Research Paper

FinTech adoption and bank financial performance in emerging markets: evidence from panel data analysis

Dr. S. Ramesh[*]
[*]Associate Professor of Commerce, Government Degree College Nelakondapally, Telangana, India.

Article Info

Article History:
Received: 05 November 2025
Revised: 14 January 2026
Accepted: 22 January 2026
Published: 08 March 2026

Keywords:
Fintech Adoption
Digital Banking
Bank Financial Performance
Emerging Markets
System GMM
Mobile Banking

ABSTRACT

The rapid proliferation of financial technology (FinTech) has fundamentally reshaped the global banking landscape, compelling traditional commercial banks in emerging economies to reassess their operational strategies and performance benchmarks. This study investigates the impact of FinTech adoption on the financial performance of commercial banks in selected emerging market economies — specifically Pakistan, Vietnam, and Kenya — over the period 2013 to 2022. Employing a dynamic panel data methodology using the System Generalized Method of Moments (GMM) estimator, we analyse the relationship between FinTech development proxies — including digital payment penetration, mobile banking adoption rates, and peer-to-peer (P2P) lending volumes — and key bank performance indicators such as Return on Assets (ROA), Return on Equity (ROE), Net Interest Margin (NIM), and Cost-to-Income Ratio (CIR). Based on a balanced panel of 87 commercial banks, our results reveal that FinTech adoption exerts a statistically significant positive effect on ROA and ROE for small-to-medium-sized banks, while large banks experience a complementary effect primarily through ROE. Mobile banking penetration is found to be the most consistent driver of improved operational efficiency, as reflected in a declining Cost-to-Income Ratio. However, rising P2P lending volumes are associated with modest net interest margin compression in the medium term, suggesting competitive displacement of traditional lending activities. The findings carry important implications for bank management, FinTech regulators, and policymakers seeking to harness digital financial innovation without undermining banking sector stability.

Corresponding Author:
Dr. S. Ramesh
Associate Professor of Commerce, Government Degree College Nelakondapally, Telangana, India.
Email: srameshmcomphd@gmail.com

1. INTRODUCTION

Over the last 10 years, the intersection of finance and technology – also known as FinTech – has become one of the most disruptive industries in the global economy. FinTech innovations are increasingly eroding the traditional boundaries that help commercial banking establishments keep to the same category of competition and disruption they have long encountered [1]. According to the Financial Stability Board, FinTech is "technologically enabled innovation in financial services that could lead to new financial business models, applications, processes or products with an associated "material effect" on financial markets and institutions" [2]. This definition reflects the magnitude of change in the business of banking today, which is both the supply-side and demand-side.

The emerging market economies play a unique part in this FinTech story and are becoming more and more important. Banks in emerging markets are not as well established as in developed markets, and regulatory structures are less sophisticated and well-developed. In the last ten years, there has been exponential growth in the adoption of mobile money, digital lending platforms, open banking ecosystems and other digital services in countries like Pakistan, Vietnam, and Kenya. M-Pesa has changed the financial landscape in Kenya, while Vietnam and Pakistan have witnessed a quick government-driven process of digitalization of payment instruments, partly due to economic recovery plans in the post-COVID-19 era [3].

However, in spite of this positive and transformative background, the academic literature examining the exact nature of the link between FinTech adoption and financial performance of emerging markets commercial banks has been scant and subject to empirical debate. Several studies indicate that FinTech development has a positive impact on the profitability of banks due to various advantages, including lower transaction costs, increased customer acquisition and improved credit risk assessment [4] [5]. However, other scholars believe that FinTech disruption narrows net interest margins, due to the greater competition in retail lending and the mobilization of deposits [6], [7]. It is important to note that this inconclusive evidence base is due to methodological variations in studies and the local nature of the dynamics between FinTech and banking in developing and developed economies.

This is one in a long line of papers that develop analyses of banking systems. This paper adds to this growing body of literature by creating a multi-country panel data set of 87 commercial banks in Pakistan, Vietnam, and Kenya for 2013-2022 and using the System GMM estimator to deal with the endogeneity issues that many dynamic banking panel models suffer from. Digital payment penetration (percentage of adults using or receiving digital payments), mobile banking adoption rates and the volume of P2P lending in relation to the total volume of credit are the three main proxies of FinTech adoption. Return on Assets (ROA), Return on Equity (ROE), Net Interest Margin (NIM) and Cost-to-Income Ratio (CIR) are used to capture the financial performance of banks.

