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The Impact of Financial Technology on Green Credit: An Empirical Analysis Based on Commercial Banks

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Abstract: This study explores how financial technology influences green credit operations in China's commercial banks, using data from over 30 listed banks (2011–2021) and a financial technology development index built with text mining. Financial technology enhances green credit by optimizing resource allocation, directing funds to environmentally compliant projects, and improving risk assessment with big data and AI, thereby lowering bad loan ratios. It also increases efficiency through automation and faster approvals, shortening credit cycles. Bank operating conditions significantly impact these benefits, highlighting financial technology's role in mitigating risks and driving China's green economic transformation.

Keywords: financial technology, green credit, commercial banks, risk management.

1. Introduction

The Chinese government prioritizes ecological issues, with "dual carbon" goals central to the 14th Five-Year Plan, positioning green development as a national strategy. As a key economic driver, China's bank-dominated financial system supports sustainability through green credit, though challenges such as unclear credit boundaries and limited engagement remain. Emerging technologies like AI, big data, and blockchain present opportunities for improvement.

The "Financial Technology Development Plan (2019–2021)" underscores fintech's role in enhancing financial institutions' operations and competitiveness. In 2021, major banks like China Bank and Agricultural Bank of China saw significant investments in fintech and green credit growth. Industrial Bank's "Green to Gold" platform demonstrates fintech's effectiveness in identifying green projects, assessing asset values, and managing environmental risks, contributing to rapid green credit expansion.

This study uses data from 36 listed Chinese commercial banks (2011–2021) to construct a fintech development index via text mining and analyze its impact on green credit. Results show that higher fintech levels are linked to larger green credit scales, influenced by bank performance.

Key contributions include the use of a large, representative dataset, enhancing research reliability and generalizability, and a detailed analysis of fintech's role in advancing green credit. Fintech helps identify risks, improve efficiency, and drive green business growth.

This study bridges gaps in existing research, which often overlook fintech's impact on green credit in commercial banks. By analyzing fintech development, its impact on green credit, and the moderating role of bank performance, the research provides empirical evidence for integrating fintech with green finance to foster sustainable economic growth.

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2. Literature Review and Hypothesis Proposal

2.1. Research on the Impact of Financial Technology on Commercial Bank Activities

First, financial technology plays an important role in risk control through big data and artificial intelligence technologies. It can comprehensively capture and analyze the data required to assess risks, building credit assessment models that lower the risk assessment costs for commercial banks and mitigate information asymmetry, thereby enhancing banks' risk-bearing capacities[1]. Second, the empowerment of financial technology has also improved commercial banks' assessment capabilities for enterprises, particularly in covering small and medium-sized clients, which helps expand the scale of loans and enhance liquidity creation capabilities[2].

2.2. Research on Financial Technology and Green Finance

Existing research on fintech and green finance largely focuses on theoretical aspects. According to the Paulson Institute's 2023 report, China leads the global green credit market and ranks second in green bonds. Fintech is increasingly integrated into green finance, driving innovation in areas like green credit, ESG investments, transition finance, and carbon asset management.

Based on this, we propose Hypothesis 1: Higher financial technology development in commercial banks promotes larger green credit scales by enhancing risk assessment, expanding credit access, and improving efficiency.

2.3. Research on Green Credit in Commercial Banks

Green finance involves financial activities for environmental protection and climate change mitigation. Key factors in green credit issuance include borrowers' environmental responsibility, information disclosure, and the relationship between green credit and bank performance. Local policies and officials also play a role. While research has focused on enterprises and government, less attention has been given to how internal bank factors, particularly fintech, influence green credit, underscoring the need for further exploration.

Hypothesis 2: Commercial banks' operating conditions, including profitability, liquidity, and asset size, moderate the impact of fintech on green credit development.

3. Research Design

3.1. Research Sample and Data Processing

This study focuses on 36 listed commercial banks in China from 2011 to 2021. The data for the financial technology development level was obtained through text analysis of annual reports; the balance of green credit data was sourced from the Guotai An database, while operational data of commercial banks also came from this database. Some missing data were manually supplemented using annual reports and social responsibility reports from each commercial bank. Furthermore, to mitigate the influence of extreme values on the empirical results, a two-sided 1% winsorization was applied to all continuous variables, resulting in a total of 207 observations for the 36 commercial banks from 2011 to 2021.

