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Does Fintech Adoption Improve Financial Performance? Evidence from Indian Commercial Banks

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Abstract
This study empirically investigates the effect of multidimensional fintech adoption on financial performance of 29 commercial banks of India for the period of 2016 to 2024. A novel Fintech development index was constructed using text mining and applied principal component analysis (PCA) in order to reduce the dimensions. Two step System GMM technique was applied in order to find out the impact of bank fintech development and bank performance, the results reveal that bank the fintech development has significant negative effect on bank performance in first lag. Study further validated hypotheses using rigorous robustness check, using alternative estimator. Moreover, sensitivity analysis was performed by excluding largest and smallest banks. Across all parameters results are robust and supported our primary conclusion that bank fintech has negative impact on financial performance of Indian commercial banks.
Keywords - Fintech, Text Mining, Commercial Banks, Profitability, Financial Performance

1. Introduction

FinTech, broadly defined as innovative financial services facilitated by advancements such as artificial intelligence, blockchain, cloud computing, and big data, has fundamentally transformed the operational landscape of the banking sector (Barbu et al., 2021). While recognized as a mainstream future trend, the specific impact of internal FinTech adoption on bank performance remains a critical area of study, particularly within emerging markets where digital ecosystems are rapidly evolving. The interaction between FinTech and traditional commercial banks is characterized by a complex duality. On one hand, FinTech intensifies competition by enhancing service convenience and "squeezing" traditional asset, liability, and intermediation businesses, effectively capturing market share from incumbents (Anand & Mantrala, 2019; Thakor, 2020). On the other hand, it generates positive knowledge spillovers that allow banks to improve operational efficiency, expand service scope, and optimize delivery channels, thereby potentially enhancing overall profitability (Chen et al., 2021; Y. Wang et al., 2021). Consequently, commercial banks are actively integrating these technologies to drive strategic transformation and foster a favourable digital ecosystem (Daud et al., 2022). In the specific context of India, this transformation has been particularly profound. Driven by rapid advancements in internet infrastructure, widespread mobile penetration, and proactive regulatory initiatives, India has developed a vibrant FinTech ecosystem that significantly enhances the accessibility and inclusivity of financial services. Unlike many developed economies, India's digital shift is not limited to new entrants; established commercial banks are increasingly adopting digital payments, mobile banking, and blockchain applications, bolstered by government-backed frameworks like the Unified Payments Interface (UPI).The contribution of this paper lies in several key areas. First, most studies rely on a single proxy for FinTech, failing to capture its multidimensional nature. This study constructs a comprehensive index based on text mining covering Information Transfer, Payments, and Technical Base. Secondly, this is the first empirical study from Indian context measuring multidimensional FinTech development using text mining , previous studies were limited to Chinese contexts (Fang et al., 2023; Guo et al., 2024). Thirdly, these empirical results substantiate the hypothesis that FinTech negatively influences bank performance, aligning with the findings of (Almulla & Aljughaiman, 2021a; Phan et al., 2020a). Moreover, this study investigates the heterogeneous effects of FinTech adoption on performance, differentiating between state-owned and private institutions, as well as varying bank sizes.

2. Literature Background and Hypothesis Formulation

The impact of Financial Technology (FinTech) on the banking sector is fundamentally driven by two competing theoretical perspectives. Consumer Theory suggests that FinTech services act as technological substitutes, allowing customers to fulfil financial needs more efficiently outside traditional banking constraints (Aaker & Keller, 1990). Complementing this, Disruptive Innovation Theory posits that agile entrants utilize technology to offer lower-cost, more convenient services, thereby intensifying competitive pressures on incumbent banks (Christensen, 1997). For traditional banks, FinTech is thus a "double-edged sword": it offers tools for internal operational efficiency and customer personalization, yet requires significant investment to counter the threat of disintermediation (Mansour, 2024).

