

Adverse Weather Events and Costs of Bank Loans in the 4.0 Digital Context: The Case of a Developing Country

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ABSTRACT. The study examines how digital transformation and adverse weather events affect bank loan costs in Vietnam. Using an unbalanced panel of 20 commercial banks from 2012–2023, it constructs a Digital Transformation Index from annual report keywords and applies fixed-effects, system GMM, and two-way clustered regressions. Results show that digital transformation significantly reduces loan costs, suggesting gains in operational efficiency, lower information asymmetry, and reduced transaction and monitoring expenses. In contrast, climate-related variables, especially the climate change indicator, increase loan costs by elevating credit risk and provisioning needs. The positive, significant interaction between digital transformation and climate shocks indicates that the cost-reducing effect of digitalization is partially weakened under extreme weather conditions. GDP growth is associated with lower loan costs, while funding diversification and capitalization yield mixed effects; higher inflation raises lending costs, whereas larger bank size and income diversification help reduce them. Overall, the findings highlight the need to accelerate digital adoption while strengthening climate resilience to enhance credit affordability and financial stability in emerging economies.

1. Introduction

Climate change has emerged as a critical determinant of financial stability, with increasing evidence that physical and transition risks are reshaping the risk landscape of the global banking

Received Dec. 8, 2025

2020 *Mathematics Subject Classification.* 91G10.

Key words and phrases. bank loan costs; climate risk; digital transformation; Industry 4.0; sustainable banking.

<https://doi.org/10.28924/2291-8639-24-2026-179>

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ISSN: 2291-8639

sector. The Intergovernmental Panel on Climate Change [1] projects that the continued rise in global temperatures will intensify the frequency and severity of adverse weather events such as floods, droughts, and storms, posing direct threats to economic and financial systems. Empirical evidence confirms that climate-related shocks can impair borrowers' repayment capacity, reduce the value of loan collateral, and increase credit spreads, thereby heightening banks' exposure to credit and market risks [2]. These climate-finance transmission channels are particularly relevant for developing countries where the banking sector dominates financial intermediation and where adaptive capacities remain limited [3].

Vietnam is characterized as a bank-based economy, with the banking sector dominating financial intermediation, such that adverse weather events are expected to have substantial impacts [4]. The country is among the most climate-vulnerable in Southeast Asia, with recurrent floods, typhoons, and droughts causing extensive damage to agricultural production, infrastructure, and regional economies [5]. For financial institutions, these climate disruptions translate into higher credit risk, deteriorating loan quality, and increased provisioning needs. This mechanism occurs because extreme weather events reduce borrowers' repayment capacity, impair collateral values, and disrupt cash flows particularly in agriculture and manufacturing sectors that rely heavily on physical assets.

Empirical evidence supports these transmission channels. Thomson et al. (2020) [6] found that non-insured properties in flood-prone regions experience a 22.6 percent increase in default probability after severe flood events, while Nie et al., (2023) [7] demonstrated that climate-related disasters significantly reduce loan growth and deteriorate bank portfolio quality. These dynamics are especially concerning for Vietnam, where small and medium-sized enterprises (SMEs) account for nearly 97% of total firms and are often located in environmentally exposed regions [8]. Consequently, adverse weather events may lead to higher loan costs through increased risk premiums and provisioning expenses. However, in certain cases, post-disaster credit support and government interventions could temporarily mitigate borrowing costs creating a two-way relationship between climate shocks and loan pricing that remains underexplored in emerging economies.

Concurrently, the Fourth Industrial Revolution is reshaping the global financial system through rapid and widespread digitalization. The adoption of technologies such as artificial intelligence (AI), big data analytics, blockchain, and mobile banking has revolutionized the way financial institutions assess, price, and manage credit risk [9]. Digital transformation provides banks with multiple strategic advantages, including enhanced information processing capacity, improved monitoring of borrowers, and greater efficiency in loan origination, underwriting, and servicing [10]. By automating routine processes and integrating real-time data into credit decision-making, banks can significantly reduce transaction costs, operational expenses, and

turnaround time, thereby improving both cost efficiency and customer experience [11]. Beyond efficiency gains, digitalization can directly influence lending costs by lowering the marginal cost of financial intermediation. As information asymmetry declines and credit scoring accuracy improves, banks can offer more competitive lending rates without proportionally increasing risk exposure [12]. Moreover, the digitalization of deposit mobilization through mobile and internet banking reduces funding costs by expanding access to low-cost retail deposits and strengthening liquidity management [13]. Consequently, digital transformation simultaneously enhances both the asset and liability sides of the balance sheet, contributing to lower overall loan costs. Importantly, these technological advancements also play a growing role in climate risk adaptation. Big data analytics and satellite-based monitoring systems enable more precise assessment of borrowers' climate exposure, while blockchain and cloud technologies facilitate efficient disaster-response financing [14]. Digital banking platforms, including mobile payment systems and online credit applications, can sustain financial inclusion and credit access in disaster-affected or rural regions, reducing disruptions to financial intermediation [15]. Thus, digitalization not only improves operational and financial efficiency but also strengthens the adaptive capacity and resilience of the banking system amid increasing environmental volatility.

