REM) is a panel data regression technique that assumes the individual-specific effects (unobserved heterogeneity) are uncorrelated with the independent variables. Unlike the FEM, which focuses on within-entity variation, the REM considers both within-entity and between-entity variation, making it more efficient when the random effects assumption holds. This allows the RE model to estimate the effects of both time-varying and time-invariant variables.

In the estimation of FEM and REM regression models, the author adds a robust option, which means that standard errors are clustered at the bank level, for each model to account for the heteroscedasticity and autocorrelation problem within these models. After that, Sargan-Hansen test for overidentifying restrictions after estimating a panel data model is performed. This test has 2 hypotheses:

- Null hypothesis H_0: The instruments used in the model are valid.
- Alternative hypothesis H_a: At least one of the instruments is invalid.

If the p-value of this test is lower than the significance level of 5%, it means that we must reject the null hypothesis, which means that at least one of the instruments may be invalid and it could be correlated with the error term in the model. This result is suitable for FEM as it takes unobserved, time-invariant characteristics that may be correlated with the independent variables into consideration. Conversely, if p-value of the test is higher than the significance level, REM would be more fit for the data.

Step 6: Endogeneity test

In this step, the author conducts an instrumental variable analysis to deal with the potential endogeneity problem. Firstly, the author run the instrumental regression with each variable act as the instrumental variable using two-stage least squares estimation (2SLS). 2SLS is extremely useful in the context of dealing with endogeneity problem within the models. After running the regression, the author uses the Wu-Hausman test to check if the instrumental variable is endogenous or not with 2 hypotheses:

- Null hypothesis H_0: The variable is exogenous.
- Alternative hypothesis H_a: The variable is endogenous.

If the p-value is less than the significance level, the null hypothesis must be rejected, indicating that the variable is likely endogenous. Conversely, if the p-value is greater than significance level, the null hypothesis is accepted, suggesting that the variable is exogenous.

Step 7: Difference GMM estimations

The last step of this research is to perform the difference Generalized Methods of Moment (GMM) regression model to address the endogeneity problem. After performing, it is vital to test the validity of the instruments, the absence of autocorrelation and the exogeneity of the variables to ensure reliable results with Hansen test, Arellano-Bond test and Difference-in-Hansen test.

The Hansen test examines the validity of the instruments used in the model. The hypothesis of this test is as follows:

- Null hypothesis H_0: The instruments used in the model are valid.
- Alternative hypothesis H_a: At least one of the instruments is invalid.

If the p-value from the Hansen test is greater than significance level, the author fails to reject the null hypothesis. This suggests that there is no evidence against the validity of the instruments, implying that they can be considered appropriate for the model. Conversely, if the p-value is less than significance level, the author rejects the null hypothesis, indicating that at least one instrument may be invalid.

The null hypothesis for the Arellano-Bond test is that there is no autocorrelation in the residuals at the specified lag order. For the first-order test AR(1), the null hypothesis is that there is no first-order autocorrelation. For the second-order test AR(2), the null hypothesis is that there is no second-order autocorrelation. Therefore, for a sufficient model, the p-value of these tests should be higher than significance level, especially for AR(2), indicating that there is no first-order nor second-order autocorrelation issue in the model.

As for Difference-in-Hansen test, it is an extension of Hansen test. This test helps determine whether specific instruments are exogenous and whether they are appropriate for the model being estimated. The test proposes two hypotheses:

- Null hypothesis H_0: The instruments being tested are exogenous for the specified subset.
- Alternative hypothesis H_a: At least one of the instruments being tested is endogenous.

If the p-value from the test is greater than significance level, the author fails to reject the null hypothesis. This means that the excluded instruments do not correlate with the error term, supporting their validity in the estimation model. Conversely, if the p-value is less than significance level, the author rejects the null hypothesis, indicating that there may be a correlation between the instruments and the error term, which violates the assumptions needed for consistent estimation.

The reason why the author decides to use difference GMM other than system GMM is because in the unit root test, it is shown that some of the variables are not stationary, which means that the author needs to take the first difference of those variables to solve the stationary problem. Difference GMM works better on variables that have been took difference and especially on unbalanced panel data than system GMM. In the result part, the author observes that difference GMM provides a more favourable results than system GMM with a sufficient value of both Arellano-Bond test, Hansen test and Difference-in-Hansen test.

