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THE IMPACT OF FINTECH ON GREEN FINANCE: EMPIRICAL EVIDENCE FROM VIETNAMESE BANKS

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ABSTRACT

Green finance is considered a critical strategy for every country striving for sustainable economic development. However, there is still limited research on the relationship between fintech and green finance at the bank level. This study analyzes the fintech index using text mining and entropy methods as proposed by Wan et al. (2023). A dataset from 27 commercial banks in Vietnam, spanning the period from 2016 to 2022, was collected for analysis. The author group conducted descriptive statistics, correlation matrices, multicollinearity tests, OLS regression, FEM, REM, tests for heteroscedasticity and autocorrelation, and ultimately used FGLS to address model deficiencies. The results of the final regression model show a strong positive impact of fintech on green finance. Additionally, the study identifies the influence of bank size and non-interest income ratio on the green credit of the banks. The research findings contribute to the proposal of various policies to promote the development of green finance in Vietnam through fintech advancement.

Keywords: Fintech, green finance, sustainable economic development

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LIST OF ACRONYMS

No	Abbreviation	Explanation
1	EM	Financial leverage
2	FEM	Fixed Effect Mode
3	FGLS	Feasible Generalized Least Square
4	FT	Fintech
5	GC	Green credit
6	GDP	Gross Domestic Product
7	GGGI	Global Green Growth Institute
8	NIIR	Non-interest income rate
9	OLS	Ordinary Least Squares
10	REM	Random Effects Model
11	SIZE	Bank size
12	VIF	Variance Inflation Factors

CHAPTER 1 : INTRODUCTION

1.1. Reason for doing the topic

Vietnam's economy has grown strongly over the past 10 years thanks to the development of industry, services, and more specifically, the finance and banking sector. The macroeconomic situation continues to remain stable; Inflation is controlled, the average consumer price index for the year increased by 3.15%; GDP growth reached 8.02%, the highest level in more than 10 years; Major balances of the economy are guaranteed. (Mai Hà, 2023)

However, this rapid economic expansion has come at a high cost to the environment. There is an urgent need to switch from extensive to sustainable development in Vietnam's economic development paradigm. With the motto of taking full advantage of the leapfrogging achievements of the 4.0 Industrial Revolution, in Vietnam, green growth in recent years has been considered a strategic approach to restructuring the economy and transforming the economic model, growth model and is an important guarantee to promote sustainable development. Based on the Government's direction, the system of legal documents and policies, including several decrees, circulars, and guiding decisions of ministries, departments, and branches on green finance, has been gradually completed, regulations on many types of tools such as green bonds, green stocks, green credit..., thereby creating conditions for businesses to mobilize domestic and international green capital.

Researchers view green finance, an emerging topic, as a key tool for accomplishing goals related to sustainable development and energy security. Unlike traditional financing, green finance necessitates that lenders take environmental preservation into account when making loan decisions and while managing risk and post-monitoring. Financial technology, or Fintech, on the other hand, is a term used to describe a group of innovative scientific and technological applications that are incorporated into the financial sector. Not only can a thorough investigation of Fintech's impact on green finance close this research gap, but it also has significant real-world applications. Both "green finance" and "financial technology" are relatively new terms that have not received much attention from the academic community. Furthermore, a clear lack of direct research publications examining the connection between these two ideas is apparent. The group decided to implement the topic: **THE IMPACT OF FINTECH ON GREEN FINANCE: EMPIRICAL EVIDENCE FROM VIETNAMESE BANKS** aims to understand the relationship between the above two concepts and provide important information for the development of government policies related to sustainable finance and the strategic development orientation of the banking industry.

1.2. Objectives of the study

Originating from the proposition that Fintech has the potential to positively impact the development of green finance, the study was conducted with the following objectives:

(1) Clarifying factors influencing and promoting the development of Green Finance and Fintech in Vietnam
(2) Comprehensively explore the positive impact of factors such as Fintech and green finance, bank size and leverage with green finance,
(3) Provide important information for government policy development related to sustainable finance and strategic development orientation of the banking industry.

1.3. Research questions

To achieve the overall goal of the study, the research question posed is:

(1) What factors affect the development of Fintech and green finance in Vietnam?
(2) How positive is Fintech and green finance in the banking industry?
(3) Are there any recommendations for developing government policy related to sustainable finance and the strategic development direction of the banking sector?

1.4. Research subjects and scopes

(1) Research subjects

The topic focuses on researching the influence of Fintech on the field of green finance, specifically at 27 banks in Vietnam in the period 2016 - 2022.

(2) Research scopes

Space: Survey information for the study is gathered from 27 banks' financial statements through Refinitiv Eikon software. In addition, the keywords used to build the Fintech index are collected through articles, seminars, etc. published and posted on official websites such as government information, etc...

(3) *Time*: From 2016 to 2022

1.5. Overall research methodology

Our index construction method is based on existing text mining techniques and has been further improved. Firstly, we narrow down the keywords to the titles of search news articles, rather than considering keywords that appear anywhere in the main body of the news. This focused approach ensures greater precision. Secondly, we manually collect the release time for each news article and categorize it by year. Instead of relying solely on the search news quantity provided by Google (which may not be entirely accurate), our approach ensures more reliable data. As a result, the Fintech index constructed using this enhanced text mining method exhibits significantly higher accuracy, making our research findings more trustworthy. Additionally, we delve into investigating the influential mechanisms of Fintech on green finance. To prove this hypothesis, we employ a two-way fixed effects regression model, testing to choose between Pooled OLS and FEM, then using the Hausman Test to choose between FEM and REM. Then, we utilize the Wooldridge test for autocorrelation, the Wald test for heteroskedasticity, and the correlation table to determine whether or not perfect collinearity occurs. We employ FGLS to address the heteroskedasticity and autocorrelation present in our models, therefore improving the consistency, objectivity, and efficiency of the model estimators. Our findings reveal that Fintech positively affects green finance by enhancing banks' risk management capabilities and operational efficiency.

1.6. Practical meanings of the topic

This paper contributes to the literature in the following ways:

(1) Novelty of the Topic. This research adds a distinct viewpoint to the body of current literature. Few quantitative research studies have directly addressed the relationship between Fintech and green finance, particularly from the perspective of banks. While some studies have explored the influence of Fintech development on environmental protection or the green economy (Zhou et al., 2022).

(2) Creation of a bank-level Fintech development index. So far, existing researchers on the Fintech index mostly adopt the Peking University Digital Inclusion Index (Deng et al., 2021; Qiu et al., 2018) or Baidu Index (Wang et al., 2021a). However because their samples are at the local or national levels, respectively, there is a chance that the conclusions of their analysis of individual bank samples may be imprecise and untrustworthy. Few researchers utilize the bank-level Fintech index; even when they employ text

mining techniques to gather original Fintech data, their findings are imprecise since they rely solely on the number of pertinent news searches that Google provides, without restricting their use to keywords found in news headlines. In this research, we do a frequency analysis of the term "fintech" in articles that are posted on the VNEXPress website. We will create a fintech index for the Vietnamese bank listings based on this data.

1.7. Research layout

The research is divided into 5 chapters:

Chapter 1: Introduction.
The authors indicate the reason for choosing the topic, objectives of the study, research questions, research subjects, scopes, and overall research methodology. In addition, the authors give practical meanings and research layouts.

Chapter 2: Literature review.
In this section, the authors briefly present the relevant concepts of fintech's performance. At the same time, we review previous empirical studies in Vietnam and abroad, develop hypotheses, and show variable measurements.

Chapter 3: Research methodology.
The authors present the Fintech index creation, and the study strategy, including the sample, data source, variable selection, and econometric modeling

Chapter 4: Results.
The team interprets the significance of the regression results based on the proposed hypotheses.

Chapter 5: Discussions and conclusions
The authors give conclusions, recommendations, limitations, and directions for further research.

CHAPTER 2 : LITERATURE REVIEW

2.1. Green finance

Green finance, a relatively new concept in the field of finance, first appeared in Sweden and Germany in the 1970s when people there became aware of the importance of environmental protection for sustainable economic development (Irfan, Razzaq, Sharif, & Yang, 2022). Since then, it quickly attracted attention and became an important topic in discussions related to both finance and the environment. It originates from the concept of creating favorable conditions for investment, operation, and risk management activities related to energy conservation, environmental protection, clean energy, and green infrastructure. The overarching goal of green finance is to improve the environment, address climate change issues, and optimize the use of resources.

In the context of Vietnam, green finance is an important strategy of the Vietnamese government to build a green economy, reduce greenhouse gas emissions, and adapt to climate change. This is a field of great significance for environmental protection and sustainable development in Vietnam. Vietnam has applied many modern green finance tools, such as green bonds, green stocks, green insurance and green credit. These tools help mobilize capital for green projects while bringing profits to investors and businesses.

