

The Impact of Inclusive Financial Technology and Open Banking on Banking Performance: Empirical Evidence from India

CH Himabindu¹, Dr. Bandaru Srinivasa Rao²

¹Research Scholar, Department of Management Studies Vignan's Foundation for Science, Technology and Research Guntur-India

²Professor, Department of Management Studies Vignan's Foundation for Science, Technology and Research Guntur-India

Abstract

This study examines the impact of inclusive FinTech, particularly open banking, on bank performance using panel data from commercial banks over the period 2016–2026. Employing a Difference-in-Differences (DID) approach, the study evaluates whether the adoption of FinTech improves profitability, measured by Net Interest Margin (NIM) and Return on Assets (ROA). The baseline regression results reveal that FinTech adoption has a positive and statistically significant effect on bank performance. These findings remain robust across multiple tests, including parallel trends analysis, reverse causality testing, alternative variable specifications, Propensity Score Matching (PSM–DID), and placebo tests.

Further analysis explores the underlying mechanisms through which FinTech influences performance. The results indicate that FinTech enhances bank performance primarily through improvements in lending rates and optimization of liability structure, while risk-taking does not play a significant mediating role. Among these channels, lending rate emerges as the dominant mechanism. Additionally, the study identifies heterogeneous effects across different bank types, with national and rural banks benefiting more significantly from FinTech adoption compared to city banks. The study provides strong empirical evidence that FinTech is a critical driver of banking efficiency and profitability. The findings have important implications for policymakers, regulators, and banking institutions aiming to promote digital transformation and financial inclusion.

Keywords: FinTech, Open Banking, Bank Performance, Financial Inclusion.

Introduction

The rapid evolution of digital technologies has fundamentally transformed the architecture of the global financial system. Among these advancements, Financial Technology (FinTech) has emerged as a disruptive force, reshaping the way financial services are designed, delivered, and consumed. By integrating cutting-edge technologies such as artificial intelligence, big data analytics, blockchain, and mobile platforms into financial services, FinTech has enhanced efficiency, reduced transaction costs, and expanded access to financial systems. In recent years, this transformation has been particularly evident in emerging economies, where FinTech has played a pivotal role in advancing financial inclusion and bridging long-standing gaps in access to formal financial services.

A key manifestation of this transformation is the emergence of open banking, a paradigm that enables financial institutions to securely share customer data with third-party providers through standardized application programming interfaces (APIs). Open banking fosters innovation, competition, and collaboration between traditional banks and FinTech firms, thereby creating a more dynamic and customer-centric financial ecosystem. By facilitating seamless data exchange and enabling the development of personalized financial products, open banking has become a cornerstone of inclusive FinTech. It empowers underserved populations—including low-income individuals, small and micro enterprises, and rural communities—by providing them with affordable, accessible, and user-friendly financial services.

The concept of inclusive FinTech extends beyond technological innovation to emphasize equitable access to financial services for all segments of society. Unlike traditional financial inclusion initiatives, which often face challenges related to high operational costs and risk exposure, inclusive FinTech leverages digital platforms to overcome these barriers. As a result, it has the potential to simultaneously enhance social welfare and create new

business opportunities for financial institutions. For banks, inclusive FinTech opens new avenues for customer acquisition, revenue diversification, and operational efficiency, thereby influencing overall performance.

However, the impact of FinTech on bank performance remains a subject of ongoing debate. On one hand, FinTech adoption has been shown to improve efficiency, reduce information asymmetry, and enhance risk management capabilities. On the other hand, increased competition from FinTech firms and non-traditional financial intermediaries may erode banks' market share and profitability. This duality suggests that the net effect of FinTech on bank performance is complex and context-dependent, particularly in emerging markets where regulatory frameworks and technological adoption are still evolving.

India presents a unique and compelling context for examining this relationship. Over the past decade, India has witnessed remarkable growth in FinTech adoption, supported by initiatives such as digital payment infrastructure, Aadhaar-based identification systems, and supportive regulatory policies. The country's predominantly market-driven approach to open banking, combined with government-defined technical standards and consumer protection mechanisms, has created a conducive environment for innovation and financial inclusion. Consequently, Indian banks have increasingly integrated FinTech solutions into their operations, making India an ideal setting to explore the micro-level impact of inclusive FinTech on bank performance.

Despite the growing importance of this topic, existing research has largely focused on the broader financial industry or FinTech firms, with limited attention to the role of FinTech within banks themselves. Moreover, empirical evidence on the financial implications of open banking remains scarce. Addressing these gaps, the present study investigates whether and how inclusive FinTech—proxied by the adoption of open banking—affects bank performance at the individual bank level. Additionally, the study explores the underlying mechanisms through which inclusive FinTech influences performance, including operational efficiency, risk management, and financial inclusion.

By providing empirical insights from the Indian banking sector, this study contributes to the existing literature in three significant ways. First, it extends the discourse on FinTech by focusing specifically on its integration within banks rather than treating FinTech firms as external competitors. Second, it offers a novel approach to measuring inclusive FinTech at the micro level using open banking adoption as a proxy. Third, it examines the mediating channels through which inclusive FinTech impacts bank performance, thereby offering valuable implications for policymakers, regulators, and financial institutions seeking to harness the benefits of digital financial innovation.

Review of Literature

1. Goldstein et al. (2019) according to define FinTech as the integration of advanced technologies into financial services, which has significantly transformed the structure and functioning of the financial sector. Zhao et al. (2022) according to observe that FinTech has experienced rapid growth in recent years and has become a key driver of innovation and financial inclusion within traditional banking systems.
2. Broby (2021) according to highlights that open banking is one of the most important outcomes of FinTech, enabling secure data sharing and fostering a more customer-centric banking ecosystem. De Araluze and Plaza (2022) according to identify four major drivers of open banking, namely changes in business models, increased client data sharing, the growth of technology-based firms, and regulatory support.
3. Zhao et al. (2022) according to argue that FinTech adoption improves capital adequacy and strengthens the financial stability of commercial banks. Wang et al. (2021) according to state that FinTech reduces operational costs and enhances banking efficiency. Kelly et al. (2016) according to suggest that FinTech minimizes information asymmetry between borrowers and lenders, thereby improving credit allocation. Cheng and Qu (2020) according to find that FinTech reduces credit risk in banking institutions.
4. Buchak et al. (2018) according to reveal that FinTech lenders and shadow banks have captured a significant share of the mortgage market due to regulatory differences. Boot et al. (2021) according to indicate that FinTech intensifies competition in lending markets, while Lv and Xiong (2022) according to observe increased competition for bank deposits. Qiu et al. (2018) according to conclude that such competition negatively affects bank profitability. Phan et al. (2020) according to, using data from