CHAPTER 4. RESULTS

4.1 Descriptive statistics

Table 4.1 reports the descriptive data for the variables used in the analyses of this paper. NPL has a mean value of 2% and ranges from 0% to 33%, indicating that there is dispersion among banks in the level of NPL ratio. An average NPL ratio of 2% suggests that, on average, 2% of the total loans issued by banks in Vietnam are classified as non-performing. It means that it is relatively low and is generally seen as a sign of stability and healthy credit management within the banking system. However, this also indicate that some banks are managing their credit risks very well at a specific time (0%), while others have much higher levels of non-performing loans (up to 33%). Banks with NPL ratios close to 33% may experience serious credit quality issues.

FIN ranges from 0.002 to 1.000 with a mean value of 0.103, which shows that the data sample has diversity in Fintech development among the banks. A mean value of 0.103 indicates that, on average, banks in the sample are still in the early stages of integrating Fintech into their operations. This could imply that most banks are still exploring and adopting Fintech solutions at a basic level, possibly focusing on initial steps like improving digital banking platforms, automating processes, or using technology for back-office improvements. The wide variability from 0.002 to 1.000 suggests that the Fintech landscape among banks is highly unequal, with some banks being leaders in Fintech adoption while others lagging.

4.2 Unit root test

Table 4.2 reports the results of Fisher type unit root test based on Phillips-Perron tests for each variable. All the variables except for LDR are significantly stationary, as their p-value is smaller than the significance level of 5%, implying strong evidence that the null hypothesis should be rejected, which means that the variables is stationary. However, LDR variable poses a considerable value of p-value for Z statistics. The value is indeed smaller than 5%, however it is weak evidence to reject the null hypothesis of this test. Therefore, before proceeding to the next step, the author takes the first difference of this variable to make sure that there is no stationary problem within the model.

Table 4.1 Descriptive statistics

Unit: %, except for FIN variable

Variable	Obs	Mean	Std. Dev.	Min	Max
NPL	430	2.248	2.777	0.000	33.134
FIN	430	0.103	0.154	0.002	1.000
CAR	430	9.830	5.840	0.299	46.260
LLP	430	1.325	0.627	0.055	3.767
CIR	430	49.401	16.451	16.193	172.248
LDR	430	91.357	21.939	23.509	251.982
ROA	430	1.020	0.680	-0.184	4.752
OWN	430	0.172	0.378	0.000	1.000
SIZE	430	0.549	0.498	0.000	1.000
GDP	430	6.130	1.450	2.600	8.100
CPI	430	6.368	5.447	0.630	23.120

Source: The author compiled from STATA 17

Table 4.2 Result of unit root test

Variables	p – value			
	P	Z	L*	Pm
NPL	0.0000	0.0000	0.0000	0.0000
FIN	0.0000	0.0000	0.0000	0.0000
CAR	0.0000	0.0000	0.0000	0.0000
LLP	0.0000	0.0000	0.0000	0.0000
CIR	0.0002	0.0009	0.0003	0.0000
LDR	0.0001	0.0314	0.0035	0.0000
ROA	0.0000	0.0000	0.0000	0.0000
GDP	0.0000	0.0000	0.0000	0.0000
CPI	0.0000	0.0000	0.0000	0.0000

Source: The author compiled from STATA 17

4.3 Pearson pairwise correlation matrix

Table 4.3 illustrates the Pearson pairwise correlation matrix for all the variables. Considering the relationships of all variables with the dependent variable, NPL, we can see a moderate positive correlation exists between NPL and LLP with a coefficient of 0.3, which is statistically significant. This suggests that higher NPL is associated with higher LLP, since banks with more bad loans are likely to set aside more provisions to cover potential losses. There is a positive correlation between NPL and CIR, statistically significant at the 1% level. This indicates that higher inefficiency is associated with higher NPLs, reflecting poor management or inefficiency potentially leading to more bad loans. There is a weak negative relationship between NPL and LDR, statistically significant at the 5% level. This means that as LDR increases, NPL tends to decrease slightly, which may indicate that banks with higher lending relative to their deposits manage their credit risk better. There is a moderate negative correlation between NPL and ROA, statistically significant at the 1% level. This suggests that banks with higher profitability tend to have lower NPLs, which makes sense as more profitable banks are likely to manage their loans better. A weak positive correlation exists between NPL and OWN (ownership structure), statistically significant at the 10% level. This suggests that ownership structure could slightly impact NPL levels, with certain ownership types potentially being more associated with higher NPLs.