According to the report Vietnam Green Infrastructure Investment Opportunities (Vietnam GIIO) by the Climate Bonds Initiative, Vietnam can mobilize about 21 billion USD from green finance tools to fund green infrastructure projects in the period 2020-2030. In addition, the authors also introduced 16 green projects in the fields of renewable energy, low-carbon transport, water infrastructure, and waste management, and a list of about 40 potential projects in similar fields. These are projects that can attract the interest of green finance investors while contributing to solving environmental and sustainable development issues in Vietnam.

Vietnam has adopted many popular green finance tools, including green bonds, green stocks, green insurance and green credit. These tools not only facilitate the funding of environmentally friendly projects but also create economic benefits for investors and businesses.

Within the framework of the green finance corporation, the Ministry of Finance of Vietnam and the Global Green Growth Institute (GGGI) signed a Memorandum of Understanding in December 2020. According to this, the two sides will cooperate to build and enhance policies for the green finance market in Vietnam and promote investment mobilization for green infrastructure projects. The Memorandum of Understanding also emphasizes the role of the Ministry of Finance of Vietnam in coordinating with relevant ministries, international organizations, and other stakeholders to implement green finance activities. This is evidence of Vietnam's commitment and cooperation in developing green finance.

Green finance is also a way for Vietnam to implement its international commitments in reducing greenhouse gas emissions. Vietnam announced its commitment to achieve net-zero emissions by 2050 at the COP26 Climate Summit. This commitment will accelerate capital mobilization through the sustainable finance market to speed up the process of decarbonizing. By focusing on green finance, Vietnam is contributing to the global effort to mitigate the impact of climate change, while creating economic opportunities for investors and businesses.

All green finance tools play an important role in funding green projects. Green bonds are a financial tool that investors can use to fund projects that benefit the environment. Green stocks allow investors to participate in companies that operate in the field of renewable energy or other environmental fields. Green insurance can help protect investors from financial risks related to climate change. Finally, green credit is a form of credit that banks provide for environmentally friendly projects.

These tools not only help fund environmentally friendly projects, but also create economic benefits for investors and businesses. Environmentally friendly projects often generate long-term and sustainable profits, while investing in green finance tools can bring attractive returns for investors. At the same time, businesses can take advantage of green finance tools to enhance their image as pioneers in the field of environmental protection and sustainable development.

According to the article Developing a green finance system to promote green economy in Vietnam by (Bang & Hang, 2023), Vietnam can learn from the experience of advanced countries in developing a green finance system, such as China, Singapore, UK, France and EU countries. The article proposes a comprehensive approach for Vietnam, both taking the central role of large financial institutions and leveraging the diffusion power of microfinance organizations.

In general, green finance is becoming an important part of Vietnam's sustainable development strategy. By utilizing various green finance tools, Vietnam not only fulfills its international commitments, but also creates economic opportunities for investors and businesses. In the future, green finance may become a key factor in promoting sustainable development and environmental protection in Vietnam.

Besides, many studies have been conducted to investigate, analyze the current situation and potential of green finance in Vietnam, as well as the challenges and solutions needed to foster its development. For example, (Institute of Strategy, Policy on Natural Resources and Environment, 2023) conducted a study to evaluate the effectiveness of green credit in supporting green businesses in Vietnam. They emphasized that green credit can enhance energy efficiency, reduce production costs and improve profitability of businesses. In another study, (Kham, 2019) examined the factors influencing the decision to issue green bonds by businesses in Vietnam. They concluded that factors such as business size, debt ratio, profitability and reputation play an important role in this decision-making process. Moreover, a study by (Nhung, Tu & Van, 2019) surveyed the current situation and proposed solutions for developing green insurance in Vietnam. The purpose of it was to support environmentally friendly business activities and mitigate climate change risks. These studies have made significant contributions to our understanding of green finance and its implementation in Vietnam.

Overall, green finance in Vietnam is a dynamic and fast-growing field, in line with the country's commitment to sustainable development and environmental protection. Through the use of different financial tools and the insights gained from the studies, Vietnam is ready to achieve remarkable progress in promoting green finance and realizing the economic and environmental benefits.

2.2. Fintech

Fintech, short for financial technology, represents the convergence of advanced technology and financial services. This innovative field encompasses various sectors, including digital payments, peer-to-peer lending, asset management, insurance, digital currencies, blockchain, and more.

In the context of Vietnam, Fintech is a rapidly growing emerging industry. Currently, there are over 200 Fintech companies operating across the country in various sectors. The expansion of Fintech in Vietnam is driven by several factors, including high demand for financial services, widespread use of smartphones and the internet, government support and regulations, as well as collaboration between Fintech companies and traditional banks.

Fintech has revolutionized how we access and use financial services. With technological advancements, Fintech has extended financial service access to millions of people worldwide, particularly those without bank accounts. This has brought about significant changes in how we transact, save, invest, and even spend money.

In Vietnam, the development of Fintech has brought about significant changes in the country's financial system. With government support, regulations, and the rapid growth of the industry, Fintech has become an integral part of Vietnam's economy. Fintech companies have introduced a range of new products and services, from mobile payment applications to online lending platforms, improving financial service access for Vietnamese citizens.

However, the growth of Fintech also poses some challenges. Issues related to risk management, data security and privacy, as well as ensuring that Fintech companies comply with financial regulations and standards, need to be addressed. Additionally, ensuring that all individuals have access to new financial services poses a significant challenge.

Therefore, Fintech is playing an increasingly important role in the global financial system, especially in Vietnam. With government support, regulations, and collaboration with traditional banks, Fintech has the potential to continue developing and improving financial service access for Vietnamese citizens. However, ensuring that this development occurs in a safe and sustainable manner will be a crucial challenge in the future.

Several articles and academic studies have delved into the topic of Fintech in Vietnam. For example, a comprehensive study published in the Banking Journal in 2022, titled "Fintech Market in Vietnam: Opportunities and Challenges" (Tuyet & Thuy, 2021) provides in-depth analysis of the current landscape, emerging trends, opportunities, and challenges in Vietnam's Fintech market. It offers valuable recommendations for relevant stakeholders.

Furthermore, an article by Forbes Vietnam in 2022, "How to Promote the Development of Fintech in Vietnam?" (Diep, 2021) provides a detailed analysis of the factors influencing Fintech development in Vietnam. It discusses factors such as the business environment, legal policies, and the startup ecosystem, while proposing measures to create favorable conditions for domestic Fintech development.

Moreover, (Mordor Intelligence, 2024) introduced four key Fintech trends in Vietnam for 2023. These trends include mobile payments, digital banking, digital currencies, blockchain, and artificial intelligence. The article also addresses the benefits and challenges these trends pose for businesses and consumers.

2.3. The influence of Fintech on Green Finance

Fintech and green finance are emerging fields that have yet to be fully explored. At the core of the financial system is the banking sector, which also serves as a foundation for the development of Fintech. This research focuses on observing the impact of Fintech on green finance, particularly from the perspective of banks.

Green credit, an important form of green finance in Vietnam, has witnessed rapid growth with significant transaction volumes. In 2020, green credit in Vietnam reached $9.1 billion, doubling the figure from 2018 (Thu, 2022). This form has enabled the government to channel capital into green projects and has encouraged financial institutions to use resources more efficiently (Linh, 2021); (Hac, 2022). The objective of this research is to explore the development process of green finance by studying the changes in green credit.

When Fintech intersects with green finance, they create a powerful combination that opens up new opportunities for the financial industry and the environment. Fintech can influence green finance through two main mechanisms: the competition effect and the technology diffusion effect.

Regarding the competition effect, the recent strong development of Fintech companies has significantly increased competition for traditional banks. Specifically, according to (Boot, Hoffmann, Laeven, & Ratnovski, 2021), Fintech provides mobile banking products, e-wallets, peer-to-peer lending platforms, and smart investment advisory, creating attractiveness for consumers. Furthermore, (Boot et al., 2021), emphasize that Fintech has significantly reduced barriers to financial services, allowing new competitors to emerge and gain market share from banks. (Li, Li, Zhu, Yao, & Casu, 2020) argue that this has increased risks for traditional banks and the financial system. Therefore, banks are compelled to reduce high-risk lending projects to maintain stability and sustainability.

Despite creating competitive pressures, Fintech also has a technology diffusion impact, promoting the development of green finance. Specifically, Fintech can participate in developing the green bond market and apply technologies such as artificial intelligence for efficient capital allocation in green projects.