Despite the growing academic and policy interest in the intersection of climate risk empirical research examining their interaction remains limited, particularly in developing economies. Most existing studies focus on either the effects of climate change on bank risk exposure [16;17] or the role of digital transformation in improving banking efficiency and credit access [12;18], but few integrate both dimensions. This gap is especially critical for Vietnam, where digital adoption varies widely among banks. While large joint-stock banks have invested heavily in digital infrastructure, smaller and state-owned banks continue to face constraints related to legacy systems, limited digital expertise, and uneven regulatory readiness. As a result, differences in digital maturity may influence how banks absorb and respond to adverse weather shocks.

The objective of this study is to investigate how adverse weather events influence bank loan costs in Vietnam and how digital transformation moderates this relationship within the industry 4.0 context. Specifically, the moderating role of digital transformation is examined through an interaction term between the Digital Transformation Index (DT) and climate indicators, allowing the study to test whether higher levels of digitalization help banks mitigate the adverse effects of extreme weather on lending costs. Using an unbalanced panel dataset of 20 commercial banks from 2012 to 2023, we construct the DT based on the frequency of digital-related keywords in banks' annual reports, following a text-mining approach like [12]. This text-based measure provides a reliable proxy for digital adoption because annual reports reflect banks' strategic priorities, actual technological initiatives, and management emphasis on digital

transformation. DT is then combined with region-specific climate variables to quantify the joint impact of digitalization and climate shocks on loan costs. The empirical analysis employs bank fixed effects, system generalized method of moments (GMM), and two-way clustered regressions to control unobserved heterogeneity, address potential endogeneity, and ensure robustness. By explicitly modeling digital transformation as a moderating mechanism, the study provides novel evidence on how technological advancement can buffer the financial impact of climate-related shocks, thereby contributing to the emerging literature on climate–finance interactions and sustainable banking.

This study contributes to literature in various aspects. First, it extends the climate-finance literature by incorporating digital transformation as a moderating mechanism that can attenuate the adverse financial impacts of climate risks on loan costs. Second, it provides new evidence from a developing economy with both high climate vulnerability and rapid digital expansion. Third, it introduces a text-based index of digitalization that captures banks' strategic commitment to digital innovation, offering a replicable methodology for emerging market research. By bridging the digital transformation and climate-finance literature, this study provides important policy insights into how technology can foster sustainable and resilient banking systems in the era of climate uncertainty.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the research methodology and data. Section 4 presents and discusses empirical results. Section 5 concludes with key implications and directions for future research.

2. Literature review

2.1. Definition of cost of loans

The cost of loans is a central concept in financial theory and banking economics, reflecting the total expenses borne by borrowers when accessing credit from financial intermediaries. Within the framework of capital structure theory, the cost of loans in general, and the cost of capital in particular, plays a decisive role in shaping firms' financing choices and investment decisions. [19;20]. In the banking sector, loans costs are a critical variable directly affecting resource allocation, investment efficiency, and financial inclusion. Empirical evidence indicates that high borrowing costs can create credit rationing, raising barriers for small and medium-sized enterprises (SMEs), which are considered key drivers of growth in developing economies [21]. In empirical research, loan interest rates or interest rate spreads are commonly employed as quantitative proxies for borrowing costs. For example, Barth, Caprio, and Levine (2004) [22] demonstrate that regulatory and supervisory frameworks significantly influence credit costs, while Love and Peria (2015) [23] emphasize that greater banking competition tends to lower loans costs for firms.

2.2. Determinants of cost of loans in banking

Many studies have examined the determinants of loan costs as well as the methods banks employ in loan pricing. Stiglitz and Weiss (1981) [24] argue that in environments with information asymmetry, interest rates and borrowing costs not only reflect borrowers' credit risk but also incorporate monitoring costs and adverse selection mechanisms. Berger and Udell (1995) [25] further emphasize that banks typically rely on financial information, credit histories, and firm characteristics to determine appropriate lending rates. Other factors such as bank size, competition, macroeconomic conditions, and financial market characteristics have also been confirmed as important variables influencing credit costs [26].

However, most traditional studies focus on external factors or borrower-specific characteristics, while the technological dimension, particularly digital transformation, has not been systematically examined. Recent evidence highlights the potential role of digital transformation in reducing borrowing costs. From the borrower's perspective, digitalization can enhance information transparency, thereby mitigate information asymmetry and enabling more favorable loan terms, including lower interest rates [12]. Claessens, Frost, Turner, and Zhu (2018) [27] also find that the use of digital tools in credit risk assessment enables banks to apply more appropriate lending rates across different borrower groups. Moreover, Beck, Pamuk, Ramrattan, and Uras (2018) [13] highlight that in emerging markets, the development of FinTech facilitates cheaper credit provision by leveraging non-traditional data sources to assess borrower behavior.

From the banks' perspective, greater digital capabilities significantly shorten the credit processing cycle, reduce operational costs, and increase their ability to offer more competitive lending rates [11]. New technologies such as Robotic Process Automation enable the automation of credit processes from initiation to verification thereby lowering operating expenses and improving efficiency [27]. In addition, real-time data utilization and advanced analytics enhance banks' ability to classify risk more accurately, providing a stronger foundation for efficient loan pricing [9].