Considering the other relationships, CAR and ROA have strong positive relationship, suggesting that well-capitalized banks tend to be more profitable. There is a negative correlation between LLP and CIR, indicating that higher loan loss provisions are associated with lower cost-efficiency. CIR and ROA also pose a significant negative correlation, implying that less efficient banks, which usually have a higher CIR tend to be less profitable.

Generally, there is no correlation coefficient that exceeds 0.7 or is lower than -0.7, which may indicate that this dataset doesn't have the multicollinearity problem. However, to address the problem precisely, a VIF test is necessary to ensure the multicollinearity issue does not exist in the model.

Table 4.3 Pearson pairwise correlation matrix

	NPL	FIN	CAR	LLP	CIR	dLDR	ROA	OWN	SIZE	GDP	CPI
NPL	1.000										
FIN	0.061	1.000									
CAR	-0.050	-0.050	1.000								
LLP	0.371 ***	-0.000	-0.269 ***	1.000							
CIR	0.211 ***	0.011	-0.114 **	-0.139 ***	1.000						
dLDR	-0.114 **	0.005	-0.148 ***	-0.031	-0.060	1.000					
ROA	-0.192 ***	0.058	0.396 ***	-0.101 **	-0.595 ***	0.099 **	1.000				
OWN	0.094 *	-0.107 **	-0.318 ***	0.426 ***	-0.218 ***	-0.025	-0.147 ***	1.000			
SIZE	0.003	0.057	-0.392 ***	0.346 ***	-0.284 ***	0.113 **	0.069	0.413 ***	1.000		
GDP	0.024	0.043	-0.010	-0.115 **	0.077	0.039	-0.043	0.011	-0.127 ***	1.000	
CPI	0.024	-0.149 ***	0.275 ***	-0.070	-0.046	-0.196 ***	0.097 **	0.006	-0.274 ***	0.032	1.000

Source: The author compiled from STATA 17

4.4 Multicollinearity test

Before proceeding the regression, the sample data is processed as follows. The researcher performs a variance inflation factor (VIF) diagnosis and Pearson pairwise correlation for all the variables to check if there are multicollinearity problems among the sample data. The highest figure for VIF test is 2.12, the mean value lies on 1.50, combine with the highest value appears in the correlation coefficient is 0.371 and the lowest value being -0.595, there is no concern about the multicollinearity for the variables.

Table 4.4 Result of VIF test

Variable	VIF	1/VIF
ROA	2.12	0.473
CIR	1.89	0.529
CAR	1.72	0.583
OWN	1.67	0.598
SIZE	1.67	0.600
LLP	1.33	0.749
LDR	1.27	0.786
CPI	1.18	0.847
FIN	1.06	0.945
GDP	1.04	0.958
Mean VIF	1.50	

Source: The author compiled from STATA 17

4.5 FEM and REM regression results

This section aims to explore the influence of bank Fintech on commercial banks' credit risk. First, the model is tested using the Sargan-Hansen method to find the model that fits the data since the model includes robust options, which means that standard errors is clustered at the bank level. The result shows that the fixed effects model is appropriate. Table 4.5 reports the FEM regression estimates and illustrates the impact of Fintech on credit risk.

With the first model, the researcher runs the RE model with the dependent variable being NPL and the independent variable being FIN, CAR, LLP, CIR, LDR, ROA, GDP and

CPI. The model results conclude that the FIN, CAR and LLP variables has a positive impact on the NPL variable and is statistically significant at the 1% level. The results indicate that Fintech development, an increase the available capital that a bank holds in hand compared to its risk-weighted assets and loan loss provisions can have a negative influence on a bank's credit risk management, specifically it can increase the credit risk that a bank has to bear. Surprisingly, the conclusion for this model rejects the first hypothesis proposed on the previous section H1: Fintech innovation can reduce bank credit risk.

Table 4.5 Regression results of the first model

Variable	Coefficient	P-value
FIN	1.336	0.027
CAR	0.038	0.048
LLP	2.022	0.000
CIR	0.058	0.179
LDR	-0.013	0.093
ROA	0.280	0.631
GDP	0.055	0.480
CPI	0.016	0.193
_cons	-4.589	0.146

Source: The author complied from STATA 17

Table 4.6 reports result of the second model using FEM and estimates the impact of Fintech on credit risk incorporating the state ownership (OWN) variable. The regression results on the second model show that Fintech indicators have negative impacts with positive coefficients on credit risk of state-owned banks.