Table 1. Recent studies on fintech development and financial performance

Measurement of Fintech	Fintech Proxy	Measurement of Performance	References
Bank Fintech Measured by own behaviour	(1) A Fintech index based on keyword frequency from annual report (2) No. of Innovative financial services offered by banks (3) Value/No. of fintech services	ROA, ROE ROA, ROE, NIM, Non-NIM, Tobin's Q	• Almulla (2021) , Nguyen-Thi-Huong et al., (2023), Kharrat et al., (2024), He et al., (2025) • Ashiru et al., (2023);
Fintech development external to the banks	(1) No. of Fintech Startups (2) Regional Levels of Fintech development (PKU_DFIIC)	ROA, ROE, NIM Tobin's Q	• Phan et al., (2020) • Haddad & Hornuf, (2023) • Naser et al., (2024)

***Source:** Compiled by author*

FinTech & financial innovations like mobile banking, ATMs, and online platforms enhanced the short- and long-run performance of Nigerian banks (Ashiru et al., 2023). When faced with new technologies or trends, institutions often remain passive rather than adapting quickly. Digital transformation has been shown to strengthen profitability particularly among larger rural commercial banks through efficiency gains and diversification (He et al., 2025). Recent studies shows that FinTech strengthens financial stability by improving profitability through cost efficiency and optimized resource allocation (Ashiru et al., 2023; Haddad & Hornuf, 2023; Naser et al., 2024). Over the last decade, Indian banks faced severe external pressures, most notably the 2016 demonetization policy, which showed a statistically significant negative impact on the ROA of commercial banks (Almaqtari et al., 2019). However, this same disruption combined with government-led initiatives like the Jan Dhan-Aadhaar-Mobile (JAM) trinity and the behavioral shifts induced by the COVID-19 pandemic exponentially accelerated the demand for digital finance and the Unified Payments Interface (UPI) (Goel & Kashiramka, 2026). Consequently, while the immediate macroeconomic shocks caused financial stress, they ultimately forced Indian banks to expedite their fintech strategies, making robust technological integration an absolute necessity for achieving long-term cost efficiency and sustainability (Goel & Kashiramka, 2026).In contrast, some research suggests that FinTech has a negative impact on bank performance rather than a positive one. These studies indicate that FinTech increases competition, which lowers profit margins for traditional banks (Almulla & Aljughaiman, 2021a). Additionally, the high cost of implementing FinTech solutions often outweighs the immediate financial gains, leading to reduced overall profitability (Phan et al., 2020a). On the other hand, evidence of adverse or heterogeneous effects persists. (Almulla & Aljughaiman, 2021b) observe that while FinTech can enhance performance, the expansion of FinTech firms often reduces bank profitability by intensifying competition, a pressure felt more acutely by conventional banks than Islamic ones. In China, (Lee et al., 2023) demonstrate that FinTech development negatively impacted the efficiency of smaller urban and rural banks. Similarly, Empirical evidence suggests that the influence of FinTech is conditional on specific firm characteristics, particularly size. regarding Market Value, research indicates a negative impact for both large and small banks; however, this adverse effect is significantly more pronounced for larger institutions. This disparity is often attributed to organizational agility, as smaller firms are able to adapt to technological innovations more rapidly than their larger, more structurally complex counterparts (Phan et al., 2020b).

Hypothesis 1. FinTech development has a significant positive impact on the financial performance of commercial banks.

Hypothesis 2. the impact of FinTech development on financial performance differs by bank size, with large banks experiencing a more significant positive impact than small banks.

3.0 Model Construction

*3.1 Data selection:*This study employs an annual panel dataset of 29 Indian commercial banks, comprising 11 state-owned and 18 public sector banks, covering the period from 2016 to 2024. Bank-level financial data were primarily extracted from the CSMAR database, with missing observations manually compiled from the respective banks' annual reports. Furthermore, macroeconomic variables were sourced from the Reserve Bank of India (RBI) and the World Bank.