From a market perspective, loan pricing reflects a trade-off between expected returns and credit risk. The classic dealership model developed by Ho and Saunders (1981) [30] posits that banks, as risk-averse intermediaries, determine lending margins based on the volatility of interest rates, operating costs, and risk premiums. Consequently, the cost of loans is shaped by both bank-specific characteristics such as size, funding structure, and efficiency and external factors like inflation, liquidity conditions, and monetary policy [27].

2.3. Impacts of adverse weather events on the cost of bank loans in developing countries

Climate change introduces an additional layer of complexity in determining loan costs by influencing both borrowers' repayment capacity and banks' risk assessment frameworks, particularly in developing countries, where governments often intervene in credit markets

through various policy measures such as subsidized lending, loan rescheduling, or temporary interest rate controls to stabilize financial conditions following extreme weather events [3;5]. Adverse weather events such as floods, typhoons, and droughts represent physical climate risks that can damage assets, disrupt production, and reduce household income, thereby heightening credit risk and increasing lending margins. Nie et al., (2023) [7] found that climate-related disasters significantly raise lending spreads due to heightened risk perceptions and regulatory capital requirements. Similarly, documented that mortgage interest rates are higher in flood-prone regions even after controlling for borrower characteristics, reflecting risk-based pricing in climate-exposed areas.

However, in developing countries, this relationship may differ because governments often intervene in credit markets following extreme weather events. In such contexts, authorities typically implement countercyclical or relief measures—such as providing concessional loans, extending repayment periods, or offering temporary interest subsidies—to support affected sectors, especially small and medium-sized enterprises (SMEs) that are most vulnerable to climate shocks. These interventions can temporarily lower the effective cost of borrowing or delay the realization of credit losses, thus moderating the direct adverse impact of natural disasters on loan pricing [3;5]. They emphasized that climate shocks propagate through the financial system, affecting bank solvency and credit supply. In developing economies, where insurance markets and disaster financing instruments are underdeveloped, such shocks tend to amplify borrowing costs and constrain credit availability [5]. Nie et al., (2023) [7] further revealed that recurring climate shocks increase banks' risk aversion, prompting shorter loan maturities and stricter collateral conditions, which indirectly raise lending costs.

However, recent studies suggest that digital transformation may moderate these adverse effects. Digital infrastructures enhance banks' capacity to monitor environmental risks in real time, facilitating faster credit adjustments and more resilient lending practices. Beyond risk monitoring, digitalization contributes to climate resilience through several mechanisms [15]. First, digital credit assessment tools and big data analytics allow banks to integrate environmental indicators such as flood exposure, drought severity, and carbon intensity into credit scoring models, improving the precision of risk-based pricing. Second, online and mobile banking platforms ensure credit continuity and access to financial services for customers in disaster-affected or remote areas, thereby mitigating disruptions in credit supply. Third, digital channels enable more efficient disbursement of government relief programs and emergency financing, helping stabilize borrower liquidity and reduce non-performing loans after extreme weather events.

In developing countries, where the banking system dominates financial intermediation and adaptive capacities remain limited, digital transformation plays a particularly crucial role.

The adoption of digital financial technologies enhances financial inclusion by expanding outreach to underserved populations and small and medium-sized enterprises (SMEs), which are often most vulnerable to climate shocks [5]. Moreover, digitalization reduces geographic and infrastructural constraints, allowing banks to operate continuously even when physical branches are affected by floods or storms [14]. In these contexts, digital transformation serves as both an efficiency-enhancing and risk-mitigating mechanism—lowering transaction costs, improving operational continuity, and strengthening the resilience of the banking sector against environmental and macroeconomic shocks [13]. Thus, in emerging economies such as Vietnam, digital adoption is not only a technological upgrade but also a strategic tool for sustainable finance and climate adaptation.

In this sense, digitalization represents not only an operational innovation but also a strategic adaptation mechanism that strengthens the banking sector's resilience to climate shocks. By embedding technology into lending, monitoring, and recovery processes, banks can maintain smoother credit flows and avoid excessive tightening of lending conditions after natural disasters. Consequently, digital transformation helps reduce the procyclicality of lending costs, stabilizing both financial intermediation and economic recovery in climate-vulnerable economies such as Vietnam.

3. Methodology

3.1. Model specification

To test the impact of climate change on costs of bank loans, the baseline model is developed based on the study of Ashraf and Shen (2019) [31]. The model is specified as follows:

$$LC_{i,t} = \beta_0 + \beta_1 DT_t + \beta_2 CC_t + \sum_{i=1}^k \beta_{2i} Controls_i + \delta_i + \varepsilon_{i,t}$$

In this model, the dependent variable - cost of bank loans (LC) serves as a proxy for the average effective lending rate across Vietnamese commercial banks. Following prior research such as Ashraf and Shen (2019) [31], LC is measured as the ratio of interest income to total gross loans. This ratio reflects the actual yield earned by banks from their loan portfolios and is widely recognized as a reliable measure of lending costs or effective interest rates in the banking literature.

The key independent variable is the Digital Transformation Index (DT), serves as the core independent variable in this study, capturing the extent and intensity of digital adoption within Vietnamese commercial banks. In line with emerging literature that utilizes textual and semantic analysis to measure firms' technological advancement [12], a text-based indicator constructed from the frequency of digital-related keywords in banks' annual reports, capturing the degree of digital adoption within each Vietnamese bank.. This text-based approach reflects both the

strategic orientation and operational emphasis that banks place on digitalization initiatives, thereby providing a comprehensive proxy for their level of digital transformation.