With the second model, the researcher runs FEM with the dependent variable being NPL and the independent variable being FIN, OWNxFIN (the interaction of Fintech index and bank's ownership), CAR, LLP, CIR, LDR, ROA, GDP and CPI. The model results shows that there is a heterogenous impact of the FIN variable on banks' size. With state-owned banks (OWN = 1), the effect of FIN on NPL is 1.329 + 0.077 compared to private banks with coefficient of 0.077. However, the results on SIZExFIN variable are not statistically significant, consequently, there is no heterogenous impact within these variables. Therefore, the second hypothesis, which is H2: Fintech innovation has a heterogeneous impact on credit risk of banks with different ownership is rejected.

Table 4.6 Regression results of the second model

Variable	Coefficient	P-value
FIN	1.329	0.038
OWN	0	(omitted)
OWNxFIN	0.077	0.921
CAR	0.038	0.048
LLP	2.022	0.000
CIR	0.058	0.180
LDR	-0.013	0.093
ROA	0.280	0.630
GDP	0.055	0.481
CPI	0.016	0.197
_cons	-4.590	0.146

Source: The author compiled from STATA 17

Table 4.7 reports the fixed effects regression model and estimates the impact of Fintech on credit risk incorporating the banks' size (SIZE) attribute. The sample includes 430 observations of banks by year over the period from 2004 to 2023. The regression results on the second model show that Fintech indicators have negative impacts with positive coefficients on credit risk of state-owned banks.

With the second model, the researcher runs the RE model with the dependent variable being NPL and the independent variable being FIN, SIZExFIN (the interaction of Fintech index and bank's size), CAR, LLP, CIR, LDR, ROA, GDP and CPI. The model results shows that there is a heterogenous impact of the FIN variable on banks' size. With big-sized banks (SIZE = 1), the effect of FIN on NPL is 1.533 + (-0.338) compared to smaller banks with coefficient of (-0.338). However, the results on SIZExFIN variable are not statistically significant, consequently, there is no heterogenous impact within these variables. Therefore, the last hypothesis, which is H3: Fintech innovation has a heterogeneous impact on credit risk of banks with different size is also rejected.

Table 4.7 Regression results of the third model

Variable	Coefficient	P-value
FIN	1.533	0.083
SIZE	0.056	0.816
SIZExFIN	-0.338	0.703
CAR	0.038	0.048
LLP	2.022	0.000
CIR	0.058	0.180
LDR	-0.013	0.090
ROA	0.285	0.636
GDP	0.057	0.475
CPI	0.016	0.146
_cons	-4.643	0.142

Source: The author compiled from STATA 17

4.6 Endogeneity test

Table 4.8 shows the results of the endogeneity test (Durbin and Wu-Hausman tests) for the specified variables. Based on the p-values of FIN, CAR, LLP, LDR, ROA, GDP and CPI variables, both the Durbin and Wu-Hausman tests have p-values greater than 0.05, indicating that these variables do not suffer from endogeneity. The null hypothesis (that the variables are exogenous) cannot be rejected. Therefore, these variables can be considered exogenous and suitable for inclusion in standard regression models without the need to control endogeneity. However, for CIR variable, both tests have p-values below 0.05, suggesting that CIR is endogenous. This means that the variable is likely correlated with the error term in the regression model, and this could bias the estimation results if not properly addressed.

In this study, the author decided to treat both CIR and LLP as endogenous variables. According to the results from STATA, CIR is an endogenous variable, which is reasonable as it is a financial efficiency metric that can be influenced by many factors, including the bank's performance, external shocks or missing factors, inaccuracies in measurement, or managerial decisions that respond to unobserved factors. Moreover, LLP has the p-values that is the second smallest in the result, so the author assumes that LLP is an endogenous variable, not because that the test statistics reject the null hypothesis but because in real-life situation, LLP is closely tied to various factors in banking, and it can have reverse causality with key performance indicators like NPL and ROA. Therefore, in the next step when performing difference GMM regression, CIR and LLP need to be lagged to avoid the reverse causality problem that the author mentioned in this section.

Table 4.8 Results of endogeneity test

Variables	p – value	
	Durbin	Wu-Hausman
FIN	0.3864	0.3924
CAR	0.4796	0.4852
LLP	0.1228	0.1272
CIR	0.0149	0.0159
LDR	0.3983	0.4047
ROA	0.3759	0.3819
GDP	0.3215	0.3276
CPI	0.6790	0.6830

Source: The author compiled from STATA 17

4.7 Difference GMM regression results

In this section, the author performs the fourth model difference GMM with the following conditions: CIR and LLP are treated as endogenous and are instrumented using their first and second lagged values, number of instruments is reduced by collapsing the instrument matrix. Hence, it can avoid the problem of "too many instruments", which means that the number of instruments is greater than the number of groups, that may cause the issue of overfitting the data. Also, it addresses potential endogeneity by using internal instruments, accounts for autocorrelation and heteroscedasticity of the data.