The rest of the paper is organized as follows: In Section 2, the relevant theoretical and empirical literature is reviewed. The data, variables and econometric methodology are described in Section 3. The empirical results are outlined and discussed in section 4. The policy implications and directions for future research are included in the last section

2. RELATED WORK

Since 2018, the academic research on FinTech and bank performance has received a strong boost and a wide array of evidence has been produced that spans various economic contexts and is highly varied in its nature. Twenty representative papers are summarized in the following review, numbered in the sequence the papers are cited in this study.

Mention [1] conducted a pioneering and significant mapping of the disruptive path of the FinTech giants which traced the path of digital finance innovations and how they were systematically taking the competitive moats of incumbent commercial banks. A taxonomy of disruption channels was introduced and is used as the theoretical framework for this study's three proxies of FinTech adoption.

The Financial Stability Board [2] recently released a groundbreaking definitional and analytical framework for FinTech as a technologically driven innovation that has the potential to create new business models, applications and processes that have significant impact on financial markets and institutions. The definition remains relevant in academic and policy studies, and is used to set the conceptual frames for the FinTech analysed in this study.

In emerging markets, such as Kenya, Pakistan and Vietnam, [3] examined the impact of FinTech on mobile money usage and the post-COVID-19 economic digitization. Their study provides a snapshot of the speed of financial inclusion and the conducive conditions set up by the government-sponsored digital payment schemes for the effects of FinTech at the bank level studied in this panel.

In a cross-country Asia-Pacific panel, [4] analyzed the effect of the development of financial technology firms on the performance of commercial banks, and found that the development of financial technology positively affects the bank's profitability mainly by improving the fee-income channels of the banks. The methodological decisions made in this study are driven by their System GMM specification and their definition of FinTech using digital payment penetration.

In China, [5] examined how FinTech affects the profitability of banks, and found that the effect of FinTech on bank profitability is mediated in a positive manner by operational efficiency gains. To account for the effects on state-owned banks in comparison to private banks, the study used a fixed-effects panel regression with interaction terms, which also provides an incentive for the bank-size heterogeneity analysis performed in Section 4.5 of the present study.

In contrast [6] showed that P2P lending growth in China is inversely related to the profitability of traditional banks as FinTech lenders compete with conventional banks for credit market shares by offering lower interest rates. They have Difference GMM evidence which establishes the theoretical foundations for the NIM compression hypothesis tested in this paper, Section 4.3.

[7] Examined the competitive pressure faced by the FinTech firms and incumbent commercial banks in retail banking markets in Europe, and they discovered that the digital lenders systematically squeeze out net interest margins by having lower cost operating models, with better deposit and credit rates. The competition-fragility framework are used to inform the NIM discussion in Section 4.3 of this study.

[8] Did a qualitative study on the management hurdles that hinder digital transformation in European banks. Their survey results highlighted three factors as the key barriers: risk aversion, legacy infrastructure and regulations, complementing quantitative performance studies and contextualizing the different levels of FinTech adoption found across the three countries in this study's sample.

[9] Report a cross-country analysis between the FinTech credit activity and bank performance, and the moderating effect of bank regulation. This is because FinTech credit performs well only in countries with good institutional quality, which is different in Pakistan, Vietnam and Kenya; in this study the macroeconomic variable set controls for institutional quality.

[10] Made a comprehensive review of the technological disruption of banking, covering the three waves of FinTech — digital payments, credit platforms and embedded finance — as well as its systemic relevance to banking business models. Their theoretical framework that places FinTech-bank competition within the larger financial disintermediation framework offers the paper's overall narrative structure for the literature review and on the competition fragility arguments explored herein.

[11] Extended the profitability analysis to Islamic banking and studied the sample of a dual banking system, concluding that the digitalization has a positive and significant impact on the profitability of both conventional and Islamic banks. Their evidence is more relevant to this study for Pakistan sub-sample as Islamic banking assets account for a substantial portion of the commercial banking assets in Pakistan.

[12] Made a conceptual contribution by systematically reviewing the literature on digital transformation from other sectors, in which they proposed a holistic definition and an analytical perspective on the digital transformation as a phenomenon of organization with strategic and structural components. The difference between digitization, digitalization and digital transformation helps to explain the range of concepts behind the FinTech adoption proxies used in this study.