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3.2 Variable definition

3.2.1 Variable selection:Explained variable: bank performance, Previous studies used different proxies to measure financial performance of banks. Most common proxies that are used in the previous studies are Return on Equity (ROE) and Return on Assets (ROA) (Nguyen-Thi-Huong et al., 2023; Kharrat et al., 2024). This study also used Return on Assets (ROA) proxies to measure financial performance of commercial banks and further uses the Return on Equity (ROE) as the proxy variable for the robustness test.Core explanatory variable: referring to the practice of (Kharrat et al., 2024) this paper uses text mining method and principal component analysis to construct FinTech development index of commercial banks as the core explanatory variable. In order to investigate the impact of different factors, this paper continues to construct the FinTech information transfer Index (FIT), FinTech payment and settlement Index (FPS), Fintech technical base Index (FTB)

Control variables: To ensure robustness, the study controls for bank-specific variables including asset size (logarithm of total assets), asset quality (NNPA), liquidity risk (LDR), and revenue diversification (NII). Additionally, it accounts for macroeconomic factors through inflation (CPI growth rate) and financial development (M2 to GDP ratio).

3.2.2 Construction of FinTech Development Index of commercial banks:To capture the multidimensional nature of FinTech, this study constructed a composite index using a three-stage methodology based on the Basel Committee's classification framework. First, adoption was categorized into three dimensions; Information Transfer, Payments and Settlements, and Technical Base with specific keywords identified for each. Second, *AntConc* software was employed to text-mine and analyse keyword frequencies within bank annual reports. Finally, Principal Component Analysis (PCA) was applied to synthesize an overall FinTech development index, with validity confirmed through significant Bartlett's Tests ($p < 0.01$), KMO scores ranging from 0.632 to 0.796, and satisfactory variance explained across dimensions (56.8%–72.6%).

Table 2. Original thesaurus of commercial bank FinTech development index.

Dimensions	Keywords
Information Transfer	E-Bank*, Online Bank*, Digital Bank*, Internet Bank*, Net Bank*, Mobile Bank*, SMS Bank*, NEFT, RTGS, IMPS, AEPS, NACH
Payments & Settlements	Credit Card, Debit Card, ATM, POS, Digital Payments, UPI, Digital Transactions, Online Transactions, E-Payments, Mobile Payments, Wallet, CBDC, Digital Currency, BHIM, FasTag
Technical Base	Artificial Intelligence (AI), Machine Learning (ML), Natural Language Processing (NLP), Big Data/Analytics, Cloud Computing, Blockchain, Chatbot, IVR, QR, Biometric, Fingerprint Recognition, Face Recognition, Automation, Cyber Security, Fraud Detection

Source: *compiled by author*

3.3.1. Descriptive statistics:In Table 3 descriptive statistics reveal that the average ROA is 0.537 with a standard deviation of 0.66, indicating substantial variability in profitability across the sampled banks, ranging from a minimum of -0.73 to a maximum of 1.38. The fintech dimensions (FIT, FPS, FTB) exhibit means close to zero but wide ranges (FPS ranges from -1.24 to 1.90), reflecting significant heterogeneity in technological adoption. The correlation matrix confirms a positive association between all fintech dimensions and profitability, with the Technical Base (FTB) showing the strongest correlation with ROA (0.435). Furthermore, NNPA displays a strong negative correlation with ROA (-0.699), consistent with the expectation that deteriorating asset quality significantly erodes bank earnings.

Table 3. Descriptive statistics

Variable type	Variable name	Character	Obs	Mean	S.D	Min.	Max.
Explained variable	Net Profit to Total Assets	ROA	261	0.537	0.66	-0.73	1.38
Core explanatory variable	Fintech development index	FT	261	-0.05	0.82	-1.20	1.73
	Fintech Information Transfer	FIT	261	-0.09	0.78	-1.20	1.66
	Fintech Payment & Settlements	FPS	261	-0.06	0.86	-1.24	1.90
	Fintech Technical Base	FTB	261	-0.12	0.66	-0.88	1.12
Control variables	Bank Asset Size	Size	261	14.16	1.99	10.4	16.29
	Assets quality	NNPA	261	0.55	0.96	-1.07	2.15
	Liquidity risk	LDR	261	0.77	0.14	0.52	1.05
	Revenue diversification	NII	261	1.30	0.48	0.59	2.35
	Inflation	INF	261	1.58	0.23	1.20	1.90
	Financial development	M2/GDP	261	13.42	2.70	9.13	15.87