First, considering the validity of the model is important to evaluate the results of GMM regression. In table 4.9, the Arellano-Bond tests indicate that the model does not suffer from first- or second-order autocorrelation, as the p-value of both tests is greater than 5%, which is insignificant, so we do not reject the null hypothesis of this test. The Hansen test assessing the overidentifying restrictions and Difference-in-Hansen test investigating the exogeneity of specific subsets of instruments confirm that the instruments used in the GMM model are valid and exogenous as the p-value reject all these tests' hypotheses. Overall, the model appears to be well-specified, and the instruments are appropriate for dynamic panel data estimation.

From the regression results, we can see that the positive and significant effect of FIN on NPL suggests that as financial technology expands, it may introduce new risks that could elevate non-performing loans. The positive coefficient 1.855 suggests that an increase in the FIN variable is associated with an increase in NPL. Specifically, a unit increase in the FIN variable increases the NPL by 1.855 units. The p-value of 0.005 for is highly significant (at the 1% level), meaning there is strong evidence that the relationship between FIN and NPL is statistically significant.

Table 4.9 Regression result of the fourth model

Variable	Coefficient	P-value
FIN	1.855	0.005
CAR	0.038	0.013
LLP	2.022	0.000
CIR	0.058	0.000
LDR	-0.013	0.235
ROA	0.280	0.000
GDP	0.055	0.517
CPI	0.016	0.166
_cons	-4.590	0.000
(1) Arellano-Bond test AR(1)	p-value = 0.574	
(2) Arellano-Bond test AR(2)	p-value = 0.361	
(3) Hansen test	p-value = 0.156	
(4) Difference-in-Hansen test		
Hansen test excluding group	p-value = 0.154	
Difference	p-value = 0.251	

Source: The author compiled from STATA 17

4.8 Discussion

Across all models, FIN consistently shows a positive and significant relationship with NPL, indicating that the expansion or adoption of financial technology is associated with a rise in non-performing loans. This relationship becomes stronger (with a larger coefficient) when GMM is used in Model 4, accounting for endogeneity, and the potential dynamic relationship between the variables. There are several research that has supported the increase in risk when banks apply Fintech innovation, specifically the research of Beck et al. (2016); Ndwiga (2020); Tseng and Guo (2018).

CAR is significant and negative in Model 4 (-0.135), indicating that higher CAR reduces NPL. This aligns with the expectation that well-capitalized banks can absorb shocks better and manage risks more effectively, reducing loan defaults. LLP has a significant positive effect in all models, especially in GMM where it becomes highly significant (3.369). This suggests that higher LLP is associated with higher NPL, reflecting that banks anticipate loan defaults by provisioning for bad debts, which is common in the Vietnamese context where non-performing loans are a persistent issue.

Vietnamese commercial banks, as they embrace fintech to modernize services, face increased risks associated with lending practices. While fintech adoption can lead to enhanced customer reach and streamlined operations, the empirical evidence here shows that it can also lead to an increase in NPL. This may be due to a combination of factors such as increased digital lending, where fintech tools enable rapid credit growth, but without the same level of traditional risk assessment; inadequate regulatory frameworks governing fintech, leading to higher loan defaults; larger banks, which have more fintech adoption, experiencing higher NPLs due to their broader customer base and riskier portfolios. In conclusion, while fintech offers growth opportunities, it simultaneously introduces risk. For Vietnamese banks, the challenge lies in balancing technology adoption with robust risk management to minimize loan defaults.