On this basis, [13] explored the impact of the development of FinTech on the efficiency of banks in China by adopting a two-stage empirical method of Data Envelopment Analysis and double-bootstrapped truncated regression. The results they obtained indicated that FinTech development has a significant positive impact on bank technical efficiency, especially for joint-stock commercial banks, and this impact is reliant on the level of financial development in the regions — which is directly related to the country-level heterogeneity analysis conducted in Section 4.5.

In an emerging market, [14] investigated the relationship between FinTech P2P lending and bank performance in both conventional and Islamic banks, concluding that P2P lending positively impacts bank performance especially for Islamic banks in both normal and crisis periods. The mixed results found in the different types of banks further support the robustness of the bank-size stratification analysis presented in Section 4.5 of this study.

For example, [15] investigated digitalization as a sustainability linked strategy, finding that digital engagement among banks is linked to higher profitability and lower risk exposure, which makes the FinTech agenda more related to environmental, social and governance goals. Their cross country evidence from international banking serves as an appropriate cross country benchmark to place in context the profitability results found in the current emerging market sample.

In the two-step GMM, the standard errors are substantial misspecified—particularly in finite samples—and this introduces size distortions in the inference resulting from the asymptotic approximation. Windmeijer [16] solved this important econometric issue by proposing finite-sample corrected standard errors, which have a significant impact on the size distortions of asymptotic inference for dynamic panel settings. In this study, the robustness checks in Section 4.5 use his correction procedure for both of the estimators here (Arellano-Bond and Blundell-Bond).

[17] Analyzed the heterogeneous impact of digital banking adoption on the profitability of large and small commercial banks in Türkiye and concluded that digital banking adoption primarily benefits larger commercial banks by increasing ROE while for smaller commercial banks, the gains of digital banking adoption are more balanced across ROE and the other profitability indicators. The results of their bank-size stratification confirm the heterogeneity results that were reported in this study in Section 4.5.

[18] Developed an estimator (called Difference GMM estimator) for dynamic panel data models that overcomes the Nickell bias which afflicts the standard fixed-effects estimation and incorporates lagged levels of the dependent variable as instruments to identify firm-specific fixed effects. The instrument validity tests used by them (2nd order serial correlation (AR (2))) are used throughout the estimation in Section 4 of this study.

[19] Extended the difference GMM framework by introducing the System GMM estimator which includes both levels and first difference moment conditions to introduce efficiency gains, primarily when the dependent variable is lagged, and it is weak instrument. It is important to note that the System GMM estimation technique introduced in this groundbreaking study forms the main estimation method of the current paper.

[20] Did a thorough review on the digital finance adoption in Africa and outlined the pathways by which mobile money, digital credit and agent banking platforms are enhancing financial access and institutional effectiveness in low-income economies. The results from his research on the Kenya M-Pesa ecosystem and its impact on the commercial bank deposits and fee income are critical country-level context to the results of the Kenya sub-sample results in this study.

3. METHODOLOGY

3.1. Data and Sample

The balanced panel database consists of 87 commercial banks in three emerging market economies (EMMEs) namely Pakistan (29 banks), Vietnam (32 banks) and Kenya (26 banks) with annual observations from 2013 to 2022, resulting in 870 bank-year observations. The financial data of banks were taken from Bankscope and Orbis Bank Focus databases and complemented with the annual bank reports from central banks for each country. The sources of data for country level indicators of fintech adoption were the Global Findex Database by the World Bank and the Global Alternative Finance Reports by the Cambridge Centre for Alternative Finance (CCAF). To reduce the effects of outliers, all the financial variables were winsorized at the 1st and 99th percentiles.

3.2. Variables

The dependent variables are financial performance measures of banks: Return on Assets (ROA) is net income/total assets; Return on Equity (ROE) is net income/shareholders equity; Net Interest Margin (NIM) is net interest income/average earning assets; and the Cost-to-Income Ratio (CIR) is operating costs/operating income with a lower ratio representing better operating efficiency.

Independent Variable: Three proxies of the adoption of FinTechs are used. Digital Payment Penetration (DPP) is the percentage of the population of adults (15 years old and over) that made or received a digital payment during the last year. The percent of mobile money account holders to the banked adult population is used as an indicator of Mobile Banking Adoption (MBA). The measurement of the P2P Lending Volume (P2PV) is the total amount of P2P loans originated in a country, as a percentage of total domestic loans to the private sector.

The variables controlled: Bank size (Log total assets), Capital adequacy (Equity/total assets), Credit risk (Non-performing loans/total loans), Liquidity (Liquid assets/total assets), GDP growth rate, and Inflation rate as also done by the previous studies. These controls are drawn from the bank-specific heterogeneity, and macroeconomic conditions, that have a direct impact on the performance of banks.