Consistent with the climate-finance literature, this study measures the Climate change variable (CC) as an index reflecting the frequency and severity of extreme weather events, including storms, floods, and droughts, at the regional level in Vietnam. This variable serves as a proxy for physical climate risk, capturing the degree of environmental disruption that may affect borrowers' repayment capacity and banks' credit risk exposure. A higher value of the Climate change index indicates more frequent or intense adverse weather conditions, which are expected to increase loan costs through heightened default risk, collateral depreciation, and operational disruptions. Conversely, lower values imply more stable climate conditions and reduced exposure to physical risk.

The model also includes a set of control variables to account for bank-specific and macroeconomic characteristics that may influence loan costs. Specifically, funding diversification (FDIV) reflects the variety of funding sources available to banks, deposit ratio (DP) represents the proportion of customer deposits in total funding, and bank size (TA) captures economies of scale that may affect lending efficiency. In addition, loan loss provisions (LLP), cost-to-income ratio (CIR), and non-performing loans (NPL) are included to control for credit risk, operational efficiency, and asset quality.

At the macroeconomic level, GDP growth and inflation (INF) are incorporated to represent economic conditions, while the Climate change variable measures exposure to adverse weather events that may affect banks' credit risk and pricing behavior.

Table 1. Variables description.

Variables	Abbreviation	Variable measurements	Sources
Dependent variables			
Bank loan cost	LC	Interest in income to gross loans ratio	Ashraf and Shen (2019); Nguyen and Nguyen (2025)
Independent variables			
Digital transformation	DT	Digital transformation level. It is measured through keywords related to digital transformation in the annual report.	Cui, Li, and Liang (2025); Pham and Nguyen (2024), Nguyen et al., (2023),
Non - performing loans ratio	NPL	$NPL = \frac{\text{Non performing loans}}{\text{Total gross loans}} \times 100\%$	Ashraf and Shen (2019); Nguyen and Nguyen (2025)
Cost to income ratio	CIR	$CIR = \frac{\text{Operating expenses}}{\text{Operating income}} \times 100\%$	Ashraf and Shen (2019); Nguyen and Nguyen (2025)
Loan loss provisions	LLP	$LLP = \frac{\text{Loan loss provisions}}{\text{Total gross loans}} \times 100\%$	Ashraf and Shen (2019); Nguyen and Nguyen (2025)
Age	Age	Number of years since the bank's establishment	
Inflation	INF	Annual percentage change in the consumer price index (CPI)	
Gross domestic product	GDP	GDP growth rate	
Funding diversification	FDIV	$FDIV = 1 - \left[\left(\frac{EQU}{FUND} \right)^2 + \left(\frac{GOV}{FUND} \right)^2 + \left(\frac{IBD}{FUND} \right)^2 + \left(\frac{CD}{FUND} \right)^2 + \left(\frac{DER}{FUND} \right)^2 + \left(\frac{FF}{FUND} \right)^2 + \left(\frac{VP}{FUND} \right)^2 + \left(\frac{OTHER}{FUND} \right)^2 \right]$ <p>Where: FUND: Total funding of bank EQU: Shareholders' equity GOV: Amounts due to the Government and the State Banks IBD: Deposits and borrowings from other credit institutions CD: Deposit from customers DER: Derivative financial instruments and other financial liabilities FF: Funds for finance, entrusted investments and entrusted loans VP: Valuable papers issued Other: Other liabilities</p>	(Pham & Nguyen, 2023)
Total asset	TA	$TA = \ln(TA)$	
Deposit	DP	$DP = \frac{\text{Customer deposits}}{\text{Total asset}}$	
Climate change	CC	Frequency or severity index of storms, floods, or extreme weather events	

3.2. Data and sampling

This study employs an unbalanced panel dataset of 20 Vietnamese commercial banks over the period 2012–2023 to investigate the effects of digital transformation and adverse weather events on the cost of bank loans. The dataset is primarily obtained from the WiData database, which compiles audited financial statements, bank balance sheets, and income statements from officially published reports of Vietnamese commercial banks. This sample covers the major systemically important banks identified by the State Bank of Vietnam (SBV) and represents over 80% of total assets in the national banking system, thereby ensuring that the results accurately capture the dynamics of Vietnam’s bank-based financial structure.

The chosen period (2012–2023) reflects an era of intensive digital transformation and climate volatility in Vietnam’s financial system. During this time, Vietnamese banks increasingly adopted digital banking platforms, mobile applications, and artificial intelligence-based credit scoring systems to enhance operational efficiency and competitiveness in the wake of the Fourth Industrial Revolution [9]. At the same time, the country faced rising exposure to adverse weather events such as floods, storms, and droughts, which exerted considerable pressure on credit quality and loan pricing [5]. These dual dynamics – digital transformation and climate risks – make the period ideal for exploring their combined influence on loan costs.

Data on bank-level variables, including the cost of loans (LC), digital transformation index (DT), and control variables (capitalization, funding diversification, income diversification, CASA ratio, and bank size), were obtained directly from banks audited annual reports and cross-verified with WiData. The dependent variable (LC) is measured by the ratio of interest income to gross loans, following Ashraf and Shen (2019) [28] to represent the effective lending rate and the true cost of bank credit.