The technology diffusion effect occurs when Fintech transfers advanced technologies to traditional banks, helping them enhance risk management capabilities, expand marketing channels, reduce operational costs, and drive innovation. This effect can encourage traditional banks to expand their green credit portfolios and attract more customers interested in green projects.

Furthermore, Fintech helps minimize operating costs for banks through automation and process optimization. This enables banks to offer green credit with more competitive interest rates, encouraging the participation of both businesses and individuals in environmentally friendly projects.

In summary, Fintech can have a significant positive impact on the development of green finance, particularly green credit, by improving resource allocation, enhancing service quality, and generating innovative solutions for environmental issues. However, Fintech also requires traditional banks to adapt to market changes and regulations, as well as address challenges related to cybersecurity, data security, and ethical compliance. This is why Fintech and green finance are considered a breakthrough combination, opening up new opportunities for the financial industry and the environment.

2.4. Influence mechanism

To discuss the relationship between green finance and development, not only environmental policies but also many other factors play an important role. Among them, the performance indicators of banks have a significant impact.

According to the study by (Zhou, Zhu, & Luo, 2022), the asset size of a bank is an important indicator to evaluate the operational capacity and competitive position of the bank in the financial sector. Banks with large asset sizes have many advantages when participating in green financial activities. These advantages include: abundant resources, rich experience and high risk tolerance.

Large asset size of banks provides abundant resources, including capital, human resources, technology and partnerships to support green projects. This includes from appraisal, monitoring to providing green financial products and services that suit the needs of customers. In addition, large asset sizes also bring rich experience in the financial field, especially in the areas related to environment, social and governance

(ESG). Banks can apply standards, procedures and methods to assess the environmental and social impacts of green projects, as well as measure the effectiveness and benefits of green financial activities. Moreover, with high risk tolerance, banks with large asset size can invest in green projects with high potential but also high risk. These include renewable energy, energy efficiency, poverty reduction, biodiversity conservation and more. They can also take advantage of green financial opportunities in the international market, such as issuing green bonds, social bonds, sustainable bonds and many other types.

Therefore, asset size has a positive impact on green finance, because it helps banks have more favorable conditions to carry out financial activities towards sustainable development goals.

In addition, the study by (Zhang, Wu, Wang, & Hao, 2021) also refers to the financial leverage of banks, defined by the ratio of assets to equity. Financial leverage indicates the level of constraint and expansion of banks in providing green financial services. The study shows that increasing financial leverage can create incentives for banks to invest in green projects and activities, while enhancing the financial capacity of banks to meet the capital demand for green projects.

Furthermore, both banks and other businesses can take advantage of green financial tools such as green bonds, green venture capital and green investment funds to mobilize capital for sustainable development projects. However, to enhance the development of green finance, there needs to be cooperation and trust between banks, businesses, governments, and other stakeholders. This requires harmonization of standards and criteria for green finance, as well as legal and policy frameworks to support.

Therefore, the asset size and financial leverage of banks can play an important role in supporting the development of green finance. However, to promote green finance and ensure sustainable development, there needs to be cooperation and trust between stakeholders and the application of appropriate standards and procedures.

Finally, the non-interest income ratio (defined by the ratio of non-interest income to total operating income) that banks earn from non-interest activities such as service fees, commissions, profits from foreign exchange, securities, etc., indicates their ability to diversify revenue sources and reduce dependence on interest income. This is an important indicator to evaluate the profitability and efficiency of banks, as well as an important factor in promoting green finance, a concept related to mobilizing and allocating capital for economic activities that are beneficial to the environment and mitigate the impact of climate change.

Banks with high non-interest income ratio usually have diversified and flexible business capabilities, allowing them to adapt to market changes and customer needs. Non-interest activities may include charging service fees, commissions, profits from foreign exchange, securities, and more. This indicates the ability of banks to diversify revenue sources and reduce dependence on interest income.

The non-interest income ratio, according to recent studies, has been found to have a negative impact on green finance. Specifically, it exerts pressure on banks to increase costs and causes fluctuations in their income (Wu & Zhu, 2023). Furthermore, it escalates the risks associated with market changes and customer demand, thereby diminishing the banks' risk resilience and financial stability (Al-Okaily, 2021).

However, increasing the non-interest income ratio also requires banks to improve their risk management capabilities, optimize operations and enhance service quality. This may require banks to invest more in technology, human resources and partnerships, as well as comply with regulations and standards on green finance.

Therefore, the performance indicators of banks have a significant impact on the development of green finance, especially green credit. Improving the business performance of banks not only improves their financial results but also contributes to supporting green and sustainable economic activities. Thus, based on this premise, we propose the following hypothesis:

Hypothesis 1. Fintech has a positive relationship with green finance.

Hypothesis 2. Asset has a positive relationship with green finance.

CHAPTER 3 : PROPOSED MODELS AND RESEARCH METHODS

3.1. Analytical framework

Table 3.1: Analytical framework

Dependent variables	Independent variables	Control variables
Green credit (GC)	Fintech (FT)	Bank size (SIZE)
		Financial leverage (EM)
		Non-interest income rate (NIIR)

Source: Compiled by the authors

By offering crucial data for the creation of government policies pertaining to sustainable finance and the banking industry's strategic development orientation, the authors hope to increase the body of theoretical knowledge already in existence. The authors use an analytical evidence framework, based on both theoretical and empirical evidence from the preceding part, because this topic has practical ramifications and is of interest. It is provided in a table. In order to create a model that predicts how Fintech will affect green finance, the study takes financial aspects into account. Regression analysis will be used to build the model using the panel data that was gathered.

3.2. Data collection methods, and data samples

Through the use of Refinitiv Eikon software, this study employs quantitative research methodologies to gather secondary data on financial indicators from 2016 to 2022 from the balance sheets and financial statements of 27 commercial banks. Furthermore, the Fintech index's keywords are gathered from papers, conferences, and other events that are published and shared on official websites including those that house government data.The acquired data was then processed by the authors using computer-aided software like Python and STATA17.

There are 189 observations in all for the survey. In order to permit observation and analysis of the changes of the object groups after the events or over time, as well as assessing the differences between the groups of research subjects, the survey sample size is moderate and appropriate for the micro-panel sample size in regression analysis.

Consequently, the authors think that a sample size of 189 will guarantee the validity of the study results when compared to the population and minimize estimation errors during implementation.

3.3. Variable measurements

3.3.1. Dependent variables

Compared to other green financial instruments such as green bonds, green equities, and green insurance, green credit (GC) has the largest trading scale and the most developed trading system, thus we adopt it to represent green finance (Shao et al., 2021). In order to gather the Green Credit, the group has studied and examined the bank's annual reports in addition to articles from reliable wedding websites. This has allowed them to filter and choose information pertaining to the bank's green credit. Additionally, banks play a significantly more significant role in Vietnam's green financial system than do the securities and insurance sectors. The quantity of green credit that banks issue is directly correlated with the level of development in the green finance space.

3.3.2. Independent variables: Determine Fintech index

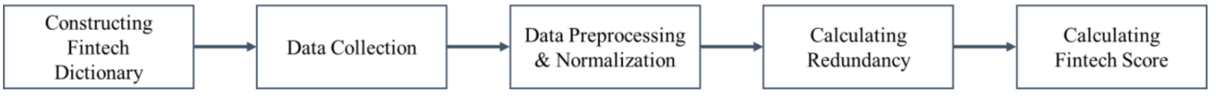
3.3.2.1. Introduction

In this research, we have applied a novel approach to evaluate the development of fintech in banks. This method is inspired by the study of (Wan, Lee, & Sarma, 2023).

Our approach involves analyzing the frequency of the keyword "fintech" in articles published on the VNEXPress website. Based on this analysis, we will construct a fintech index for the banks listed in Vietnam.

This fintech index will reflect the level of access and interaction of banks with the fintech sector, thereby aiding in the assessment of their fintech development. We believe that this method will open up a new approach to evaluating and comparing the development of fintech in the banking industry.