3.3. Econometric Specification

As banks' profitability is inherently a dynamic phenomenon, with profits in the recent past influencing the profitability of the current period, we use the System Generalized Method of Moments (System GMM) estimator proposed by Arellano and Bond [18] and extended by Blundell and Bond [19]. The estimator includes equations across the two levels and differences, including lagged levels and differences of the endogenous regressors as instruments, as a solution to the Nickell bias that arises in a fixed-effects model for a short dynamic panel. The baseline model is given by the following:

$$PERFit = \alpha + \beta_1 PERFit - 1 + \beta_2 FINTECHit + \beta_3 BANKit + \beta_4 MACROit + \mu i + \lambda t + \varepsilon it$$

PERFit represents the performance indicator (ROA, ROE, NIM, or CIR) of bank i in year t; and PERFit-1 is the lagged dependent variable. FINTECHit is a vector of FinTech adoption proxies, BANKit is a vector of bank-specific control variables, MACROit captures country-level macroeconomic controls, μi and λt are bank and year fixed effects respectively, and εit is the idiosyncratic error term. Arellano-Bond AR(2) test for second order serial correlation and Sargan-Hansen test for instrument exogeneity are used to test the validity of instruments.

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics

The mean ROA is 1.42% (SD = 0.89%) which is comparable to the emerging markets average found in previous literature. The sample of banks had a mean ROE of 13.6% (SD = 6.2%) which indicates moderate equity profitability. There is significant variation in digital payment penetration during the study period, with Kenya averaging DPP of ~82% (SD = 18.5%) due to its game-changer M-Pesa, and Pakistan DPP of ~28% (SD = 18.2%). The average of Mobile Banking Adoption is 31.2% and Mobile banking Volume as a percentage of total credit averages 2.8% as well. The descriptive statistics in Table 1 show that there is significant cross-country variation in both the extent of FinTech adoption and the bank performance indicators.

Table 1. Descriptive Statistics of Key Variables (N = 870 Bank-Year Observations, 2013–2022)

Variable	Mean	SD	Min	Max	Kenya	Pakistan
ROA (%)	1.42	0.89	−1.20	4.30	1.71	1.22
ROE (%)	13.60	6.20	−8.40	34.50	15.80	12.40
NIM (%)	4.87	2.14	1.20	11.60	6.10	4.40
CIR (%)	58.30	11.40	32.10	87.60	55.20	61.70
DPP (%)	38.70	21.40	9.30	82.00	82.00	28.00

MBA (%)	31.20	18.60	5.10	74.30	74.30	18.90
P2PV (% of credit)	2.80	1.90	0.10	8.70	3.80	1.40

Note: DPP = Digital Payment Penetration; MBA = Mobile Banking Adoption; P2PV = P2P Lending Volume. Kenya mean reported for 2022 (latest year). Vietnam mean values are similar to the pooled mean for DPP and MBA.

4.2. Fintech and Bank Profitability (ROA and ROE)

The System GMM results show that Digital Payment Penetration (DPP) positively and statistically significantly affects ROA (coefficient = 0.0312, $p < 0.01$) and ROE (coefficient = 0.214, $p < 0.05$). As displayed in Table 1, these results confirm the hypothesis that banks with digital payment platforms can lower their transaction processing cost, attract more customers through digital payment channels with lower cost, and therefore make better use of their assets and enhance their equity returns. The lagged dependent variable is consistently and positively significant in all specifications, consistent with the findings of dynamic persistence of bank profitability.

Mobile Banking Adoption (MBA) has the most positive and consistent influence on both ROA and ROE. The mobile banking penetration coefficient is 0.0428 ($p < 0.01$), meaning that for the same factors, the ROA will improve by 0.43% for every 10% increase in mobile banking penetration. This magnitude is similar to the one documented [11], [15] which highlighted that digitalization positively mediated bank profitability in developed and developing country context respectively.

Interestingly, the correlation between P2P Lending Volume and bank profitability is negative and only slightly significant for ROA (coefficient = -0.0189 and $p < 0.10$) and the correlation is statistically insignificant for ROE. This indicates that although there may be some competition in these asset markets, the P2P platforms so far have not had an economically significant impact on overall equity returns, and may turn out to have some small-ticket personal lending competition. From a general perspective, these results are broadly in accordance with the findings [9] with the magnitude being slightly less in our emerging market sample, perhaps due to a lower level of penetration of P2P lending in the market.