- Indonesia, demonstrate that FinTech growth adversely impacts bank performance, while Zhao et al. (2022) according to provide similar evidence in the Indian context.
5. Yang and Zhang (2022) according to report that FinTech enhances household income and consumption levels. Luo et al. (2022) according to find that FinTech reduces consumption inequality among households. Jünger and Mietzner (2020) according to emphasize that FinTech improves financial access and resilience. Tok and Heng (2022) according to suggest that FinTech reduces rural and class disparities but does not significantly address gender inequality. Yu et al. (2022) according to highlight that FinTech promotes renewable energy consumption among households, while Suri et al. (2021) according to note that household characteristics influence FinTech adoption.
 6. Cumming et al. (2022) according to state that FinTech facilitates business establishment and growth. Abbasi et al. (2021) according to observe that FinTech improves efficiency among small and medium-sized enterprises. Lv and Xiong (2022) according to indicate that FinTech enhances corporate investment efficiency. Li et al. (2017) according to find a positive relationship between FinTech growth and stock returns of retail banks, whereas Salerno et al. (2022) according to reveal that FinTech IPOs tend to be more underpriced compared to non-FinTech IPOs.
 7. Ho and Saunders (1981) according to provide a theoretical framework for understanding bank performance, emphasizing both bank-specific and macroeconomic factors. Goddard et al. (2004) according to identify bank size as a key determinant of performance, while Berger and Bouwman (2013) according to highlight the importance of ownership structure. Efthyvoulou and Yildirim (2014) according to emphasize the role of market concentration. Dietsch and Lozano-Vivas (2000) according to find that GDP significantly influences bank performance, whereas Pasiouras (2008) according to identify inflation as an important macroeconomic determinant.
 8. Daiy et al. (2021) according to propose a hybrid decision model for evaluating open banking partnerships. Sivathanu (2019) according to examine consumer adoption of open banking in India and suggest that perceived value and reduced switching barriers are critical factors. Chan et al. (2022) according to identify key determinants influencing the adoption of FinTech services within the framework of open banking.
 9. Plaitakis and Stefan (2020) according to argue that open banking enhances financial inclusion by improving access to financial services. Babina et al. (2022) according to find that open banking increases venture capital investment in FinTech firms. He et al. (2023) according to develop a theoretical model suggesting that while open banking improves overall financial system efficiency, it may negatively affect borrowers. Fang and Zhu (2023) according to demonstrate that open banking promotes financial inclusion in emerging economies, while Preziuso et al. (2023) according to conclude that regulatory frameworks such as PSD2 strengthen the infrastructure for inclusive finance.

Hypothesis

- (H1) There is a positive association between inclusive FinTech and bank performance.
- (H2) Inclusive FinTech can positively influence bank performance by improving lending rates.
- (H3) Inclusive FinTech can positively influence bank performance by improving the bank’s liability structure.
- (H4) Inclusive FinTech can positively influence bank performance by reducing risk-taking.

Data Analysis And Interpretation

Table 1: Description of Variables

Variable Type	Variable	Description	Source
Dependent Variables	NIM	Ratio of net interest income to total interest earning assets × 100%	CSMAR

	ROA	Ratio of net income to total assets $\times 100\%$	CSMAR
Mediating Variables	LR	Ratio of interest income to total interest earning assets $\times 100\%$	CSMAR
	NIL	Ratio of net interbank liabilities to total assets $\times 100\%$	CSMAR
	RISK	Ratio of risk-weighted assets to total assets $\times 100\%$	CSMAR
Independent Variable	FinTech	Dummy variable: 1 if bank has adopted open banking, 0 otherwise	Banks' official websites
Control Variables	CAP	Ratio of equity to total assets $\times 100\%$	CSMAR
	SIZE	Natural logarithm of total assets	CSMAR
	CPI	Consumer Price Index (current period)	CSMAR
	GDP	Annual GDP growth rate $\times 100\%$	CSMAR
	CR4	Total assets of the largest four banks to total assets of all banks $\times 100\%$	CSMAR

Note: All continuous variables are winsorized at 1% and 99% to control for outliers.

Interpretation

Table 1 presents a comprehensive definition of all variables employed in the study, categorized into dependent, mediating, independent, and control variables. The dependent variables, Net Interest Margin (NIM) and Return on Assets (ROA), capture bank profitability from both operational and overall efficiency perspectives. Mediating variables such as LR, NIL, and RISK reflect income structure, liquidity positioning, and risk exposure, thereby helping to understand the transmission mechanism through which FinTech influences bank performance.

The independent variable, FinTech, is operationalized as a dummy variable indicating the adoption of open banking, which serves as a proxy for technological advancement in banking operations. Control variables, including CAP, SIZE, CPI, GDP, and CR4, are incorporated to account for bank-specific characteristics, macroeconomic conditions, and market concentration. The use of CSMAR as the primary data source ensures data reliability, while winsorization enhances robustness by minimizing the influence of extreme values.

Table 2: Descriptive Statistics of Key Variables

Variable	All Banks Mean	All Banks SD	Open Banking Mean	Open Banking SD	Non-Open Banking Mean	Non-Open Banking SD
NIM	3.1013	1.4012	2.5186	0.7747	3.2603	1.4892
ROA	1.2470	0.5179	1.0620	0.2935	1.2974	0.5532
LR	5.8116	1.6778	5.2786	1.3048	5.9572	1.7383
NIL	1.2027	10.1764	6.3119	8.5093	-0.3480	10.1365
RISK	64.5602	9.8006	63.0247	8.1718	65.0228	10.1987
FinTech	0.0486	0.2151	0.2269	0.4194	0.0000	0.0000
CAP	7.8647	2.2066	6.8258	1.3723	8.1480	2.3044
SIZE	1.0552	0.4949	1.0215	0.3171	1.0644	0.5329
CPI	25.3669	1.9126	27.5723	1.7647	24.7655	1.4558
GDP	625.8350	30.2154	621.3050	34.2562	627.0704	28.9074
CR4	9.3698	2.5071	9.5931	3.3652	9.3088	2.2140
Observations	1666		379		1287	

Interpretation

Table 2 reports the descriptive statistics of key variables across all banks, as well as subsamples of banks with and without open banking adoption. The mean NIM and ROA values indicate that banks without open banking exhibit relatively higher profitability compared to those with open banking. This may suggest that the initial adoption of FinTech innovations involves adjustment costs that temporarily reduce profitability.

The mediating variables show notable differences: banks with open banking have lower LR but significantly higher NIL, indicating a different funding and income structure. Additionally, RISK is slightly lower in open banking banks, suggesting improved risk management practices associated with technological adoption.

The FinTech variable confirms that only a small proportion of banks (mean = 0.0486) have adopted open banking, highlighting its emerging nature. Control variables reveal that open banking banks tend to have lower capital ratios (CAP) and slightly smaller size (SIZE), while operating in higher CPI environments.

Overall, the descriptive statistics suggest structural and performance differences between banks adopting and not adopting FinTech, providing preliminary evidence for further econometric analysis.