3.2. Variable Definitions

3.2.1. Green Credit

The measurement of green credit is based on the logarithm of the balance of green credit (GC).

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3.2.2. Financial Technology Development Level

The academic literature presents three main methods for calculating the financial technology development level:

The primary method relies on the Digital Inclusive Finance Index, created by the Peking University Digital Finance Research Center[4]. The second method assesses the level of financial technology development in regions by counting the number of local financial technology companies, as demonstrated by Song Min[5].The third method employs text mining techniques to measure financial technology development levels through the search results of relevant keywords[6].

However, the first two measurement methods are primarily utilized for macro-level research at the national or provincial level. In contrast, the financial technology index constructed through text mining is more suitable for micro-level analyses of commercial banks (including publicly listed companies). Consequently, this study adopts the methodology[7]. By applying machine learning and text mining techniques, this study extracts the frequency of 124 financial technology keywords related to six dimensions. The results are then logarithmically transformed to determine the financial technology development level for each commercial bank in each year.

Table 1: Financial Technology Keyword Database

Dimension	Keywords Related to Financial Technology
Artificial Intelligence	Artificial intelligence, machine learning, deep learning, neural networks, facial recognition, biological recognition, voice recognition, image recognition, facial payment, virtual reality, augmented reality, knowledge graph, smart payment, smart lending, smart contract, smart loans, smart credit, smart wealth management, smart banking, intelligent finance, intelligent automation, natural language processing
Blockchain	Blockchain, distributed ledger, supply chain, Internet of Things, proximity, chip, quantum communication, data encryption, digital currency, and electronic currency
Cloud Computing	Distributed, distributed storage, distributed structure, distributed database, financial cloud, trusted computing, cloud terminal, cloud services, cloud service platform, virtualization, cloud computing, cloud architecture, cloud platform, cloud system, and cloud exchange
Big Data	Big data, big data analysis, big data services, big data platform, big data mining, big data database, big data technology, big data management, data center, digital signature, digital contract, digital credit card, digital banking, and digital marketing
Online Services	Electronic, electronic finance, electronic banking, electronic commerce, e-banking, electronic payment, Internet, Internet finance, fintech, digital technology, online finance, online management, online lending, online marketing, online banking, online payment, online credit, and online and offline integration
Mobility	Scenario-based, scenario finance, API, open platform, open banking, platformization, development tools, mobile banking, mobile payment, QR code payment, mobile e-commerce, mobile internet, mobile finance, mobile payment, digital wallet, app development interface, and direct banking

3.2.3. Control Variables

Drawing from prior studies, this research posits that the operational features of commercial banks might influence green credit levels. Variables considered include return on assets (ROA) for profitability, liquidity ratio (LDR) for liquidity, total assets logarithm (TC), capital adequacy ratio (CAR), and non-performing loan ratio (NPL). Table 2 details these variables.

3.2.4. Model Construction

According to the previous analysis, to search the association between the development level of financial technology and green credit in commercial banks, this paper designs the following model, where GCi;t is the logarithm of the green credit balance of bank i in year t, FINTECH_{i,t}is the financial technology development level of bank i in year t, Control_{i,t}represents control variables, andε²i;t is the error term. The paper mainly concentrates on the result of the coefficientβ1. If β1 is significantly greater than 0, it indicates that the development level of fintech positively impacts the scale of green credit business, thereby confirming Hypothesis 1. If γ is significantly different from 0, it suggests that the operational status of commercial banks has a corresponding influence on green credit, thereby confirming Hypothesis 2.

$$\mathrm{LnGCi,t} = \beta 0 + \beta 1\mathrm{FT1,t} + \varepsilon 2\mathrm{i,t}$$

4. Empirical Results Analysis

4.1. Hierarchical regression

Hierarchical regression was used to assess the impact of control variables and financial technology on green credit.

As shown in Table 2, after adding control variables, the coefficient of the financial technology development index is 1.698, significant at the 1% level, confirming that higher fintech levels correlate with larger green credit scales, thus supporting Hypothesis 1. Additionally, the R^2 increased from 0.202 to 0.295, indicating that financial technology explains additional variance and demonstrates its potential contribution.