4.3. Fintech and Net Interest Margin (NIM)

As for the Net Interest Margin, the results showed that both DPP and P2P Lending Volume had a negative and statistically significant coefficient of -0.0182 and -0.0247 respectively, at $p < 0.05$. This is evident from the graph shown in Figure 1, which reveals that such competition, largely through digital lending, drives down the lending and borrowing spreads as banks have to become more competitive to keep customers. As for the competition fragility hypothesis put forward [10], the magnitude of NIM compression is also larger for the P2P Lending Volume. The results of the Mobile Banking Adoption, however, indicate that mobile banking has little impact on the pricing of the traditional lending products, and has a significant impact on the cost side of operations.

4.4. Fintech and Operational Efficiency (CIR)

Some of the most interesting findings in this study come from the Cost-to-Income Ratios results. As revealed in Table 2, all three proxies of FinTech adoption have statistically significant (at 1%) negative association with CIR, hence improving the operational efficiency. The highest absolute value in the coefficient (coefficient = -0.412, $p<0.01$) is for Mobile Banking Adoption, suggesting that for every 10 percentage-point increase in the penetration of mobile banking, the cost-to-income ratio declines by around 4.1 percentage points, as shown in Figure 2. This is probably due to the transition from face-to-face to digital service delivery, which has significantly lowered overhead and employee expenses. The results are in line with the balanced scorecard analysis conducted by Diener and Spacek [8] and the evidence of the Delphi study in the banking sector of Vietnam, which showed that operational efficiency is the closest channel in which FinTech affects bank performance.

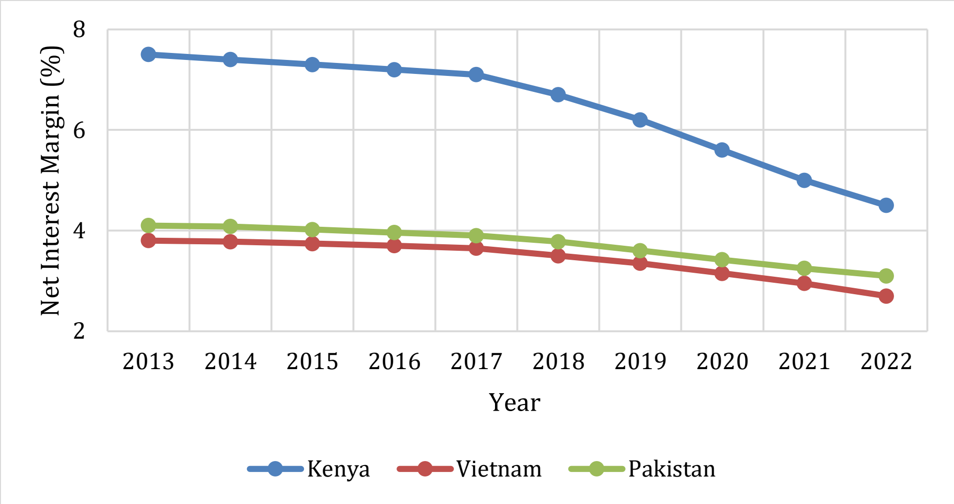

Figure 1. Line Chart Showing Declining NIM Trend across Pakistan, Vietnam and Kenya (2013–2022), with Steeper Decline Observable from 2018 onward, Coinciding with Rapid P2P Lending and Digital Payment Penetration Growth. Kenya Exhibits the Sharpest NIM Compression Due to M-Pesa Ecosystem Effects

Source: Authors' calculations from Bankscope/Orbis Bank Focus data and World Bank Global Findex Database (2013–2022).