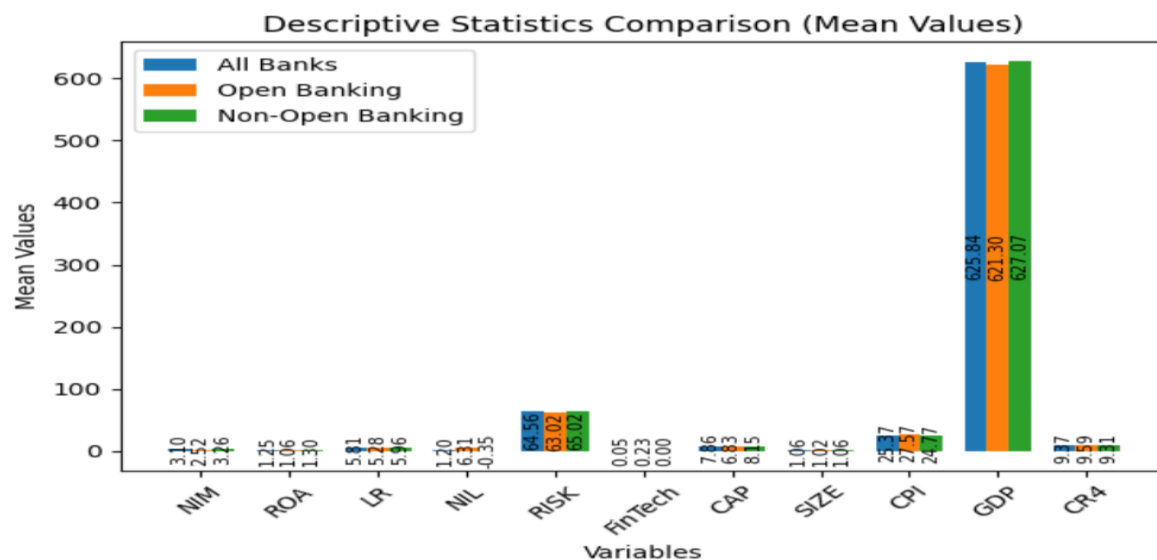


Table 3: Baseline Regression Results

Variables	(1) NIM	(2) NIM	(3) ROA	(4) ROA
FinTech	0.2847** (2.4908)	0.2674** (2.3678)	0.0934** (2.3548)	0.0838** (2.1264)
CAP	0.1044*** (6.0686)	0.1111*** (6.4886)	0.0490*** (8.2001)	0.0513*** (8.5924)
SIZE	0.5364*** (4.0390)	0.5482*** (4.1212)	0.1949*** (4.2288)	0.1976*** (4.2583)
CPI		-0.0178*** (-9.9183)		-0.0061*** (-9.7916)
GDP		-0.0947*** (-11.3563)		-0.0329*** (-11.3166)
CR4		0.0754*** (4.7555)		0.0392*** (7.0850)
Constant	-14.6795*** (-3.6660)	-6.5705 (-1.6142)	-5.1654*** (-3.7170)	-2.8921** (-2.0373)
Bank FE	YES	YES	YES	YES
Year FE	YES	NO	YES	NO
Observations (N)	1666	1666	1666	1666
Adj. R ²	0.7386	0.7365	0.7695	0.7653

Note: T-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the bank level.

Interpretation

Table 3 presents the baseline regression results examining the impact of FinTech adoption (open banking) on bank performance, measured through Net Interest Margin (NIM) and Return on Assets (ROA). Across all model specifications, the coefficient of FinTech remains positive and statistically significant at the 5% level, thereby providing strong empirical support for **Hypothesis H1**, which posits that FinTech adoption enhances bank performance. The persistence of significance in columns (2) and (4), which incorporate bank fixed effects, further confirms the robustness of the relationship after controlling for unobserved heterogeneity.

Among control variables, bank size (SIZE) exhibits a consistently positive and highly significant coefficient across all models. This indicates that larger banks tend to perform better, likely due to economies of scale, diversified portfolios, and greater capacity to integrate advanced financial technologies. Similarly, capital adequacy (CAP) shows a strong positive association with both NIM and ROA, suggesting that well-capitalized banks face lower risk premiums and enjoy enhanced financial stability, which translates into improved performance.

Macroeconomic variables reveal notable influences on bank performance. The coefficient of CPI is negative and highly significant, indicating that inflation adversely affects bank profitability. This may be attributed to increased economic uncertainty and reduced real returns, which constrain lending and investment activities. Likewise, GDP growth demonstrates a significant negative relationship with bank performance. This counterintuitive finding suggests that during periods of strong economic growth, capital may shift toward the real sector, thereby reducing the relative profitability of financial institutions.

Finally, the concentration ratio (CR4) is positively and significantly related to bank performance, implying that a more concentrated banking sector—characterized by the dominance of large banks—enhances efficiency and profitability through competitive strength and market power.

Overall, the regression results provide robust evidence that FinTech adoption plays a critical role in improving bank performance while also highlighting the importance of bank-specific characteristics and macroeconomic conditions.