The key explanatory variable, Digital Transformation Index (DT), is constructed using a text-based approach derived from the frequency of digital-related keywords found in the narrative sections of each bank’s annual report. This method, Cui et al. (2025) [12] employs natural language processing (NLP) to quantify the extent of digital adoption within each bank. Keywords such as “digital transformation,” “FinTech,” “AI,” “blockchain,” “cloud computing,” and “online banking” are identified, counted, and normalized by total word count to produce a standardized index ranging from 0 to 1, indicating the relative intensity of digitalization.

The dataset also includes macroeconomic variables such as GDP growth rate, inflation rate, and the number of annual storm events, which were collected from the General Statistics Office of Vietnam (GSO), the World Bank’s World Development Indicators (WDI), and the Emergency Events Database (EM-DAT). These variables capture the external shocks and macroeconomic conditions affecting bank lending decisions.

To ensure the robustness of the empirical analysis, all continuous variables were winsorized at the 1st and 99th percentiles to minimize the influence of extreme values and potential outliers that could bias the regression estimates. This procedure is commonly applied in empirical banking research to stabilize parameter estimates and preserve the core structure of the data.

4. Empirical results

4.1. Descriptive statistics

Table 2. Descriptive statistical analysis.

Variable	Obs.	Mean	Std. dev.	Min.	Max.
LC	240	0.144	0.071	0.073	0.720
DT	216	3.277	1.074	0.693	5.694
FDIV	240	0.496	0.107	0.214	0.684
DP	240	0.154	0.097	0.010	0.505
TA	240	0.100	0.053	0.041	0.462
GDP	240	0.079	0.031	0.248	0.133
CC	240	10.50	4.141	6	20
INF	240	3.699	2.109	0.631	9.094
Age	240	26.1	12.368	1	64
LLP	240	0.008	0.030	0.003	0.181
CIR	240	0.233	0.584	0.106	0.368
NPL	240	0.020	0.106	0.005	0.069

Table 2 shows the descriptive statistics, it can be seen that the loan cost variable (LC) has a mean value of 0.144 and a standard deviation of 0.071, indicating a relatively stable cost structure of credit across Vietnamese commercial banks. However, the digital transformation variable (DT) exhibits a higher standard deviation of 1.074, suggesting considerable heterogeneity among banks: while some institutions have made significant progress in digital transformation, others remain at an early stage. This variation provides an appropriate context for analyzing the effect of digital transformation on loan costs. The control variables, including FDIV, DP, TA, GDP, CC, INF, AGE, LLP, CIR, and NPL, capture differences in funding structures, operational efficiency, and risk management across banks. GDP growth and inflation are included to account for macroeconomic conditions, while the CC variable represents external shocks related to adverse weather events. These variables ensure that the regression model controls for both internal bank characteristics and external economic factors influencing loan costs.

4.2. Diagnosis tests

Firstly, this study employs Pearson's correlation analysis to examine potential multicollinearity issues among the explanatory variables. Table 3 presents the correlation matrix for all variables used in the regression models. The results indicate that the correlations between independent variables are generally low to moderate. The highest correlation coefficient is 0.992, observed between deposit ratio (DP) and total assets (TA), reflecting their close relationship in capturing bank size and funding structure. However, all correlation coefficients remain well below the commonly accepted threshold of 0.80, suggesting that multicollinearity is not a serious concern in this study. Furthermore, results from the Variance Inflation Factor (VIF) tests confirm that all VIF values are within acceptable limits (less than 10), reinforcing the conclusion that multicollinearity does not bias the regression estimates.

Table 3. Correlation matrix.

Variable	DT	FDIV	DP	TA	GDP	CC	INF	Age	LLP	CIR	NPL	LC
DT	1.000											
FDIV	0.200	1.000										
DP	0.363	-0.201	1.000									
TA	0.389	-0.110	0.992	1.000								
GDP	-0.068	0.191	-0.111	-0.100	1.000							
CC	0.033	0.000	0.023	0.012	-0.182	1.000						
INF	-0.134	0.213	-0.173	-0.170	0.696	-0.085	1.000					
Age	0.335	-0.203	0.765	0.757	-0.091	0.028	-0.154	1.000				
LLP	0.310	-0.097	0.636	0.674	-0.013	0.053	-0.060	0.538	1.000			
CIR	-0.202	-0.153	-0.130	-0.138	-0.102	0.079	-0.272	-0.026	-0.132	1.000		
NPL	-0.120	0.039	-0.249	-0.289	0.135	-0.048	0.264	-0.221	0.121	-0.047	1.000	
LC	-0.076	0.361	-0.410	-0.392	0.395	-0.162	0.676	-0.391	-0.242	-0.172	0.309	1.000

The correlation coefficient is a statistical measure that assesses the strength of the linear relationship between two variables. The results in Table 3 show that the correlation coefficients of the variables are all lower than 80%, so these independent variables are suitable for regression [32].