Figure 3.1: Implementation model



Source: Compiled by the authors

3.3.2.2. General concept

(1) Data normalization: is the process of adjusting numerical values in a dataset to make them comparable. In this case, our research team utilizes the Min-Max normalization method, which transforms the original value x into the normalized value x' according to the formula:

$$x' = \frac{x - min(x)}{max(x) - min(x)}$$

(2) Normalized values are unitless: the process of transforming the normalized value x' into a unitless normalized value x" such that the sum of all unitless normalized values is equal to 1. The formula for calculating the unitless normalized value of each keyword is:

$$x'' = \frac{x'}{\sum_{i=1}^{n} x'}$$

(3) Entropy Value: is a concept in information theory that measures the level of uncertainty, randomness, or disorder in data. The formula for calculating the entropy value of each keyword is:

$$E = -\sum_{i=1}^{n} (p_i log_2 p_i)$$

(4) Surplus Value: the surplus value of a keyword is calculated by subtracting the entropy value of that keyword from 1. The formula for calculating the surplus value of a keyword is:

$$R = 1 - E$$

(5) Weight: the weight of each keyword is calculated based on its surplus value. The sum of all surplus values is used to normalize the weights, ensuring that the sum of all weights equals 1. The formula for calculating the weight of each keyword is:

$$W = \frac{R}{\sum_{i=1}^{n} R}$$

(6) Fintech Score: the Fintech Score for each bank is calculated based on the weight of each keyword and the normalized unitless value of each keyword in the data. The formula for calculating the Fintech Score for each bank is:

$$F = \sum_{i=1}^{n} (W_i \times x_i^n)$$

3.3.2.3. Building the Fintech dictionary

To conduct an effective evaluation of banks based on fintech criteria, the first step in this process is to build a comprehensive list of keywords related to fintech. These keywords will encompass the most important technologies, services, products, and trends in the fintech field that the research team believes will impact the operational performance of banks.

Creating this keyword list not only helps the team identify the most important factors to evaluate but also establishes a common standard for assessing and comparing the performance of different banks. In this research, the team constructs a Fintech Dictionary consisting of 40 keyword clusters, with the following content:

Table 3.2: Fintech dictionary

Keywords					
Công nghệ	Dữ liệu lớn	Fintech	Điện toán đám mây	Blockchain	Trí tuệ nhân tạo
Số hóa	Ứng dụng công nghệ	Nhận dạng khuôn mặt	Mã QR	Cố vấn đầu tư thông minh	Thông minh
Robot	Kiểm soát rủi ro	Tiền điện tử	Nền tảng ứng dụng	Ứng dụng	Ngân hàng di động
Ngân hàng số	Ngân hàng thông minh	Ngân hàng Internet	Nền tảng đám mây	Công nghệ đám mây	Đám mây
Internet	Internet kết	Thanh toán	Thanh toán	Thanh toán	Thanh toán

	nối di động	qua điện thoại	trực tuyến	di động	đám mây
Thanh toán bên thứ 3	Tiền gửi	Cho vay	Bảo hiểm	Cho vay trực tuyến	Tài chính mạng
Tài chính chuỗi cung ứng	Tài chính trực tuyến	Tài chính bao gồm mọi người	Bảo hiểm trực tuyến	Thanh toán flash qua đám mây	AI

Source: Compiled by the authors

3.3.2.4. Fintech data collection

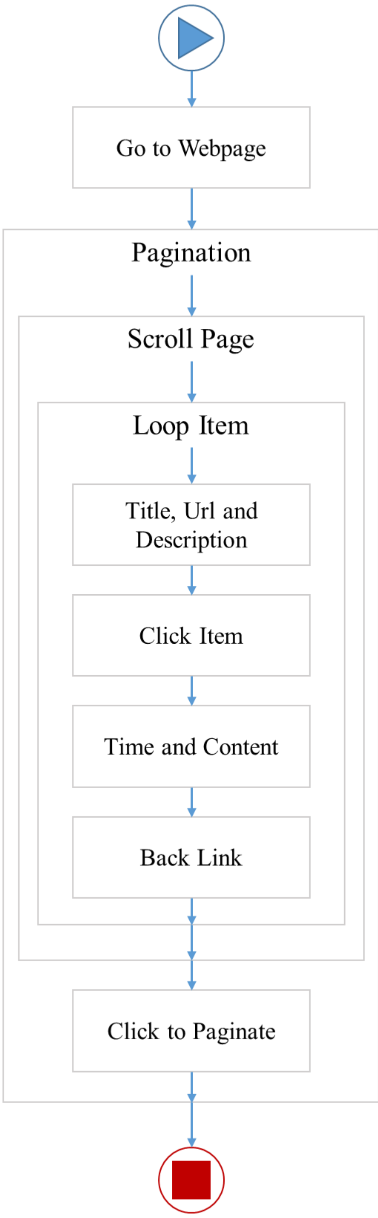
To collect data automatically and efficiently, the research team utilized Octoparse - a powerful web scraping tool. Octoparse enables the team to automate the process of gathering information from websites, saving research time.

Specifically, the research team used Octoparse to collect data from the VNExpress website, one of the leading news portals in Vietnam. The team focused on the Business - Ebank - Banking section of the website (specifically: Tin tức ngân hàng- tài chính, nguồn lực, vay nợ, cơ cấu (vnexpress.net)), which provides updated information on banking activities.

By utilizing Octoparse, the research team was able to quickly and accurately gather a large amount of data from VNExpress, allowing for a deeper understanding of banking operations. This data was then used for analysis and evaluation of the performance of banks based on the fintech criteria determined by the team.

The tree structure used by the team to navigate the content on Octoparse is as follows:

Figure 3.2: Octoparse browser tree structure



Source: Author's group built by Octoparse

The results obtained from data preprocessing are as follows:

Table 3.3: Data after preprocessing

Bank	Time	Title	Description	News
Bac A Bank	04/12/2023	Chiến lược …	TPBank đạt 12	Với mục tiêu

		người dùng	triệu …	sát cánh …
VietinBank	03/06/2023	VietinBank đặt bán lẻ … chủ lực	Bán lẻ dần trở thành một …	Đó là chia sẻ của ông …
Vietcombank	05/02/2023	Vietcombank … quản trị	Ông Đỗ Việt Hùng, …	Cuối năm là dịp nhu …

Source: Compiled by the authors

3.3.2.5. Data Standardization

During the data processing, data standardization plays a crucial role in ensuring consistency and uniformity for subsequent processing and calculations. In particular, it helps bring values within the appropriate range, facilitating the calculation of Fintech Scores for banks. Specifically, the data standardization process includes the following steps:

(1) *Keyword Frequency Standardization*: The frequency of keywords is calculated by counting the number of occurrences of the keyword in the input data. To standardize the keyword frequency, we use the formula:

$$non\_dimensional\_frequency = \frac{total\_frequency}{frequency}$$

Where:

- frequency is the number of occurrences of the keyword,
- total_frequency is the total frequency of all keywords.

(2) *Excess Residual Standardization*: The excess residual of a keyword is the difference between the frequency of the keyword in a bank and the average frequency of the keyword across all banks. To standardize the excess residual, we use the formula:

$$non\_dimensional\_residual = \frac{total\_residual}{residual}$$

Where:

- residual is the excess residual value of the keyword,
- total_residual is the total value of excess residuals for all keywords.

(3) *Weight Calculation*: The weight of a keyword is calculated by dividing the excess residual value of the keyword by the total value of excess residuals for all keywords. This process helps determine the importance of keywords in calculating the Fintech Score.

After the data standardization process, the research team obtained standardized keyword frequencies and excess residuals, which are ready for calculating the Fintech Score for each bank. The weights have been computed based on the standardized excess residuals of the keywords, and the team will use them to calculate the Fintech Score for each bank. Therefore, through the standardization process, the team has standardized keyword frequencies and excess residuals, thereby determining the weights for each keyword. The data standardization process is an important step in data processing and analysis, ensuring the accuracy and reliability of the final results.

3.3.2.6. Calculating Excess Residuals

To determine the importance of Fintech keywords for each bank, the research team computed the excess residuals for these keywords based on their frequency of occurrence in the data. The process involved the following steps:

1. Initializing a dictionary to store the excess residual values for each keyword.
2. Iterating through each bank in the input data.
3. Calculating the total frequency of occurrence for the keyword across the entire dataset.
4. Computing the average frequency of occurrence for the keyword across the entire dataset.
5. Calculating the excess residual for each keyword by subtracting the frequency of occurrence in the current bank from the average frequency of occurrence across the dataset.

The final result is a list of excess residual values corresponding to each keyword, which helps assess the importance of keywords for each bank. These values can be utilized in subsequent analyses or decision-making processes. This process focuses on computing the excess residuals for Fintech keywords to determine their significance within the banking dataset.

3.3.2.7. Calculating the Fintech Score

The Fintech Score is an important measure for evaluating the level of financial technology utilization by banks, determining their modernity and advancement in applying financial technology.

To calculate the Fintech Score for each bank, the team multiplies the weight of each keyword by its corresponding frequency of usage in the bank's operations and aggregates the results.

The Fintech Score reflects the level of financial technology utilization by each bank, with higher values indicating a greater readiness in embracing technology.

It is important to note that due to the standardization process, the Fintech scores of the banks will range between [0, 1].