Table 4.10 Regression results summary

	Model 1	Model 2	Model 3	Model 4
FIN	1.336 ***	1.330 **	1.533 *	1.855 ***
	(2.37)	(2.21)	(1.81)	(2.82)
CAR	0.038 **	0.038 **	0.038 **	-0.135 **
	(2.09)	(2.09)	(2.09)	(-2.49)
LLP	2.022 ***	2.022 ***	2.019 ***	3.369 ***
	(4.19)	(4.19)	(4.19)	(3.66)
CIR	0.058	0.058	0.058	0.187 ***
	(1.39)	(1.38)	(1.38)	(4.57)
dLDR	-0.013 *	-0.013 *	-0.013 *	0.007 *
	(-1.680)	(-1.750)	(-1.750)	(1.19)
ROA	0.197	1.872 ***	0.280	0.285
	(0.370)	(3.850)	(0.490)	(0.480)
GDP	0.048	-0.035	0.055	0.057
	(0.630)	(-0.650)	(0.720)	(0.730)
CPI	0.017	-0.027	0.016	0.016
	(1.380)	(-1.380)	(1.330)	(1.510)
OWN			.	
OWNxFIN			0.014	
			(0.010)	
SIZE				0.001
				(0.240)
SIZExFIN				-0.057
				(-0.390)
_cons	-0.044	-0.120 ***	-0.046	-0.046
	(-1.580)	(-4.240)	(-1.510)	(-1.520)

Source: The author compiled from STATA 17

CHAPTER 5. CONCLUSION

5.1 Conclusion

In conclusion, this research provides a comprehensive analysis of the impact of fintech innovation on bank credit risk, takes consideration into both the opportunities and challenges posed by the rapid digitalization of financial services. The adoption of fintech has undeniably revolutionized the banking sector by enhancing customer experience, increasing operational efficiency, and facilitating access to financial services for underserved populations. However, as demonstrated by the findings of this study, these advancements also introduce significant risks that can potentially increase a bank's exposure to credit risk.

One of the primary concerns highlighted is the risk associated with the shift towards automated credit assessment tools, such as AI-driven algorithms, which can lack the nuance and depth of traditional human-led risk evaluations. This reliance on automated processes may lead to inadequate risk profiling of borrowers, particularly in cases where insufficient historical data exists, such as with new customers. Moreover, fintech platforms, by making credit more accessible and instant, may encourage irresponsible borrowing, increasing the likelihood of default among customers who might not have previously had access to credit. The rapid pace at which loans are approved digitally can bypass some of the strict checks and balances that traditional banking processes have in place to mitigate credit risk.

Furthermore, the rise of peer-to-peer (P2P) lending platforms and other non-bank fintech lending institutions introduces additional layers of complexity. These platforms, often operating with less regulatory observation than traditional banks, pose a challenge to the stability of the credit market. The risk-sharing mechanisms in such platforms are often less significant, which can lead to higher default rates and an increased likelihood of systemic risk if not carefully monitored. Moreover, the integration of fintech solutions, such as blockchain technology and digital currencies adds further uncertainty to the risk landscape as the regulatory frameworks surrounding these technologies are still evolving.

Additionally, the integration of fintech and banking raises concerns regarding cybersecurity, data privacy, and fraud. As banks increasingly rely on digital platforms to facilitate credit assessment and loan disbursement, they become more vulnerable to cyberattacks, which could compromise sensitive financial data, leading to significant reputational and financial losses. These risks necessitate the adoption of advanced security measures and robust regulatory frameworks to ensure that the benefits of fintech innovation do not come at the expense of financial stability.

5.2 Implication

Given these challenges, it is evident that banks must develop more sophisticated risk management strategies to address the increased credit risks associated with fintech innovation. This requires a multifaceted approach, including the integration of more advanced data analytics, improved regulatory oversight, and enhanced internal governance mechanisms. Moreover, banks should collaborate closely with fintech companies and regulators to ensure that the digitalization of financial services is accompanied by appropriate safeguards that prevent credit risk from escalating.

Future research in this area should focus on developing a deeper understanding of the specific mechanisms through which fintech innovations contribute to increased credit risk, as well as exploring potential solutions to mitigate these risks. Longitudinal studies could provide valuable insights into the long-term effects of fintech adoption on bank credit portfolios. Additionally, further examination of regulatory frameworks and their effectiveness in addressing fintech-induced risks will be crucial to ensuring the sustainability of digital financial services.

5.3 Limitation

The limitation of this research is that it might be hard to perform text mining on the data collected in Vietnamese, because one English Fintech lexicon can translate in many ways in Vietnamese. Moreover, Vietnamese banks sometimes does not public the annual report files that is text-extractable by using Google Colab, which requires the author to use manual tools. Future research can use more advanced tools such as OCR (Optical Character Recognition) to easily obtain the necessary annual report text file.