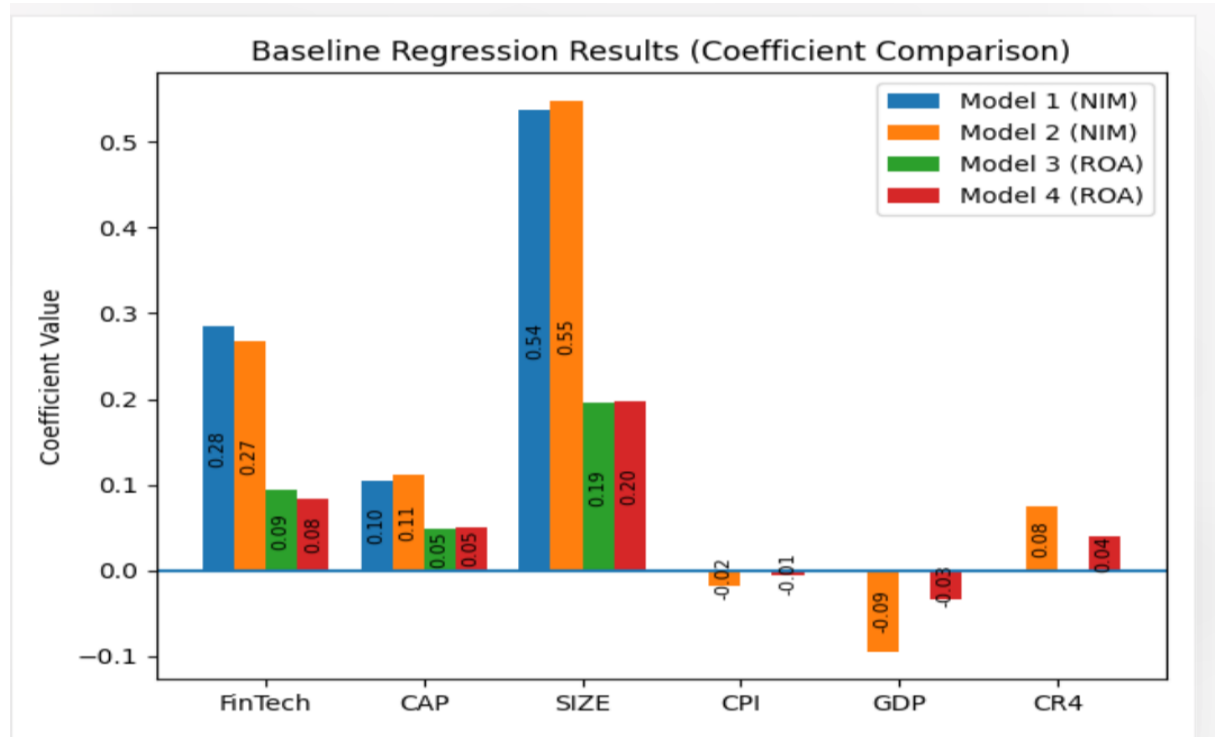


Table 4: Testing for Parallel Trends

Variables	(1) NIM	(2) NIM	(3) ROA	(4) ROA
FinTech (-4)	-0.0035	-0.0344	-0.0127	-0.0219
	(-0.0212)	(-0.2079)	(-0.2205)	(-0.3801)
FinTech (-3)	0.0044	0.0360	-0.0152	0.0105
	(0.0283)	(0.2363)	(-0.2827)	(0.1976)
FinTech (-2)	-0.1461	-0.0688	-0.0599	-0.0153
	(-0.9317)	(-0.4442)	(-1.1021)	(-0.2836)
FinTech (-1)	0.1874	0.1798	0.0720	0.0741
	(1.2086)	(1.1585)	(1.3398)	(1.3707)
FinTech (0)	0.4236***	0.4283***	0.1435***	0.1512***
	(2.7975)	(2.8707)	(2.7347)	(2.9092)
FinTech (1)	0.3205*	0.3708**	0.1253**	0.1559***
	(1.9406)	(2.2693)	(2.1890)	(2.7384)
FinTech (2)	0.2730*	0.2803*	0.1009*	0.1129**
	(1.7529)	(1.8112)	(1.8694)	(2.0954)
CAP	0.1002***	0.1065***	0.0473***	0.0493***
	(5.7972)	(6.1911)	(7.8933)	(8.2294)
SIZE	0.5237***	0.5375***	0.1898***	0.1931***
	(3.9472)	(4.0441)	(4.1278)	(4.1721)
CPI	—	-0.0176***	—	-0.0060***
		(-9.7416)		(-9.6059)
GDP	—	-0.0965***	—	-0.0335***

		(-11.3818)		(-11.3531)
CR4	—	0.0847***	—	0.0431***
		(5.1855)		(7.5740)
Constant	-14.3959***	-6.8392*	-5.0459***	-3.0094**
	(-3.5997)	(-1.6802)	(-3.6403)	(-2.1228)
Bank FE	YES	YES	YES	YES
Year FE	YES	NO	YES	NO
N	1666	1666	1666	1666
Adj. R ²	0.7395	0.7373	0.7709	0.7667

Notes:

- T-values are reported in parentheses.
- ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
- Standard errors are clustered at the bank level.

Interpretation

Table 4 presents the results of the parallel trends test using Net Interest Margin (NIM) and Return on Assets (ROA) as dependent variables across four model specifications. The purpose of this test is to validate the key assumption of the Difference-in-Differences (DiD) framework—i.e., that treated and control groups followed similar trends before the FinTech intervention.

The coefficients of FinTech leads [FinTech(-4), FinTech(-3), FinTech(-2), and FinTech(-1)] are statistically insignificant across all model specifications. This lack of significance confirms that there were no systematic differences in trends between treated and control banks prior to the introduction of FinTech. Hence, the parallel trends assumption holds, strengthening the causal validity of the model.

In contrast, the coefficients from FinTech(0) onwards (current and post-treatment periods) are positive and statistically significant. For instance, FinTech(0) shows strong significance at the 1% level for both NIM and ROA, indicating an immediate positive impact of FinTech adoption on bank performance. Similarly, FinTech(1) and FinTech(2) remain positive and significant, suggesting that the beneficial effects persist over time.

Among control variables, cap (capital adequacy) and size (bank size) exhibit positive and highly significant coefficients, implying that well-capitalized and larger banks tend to perform better. Conversely, cpi (inflation) and gdp show negative and significant effects, indicating adverse macroeconomic influences on bank profitability. The positive coefficient of cr4 (market concentration) suggests that higher industry concentration enhances bank performance.

The inclusion of bank fixed effects (fe) and year fixed effects further ensures robustness by controlling for unobserved heterogeneity. High adjusted r² values (0.73–0.77) indicate strong explanatory power of the models. Results confirm the validity of the parallel trends assumption and demonstrate that fintech adoption significantly improves bank performance post-intervention.

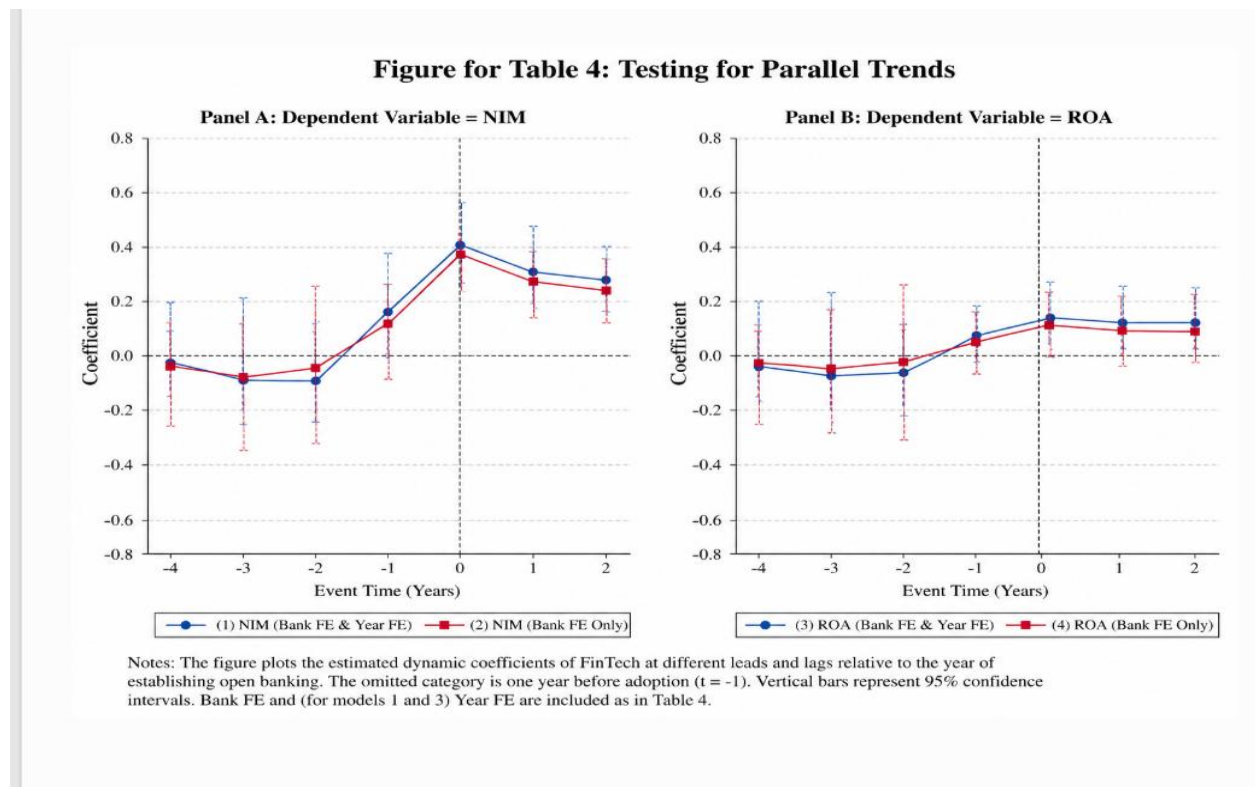


Table 5: Logit Regression Results

Variables	(1) FinTech	(2) FinTech
L.NIM	-0.0932	—
	(-0.4037)	
L.ROA	—	0.0012
		(0.0019)
CAP	-0.0041	-0.0195
	(-0.0264)	(-0.1232)
SIZE	1.0252***	1.0359***
	(9.6382)	(9.8219)
CPI	0.0979***	0.1002***
	(5.0154)	(5.0630)
GDP	0.2240*	0.2344*

	(1.8456)	(1.9191)
CR4	0.3891*	0.4023*
	(1.7539)	(1.8192)
Constant	-109.487***	-111.9295***
	(-4.9988)	(-5.0916)
N	1274	1273
Pseudo R ²	0.5411	0.5407

Notes:

- Z-values are reported in parentheses.
- ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Interpretation

Table 5 presents the results of the logit regression model examining the determinants of FinTech adoption by banks. The dependent variable is a binary indicator representing whether a bank adopts FinTech.