Source: *compiled by author*

Table 4. Correlation matrix

Variable	ROA	FT	FIT	FPS	FTB	Size	NNPA	LDR	NII	INF	M2/GDP
ROA	1.00										
FT	0.310	1.00									
FIT	0.161	0.840	1.00								
FPS	0.230	0.923	0.667	1.00							
FTB	0.435	0.875	0.580	0.765	1.00						
Size	0.055	0.358	0.293	0.364	0.275	1.00					
NNPA	-0.699	-0.292	-0.107	-0.241	-0.439	0.180	1.00				
LDR	0.498	0.244	0.014	0.277	0.363	0.018	-0.478	1.00			
NII	0.489	0.356	0.192	0.388	0.364	0.071	-0.411	0.580	1.00		
INF	0.259	0.276	0.226	0.168	0.358	0.062	-0.147	0.023	0.006	1.00	
M2/GDP	0.300	0.438	0.345	0.293	0.568	0.102	-0.217	0.050	0.027	0.708	1.00

Source: *compiled by author*

3.4.1. Model setting

3.4.2. Static panel model: To explore the impact of FinTech development level of commercial banks on bank performance, following static panel regression models are established:

$$ROA_{\{i,t\}} = \alpha + \beta_1 FT_{\{i,t\}} + \beta_2 X_{\{i,t\}} + \mu_i + \epsilon_{\{i,t\}}$$

$$ROA_{\{i,t\}} = \alpha + \beta_1 FT_{\{i,t-1\}} + \beta_2 X_{\{i,t\}} + \mu_i + \epsilon_{\{i,t\}}$$

Table 5. Static panel estimation results (Fixed effect using Driscoll-Kraay standard errors)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
	Contemporaneous Models				Lagged Models			
FT	-0.0327 (0.019)							
FIT		0.0290 (0.020)						
FPS			-0.0706** (0.029)					
FTB				-0.0692 (0.037)				
FT t -1					-0.1588** (0.045)			
FIT t-1						-0.0521 (0.028)		
FPS t -1							-0.2089**	

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							(0.066)	
FTB t -1								-0.1962** (0.075)
Size	0.3113 (0.183)	0.2826 (0.185)	0.3328 (0.181)	0.3243 (0.174)	0.5342*** (0.110)	0.4999*** (0.109)	0.5220*** (0.098)	0.5414*** (0.113)
NNPA	-0.369*** (0.045)	-0.362*** (0.047)	-0.366*** (0.045)	-0.374*** (0.045)	-0.333*** (0.036)	-0.325*** (0.037)	-0.318*** (0.036)	-0.340*** (0.035)
LDR	0 .6712* (0.345)	0.6701 (0.381)	0.6706* (0.319)	0.6686* (0.345)	0.7237* (0.345)	0.7267 (0.3979)	0.6872* (0.322)	0.5845 (0.320)
NII	0.3890*** (0.108)	0.3598** (0.109)	0.4093*** (0.106)	0.3841*** (0.107)	0.4182*** (0.106)	0.3799** (0.116)	0.4586*** (0.095)	0.3845** (0.121)
INF	0.3646* (0.161)	0.3694** (0.153)	0.3563* (0 .161)	0.3571* (0.160)	0.1165 (0.307)	0.2210 (0.298)	0.0493 (0.296)	0 .1329 (0.310)
M2/GDP	0.0000 (0.020)	-0.0046 (0.019)	0.0012 (0.020)	0.0045 (0.0209)	0.0270 (0.032)	0.0068 (0 .032)	0.0343 (0.032)	(0.0315) (0.034)
Cons	-5.2734* (2.593)	-4.770 (2.636)	-5.6106* (2.547)	-5.5011* (2.462)	-8.549*** (1.731)	-7.888*** (1.732)	-8.410*** (1.481)	-8.605*** (1.784)
Year FE	No	No	No	No	No	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	261	261	261	261	232	232	232	232
Adj. R^2	0.5086	0.5086	0.5124	0.5096	0.5332	0.5170	0.5487	05292