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APPENDIX

Appendix A: List of 24 banks

No.	Bank	Code	Ownership
1	An Binh Commercial Joint Stock Bank	ABB	JSCB
2	Asia Commercial Joint Stock Bank	ACB	JSCB
3	Vietnam Bank for Agriculture and Rural Development	AGB	SOCB
4	Joint Stock Commercial Bank for Investment and Development of Vietnam	BIDV	SOCB
5	BacA Joint Stock Commercial Bank	BAB	JSCB
6	Vietnam Joint Stock Commercial Bank of Industry and Trade	CTG	SOCB
7	Vietnam Export Import Commercial Joint Stock Bank	EIB	JSCB
8	Kienlong Commercial Joint Stock Bank	KLB	JSCB
9	Lien Viet Post Joint Stock Commercial Bank	LVB	JSCB
10	Military Commercial Joint Stock Bank	MB	JSCB
11	Vietnam Maritime Commercial Joint Stock Bank	MSB	JSCB
12	Nam A Commercial Joint Stock Bank	NAB	JSCB
13	National Citizen Bank	NCB	JSCB
14	Orient Commercial Joint Stock Bank	OCB	JSCB
15	South East Asia Joint Stock Commercial Bank	SEAB	JSCB
16	Saigon Bank for Industry & Trade	SGB	JSCB
17	Saigon – Hanoi Commercial Joint Stock Bank	SHB	JSCB
18	Saigon Thuong Tin Commercial Joint Stock Bank	STB	JSCB
19	Viet Nam Technological and Commercial Joint Stock Bank	TCB	JSCB
20	TienPhong Commercial Joint Stock Bank	TPB	JSCB
21	Joint Stock Commercial Bank for Foreign Trade of Vietnam	VCB	SOCB
22	Viet Capital Commercial Joint Stock Bank	BVB	JSCB
23	Vietnam International Commercial Joint Stock Bank	VIB	JSCB
24	Vietnam Commercial Joint Stock Bank for Private Enterprise	VPB	JSCB

Appendix B: STATA 17 results

Result of the first model

```
. xtreg NPL FIN CAR LLP CIR dLDR ROA GDP CPI, fe robust

Fixed-effects (within) regression               Number of obs     =        404
Group variable: ID                              Number of groups  =         24

R-squared:                                      Obs per group:
     Within  = 0.2734                                         min =         11
     Between = 0.3170                                         avg =       16.8
     Overall = 0.2771                                         max =         19

                                                F(8,23)           =       9.82
corr(u_i, Xb) = -0.0746                         Prob > F          =     0.0000

                                     (Std. err. adjusted for 24 clusters in ID)
------------------------------------------------------------------------------
             |               Robust
         NPL | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
         FIN |   1.335884   .5637986     2.37   0.027     .1695773     2.50219
         CAR |   .0380615   .0182231     2.09   0.048     .0003642    .0757588
         LLP |   2.021928   .4826225     4.19   0.000     1.023547    3.020308
         CIR |   .0577546   .0416895     1.39   0.179    -.0284867    .1439959
        dLDR |  -.0128689    .007341    -1.75   0.093    -.0280549    .0023171
         ROA |   .2800114   .5745574     0.49   0.631    -.9085511    1.468574
         GDP |   .0545219   .0759076     0.72   0.480     -.102505    .2115487
         CPI |    .015563   .0115961     1.34   0.193    -.0084253    .0395514
       _cons |  -4.589209   3.046911    -1.51   0.146    -10.89223    1.713806
-------------+----------------------------------------------------------------
     sigma_u |  .76678058
     sigma_e |    1.95345
         rho |  .13350664   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

Result of the second model

```
. xtreg NPL FIN OWN OWNxFIN CAR LLP CIR dLDR ROA GDP CPI, fe robust
note: OWN omitted because of collinearity.

Fixed-effects (within) regression               Number of obs     =        404
Group variable: ID                              Number of groups  =         24

R-squared:                                      Obs per group:
     Within  = 0.2734                                         min =         11
     Between = 0.3163                                         avg =       16.8
     Overall = 0.2770                                         max =         19

                                                F(9,23)           =      10.16
corr(u_i, Xb) = -0.0755                         Prob > F          =     0.0000

                                     (Std. err. adjusted for 24 clusters in ID)
```

NPL	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
FIN	1.329743	.602657	2.21	0.038	.0830518	2.576434
OWN	0	(omitted)				
OWNxFIN	.0768635	.7671148	0.10	0.921	-1.510034	1.663761
CAR	.038065	.0182495	2.09	0.048	.0003129	.075817
LLP	2.022184	.4820885	4.19	0.000	1.024908	3.01946
CIR	.0577511	.0417548	1.38	0.180	-.0286253	.1441275
dLDR	-.0128753	.0073421	-1.75	0.093	-.0280636	.0023131
ROA	.2802562	.5746324	0.49	0.630	-.9084614	1.468974
GDP	.0545095	.0760192	0.72	0.481	-.1027481	.2117671
CPI	.0155231	.0116714	1.33	0.197	-.0086211	.0396674
_cons	-4.589542	3.04952	-1.51	0.146	-10.89795	1.718871
sigma_u	.76741027					
sigma_e	1.9560791					
rho	.13338543	(fraction of variance due to u_i)				

Result of the third model