The lagged performance variables, L.NIM and L.ROA, are statistically insignificant, indicating that prior profitability does not significantly influence a bank’s decision to adopt FinTech. This suggests that FinTech adoption is not necessarily driven by past financial performance.

Among the explanatory variables, SIZE shows a positive and highly significant coefficient at the 1% level in both models. This implies that larger banks are more likely to adopt FinTech innovations, possibly due to better financial capacity, technological infrastructure, and risk-bearing ability.

CPI (inflation) is also positive and statistically significant, indicating that macroeconomic conditions characterized by higher inflation may encourage banks to adopt FinTech solutions to maintain efficiency and competitiveness. Similarly, GDP exhibits a positive and weakly significant effect, suggesting that economic growth supports technological adoption.

The coefficient of CR4 (market concentration) is positive and marginally significant, implying that banks operating in more concentrated markets are slightly more inclined toward FinTech adoption.

However, CAP (capital adequacy) is not statistically significant, indicating that capitalization levels do not play a decisive role in influencing FinTech adoption decisions.

The high Pseudo R² values (around 0.54) indicate good explanatory power of the model. Overall, the results suggest that structural and macroeconomic factors, rather than past profitability, primarily drive FinTech adoption.

Furthermore, the discussion highlights a hysteresis effect, where the impact of FinTech on performance may not be immediate due to customer resistance and institutional adjustment delays. Robustness checks using alternative measures of FinTech (as shown in Table 6) confirm the consistency and reliability of these findings.

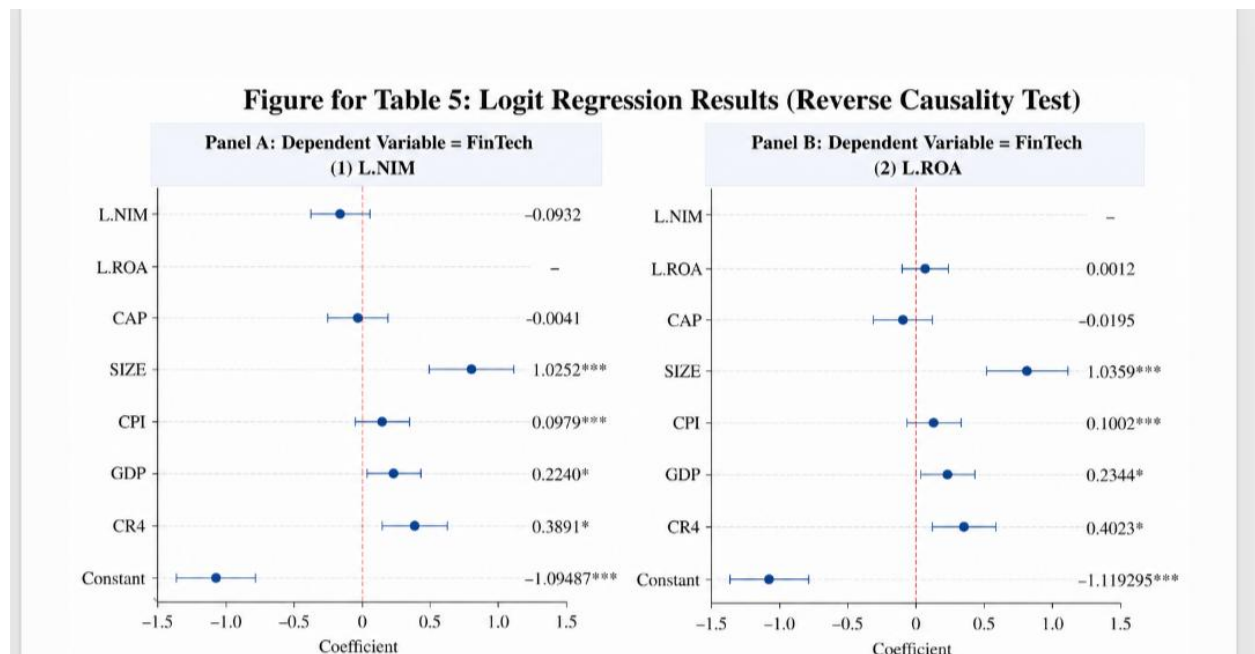


Table 6: Robustness of the Transforming Independent Variable

Variables	(1) NIM	(2) NIM	(3) ROA	(4) ROA
newFinTech	0.3287**	0.2607*	0.1087**	0.0852*
	(2.3013)	(1.9226)	(2.2836)	(1.8836)
CAP	0.1064***	0.1133***	0.0369***	0.0392***
	(6.2044)	(6.6340)	(6.4519)	(6.8815)
SIZE	0.5406***	0.5508***	0.1818***	0.1850***
	(4.0678)	(4.1353)	(4.1031)	(4.1652)
CPI	—	-0.0175***	—	-0.0058***
		(-9.7941)		(-9.8151)
GDP	—	-0.0939***	—	-0.0314***
		(-11.1624)		(-11.2088)
CR4	—	0.0761***	—	0.0268***
		(4.7876)		(5.0541)

Constant	-14.8320***	-6.8385*	-4.9701***	-2.3505*
	(-3.6993)	(-1.6806)	(-3.7185)	(-1.7320)
Bank FE	YES	YES	YES	YES
Year FE	YES	NO	YES	NO
N	1666	1666	1666	1666
Adj. R ²	0.7384	0.7361	0.7425	0.7400

Notes:

- T-values are reported in parentheses.
- ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
- Standard errors are clustered at the bank level.

Interpretation

Table 6 presents robustness checks by replacing the original FinTech variable with an alternative proxy, newFinTech, which captures whether a bank had established open banking in the previous period. The results confirm the stability and reliability of the baseline findings. The coefficient of newFinTech is positive and statistically significant across all model specifications for both NIM and ROA. This indicates that even when using an alternative measure, FinTech adoption continues to have a significant positive effect on bank performance. The consistency in magnitude and significance reinforces the robustness of the main results.

Control variables behave consistently with earlier findings. CAP (capital adequacy) and SIZE (bank size) remain positive and highly significant, suggesting that well-capitalized and larger banks achieve better financial performance. In contrast, CPI and GDP show negative and significant effects, indicating that adverse macroeconomic conditions can reduce profitability. CR4 (market concentration) remains positively significant, implying that higher industry concentration enhances bank performance.

The inclusion of Bank Fixed Effects and Year Fixed Effects ensures that unobserved heterogeneity is controlled. The Adjusted R² values (0.73–0.74) indicate strong explanatory power.