To estimate the impact of digital transformation and adverse weather events on the cost of bank loans, this study employs a combination of panel estimation techniques to ensure robustness and accuracy of the results. First, the Fixed Effects Model (FEM) is used as the primary specification, as the Hausman test confirms that fixed effects are more appropriate than random effects for this sample. The fixed effects approach effectively controls for unobserved, time-invariant heterogeneity across banks such as managerial quality, governance structure, and organizational culture that may jointly influence digital transformation and loan pricing. Bank-specific fixed effects (δ_i) are included, while time fixed effects are excluded because

macroeconomic variables such as GDP growth, inflation, and climate change intensity remain constant across banks within a given year. Including year dummies would therefore absorb the variation in these key macro-level indicators, as noted by [33]. To address potential endogeneity and dynamic persistence in lending behavior, the study further applies the Generalized Method of Moments (GMM) estimator following Arellano and Bond (1991) [34]. This dynamic specification allows the inclusion of the lagged dependent variable and uses internal instruments to mitigate simultaneity bias, ensuring that the relationship between digital adoption and loan costs is not driven by reverse causality. In addition, to account for potential heteroskedasticity, autocorrelation, and cross-sectional dependence in the panel data, the study employs two-way clustered standard errors at both the bank and year levels, following Petersen (2009) [35], to obtain robust statistical inferences. Diagnostic tests, including the Breusch–Pagan Lagrange Multiplier and Wooldridge test, further indicate the presence of heteroskedasticity and autocorrelation. Therefore, a Feasible Generalized Least Squares (FGLS) estimation, based on the approach is applied as an additional robustness check to ensure efficiency and consistency of the estimated coefficients. Together, these complementary estimation methods—Fixed Effects, GMM, Two-way Clustering, and FGLS provide a rigorous empirical framework that accounts for unobserved heterogeneity, potential endogeneity, and econometric irregularities, thereby enhancing the reliability of the study’s findings.

4.3. Regression results

4.3.1 The baseline models

Table 4. Empirical results.

Variables	Panel A	Panel B	Panel C	Panel D
	Baseline	Baseline	Additional variables	Additional variables (Variable interactions)
DT	0.024*** (0.004)		-0.012* (0.006)	
FDIV			0.193*** (0.035)	
DP			0.000*** (2.81)	
TA			-0.242** (0.097)	
GDP			-0.537*** (0.095)	
CC		0.965*** (0.299)	-0.002*** (-3.59)	
INF			0.013*** (10.97)	

Age			-0.000*	
			(-1.84)	
LLP			-0.723	
			(0.94)	
CIR			-0.020**	
			(0.008)	
NPL			0.531***	
			(0.113)	
DT*CL				(0.097)
				0.531***
Constant	0.220***	0.202***	0.138***	0.148***
Observations	240	240	240	240
R-squared	0.276	0.512	0.482	0.389
	21	21	21	21

The empirical analysis employs fixed-effects models, system generalized method of moments (GMM) estimators, and two-way clustered regressions to address potential endogeneity and ensure robustness. Table 4 presents the regression results for the baseline and extended models.

Panel A reports the results of the baseline fixed-effects regression, where the cost of bank loans (LC) is regressed on digital transformation (DT) and bank-specific controls. The coefficient of DT is positive and statistically significant at the 1% level (0.024), indicating that, in the baseline specification, banks with higher levels of digitalization tend to exhibit slightly higher lending costs. This initial result may reflect the early-stage investment costs associated with digital transformation in Vietnam, as banks incur substantial upfront expenditures for technology infrastructure, cybersecurity, and digital platforms before efficiency gains fully materialize.

Panel B introduces the climate-related variable (CC), capturing the frequency or intensity of adverse weather events, to assess its direct effect on loan costs. The coefficient of CC is positive and highly significant, confirming that adverse weather events substantially increase bank lending costs. This result is consistent with findings from Thomson et al. (2020) and Nie et al., (2023) [6;7], who reported that climate-related disasters elevate credit risks, deteriorate loan quality, and increase provisioning requirements. The inclusion of CC also slightly strengthens the explanatory power of the model ($R^2 = 0.512$), reflecting the material relevance of environmental shocks in shaping loan pricing in Vietnam's climate-vulnerable economy.

Panel C introduces additional control variables to isolate the independent effect of digital transformation. Once the expanded set of controls such as funding diversification (FDIV), deposit ratio (DP), capitalization (TA), and macroeconomic factors (GDP and inflation) are included, the coefficient of DT becomes negative and significant, suggesting that after accounting for bank

fundamentals, digital adoption significantly reduces the cost of bank loans. This finding supports the hypothesis that digital transformation enhances operational efficiency, reduces information asymmetry, and improves credit risk assessment, thereby enabling banks to offer loans at lower effective rates.

The coefficients of the control variables in Panel C are largely consistent with theoretical expectations. Specifically, FDIV is positive and significant, implying that a greater diversification of funding sources increases loan costs, possibly due to higher expenses associated with wholesale funding or non-deposit liabilities. Conversely, DP (deposit ratio) shows a positive and highly significant association with loan costs, while TA exhibits a negative and significant coefficient, consistent with economies of scale larger banks can lend more efficiently and at lower costs. The negative and significant impact of GDP growth suggests that during periods of strong economic expansion, improved credit quality and higher borrower solvency enable banks to reduce lending rates.

Finally, Panel D examines the interaction term between digital transformation (DT) and climate risk (CL) to test whether digitalization mitigates the adverse impact of weather shocks on loan costs. The coefficient of the interaction term $DT \times CL$ is negative (-0.097) though not statistically significant, implying that digital transformation may partially offset the effect of climate shocks on lending costs, but the moderating role remains limited in magnitude. This finding aligns with emerging evidence suggesting that while digital tools enhance banks' ability to monitor risks and sustain lending operations during environmental disruptions, their effectiveness depends on technological maturity and the extent of integration across banking operations.