Notes: *Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

3.4.3. Dynamic panel model

Bank performance exhibits significant persistence, as current outcomes are strongly influenced by previous years' results. To effectively model this dynamic process and mitigate potential endogeneity, we incorporate a lagged dependent variable (ROA) and estimate the equation utilizing the two-step System-GMM approach. The model is specified as follows

$$ROA_{\{i,t\}} = \alpha ROA_{\{i,t-1\}} + \beta_1 FT_{\{i,t\}} + \beta_2 X_{\{i,t\}} + \mu_i + \delta_t + \epsilon_{\{i,t\}}$$

$$ROA_{\{i,t\}} = \alpha ROA_{\{i,t-1\}} + \beta_1 FT_{\{i,t-1\}} + \beta_2 X_{\{i,t\}} + \mu_i + \delta_t + \epsilon_{\{i,t\}}$$

Where the subscripts i and t denote the individual bank and the year, respectively. The dependent variable, $ROA_{\{i,t\}}$ represents bank performance, while $FT_{\{i,t\}}$ denotes the FinTech development of the commercial banks. Term $X_{\{i,t\}}$ captures a vector of control variables, Furthermore, μ_i and δ_t account for the firm-specific and time-specific fixed effects. Finally, $\epsilon_{\{i,t\}}$ represents the error term.

4.0 Empirical results and analysis

4.1 Benchmark inspection

4.1.1 Impact of FinTech development of performance of commercial banks: Although the Hausman test results did not explicitly reject the null hypothesis, this study employs a Fixed Effects model with Driscoll-Kraay standard errors to ensure robust inference against cross-sectional dependence and heteroscedasticity. The regression analysis in Table 5 is bifurcated to capture temporal dynamics: Models 1–4 examine the contemporaneous (immediate) impact of FinTech adoption, while Models 5–8 utilize a one-year lagged specification to mitigate simultaneity bias and account for the delayed realization of returns. Specifically, Models 1 and 5 assess the aggregate FinTech Development Index, whereas the remaining models decompose the impact across its three distinct dimensions.

4.1.2. The impact of different application dimensions of FinTech on performance of bank: The regression analysis decomposes FinTech adoption into Information Transfer (FIT), Payments (FPS), and Technical Base (FTB). Contemporaneous results (Table 5, Models 2–4) indicate that, unlike FIT, other dimensions negatively impact ROA, with FPS exerting a significant negative effect (-0.0706). While lagged specifications (Models 5, 7, and 8) confirm a persistent negative trend on overall performance, the specific significance of FPS dissipates over time. These results are supporting previous of (Nguyen-Thi-Huong et al., 2023; L.-H. Wang & Cao, 2022). This profitability dip stems from the high costs of legacy modernization and competitive margin compression. Consequently, rather than curbing investment, banks should prioritize organizational restructuring and human capital upskilling to convert these initial expenditures into long-term efficiency.

4.2 Endogenous problem

4.2.1 Two-step system-GMM: To address potential endogeneity, we extend our analysis to a dynamic panel model by incorporating a lagged dependent variable and employing the two-step System GMM estimator. The estimation results in Table 6 reveal that the FinTech (FT) coefficient is statistically insignificant contemporaneously but significantly negative in the lagged model, confirming that endogeneity bias does not reverse the baseline findings. The empirical evidence clearly demonstrates that commercial banks' FinTech development diminishes overall financial performance. In the lagged models' coefficients of FT_{t-1} (-0.178), FIT_{t-1} (-0.140) are significant at 1% level of significance and FTB_{t-1} is also significant at 5% and FPS_{t-1} is significant at 10%.indicating that the development of FinTech and FinTech information transfer services reduces the performance of commercial banks, these results are consistent with (Almulla & Aljughaiman, 2021b; Nguyen-Thi-Huong et al., 2023; L.-H. Wang & Cao, 2022). These studies indicate that there is negative relationship between fintech development and bank performance due to high cost of digital solution development and banks are also facing competition from fintech firms.