For example, after calculating the Fintech Score for the banks, the team might obtain results like the following:

Bank	
Vietcombank	0.922039
ACB	0.694749
Agribank	0.772167
BIDV	0.843072

The above results indicate that Vietcombank has the highest Fintech Score, showcasing the most advanced level of financial technology utilization among the evaluated banks. Agribank and BIDV also have relatively high Fintech Scores, while ACB has a lower Fintech Score compared to the other banks.

These Fintech Score results can be used to compare and evaluate the level of advancement in applying financial technology among the banks and may aid in decision-making when selecting a bank that aligns with personal or business needs.

3.3.3. Control variables

Numerous characteristics, such as bank size,leverage, and business diversification, have been found in prior research to have an impact on the growth of green finance. We adjusted for the aforementioned variables in order to improve the estimations of our relevant variables. In order to lessen the impact of variations in bank size (SIZE) on green finance, we first adjusted for total assets (Cubillas and Gonzalez, 2014). In addition, we control the equity multiplier in order to mitigate the impact of different financial leverage (EM) on green finance. The computation of this ratio involves dividing the total assets by the total equity, as stated by Berger and Bouwman (2017) and Diamond and Rajan (2012). Next, in order to mitigate the effect of banks' differing business diversification capabilities on green finance, we adjusted for non-interest income rate (NIIR) (Demirgüç-Kunt and Huizinga, 2010).

Table 3.4: Calculation and expectations of sign of variables

Variables	**Variables name**	**Calculation**	**Expectations of coefficient's sign**	**Previous experimental research**
Dependent variables				
GC	Green credit		-	Shao et al., 2021
Independent variables				
FT	Fintech	Analyzing the frequency of the keyword "fintech" in articles published on the VNEXPress website.	+	Wan, Lee, & Sarma, 2023
Control variables				
SIZE	Bank size	The natural logarithm of total bank assets	+	Cubillas and Gonzalez, 2014

EM	Financial leverage	Total assets/Total equity	+	Berger and Bouwman (2017) and Diamond and Rajan (2012)
NIIR	Non-interest income rate	Non-interest income/Total operating income	-	Demirgüç-Kunt and Huizinga, 2010

Source: Compiled by the authors

3.4. Research models

In this research, we build the empirical model adjusted to suit Vietnamese conditions to test the effects of Fintech on green finance and to verify hypothesis 1 based on the research of *Wan, S., Lee, Y. H., & Sarma, V. J. (2023).*

$$\boldsymbol{GC_{it} = a_0 + \beta_1 FT_{it} + \beta_2 SIZE_{it} + \beta_3 EM_{it} + \beta_4 NIIR_{it} + \varepsilon_{it}}$$

Where:

(1) i: code of each bank

(2) t: year periods

(3) α: the intercept

(4) $\beta_1, \beta_2, \beta_3, \beta_4$: regression parameters of the estimators.

(5) GC_{it}: Green finance variable. The unit of measurement of green credit is trillion of VND.

(6) FT_{it}: Fintech variables are measured by analyzing the frequency of occurrence of the keyword Fintech in articles posted on the VnExpress website.

(7) $SIZE_{it}$: Bank size variable, presented as the natural logarithm of total bank assets.

(8) EM_{it}: Leverage variable, expressed as Total assets/Total equity

(9) $NIIR_{it}$: Non-interest income rate variable, presented as Non-interest income/Total operating income

(10) ε_{it}: Error term

3.5. Data processing methods

3.5.1. Descriptive statistical analysis method

By summarizing or explaining the main characteristics of a data collection, descriptive statistics offer a general overview of the research sample. The two primary types of measurements used in descriptive statistics are measures of the mean and measures of variability (or dispersion). It will be beneficial to quickly examine the dependent variables, independent variables, and control variables using this method in order to provide the mean, the maximum value, the minimum value, and the standard deviation of the data.

3.5.2. Pearson correlation coefficient matrix method

The link between the model's variables is examined using the correlation coefficient matrix analysis approach. This study aids in determining if the model's variables are multicollinear or not. The variables in the model will be correlated to a certain degree of confidence. If there are positive or negative associations between the variables, it will be clear from the sign of the correlation coefficient. The model's predictions can be assessed using the findings of the correlation coefficient matrix analysis. With the strength of the correlation between the variables, the likelihood of multicollinearity rises.

3.5.3. Testing to choose between Pooled OLS and FEM

Regression models such as REM, FEM, and pooled OLS are frequently used with panel data. The level of influence that the independent variable has on the dependent variable, which was identified by regression analysis, is measured by the p-value of the regression results.

3.5.3.1. Pooled ordinary least squares regression (Pooled OLS)

This model has no impact on the assumptions of autocorrelation, heteroscedasticity, or the differences in space and time between any observed variable. Thus, it is assumed that the slopes of the coefficients and the y-axis are constant across time and for each variable. In this illustration, only the ordinary least squares (OLS) regression model is calculated, with the time and spatial aspects of the panel data being disregarded. Yet, in actuality, different sample observation times and sample firms have distinct characteristics, and the individual problem is a frequent occurrence in empirical studies.

Due to its simplicity and ease of use, the Pooled OLS regression model has the drawback that it can lose track of the link between the variables. Below is a display of the regression model:

$$\boldsymbol{Y_{it} = \alpha + \beta_1 X_{1_{it}} + \beta_2 X_{2_{it}} + \ldots + \beta_k X_{k_{it}} + \mu_{it}}$$

Where:

(1) Y_{it}: dependent variable
(2) $X_{1_{it}}$, $X_{2_{it}}$, ..., $X_{k_{it}}$: independent variables
(3) $\beta_1, \beta_2, \ldots, \beta_k$: parameters of the independent variables
(4) i: cross-sectional unit
(5) t: time-series unit
(6) μ_{it}: error term

3.5.3.2. Fixed effects model (FEM)

Because it does not ignore the impacts of time series and cross units, the fixed effects model has solved the shortcomings of the traditional linear regression model Pooled OLS. We lose the ability to estimate the effects of all the variables that affect Yit but do not vary over time, but the model has the advantage of using panel data to estimate with high confidence the influence of the independent variable on the dependent variable. The following is a depiction of the fixed effects model:

$$\boldsymbol{Y_{it} = \alpha + \beta_1 X_{1_{it}} + \beta_2 X_{2_{it}} + \beta_3 X_{3_{it}} + \cdots + \beta_k X_{k_{it}}}$$
$$\boldsymbol{+\lambda_1 D_{1_i} + \lambda_2 D_{2_i} + \lambda_3 D_{3_i} + \cdots + \lambda_n D_{n_i} + \nu_{it}}$$

Where:

(1) Y_{it}: dependent variable
(2) $X_{1_{it}}$, $X_{2_{it}}$, ..., $X_{k_{it}}$: independent variables
(4) $\beta_1, \beta_2, \ldots, \beta_k$: parameters of the independent variables
(5) i: cross-sectional unit
(6) t: time-series unit
(7) D_{1_i}, D_{2_i}, D_{3_i}, ... , D_{n_i}: entity dummies
(8) $\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_n$: parameters of entity dummies
(9) ν_{it}: idiosyncratic error

We utilize the p-value of the F-test to evaluate whether or not to reject the null hypothesis and which model (Pooled OLS or FEM) to apply. The test can be written as:

(1) $H_0: \lambda_1 = \lambda_2 = \lambda_3 = \lambda_n = 0$

(2) H_1: H_0 is not true

We reject the null hypothesis and come to the conclusion that the unobserved heterogeneity (entity-fixed effect) in the model causes the FEM to perform better than Pooled OLS, and vice versa if the p-value of the F-test is less than 5% significant level.

3.5.4. Testing to choose between FEM and REM by using Hausman Test

3.5.4.1. Random effects model (REM)

The fixed effects model is fiercely competitive with the error components model, sometimes known as the random effects model. The random effects approach makes different intercept terms for each entity, just as fixed effects, and these intercepts stay the same over time. It is expected that the associations between the independent and dependent variables in both effects are the same both cross-sectionally and temporally. The random effects model (REM) differs from FEM in that it is predicated that the intercepts for each cross-sectional unit are derived from a common intercept (which is the same for all cross-sectional units and over time) plus a random variable εi that varies cross-sectionally but is constant over time. εi represents the random difference between the intercept terms for each entity and the "global" intercept term. You may write the random effects panel model as:

$$\boldsymbol{Y_{it} = \alpha + \beta_1 X_{1_{it}} + \beta_2 X_{2_{it}} + \beta_3 X_{3_{it}} + \cdots + \beta_k X_{k_{it}}}$$
$$\boldsymbol{+ \omega_{it} = \varepsilon_i + \nu_{it}}$$

Where:

(1) Y_{it}: dependent variable
(2) $X_{1_{it}}, X_{2_{it}}, \ldots, X_{k_{it}}$: independent variables
(3) $\beta_1, \beta_2, \ldots, \beta_k$: parameters of the independent variables
(4) i: cross-sectional unit
(5) t: time-series unit
(6) ω_{it}: comprehensive(or composite) error term
(7) ε_i: unobserved time-invariant effect that has zero mean, constant variance σ2ε and follow normal distribution

(8) v_{it}: idiosyncratic error

3.5.4.2. Hausman test

In order to help researchers choose between a FE model and a RE model, Hausman (1978) created tests. This test is referred to as a model error test, and it determines whether or not the entity fixed effect is uncorrelated with all independent variables. Using assumptions:

(1) H_0: appropriateness of the random-effects estimator

(2) H_1: appropriateness of the fixed-effects estimator

If P-value < significance level: reject H0, FEM model is suitable.