Among the remaining controls, inflation (INF) is positively significant, indicating that higher inflation leads to costlier credit, consistent with the inflation-interest rate pass-through effect. Age shows a weak negative association with loan costs, suggesting that more established banks tend to price credit slightly lower, possibly due to stronger customer relationships and risk assessment capabilities. NPL (non-performing loans) is positive and significant, reaffirming that deteriorating asset quality is associated with higher credit risk premiums and loan costs.

Overall, the models yield consistent and robust results across different specifications, with R^2 values ranging from 0.276 to 0.512. The results collectively indicate that digital transformation plays a cost-reducing role in bank lending once its initial investment effects are controlled for, while adverse weather events impose upward pressure on borrowing costs. The interplay between these two forces highlights the dual challenges and opportunities for Vietnamese banks in balancing technological modernization with climate resilience

4.3.2 Robustness tests

Table 5. Robustness tests

Variables	Panel E	Panel F
	GMM	Two-way cluster
LC	0.116*** (0.032)	
DT	-0.004** (0.002)	-0.012** (0.005)
FDIV	0.249*** (0.018)	0.193*** (0.031)
DP	0.000*** (2.80)	0.041** (2.39)
TA	-0.246*** (0.054)	-0.242*** (0.057)
GDP	-0.407*** (0.042)	-0.537*** (0.122)
CL	-0.002*** (-4.99)	-0.002*** (-4.64)
INF	0.009*** (8.50)	0.011*** (11.22)
Age	-0.003 (-5.29)	-0.001 (-3.62)
LLP	-1.406** (-2.27)	-0.411 (0.67)
CIR	-0.022*** (0.003)	-0.020*** (0.006)
NPL	0.531*** (0.111)	
DT*CL	0.511*** (0.057)	
Constant	0.138*** (0.013)	0.127*** (0.075)
Observations	202	101
R-squared		0.583
Number of bank	21	21

The empirical robustness of the main findings is assessed using two additional estimation techniques: the System Generalized Method of Moments (GMM) and two-way clustered regressions. These methods are employed to address potential endogeneity, autocorrelation, and

heteroskedasticity issues that may bias the fixed-effects estimates. Table 5 reports the results from both approaches.

Panel E presents the results obtained from the System GMM estimation, which controls for potential reverse causality between digital transformation (DT) and loan cost (LC). The coefficient of DT remains negative and statistically significant ($\beta = -0.004$, $p < 0.05$), confirming that higher levels of digital adoption lead to lower lending costs. This outcome strengthens the earlier evidence that digital transformation enhances efficiency, reduces information asymmetry, and mitigates credit risk, thereby lowering the cost of bank loans. Additionally, the coefficient of the interaction term (DT \times CL) is positive and significant, suggesting that the moderating effect of climate-related shocks reduces the efficiency of digital transformation in mitigating loan costs. In other words, adverse weather conditions partially offset the cost-reducing impact of digital adoption, reflecting that even digitally advanced banks remain vulnerable to extreme climate events.

Panel F reports the results of the two-way clustered regression, where standard errors are adjusted for both bank- and year-level clustering. The results are consistent with those obtained in the fixed-effect and GMM models. Specifically, DT retains its negative and significant effect ($\beta = -0.012$, $p < 0.05$), reaffirming the robustness of the main findings. Among the control variables, FDIV and DP exhibit positive coefficients, implying that funding diversification and deposit ratio are associated with higher lending costs, possibly due to increased complexity and funding competition. In contrast, TA and GDP display significant negative coefficients, indicating that larger banks and periods of economic growth are correlated with lower lending costs. The Climate change variable maintains a negative and significant coefficient ($\beta = -0.002$, $p < 0.01$), suggesting that climate-related shocks increase risk premiums and operational costs for banks.

Overall, the robustness checks reinforce the main conclusion that digital transformation reduces bank loan costs and enhances efficiency, while climate shocks exert a counteracting effect by elevating risk and cost structures. The consistency of the results across estimation methods confirms that the study's findings are stable, reliable, and free from major econometric biases.

4.4. Discussion

Prior studies have documented that digital transformation can significantly affect the cost and efficiency of bank lending. Vives (2019) [9] emphasized that digitalization enhances transparency and reduces information asymmetry, thereby lowering transaction costs in financial intermediation. Similarly, Cui et al., (2025) [12] found that digital adoption improves credit assessment efficiency, shortens loan processing time, and enables banks to offer credit at more competitive rates. Claessens, Frost, Turner, and Zhu (2018) [27] also argued that fintech-based technologies facilitate more accurate risk pricing and promote efficiency in lending operations.

Regarding bank-specific characteristics, [22] revealed that banks with greater reliance on low-cost deposits can transfer their funding advantages to borrowers through lower lending rates. In contrast, [21] suggested that well-capitalized banks tend to price loans more conservatively, reflecting a trade-off between stability and competitiveness. At the macroeconomic level, GDP growth is generally associated with lower loan costs, as improved economic conditions enhance borrowers' repayment capacity and reduce perceived risk [22].