Table 6. Two-step system-GMM estimation results

	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**
	Contemporaneous Models				Lagged Models			
ROA $_{t-1}$	0.5317*** (0.153)	0.5815*** (0.164)	0.6587** (0.250)	0.5260*** (0.160)	0.5247*** (0.178)	0.5777*** (0.117)	0.5347*** (0.116)	0.4618*** (0.219)
FT	-0.0456 (0.057)							
FIT		-0.0541 (0.078)						
FPS			0.0246 (0.068)					
FTB				-0.0678 (0.083)				
FT $_{t-1}$					-0.178*** (0.064)			
FIT $_{t-1}$						-0.140*** (0.041)		
FPS $_{t-1}$							-0.1414* (0.070)	
FTB $_{t-1}$								-0.1616** (0.075)
Cons	-1.1928 (0.532)	-0.1110 (0.691)	0.1824* (0.297)	-1.7601** (0.820)	-0.7315** (0.275)	-1.731*** (0.509)	-1.3861** (0.570)	-1.719*** (0.595)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	232	232	232	232	232	232	232	232
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AR (2)	0.437	0.451	0.465	0.392	0.367	0.314	0.371	0.464
Sargan	0.240	0.523	0.598	0.169	0.865	0.662	0.751	0.772

Notes: *Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

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4.2.2 Robustness test: To ensure the validity of our findings, we conducted two key robustness checks. First, we excluded the largest and smallest banks (State Bank of India and Punjab & Sind Bank) to mitigate outlier bias (Table 7). The lagged FinTech coefficient remained negative and significant, confirming the 'productivity paradox' is a systemic sectoral feature rather than an artifact of size heterogeneity. Second, replacing Return on Assets (ROA) with Return on Equity (ROE) yielded consistent results (Table 8), further validating that the initial costs of FinTech adoption exert a structural drag on performance regardless of the profitability metric employed.

Table 7. Robustness test results 1 (By dropping largest and smallest bank)

	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**
	Contemporaneous Models				Lagged Models			
ROA $_{t-1}$	0.5408***	0.5720***	0.6060***	0.5521***	0.5502***	0.6117***	0.4330**	0.4910***
	(0.165)	(0.173)	(0.154)	(0.193)	(0.189)	(0.146)	(0.176)	(0.154)
FT	-0.0210							
	(0.057)							
FIT		-0.0282						
		(0.080)						
FPS			0.0009					
			(0.038)					
FTB				-0.0712				
				(0.106)				
FT $_{t-1}$					-0.1699**			
					(0.067)			
FIT $_{t-1}$						-0.119***		
						(0.039)		
FPS $_{t-1}$							-0.1636** (0.075)	
FTB $_{t-1}$								-0.2090*
								(0.108)
Cons	-1.568**	-1.1327*	-1.1231*	-1.7843	-1.273**	-1.624***	-1.6121**	-0.7760**
	(0.732)	(0.703)	(0.606)	(0.973)	(0.463)	(0.540)	(0.582)	(0.328)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	216	216	216	216	216	216	216	216
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AR (2)	0.214	0.242	0.248	0.168	0.209	0.170	0.184	0.174
Sargan	0.278	0.648	0.524	0.152	0.608	0.446	0.543	0.703

Notes: *Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

Table 8. Robustness test results 2 (By replacing core explained variable)

	Model (1)	**Model (2)**
	Panel A: Contemporaneous Models	**Panel B:** Lagged Models
ROE t-1	0.6488***	0.6194***
	(0.082)	(0.076)
FT	-0.9289	
	(1.100)	
FT $_{t-1}$		-2.082*
		(1.025)
Cons	-3.1615	-5.8317
	(5.506)	(4.326)
Control	Yes	Yes
N	232	232
Time FE	Yes	Yes
Bank FE	Yes	Yes
AR (2)	0.191	0.338
Sargan	0.191	0.240

Notes: *Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

4.2.3. Heterogeneity Analysis

In order to investigate the how the ownership structure on a bank effect along with fintech development influences the bank performance, in table 9. this study divided the sample into two groups one is state-owned and second is private commercial banks. These subsample analysis reveals that state-owned banks had strongly negative, significant impact on bank performance. On the other hand, private banks also experienced negative impact on bank performance but that is limited up to information transfer technology. This disparity indicate that state owned commercial banks, which are operating in deeper bureaucratic control, strict regulatory compliance and older legacy infrastructures, facing more profitability reduction with the high financial and adjustment cost of fintech development. Private banks appear to possess slightly more organisation flexibility, which help them to absorb these disruptive technological changes without reduction more profits (Goel & Kashiramka, 2026).