If P-value > significance level: accept hypothesis H0, REM model is suitable.

3.5.5. Testing for multicollinearity

Using the Variance Inflation Factor (VIF), it is possible to assess the degree of connection between the independent variables. When the independent variables in a regression model are correlated, multicollinearity happens. Because the independent variables need to be independent, this correlation is problematic. If the correlation between the variables is strong enough, it may be difficult to fit the model and interpret the findings.

The variance exaggeration factor (VIF) was utilized by Garrett Lane Cohee, Ronald F. Piccolo, and Halil Kiymaz (2009) to examine the multicollinearity phenomenon. Calculations\formula:

VIF = 1 / (1 − correlation coefficient between variables)

When the correlation coefficient approaches 1, the larger the VIF coefficient,

and then multicollinearity occurs.

(1) VIF coefficient < 10: The model has low multicollinearity.

(2) VIF coefficient > 10: The model has high multicollinearity.

3.5.6. Testing for autocorrelation

Errors that are associated across time are referred to as autocorrelation. When there is autocorrelation, the OLS model estimate is still fair and consistent with the normal distribution, but it is no longer effective. The t-test and F-test are therefore probably no longer applicable. To resolve the issue, we can use a more effective estimator, such as GLS, WLS, FGLS, log the variable, or a cluster.

The Wooldridge test, Breusch-Pagan-Godfrey test, LM test, Pasaran CD test, and Durbin-Waston test are autocorrelation tests with the following presumptions:

The hypothesis of the autocorrelation test is as follows:

(1) H_0: The model has no autocorrelation

(2) H_1: The model has autocorrelation

If P-value < significance level: reject H0, the model has no autocorrelation.

If P-value > significance level: accept H0, the model has autocorrelation.

3.5.7. Testing for heteroskedasticity

When error variances vary across observations, this is known as heteroscedasticity. The OLS estimate is neither biased nor unstable when the model contains this flaw, but the coefficients and t and F statistics are no longer accurate. As a result, the OLS estimator is now RED. To deal with the variance, we can find a more effective estimator: Use Robust, log the variable, GLS, WLS, or FGLS.

The White test, Wald test, Breusch-Pagan test, LM test, and other tests for heteroscedasticity are conducted under the following presumptions:

(1) H_0: The variance of errors does not vary over the observations.

(2) H_1: the variance of errors varies over the observations.

If P-value < significance level: reject H_0, the model has a heteroscedasticity problem.

If P-value > significance level: accept H_0, the model is homoscedasticity.

3.5.8. Feasible generalized least squares (FGLS) to deal with heteroskedasticity and autocorrelation

The GLS model can be expressed as follows, assuming that the functional form has linear parameters and that the error component has a mean of zero, is nonspherical, has a normal distribution, and is uncorrelated with each independent variable:

$$\boldsymbol{Y_t = \alpha + \beta_1 X_{1_t} + \beta_2 X_{2_t} + \ldots + \beta_k X_{k_t} + \mu_t}$$

With:

$$var(\hat{\beta}) = (\mathrm{XTW} - \mathrm{X}) - 1, \text{ and } \mathrm{var}(\mu_{it}) = \sigma_{it}$$

Despite the heteroscedasticity and autocorrelation included in the GLS model, this estimator is nonetheless objective, effective, and comparable to the maximum likelihood estimator. Furthermore, impartial and consistent are estimated standard errors. Consequently, it is appropriate to analyze hypothesis tests. Yet, we are unable to determine the elements' actual worth in the matrix of disturbances.

To perform FGLS, we use the sample data to estimate the weights: $W_t = 1/\sigma_t$, and then regress: $W_t Y_t = W_t + W_t X_{1_t} + W_t X_{2_t} + \ldots + W_t X_{k_t}$. To prevent a shortage of degrees of freedom, the sample size must be raised.

CHAPTER 4 : RESEARCH RESULT

4.1. Descriptive statistics

Table 4.1: Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
GC	189	8.920834	1.348644	2.772589	11.61855
FT	189	.6906562	.1813264	.2225	.985208
SIZE	189	17.51146	2.403052	12.8003	19.91009
EM	189	13.77418	4.236663	5.419061	27.55365
NIIR	189	-.03985	.1140232	-.2643919	.0608279

Source: Author's group synthesized by Stata

Note: This table reports the results of descriptive statistics. These 5 variables used in this study include: Green finance (GC), Fintech (FT), Bank size (SIZE), Leverage (EM), and Non-interest income rate (NIIR).

The authors conducted descriptive statistics for the research sample. The data set includes 27 commercial banks in Viet Nam, collected from 2016 to 2022, comprising a total of 189 observations. Table 4.1 presents descriptive statistics that illustrate the observations, encompassing the mean value, standard deviation, maximum, and minimum values of the data sample for the variables used in the study. The results of the descriptive statistics indicate that the average value of green credit is 8.92 with a relatively large standard deviation. The minimum and maximum values are 2.77 and 11.618, respectively. Next, the fintech index has an average value of 0.69, ranging from 0.225 to 0.985, demonstrating significant differences in fintech development interest among commercial banks in Vietnam. Additionally, the bank size (natural logarithm) has an average value of 17.511, with the minimum and maximum values being 12.8 and 19.91, respectively. The leverage index shows a considerable difference, ranging from 5.41 to 27.55, with an average value of 13.77. Finally, the non-interest income rate of commercial banks in Vietnam has an average value of -0.039, with the minimum and maximum values being -0.264 and 0.0608, respectively, indicating a relatively small proportion of this income in the overall profit structure of the banks.

4.2. Correlation matrix

The results of the correlation matrix analysis for the variables are presented in Table 4.2. At a significance level of 5%, the dependent variable fintech (FT) shows a positive correlation with green finance (GC) with a correlation coefficient of 0.1662. The leverage coefficient also indicates a positive correlation with green finance at a 1% significance level (0.3132) and a negative correlation with bank size at a 5% significance level (-0.1811). Lastly, the non-interest income rate (NIIR) coefficients mostly exhibit a negative correlation with the variables in the model. The correlation coefficients in the results table are not high (<0.6), so the authors expect that the model does not suffer from multicollinearity issues (Gujarati, 2011).

Table 4.2: Pearson correlation matrix

	GC	FT	SIZE	EM	NIIR
GC	1.0000				
FT	0.1662**	1.0000			
SIZE	0.0616	-0.0622	1.0000		
EM	0.3132***	-0.1062	-0.1811**	1.0000	
NIIR	-0.2408***	-0.2735***	-0.1057	0.1514**	1.0000

Source: Author's group synthesized by Stata

*Note: Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively. This table reports the results of Pearson correlation analysis. Statistics are based on annual data for the years 2016 - 2022. Green finance (GC) is the dependent variable. The other independent variable and control variables: Fintech (FT), Bank size (SIZE), Leverage (EM), and Non-interest income rate (NIIR).*

4.3. Multicollinearity test

The table below displays the results of the Variance Inflation Factors test (VIF). All VIF values for individual variables are below 10, with the highest VIF reaching 1.11. This affirms the absence of multicollinearity issues in the regression model (Trong & Ngoc, 2008).

Table 4.3: Multicollinearity test

Variable	VIF	1/VIF
NIIR	*1.11*	*0.899738*
FT	*1.10*	*0.910051*
EM	*1.06*	*0.942550*
SIZE	*1.05*	*0.949611*
Mean VIF	*1.08*	

Source: Author's group synthesized by Stata

Note: This table reports the results of a test of Multicollinearity. Statistics are based on annual data for the years 2016 - 2022. Moreover, there are five variables: Green finance (GC), Fintech (FT), Bank size (SIZE), Leverage (EM), and Non-interest income rate (NIIR).