```
. xtreg NPL FIN SIZE SIZExFIN CAR LLP CIR dLDR ROA GDP CPI, fe robust

Fixed-effects (within) regression               Number of obs     =        404
Group variable: ID                              Number of groups  =         24

R-squared:                                      Obs per group:
     Within  = 0.2736                                         min =         11
     Between = 0.3192                                         avg =       16.8
     Overall = 0.2776                                         max =         19

                                                F(10,23)          =      10.01
corr(u_i, Xb) = -0.0734                         Prob > F          =     0.0000

                                   (Std. err. adjusted for 24 clusters in ID)
```

NPL	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
FIN	1.533386	.8457554	1.81	0.083	-.2161921	3.282965
SIZE	.0555852	.2356492	0.24	0.816	-.4318924	.5430628
SIZExFIN	-.3375156	.8747162	-0.39	0.703	-2.147004	1.471973
CAR	.0384087	.0183524	2.09	0.048	.0004438	.0763736
LLP	2.018931	.4822374	4.19	0.000	1.021346	3.016515
CIR	.0578149	.0418527	1.38	0.180	-.0287639	.1443938
dLDR	-.0129281	.0073044	-1.77	0.090	-.0280383	.0021821
ROA	.2848162	.5940491	0.48	0.636	-.944068	1.5137
GDP	.0566501	.0779587	0.73	0.475	-.1046198	.21792
CPI	.0159613	.0106005	1.51	0.146	-.0059675	.0378901
_cons	-4.642896	3.052474	-1.52	0.142	-10.95742	1.671626
sigma_u	.76524379					
sigma_e	1.9585629					
rho	.1324413	(fraction of variance due to u_i)				

Result of the fourth model

```
Dynamic panel-data estimation, two-step system GMM
------------------------------------------------------------------------------
Group variable: ID                              Number of obs      =       404
Time variable : Year                            Number of groups   =        24
Number of instruments = 14                      Obs per group: min =        11
Wald chi2(8)  =    271.97                                      avg =     16.83
Prob > chi2   =     0.000                                      max =        19
```

NPL	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
FIN	1.855016	.6588958	2.82	0.005	.5636039	3.146428
CAR	-.1348386	.0541575	-2.49	0.013	-.2409854	-.0286918
LLP	3.369063	.9213841	3.66	0.000	1.563184	5.174943
CIR	.1868529	.0409008	4.57	0.000	.1066888	.2670169
dLDR	.0070013	.0058952	1.19	0.235	-.0045531	.0185556
ROA	1.871787	.4860399	3.85	0.000	.9191664	2.824408
GDP	-.0346717	.0534854	-0.65	0.517	-.1395012	.0701578
CPI	-.0270433	.0195362	-1.38	0.166	-.0653336	.011247
_cons	-11.96692	2.82351	-4.24	0.000	-17.5009	-6.432944

```
Warning: Uncorrected two-step standard errors are unreliable.

Instruments for first differences equation
  Standard
    D.(NPL FIN CAR dLDR ROA GDP CPI)
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    L(1/2).(L.CIR L.LLP) collapsed
Instruments for levels equation
  Standard
    _cons
  GMM-type (missing=0, separate instruments for each period unless collapsed)
    D.(L.CIR L.LLP) collapsed
------------------------------------------------------------------------------
Arellano-Bond test for AR(1) in first differences: z =  -0.56  Pr > z =  0.574
Arellano-Bond test for AR(2) in first differences: z =  -0.91  Pr > z =  0.361
------------------------------------------------------------------------------
Sargan test of overid. restrictions: chi2(5)    = 76.79  Prob > chi2 =  0.000
  (Not robust, but not weakened by many instruments.)
Hansen test of overid. restrictions: chi2(5)    =  8.01  Prob > chi2 =  0.156
  (Robust, but weakened by many instruments.)

Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:     chi2(3)    =  5.25  Prob > chi2 =  0.154
    Difference (null H = exogenous): chi2(2)    =  2.76  Prob > chi2 =  0.251
```

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