Table 9. Heterogeneity test (On the basis of ownership)

	Model (17)	**Model (18)**	**Model (19)**	**Model (20)**	**Model (21)**	**Model (22)**	**Model (23)**	**Model (24)**
	State Owned Banks (Lagged effect)				Private Banks (Lagged effect)			
ROA t-1	0.683***	0.674***	0.660***	0.716***	0.462***	0.534***	0.443***	0.495**
	(0.114)	(0.115)	(0.106)	(0.164)	(0.125)	(0.117)	(0.121)	(0.217)
FT × Own $_{t-1}$	-0.126**				-0.111			
	(0.061)				(0.105)			
FIT × Own $_{t-1}$		-0.106**				-0.128**		
		(0.054)				(0.137)		
FPS × Own$_{t-1}$			-0.148*				-0.115	
			(0.080)				(0.078)	
FTB × Own $_{t-1}$				-0.167				-0.137
				(0.119)				(0.084)
Cons	0 .026	-1.028*	-0.934**	-1.012**	-0.658**	-1.699***	-1.626***	-1.61**
	(0.169)	(0.503)	(0.407)	(0.447)	(0.292)	(0.4439)	(0.582)	(0.659)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	232	232	232	232	232	232	232	232
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AR (2)	0.438	0.432	0.447	0.438	0.377	0.341	0.405	0.509
Sargan	0.566	0.55	0.532	0.214	0.453	0.698	0.736	0.751

Notes: *Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

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To investigate whether the scale of operations mediates the impact of FinTech on financial performance, we stratified the total sample based on annual average asset size. The top 15 institutions were classified as large banks, while the remaining 14 were categorized as small banks. The sub-sample regression results, presented in Table 10, reveal a negative relationship between FinTech development and performance across both groups.

However, a distinct asymmetry emerges in the magnitude and significance of these effects. Table 10 shows that coefficient for large commercial banks is negative, statistically significant, and notably larger in magnitude than that of small banks, indicating that the 'productivity paradox' is disproportionately concentrated among larger institutions. Conversely, while the impact on small banks remains negative, it lacks statistical significance. This heterogeneity lends strong empirical support to the Legacy Rigidity Hypothesis. It suggests that large institutions, encumbered by complex legacy infrastructure and extensive organizational hierarchies, incur significantly higher adjustment costs and structural inertia during digital transition, creating a measurable drag on short-term profitability.

Table 10. Heterogeneity test (On the basis of bank size)

	Fixed effect	System GMM	Fixed effect	System GMM
	Large Banks (Lagged effect)		Small Banks (Lagged effect)	
ROA t-1		0.5831***		0.6501***
FT_{t-1}	-0.1426***	-0.2471***	-0.0943	-0.0136
Cons	-7.5658***	-0.3580	-8.1545	0.0264
Control	Yes	Yes	Yes	Yes
N	232	232	232	232
R^2	0.5264		0.5174	
AR (2)		0.353		0.452
Sargan		0.433		0.453

Notes: *Standard errors are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

5. Conclusion and suggestion

This study measure bank performance using FinTech development index based on a novel text-mining technique. Using two-step system GMM estimation, the results confirm that the substantial capital and operational costs associated with digital transformation particularly in payments and technical infrastructure currently outweigh immediate efficiency gains, creating a "gestation lag" in profitability. These findings remain robust across alternative performance proxies (ROE) and outlier exclusions. Furthermore, heterogeneity analysis strongly supports the "Legacy Rigidity Hypothesis," revealing that large institutions endure a significantly higher performance drag due to complex legacy structures, whereas smaller banks benefit from an "Agility Premium" that mitigates these disruptive costs. Consequently, the study concludes that while FinTech is essential for future relevance, its current integration serves as a structural burden on short-term returns, necessitating a strategic shift from pure technological acquisition to organizational restructuring and human capital upskilling.

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