4.4. Regression results of OLS, FEM, REM model

Table 4.4: Regression results of OLS, FEM, REM model

	OLS	FEM	REM
	[1]	[2]	[3]
FT	**1.092****	**1.246*****	**1.246*****
	[2.14]	**[3.76]**	**[3.79]**
SIZE	0.0644*	0.0795***	0.0789***
	[1.71]	[3.24]	[3.23]

EM	0.123***	0.0397*	0.0560***
	[5.74]	[1.71]	[2.59]
NIIR	-2.922***	-0.912	-1.189*
	[-3.58]	[-1.37]	[-1.83]
_cons	5.226***	6.086***	5.860***
	[5.90]	[9.46]	[8.91]
Breusch - Pagan LM test			0.0000
Wooldridge test			0.0001
Hausman test			0.2499
R-sq	0.1950	0.1423	0.1729

Source: Author's group synthesized by Stata

*Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively. The model is* $\boldsymbol{GC_{it} = a_0 + \beta_1 FT_{it} + \beta_2 SIZE_{it} + \beta_3 EM_{it} + \beta_4 NIIR_{it} + \varepsilon_{it}}$ *where GC represents green finance, FT stands for fintech and the others are control variables: Bank size (SIZE), Leverage (EM), Non-interest income rate (NIIR). Column 1 showed a regression model of OLS. Column 2 showed a regression model of FEM. Column 3 showed a regression model of REM.*

Table 4.4 presents the regression results of the OLS, FEM, and REM models. The results from the table indicate that fintech (FT) exhibits a strong positive relationship with the dependent variable in all three models, with beta coefficients of 1.902, 1.246, and 1.246 at the 5%, 10% significance levels, respectively. Similarly, bank size (SIZE) also shows a positive relationship with green finance in all three models, with regression coefficients of 0.0644, 0.0795, and 0.0789, and high levels of significance. The leverage of the bank also demonstrates a positive relationship with the green credit of the bank. In the OLS model, leverage shows a significant positive correlation at the 1% level with a beta coefficient of 0.123. In the FEM and REM models, the leverage correlation coefficients are 0.0397 and 0.0560, respectively. Finally, the non-interest income rate shows an inverse correlation with the dependent variable. The authors conducted the Hausman test to choose between the FEM and REM models, and the test result with a p-value of 0.2499 suggests that REM is more appropriate. Furthermore, the authors performed tests for autocorrelation and heteroscedasticity for the REM model. The results of the tests, including the Breusch-Pagan LM test and Wooldridge test, both have p-values less than 5%, indicating the presence of autocorrelation and heteroscedasticity in the model. Therefore, the authors decided to use the FGLS method to address these model shortcomings, and the results are summarized in Table 4.5.

4.5. Regression results of FGLS model

Table 4.5: The effect of fintech on green finance – FGLS model

	GC
FT	**0.562****
	[2.32]
SIZE	0.0293**
	[2.11]
EM	0.0470***
	[2.93]
NIIR	-0.911**
	[-2.40]
_cons	7.383***
	[-6.96]

Source: Author's group synthesized by Stata

*Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively. Where the Model is* $\boldsymbol{GC_{it} = a_0 + \beta_1 FT_{it} + \beta_2 SIZE_{it} + \beta_3 EM_{it} + \beta_4 NIIR_{it} + \varepsilon_{it}}$ *where GC represents green finance, FT stands for fintech and the others are control variables: Bank size (SIZE), Leverage (EM), Non-interest income rate (NIIR).*

Table 4.5 presents the regression results using the FGLS method. The research team's analysis indicates that fintech has a positively correlated impact on green finance. At the

5% significance level, fintech shows a positive relationship with green finance, with a beta coefficient of 0.562. This result aligns with findings from studies by Wan et al. (2023) and Zhou et al. (2022). This implies that the rise of fintech contributes to the growth of green finance. The impact of fintech innovation on green finance is primarily reflected in fintech promoting the growth of green finance through green credit (Zhou et al., 2022). The results demonstrate that fintech improves green credit, indicating that financial technology innovation can drive economic growth through green credit.

Furthermore, bank size shows a positive correlation with green credit at the 5% significance level, with a correlation coefficient of 0.0293. As the bank's scale increases, the green credit portfolio of the bank also grows. This is understandable, as larger banks have more financial resources, allowing them to allocate a higher proportion of capital structure to green credit (Chen et al., 2021). Lastly, the leverage ratio demonstrates a positive correlation with green finance at the 1% significance level, with a coefficient of 0.047, while the non-interest income rate shows an inverse relationship with green finance at the 5% significance level, with a correlation coefficient of -0.911.

Summary of chapter 4

In Chapter 4, the authors conducted descriptive statistical analysis, correlation matrix, OLS, FEM, and REM regression analyses, and checked for model deficiencies such as multicollinearity, heteroscedasticity, and autocorrelation. Finally, the authors utilized the FGLS method to address model deficiencies.

The regression results are consistent with several hypotheses set by the authors. Specifically, the authors found evidence indicating that fintech has a positive impact on green finance at the 5% significance level. Furthermore, there is a positive relationship between bank size and leverage with green finance, as represented by SIZE and EM variables. Lastly, the authors discovered an inverse relationship between non-interest income rates and green finance at the 5% significance level.

CHAPTER 5 : DISCUSSION

Fintech developments significantly improve the efficiency and reach of financial services that support the real economy, thus playing a central role in promoting green economic development and attracting attention. Furthermore, previous research has overlooked the relationship between Fintech and green finance. Therefore, this article presents theoretical implications for scholars and researchers to learn and study the impact of Fintech growth on green finance.

This study explores the potential influence of banking Fintech developments on green finance in Vietnam.

5.1. Conclusion

The data set includes 27 commercial banks in Viet Nam, collected from 2016 to 2022, comprising a total of 189 observations, the authors present four main factors affecting Green finance activities of banks in Vietnam including Fintech (FT), Bank size (SIZE), Leverage (EM), and Non-interest income rate (NIIR).

Fintech (FT) has a positive effect on green finance, so it is consistent with *Hypothesis 1*. The reason is that Fintech provides convenient and popular features and functions to businesses, opening up a modern technology platform that people can access to check their finances. The development of fintech leads to more diverse financial information and investment decisions by banks in many fields to meet customer needs, care for the surrounding environment, and fulfill the social responsibility of that bank. (Zhou, Zhu, & Luo, 2022)

Bank size (SIZE) has a positive effect on Green finance, so it is consistent with *Hypothesis 2*. Banks with larger asset have higher financial resources, human resources, and technological capabilities. This allows them to provide many green financial products and services as well as carry out funding projects, environmental research and development as well as obligations to improve lives and social development. In addition, with its high reputation, Big banks also bring green finance to more customers, making it easier to achieve their goals in implementing green finance (Cubillas and González, 2014).

Leverage (EM) has a positive effect on Green finance. Financial leverage allows banks to use equity to mobilize additional loans, thereby increasing their ability to invest in green financial projects (Zhang, Wu, Wang, & Hao, 2021).

Non-interest income rate (NIIR) has a negative effect on Green finance. High NIIR can incentivize banks to prioritize profitable but potentially unsustainable activities over long-term investments in green projects. This could lead to focusing on short-term gains rather than supporting long-term sustainable development (Wang et al., 2023a).

5.2. Recommendation

Based on the results of the model, the current social situation as well as the impact between variables, we propose a number of ways for businesses and the government to improve the efficiency of green finance activities in Vietnam.

Firstly, with the positive impact of Fintech, banks need to take actions to enhance their resources, and innovate technological factors in financial aspects, customer care, and service promotion, thereby improving green credit activities. The government's encouragement and creation of favorable conditions for banks to enhance Fintech is also crucial to promoting green investment for the environment and people in Vietnam.

Furthermore, for banks with modest asset bank sizes, it is advisable to establish cooperative policies with other banks or financial institutions in green finance-related activities. This approach ensures the adequacy of existing capital conditions while presenting a positive image to customers.

Banks need to periodically and continuously carry out financial leverage activities to mobilize loans from equity sources so that they can invest in green and long-term sustainable projects in the future.

The Non-interest income rate growth of banks does not necessarily have a negative impact on green finance. However, banks need to have appropriate and serious policies and orientations towards green finance, aiming for a sustainable and long-term economy that limits investment activities that generate quick profits but have negative impacts on the environment and surrounding society.

5.3. Limitation

In this study, the authors have synthesized and selected multiple sources of information as well as methods to exploit this topic from previous studies. However, limitations are inevitable. We have recognized and listed them below.

First of all, the observation sample is relatively small, focusing only on large banks, so it is impossible to generalize the entire scale of the economy and finance in Vietnam.