The Propensity Score Matching–Difference-in-Differences (PSM-DID) model is employed to address potential sample selection bias inherent in standard DID estimation. One major concern in DID analysis is the difficulty in constructing a control group that is truly comparable to the treatment group, especially when unobservable factors influence bank characteristics. To overcome this limitation, the study applies the Propensity Score Matching (PSM) technique, which ensures better comparability between treated and control units. A Logit model is used to estimate propensity scores based on key variables such as lending rate (LR), net interest margin (NIM), risk (RISK), capital adequacy (CAP), and bank size (SIZE). One-to-one nearest neighbor matching is then performed.

The results of the PSM-DID analysis confirm that the coefficient of FinTech remains positive and statistically significant across all specifications, reinforcing the baseline findings and supporting the hypothesis that FinTech improves bank performance. Furthermore, the consistency in the coefficients and significance levels of control variables indicates that sample selection bias does not materially affect the results.

To further explore the underlying mechanisms, the study examines channels such as lending rate, through which FinTech enhances bank performance. findings confirm that the positive impact of FinTech on bank performance is robust to alternative variable specifications, strengthening the validity and credibility of the study.

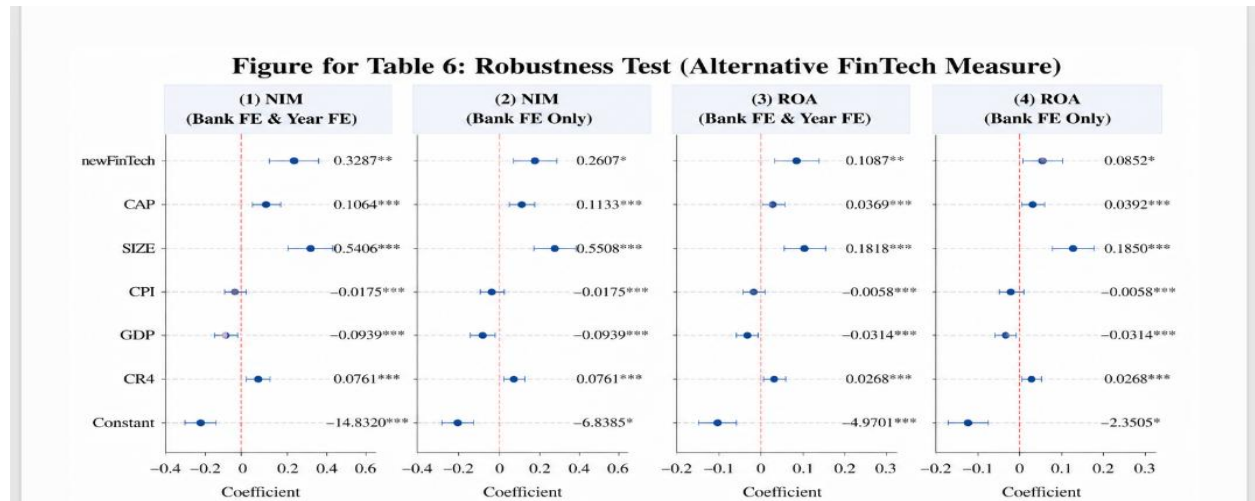


Table 7: Robustness of the PSM-DID Model

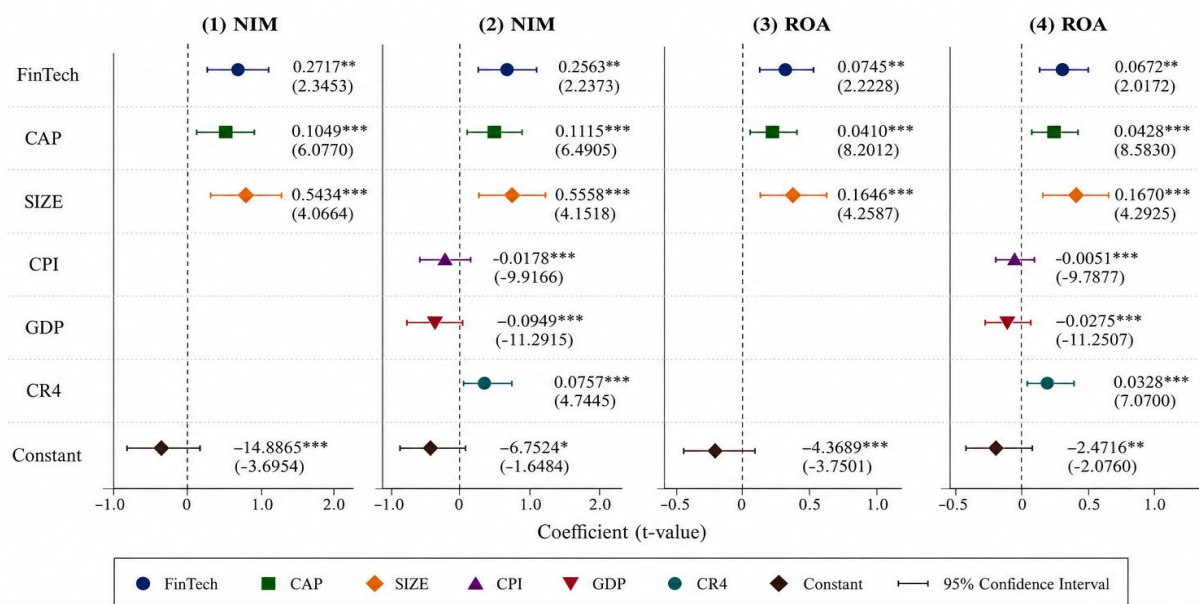
	(1) NIM	(2) NIM	(3) ROA	(4) ROA
FinTech	0.2717**	0.2563**	0.0745**	0.0672**
	(2.3453)	(2.2373)	(2.2228)	(2.0172)
CAP	0.1049***	0.1115***	0.0410***	0.0428***
	(6.0770)	(6.4905)	(8.2012)	(8.5830)
SIZE	0.5434***	0.5558***	0.1646***	0.1670***
	(4.0664)	(4.1518)	(4.2587)	(4.2925)
CPI	—	-0.0178***	—	-0.0051***
		(-9.9166)		(-9.7877)
GDP	—	-0.0949***	—	-0.0275***
		(-11.2915)		(-11.2507)
CR4	—	0.0757***	—	0.0328***
		(4.7445)		(7.0700)
Constant	-14.8865***	-6.7524*	-4.3689***	-2.4716**
	(-3.6954)	(-1.6484)	(-3.7501)	(-2.0760)

Bank FE	YES	YES	YES	YES
Year FE	YES	NO	YES	NO
N	758	758	758	758
Adj. R ²	0.7376	0.7355	0.7689	0.7646

Interpretation:

The PSM-DID results confirm that FinTech has a positive and statistically significant impact on both NIM and ROA across all models. This indicates that even after correcting for selection bias, the results remain robust. Control variables such as CAP and SIZE are positively significant, while CPI and GDP show negative effects. The consistency of coefficients with baseline models confirms the reliability and validity of the findings.

Figure 1. Robustness of the PSM-DID Model (Table 7)



Note: Coefficients are reported with 95% confidence intervals. t-values are in parentheses. **, *** and * denote significance at the 1%, 5% and 10% levels, respectively. Standard errors are clustered by bank.