The coefficient of digital transformation (DT) is negative and statistically significant in most specifications, supporting the hypothesis that greater digital adoption reduces loan costs. In the baseline model (Panel A), the coefficient of DT is positive and significant; however, after including additional bank-specific and macroeconomic controls in Column (2), the sign turns negative and remains significant across the GMM and two-way clustered regressions. This shift indicates that once potential omitted-variable bias and endogeneity are addressed, digital transformation consistently contributes to lowering lending costs. This finding aligns with Vives (2019) [9] who emphasized that digital technologies enhance operational efficiency and reduce the marginal cost of intermediation.

Among the control variables, FDIV shows a positive and highly significant coefficient across all models, indicating that a higher degree of funding diversification tends to increase loan costs. This result supports who argued that diversification into more volatile or expensive funding sources may raise banks' overall funding cost. The deposit ratio is positively related to loan cost in most cases, suggesting that Vietnamese banks may not yet fully transfer the benefits of low-cost deposits to borrowers, possibly due to market rigidities or concentration effects.

Total asset has a negative and significant impact on loan cost, consistent with the economies of scale hypothesis, as larger banks can spread fixed costs and access cheaper funding [22]. The GDP coefficient is negative and highly significant, implying that higher economic growth improves credit quality and reduces lending rates, in line with macro-financial theory. The inflation (INF) coefficient is positive and significant, reflecting that higher inflation leads to higher nominal interest rates and thus increases the cost of loans.

Climate change variable is negative and significant across specifications, suggesting that in years with higher occurrences of adverse weather events, lending costs decrease slightly. Although counterintuitive, this result may reflect the influence of government interventions, such as credit support or refinancing programs following climate shocks, which help reduce effective borrowing costs. Similar findings were reported, who observed that disaster-related policy responses can temporarily mitigate credit tightening.

The loan loss provision ratio (LLP) and cost-to-income ratio (CIR) show negative coefficients, though the significance levels vary across models. The negative sign of CIR indicates that more efficient banks tend to offer lower lending rates. Finally, the non-performing loan ratio

(NPL) is positive and highly significant, confirming that higher credit risk is associated with higher lending costs, consistent with Stiglitz and Weiss's (1981) [24] credit rationing theory.

Overall, the results demonstrate that digital transformation significantly reduces loan costs in Vietnamese commercial banks, even after controlling for risk, efficiency, and macroeconomic conditions. These findings are consistent with global evidence that digital adoption enhances cost efficiency, reduces information asymmetry, and improves financial inclusion [9].

5. Conclusion

Using an unbalanced panel dataset of 28 commercial banks from 2007 to 2023, the study constructs a text-based digital transformation index derived from the frequency of digital-related keywords in annual reports. Employing fixed effects, generalized method of moments (GMM), and two-way clustered estimations, the results consistently reveal that digital transformation significantly reduces loan costs. This finding supports the theoretical expectation that digital adoption enhances operational efficiency, mitigates information asymmetry, and improves credit risk pricing. The results also show that funding diversification increases loan costs, while larger bank size and stronger GDP growth contribute to lower lending rates.

The findings have several important implications for policymakers and bank managers. First, accelerating digital transformation should be considered a strategic priority for improving banking sector efficiency and credit affordability. Policymakers can facilitate this process by developing a clear digital finance roadmap, investing in digital infrastructure, and providing fiscal or regulatory incentives for technology adoption. Second, the government and the State Bank of Vietnam should strengthen cybersecurity frameworks and promote open banking standards to enhance transparency and data interoperability, which are essential for reducing information asymmetry and lending costs. Third, digital transformation can serve as a tool to improve financial inclusion especially by lowering borrowing costs for small and medium-sized enterprises (SMEs) and households traditionally excluded from formal credit markets. Finally, banks should adopt data-driven lending models and integrate climate risk assessment into digital platforms, thereby improving resilience to external shocks such as adverse weather events.

Despite these contributions, the study has several limitations. First, the digital transformation index is based on textual analysis of annual reports, which may not fully capture the intensity or quality of actual technological investments. Second, the dataset is limited to commercial banks, excluding smaller financial institutions and fintech lenders that may also influence market dynamics. Third, potential measurement errors in climate-related variable (Climate change) and other macro controls could affect the robustness of some coefficients. Finally, while endogeneity concerns are mitigated through GMM estimation, unobserved factors such as management quality or risk appetite may still bias the results.

Future research could extend this work in several directions. One promising avenue is to incorporate more granular data on banks' digital expenditures, fintech collaborations, and customer usage metrics to better capture the intensity of digital adoption. Additionally, future studies could explore how digital transformation interacts with climate-related risks and sustainability performance to influence credit pricing and resilience. Cross-country comparative analyses within ASEAN or other emerging economies could also provide broader insights into the role of digital transformation in reducing credit costs. Lastly, employing machine learning techniques or high-frequency data could enhance predictive accuracy and uncover nonlinear dynamics between digitalization, risk management, and lending costs.

Acknowledgment: The authors gratefully acknowledge the financial support from the Banking Academy of Vietnam

Funding detail: The authors gratefully acknowledge the financial support from the Banking Academy of Vietnam, under the Grant 2500/HD-HVNH-VNC1.

Conflict of interest: The authors declare that there are no conflicts of interest regarding the publication of this paper.

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