Secondly, the research period is only from 2019 to 2023, which is not long enough to see the full development and impact of Fintech on banking and green finance. This is because the authors used the keyword method, and Fintech topics have only recently emerged and gained popularity

Another limitation is that we have not performed an Endogeneity test for this study. It talks about testing the relationship of the quantities with the use of the Lag factor.

Finally, the geographical area and financial scale of banks have not yet been divided, leading to assessments of Fintech as well as green finance that are not positive for the research topic.

5.4. Direction of topic development

Based on the limitations identified in the study, the authors suggest many future development directions on this topic to clearly state the research purpose and the relationship of related variables.

Expanding the research observation sample to include joint-stock commercial banks, foreign bank branches, state-owned banks, financial companies... to be able to more accurately reflect the overall economic landscape as well as Fintech's relationship in Vietnam. Divide the sample into groups based on asset size and geographic location to assess the impact of Fintech on each bank segment.

Expanding the research time and dividing it into specific periods to easily analyze the impacts of Fintech on the financial model.

Fintech is a trend in the global economy in general and Vietnam in particular. The authors believe that in the near future, there will be more appropriate and accurate fintech measurement scales. Therefore, future research on the topic of fintech can choose more accurate measurement methods for their research purposes.

Future research teams should analyze the model with a lag factor, to consider the impacts as well as the relationship between the previous year and the next year between variables affecting Green finance.

The suggestions above will be the appropriate direction to help future research express the general research purpose of the topic, clearly highlighting the relationships between the variables Fintech, green finance, technology, etc. From there, we have a view of Vietnam's economy in the future development stage.

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APPENDIX

(1) Source code: NNCT-2024: The impact of Fintech on Green Finance: Empirical Evidence from Vietnamese Banks (github.com)

(2) Descriptive statistics

```
. sum GC FT SIZE EM NIIR
```

Variable	Obs	Mean	Std. dev.	Min	Max
GC	189	8.920834	1.348644	2.772589	11.61855
FT	189	.6906562	.1813264	.2225	.985208
SIZE	189	17.51146	2.403052	12.8003	19.91009
EM	189	13.77418	4.236663	5.419061	27.55365
NIIR	189	-.03985	.1140232	-.2643919	.0608279

(3) Correlation matrix

```
. pwcorr GC FT SIZE EM NIIR, sig
```

	GC	FT	SIZE	EM	NIIR
GC	1.0000				
FT	0.1662	1.0000			
	0.0223				
SIZE	0.0616	-0.0622	1.0000		
	0.3997	0.3949			
EM	0.3132	-0.1062	-0.1811	1.0000	
	0.0000	0.1459	0.0126		
NIIR	-0.2408	-0.2735	-0.1057	0.1514	1.0000
	0.0008	0.0001	0.1476	0.0376	

(4) Model results:

```
.
. reg GC FT SIZE EM NIIR
```

Source	SS	df	MS
Model	72.5484974	4	18.1371244
Residual	269.39346	184	1.46409489
Total	341.941958	188	1.8188402

Number of obs	=	189
F(4, 184)	=	12.39
Prob > F	=	0.0000
R-squared	=	0.2122
Adj R-squared	=	0.1950
Root MSE	=	1.21

GC	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
FT	1.092254	.5101663	2.14	0.034	.0857261	2.098782
SIZE	.0643711	.0376851	1.71	0.089	-.0099794	.1387216
EM	.1231898	.0214551	5.74	0.000	.0808602	.1655193
NIIR	-2.921934	.8159332	-3.58	0.000	-4.531722	-1.312147
_cons	5.225953	.885382	5.90	0.000	3.479146	6.972759

```
.
. vif
```

Variable	VIF	1/VIF
NIIR	1.11	0.899738
FT	1.10	0.910051
EM	1.06	0.942550
SIZE	1.05	0.949611
Mean VIF	1.08	

```
. xtreg GC FT SIZE EM NIIR, fe

Fixed-effects (within) regression               Number of obs     =        189
Group variable: Code                            Number of groups  =         27

R-squared:                                      Obs per group:
     Within  = 0.1665                                         min =          7
     Between = 0.1976                                         avg =        7.0
     Overall = 0.1423                                         max =          7

                                                F(4,158)          =       7.89
corr(u_i, Xb) = 0.1593                          Prob > F          =     0.0000
```

GC	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
FT	1.245604	.3313578	3.76	0.000	.5911414	1.900066
SIZE	.0795066	.0245683	3.24	0.001	.0309819	.1280314
EM	.0396618	.0232379	1.71	0.090	-.0062351	.0855588
NIIR	-.9118896	.6669739	-1.37	0.174	-2.229224	.4054453
_cons	6.085625	.6430917	9.46	0.000	4.815459	7.35579
sigma_u	1.0992243					
sigma_e	.70683342					
rho	.7074704	(fraction of variance due to u_i)				

```
F test that all u_i=0: F(26, 158) = 14.66                    Prob > F = 0.0000
```

```
. xtreg GC FT SIZE EM NIIR, re

Random-effects GLS regression                   Number of obs     =        189
Group variable: Code                            Number of groups  =         27

R-squared:                                      Obs per group:
     Within  = 0.1639                                         min =          7
     Between = 0.2353                                         avg =        7.0
     Overall = 0.1729                                         max =          7

                                                Wald chi2(4)      =      35.47
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0000
```

GC	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
FT	1.246272	.3289585	3.79	0.000	.6015249	1.891019
SIZE	.078884	.0244536	3.23	0.001	.0309557	.1268122
EM	.0560296	.0216741	2.59	0.010	.013549	.0985101
NIIR	-1.188921	.6487372	-1.83	0.067	-2.460422	.0825806
_cons	5.859576	.6577886	8.91	0.000	4.570334	7.148818
sigma_u	1.0280057					
sigma_e	.70683342					
rho	.67899605	(fraction of variance due to u_i)				

```
. hausman fe re

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |       fe           re         Difference       Std. err.
-------------+----------------------------------------------------------------
          FT |    1.245604     1.246272        -.000668        .0398035
        SIZE |    .0795066      .078884        .0006227        .0023713
          EM |    .0396618     .0560296       -.0163677        .0083804
        NIIR |   -.9118896    -1.188921        .2770313        .1549009
------------------------------------------------------------------------------
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(4) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =   5.39
Prob > chi2 = 0.2499
(V_b-V_B is not positive definite)
```

```
. xttest0

Breusch and Pagan Lagrangian multiplier test for random effe

        GC[Code,t] = Xb + u[Code] + e[Code,t]

        Estimated results:
                         |       Var     SD = sqrt(Var)
                ---------+-----------------------------
                      GC |   1.81884       1.348644
                       e |  .4996135       .7068334
                       u |  1.056796       1.028006

        Test: Var(u) = 0
                             chibar2(01) =   215.54
                          Prob > chibar2 =   0.0000

.
. xtserial GC FT SIZE EM NIIR

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      26) =     22.904
           Prob > F =      0.0001
```


```
. xtserial GC FT SIZE EM NIIR

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      26) =     22.904
           Prob > F =      0.0001
```

```
.
. xtgls GC FT SIZE EM NIIR, corr(ar1) panels(h) force

Cross-sectional time-series FGLS regression

Coefficients:  generalized least squares
Panels:        heteroskedastic
Correlation:   common AR(1) coefficient for all panels  (0.7087)

Estimated covariances      =        27          Number of obs     =        189
Estimated autocorrelations =         1          Number of groups  =         27
Estimated coefficients     =         5          Time periods      =          7
                                                Wald chi2(4)      =      19.46
                                                Prob > chi2       =     0.0006

------------------------------------------------------------------------------
          GC | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
          FT |   .5623673   .2426853     2.32   0.020     .0867128    1.038022
        SIZE |   .0293224   .0138701     2.11   0.035     .0021376    .0565072
          EM |   .0470026    .016059     2.93   0.003     .0155275    .0784776
        NIIR |  -.9112041   .3803289    -2.40   0.017    -1.656635   -.1657731
       _cons |   7.383295     .43147    17.11   0.000     6.537629     8.22896
------------------------------------------------------------------------------
```

```
. esttab ols fe re, star(* 0.1 ** 0.05 *** 0.01)
```

	(1) GC	(2) GC	(3) GC
FT	1.092**	1.246***	1.246***
	(2.14)	(3.76)	(3.79)
SIZE	0.0644*	0.0795***	0.0789***
	(1.71)	(3.24)	(3.23)
EM	0.123***	0.0397*	0.0560***
	(5.74)	(1.71)	(2.59)
NIIR	-2.922***	-0.912	-1.189*
	(-3.58)	(-1.37)	(-1.83)
_cons	5.226***	6.086***	5.860***
	(5.90)	(9.46)	(8.91)
N	189	189	189

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01