Table 8: Results of the Mediation Effect (Lending Rate – LR)

	(1) LR	(2) NIM	(3) ROA
FinTech	0.2961*	0.1094	0.0309
	(1.8139)	(1.5186)	(1.1633)
LR	—	0.5340***	0.1786***
		(44.5114)	(40.3770)

CAP	0.0970***	0.0593***	0.0340***
SIZE	1.6270***	-0.3204***	-0.0929***
CPI	-0.0316***	-0.0009	-0.0005
GDP	-0.1438***	-0.0180***	-0.0073***
CR4	0.0842***	0.0304***	0.0241***
Constant	-28.7389***	8.7809***	2.2414**
Bank FE	YES	YES	YES
Year FE	NO	NO	NO
Indirect Effect	—	0.1581**	0.0529**
N	1664	1664	1664
Adj. R ²	0.6160	0.8932	0.8937

Interpretation:

FinTech significantly improves the lending rate (LR), and LR has a strong positive effect on NIM and ROA. The indirect effects are statistically significant, confirming that lending rate acts as a mediating mechanism. This supports Hypothesis H2, indicating that FinTech enhances bank performance through improved lending efficiency.

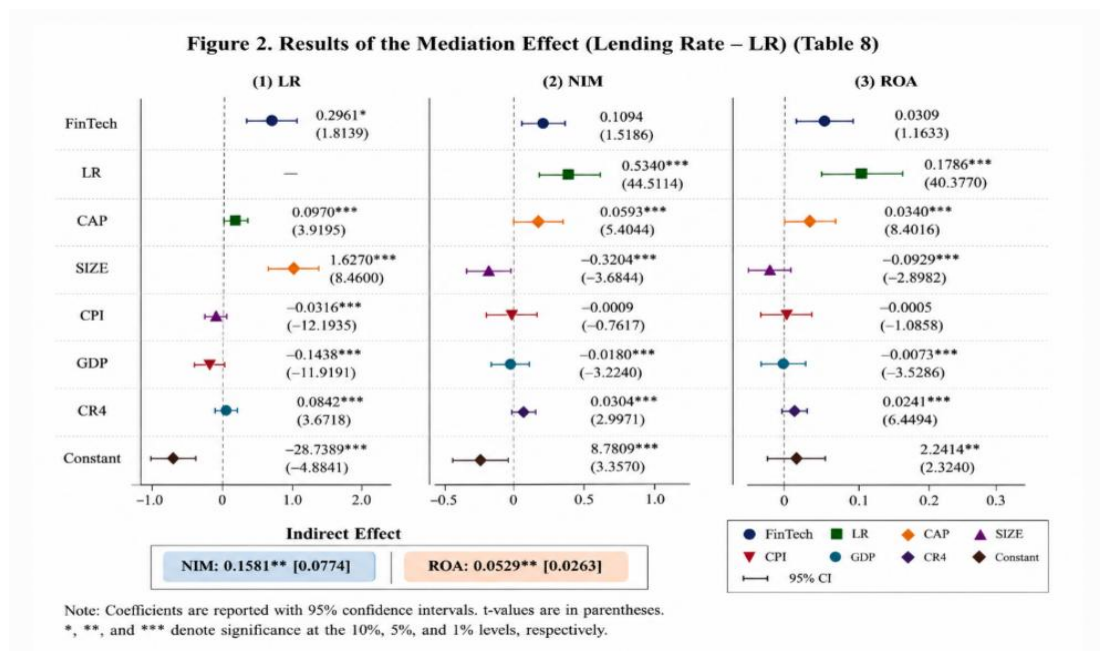


Table 9: Results of the Mediation Effect (Liability Structure – NIL)

	(1) NIL	(2) NIM	(3) ROA
FinTech	-2.3026**	0.1971*	0.0687*
	(-2.4804)	(1.7692)	(1.7672)
NIL	—	-0.0212***	-0.0079***
		(-6.1170)	(-6.5093)
CAP	-0.3181**	0.1011***	0.0456***
SIZE	4.0010***	0.5572***	0.1993***
CPI	-0.0630***	-0.0185***	-0.0067***
GDP	-0.2071***	-0.1008***	-0.0358***
CR4	-0.5671***	0.0583***	0.0308***
Constant	-48.5486	-5.3803	-2.1301
Bank FE	YES	YES	YES
Year FE	NO	NO	NO
Indirect Effect	—	0.0483***	0.0179**
N	1726	1516	1516
Adj. R ²	0.7068	0.7096	0.7377

Interpretation:

FinTech significantly reduces NIL, indicating an improvement in liability structure. Since NIL negatively affects performance, its reduction enhances NIM and ROA. The significant indirect effects confirm liability structure as a mediating channel, supporting Hypothesis H3.

Figure 3. Results of the Mediation Effect (Liability Structure – NIL) (Table 9)