Among the control variables, the return on assets (ROA) shows a significant negative coefficient of -3.4, suggesting that higher ROA is associated with smaller green credit scales. This may be due to the higher capital costs and risks of green credit, which may deter banks with high ROA from investing in it. The loan-to-deposit ratio (LDR) is also negatively correlated with green credit, as banks with higher liquidity may prefer short-term, liquid investments over long-term green credit projects. Additionally, both total assets (LnTC) and the capital adequacy ratio (CAR) are significant at the 1% level.

These results highlight that commercial banks' operational characteristics significantly affect the scale of green credit, supporting Hypothesis 2.

Table 2: Regression result

Without FT		WITH FT	
Variable	Coefficient	VARIABLES	Coefficient
Constant	-4.4438 (0.004)	Constant	-10.68***(1.794)
LDR	-0.9174 (0.338)	LDR	-1.975**(0.987)
NPL	4.2930 (0.609)	NPL	3.409(7.840)
ROA	-2.3052 (0.000)	ROA	-3.400***(0.572)

Table 2: (continued).

TC	2.247e-06 (0.222)	lnTC	-0.713***(0.202)
CAR	33.6197 (0.000)	CAR	31.92***(6.681)
		FT	1.698***(0.361)
Observations	207	Observations	207
R-squared	0.202	R-squared	0.295

4.2. Endogeneity Test

Green credit policies often exhibit some degree of persistence over time, meaning the current scale of green credit is likely influenced by the previous period's green credit scale. To eliminate the endogeneity problem caused by this influence, this paper adds a lagged dependent variable (L.LnGC) to the original model. Displayed in the table below, the coefficient of the financial technology development index, following the analysis, is revealed to be 2.415, which is affirmative at the 1% level of significance. This signifies that, notwithstanding the temporal correlation of the green credit volume, the affirmative influence of financial technology on the scale of green credit continues to hold.

Table 3: GMM Regression results

VARIABLES	lnGC
L.lnGC	-0.437***(0.0685)
FT	2.415**(1.150)
LDR	-4.132***(1.562)
NPL	-2.576(12.43)
ROA	-5.480***(0.990)
lnTC	-1.133*(0.631)
CAR	41.73**(16.70)
Constant	-11.72***(3.957)
Observations	166
Number of id	30

Table 4: Robustness test

VARIABLES	lnGC
FT	1.708***(0.360)
LDR	-1.912*(0.975)
ROA	-3.398***(0.570)
lnTC	-0.725***(0.200)
CAR	32.26***(6.624)
Observations	207
R-squared	0.294

4.3. Robustness Test

A robustness test was conducted by removing the control variable NPL and using the same model as in the baseline regression(Table 4).The coefficient of the core explanatory variable (1.708) remains significant at the 1% level, consistent with the baseline regression, indicating that the removal of NPL does not affect the sign or significance of the fintech (FT) coefficient. The coefficients of other variables also retain their signs and significance, confirming the robustness of their effects. Furthermore, the R-squared value (0.295) remains unchanged, indicating the model's explanatory power is stable. These results demonstrate that the core explanatory variable's impact remains robust, and the control variables' effects are consistent, verifying the reliability of the baseline regression results and their independence from NPL.

5. Conclusion and Implications

5.1. Conclusion

From 2011 to 2021, using information from 36 listed Chinese commercial banks, this study examines the effect of financial technology on green credit operations. The results show that higher fintech

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levels in banks are linked to more extensive green credit operations, with the operational state of banks also influencing green credit development.

5.2. Policy Implications

The government should encourage commercial banks to invest more in fintech, using technologies like data mining, AI, and blockchain to better identify green projects, assess green assets, and monitor environmental risks, thus reducing costs and improving efficiency. It could also create a green credit platform to integrate data and provide technical support to banks, reducing information asymmetry.

Commercial banks should fully integrate fintech into green credit, developing risk models, databases, and products to promote the fusion of green finance and fintech.

In terms of regulation, the government should establish a clear green credit evaluation system and provide policy guidance. Incentives like tax breaks, subsidies, and risk compensation could encourage banks to offer green credit, reducing operational risks. Stronger supervision is needed to prevent "greenwashing" and ensure funds are used for legitimate green projects.

Finally, the government should support green industries and innovation to stimulate green credit demand and attract more investment in sustainable projects.

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