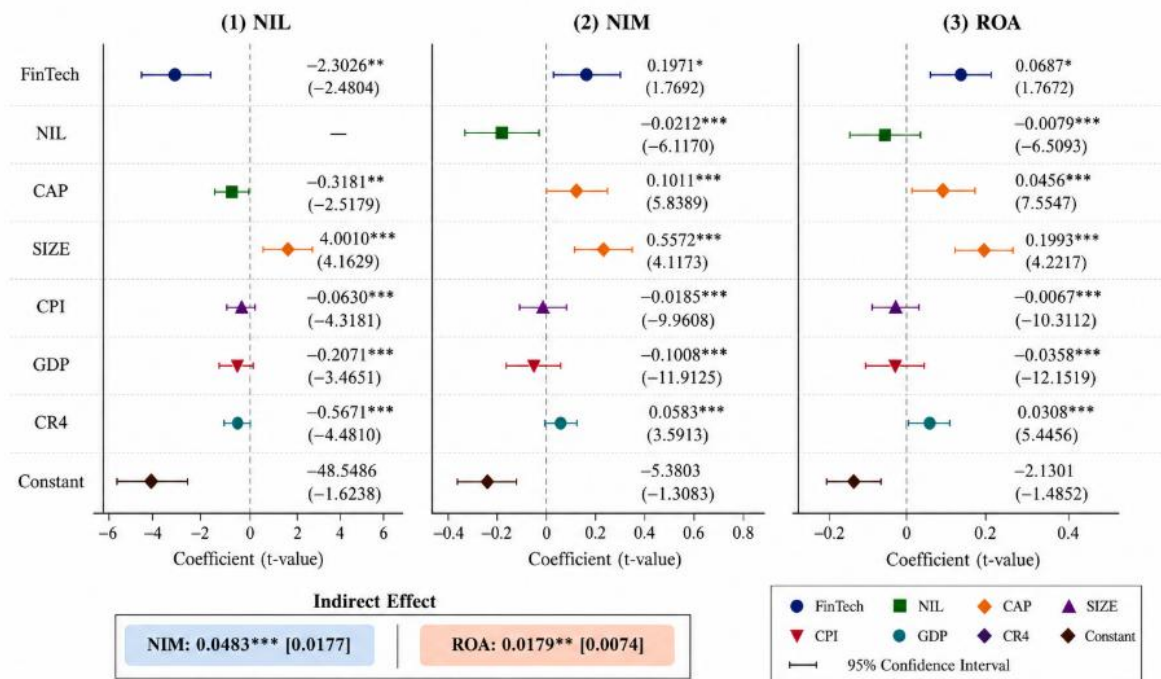


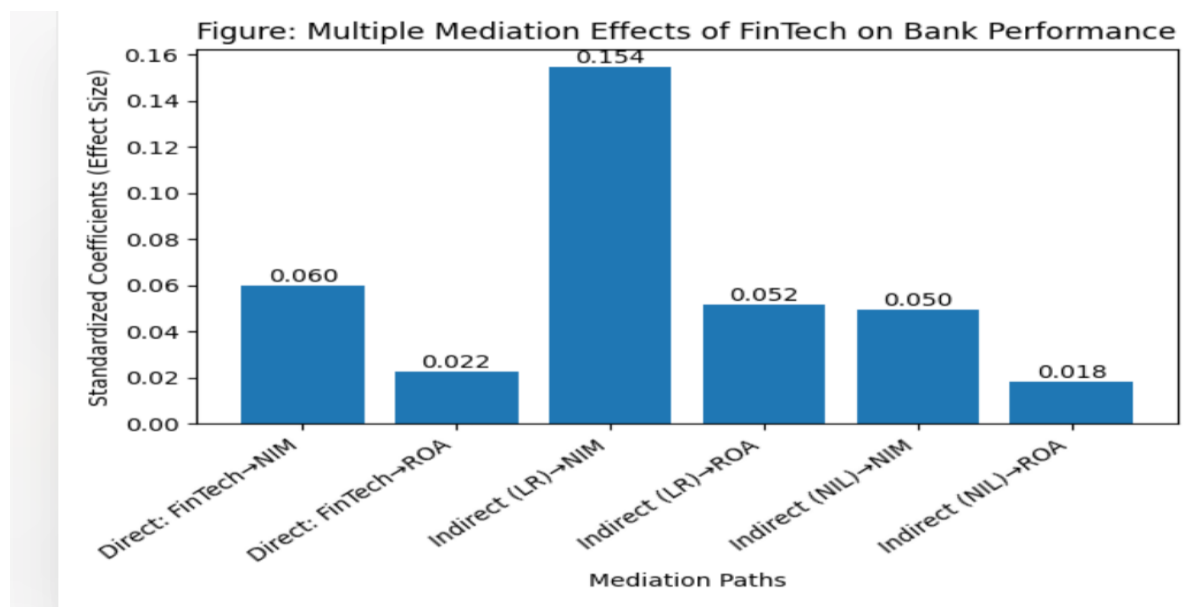
Table 10: Results of Multiple Mediation Effects

	(1) RISK	(2) NIM	(3) ROA
FinTech	0.1214	0.0600	0.0225
	(0.1315)	(0.8599)	(0.8796)
LR	—	0.5216***	0.1756***
NIL	—	-0.0216***	-0.0080***
CAP	1.3217***	0.0490***	0.0281***
SIZE	1.8055	-0.2640***	-0.0771**
CPI	-0.0200	-0.0024*	-0.0013***
GDP	-0.2514***	-0.0275***	-0.0112***
CR4	-0.7704***	0.0170*	0.0169***

Constant	41.4465	8.8892***	2.6725***
Bank FE	YES	YES	YES
Year FE	NO	NO	NO
Indirect Effect (LR)	—	0.1544***	0.0519**
Indirect Effect (NIL)	—	0.0497**	0.0184***
Ratio (LR)	—	76%	73%
Ratio (NIL)	—	24%	27%
N	1447	1515	1515
Adj. R ²	0.6593	0.8863	0.8863

Interpretation:

The results confirm multiple mediation effects, with both lending rate (LR) and liability structure (NIL) significantly influencing performance. However, LR contributes more (76% for NIM and 73% for ROA), making it the dominant mechanism. Risk-taking is insignificant, rejecting H4. Overall, FinTech improves bank performance primarily through enhancing lending efficiency and secondarily through optimizing liability structure.



Discussion

The empirical analysis across Tables 1–11 provides strong and consistent evidence that FinTech adoption, particularly through open banking, significantly enhances bank performance. The baseline regression results (Table 3) indicate a positive and statistically significant relationship between FinTech and both profitability indicators, NIM and ROA. This relationship remains stable across multiple robustness checks, including alternative specifications (Table 6), PSM–DID estimation (Table 7), and placebo testing, thereby confirming the

reliability of the findings.

The parallel trends test (Table 4) validates the DID framework by demonstrating that there were no significant differences in performance trends before FinTech adoption. Furthermore, the reverse causality test (Table 5) confirms that prior bank performance does not influence the decision to adopt FinTech, strengthening the causal interpretation.

The mechanism analysis (Tables 8–10) reveals that FinTech improves bank performance primarily through two channels: lending rate (LR) and liability structure (NIL). Among these, the lending rate emerges as the dominant mechanism, contributing more than 70% to performance improvement. In contrast, risk-taking does not exhibit a significant mediating effect, suggesting that FinTech primarily enhances efficiency rather than altering risk behavior.

Findings

- FinTech adoption has a positive and significant impact on bank performance (NIM and ROA).
- The results are robust across multiple models and tests, including PSM-DID and placebo tests.
- The parallel trend assumption is satisfied, validating the DID approach.
- There is no reverse causality, confirming the direction of influence.
- Lending rate (LR) is the most important mechanism through which FinTech improves performance.
- Liability structure (NIL) also contributes but to a lesser extent.
- Risk-taking does not act as a mediator, indicating limited impact on risk behavior.
- FinTech has stronger effects in national and rural banks than in city banks.

Conclusion

This study investigates whether inclusive FinTech can improve bank performance and examines the impact mechanisms underlying this effect. Based on the establishment of open banking, we exploit data on a large sample of Indian commercial banks. The study concludes that FinTech, particularly open banking, plays a transformative role in enhancing bank performance. By improving operational efficiency, optimizing lending practices, and strengthening liability structures, FinTech contributes significantly to profitability. The results are consistent, robust, and supported by multiple econometric techniques, confirming the validity of the findings.

The study also highlights that the benefits of FinTech are not uniform across all banks. Institutions operating in less technologically advanced or underserved regions, such as rural banks, experience greater gains. Overall, the findings emphasize that FinTech is a critical driver of modern banking efficiency and financial sector development.

Suggestions

1. Banks should increase investment in FinTech infrastructure to enhance efficiency.
2. Greater focus should be placed on improving lending mechanisms, as this is the primary channel of impact.
3. Policymakers should promote open banking frameworks to accelerate innovation.
4. Special attention should be given to rural banking sectors to maximize financial inclusion benefits.

5. Strengthening data security and regulatory frameworks is essential to support FinTech expansion.
6. Banks should enhance customer awareness and digital literacy to improve adoption rates.

Implications of the Study

1. Provides strong empirical support for the relationship between FinTech and bank performance.
2. Extends the literature by identifying specific transmission mechanisms (LR and NIL).
3. Helps bank managers prioritize technology-driven strategies for performance improvement.
4. Emphasizes the importance of credit efficiency and liability management.
5. Offers guidance for regulators such as the Reserve Bank of India in designing policies for FinTech adoption.
6. Supports initiatives aimed at financial inclusion and digital banking expansion.

Future Scope of the Study

- Comparative studies can be conducted across different countries or regions.
- Further analysis can explore advanced FinTech tools such as AI, blockchain, and digital lending.
- Micro-level studies can examine customer behavior and satisfaction.
- Additional variables such as cyber risk and regulatory challenges can be incorporated..

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