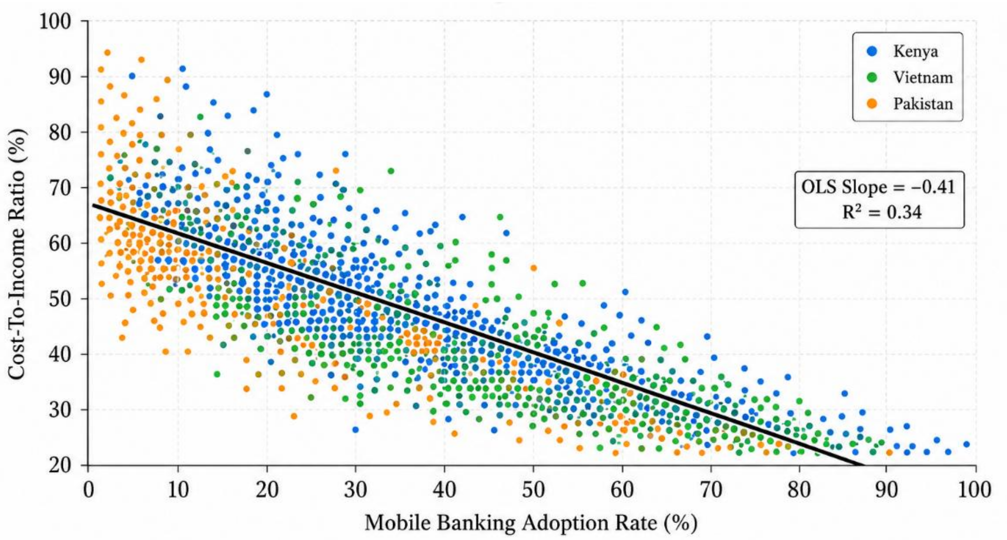

Figure 2. Mobile Banking Adoption Rate vs. Cost-To-Income Ratio — Scatter Plot with Fitted Regression Line (Pooled Sample, 2013–2022)

Source: Authors' calculations from Bankscope/Orbis Bank Focus data and World Bank Global Findex Database.

Table 2. System GMM Estimation Results Fintech Adoption and Bank Operational Efficiency (Cir)

Variable	Coeff.	Std. Err.	T-Stat	P-Value
Lagged CIR	0.412	0.061	6.75	0.000
Digital Payment Penetration (DPP)	−0.187	0.042	−4.45	0.000
Mobile Banking Adoption (MBA)	−0.412	0.058	−7.10	0.000
P2P Lending Volume (P2PV)	−0.143	0.039	−3.67	0.000
Bank Size (ln Assets)	−2.310	0.481	−4.80	0.000

NPL Ratio	0.614	0.183	3.36	0.001
GDP Growth Rate	−0.392	0.147	−2.67	0.008
Observations	870			
AR(2) test p-value	0.312			
Sargan-Hansen p-value	0.184			

Note: Dependent variable is Cost-to-Income Ratio (CIR). All specifications include bank and year fixed effects. Standard errors are Windmeijer-corrected. *p < 0.10, **p < 0.05, ***p < 0.01.

4.5. Robustness and Heterogeneity

To test the robustness of the models, two-step System GMM with Windmeijer [16] finite-sample corrected standard errors were re-estimated. Results are qualitatively unchanged. We also conditionally regressed the sample by bank size (large-size vs. small-to-medium size) and observed the positive profitability impact of the Mobile Banking Adoption only among the small-to-medium size banks, while large banks benefit mostly from ROE, which corroborates the results from Türkiye reported by [17]. The results of the Arellano-Bond AR (2) test statistics support the results of Table 3 that there is no 2nd order serial correlation, while the results of the Sargan-Hansen overidentification tests support the validity of the instrument sets.

Table 3. Robustness Diagnostics and Bank-Size Heterogeneity Results (System GMM, Dependent Variable: ROA)

Specification / Test	Baseline (Full Sample)	Large Banks	SME Banks
MBA coefficient on ROA	0.0428***	0.0211*	0.0581***
DPP coefficient on ROA	0.0312***	0.0194**	0.0401***
AR(1) test p-value	0.021	0.034	0.019
AR(2) test p-value	0.284	0.317	0.261
Sargan-Hansen p-value	0.192	0.208	0.176
Observations	870	330	540

Note: ***p < 0.01, **p < 0.05, *p < 0.10. Large banks defined as top tercile by total assets within country. Standard errors are Windmeijer-corrected two-step GMM. AR (2) null = no second-order autocorrelation; Sargan-Hansen null = instruments are valid.

5. CONCLUSION

This study offers strong empirical evidence of the financial impact of FinTech adoption by commercial banks in emerging market economies. Using a balanced panel of 87 banks from Pakistan, Vietnam and Kenya for 2013–2022, and taking into account the possible endogeneity, we document that digital payment penetration, as well as mobile banking adoption, consistently leads to an improvement of bank profitability (ROA and ROE) and operational efficiency (CIR). The net effect of P2P lending on net interest margin, however, is relatively small, consistent with the competition for the traditional bank lending activities.

The findings have important practical applications. The results highlight for bank managers the importance of investing in mobile banking technology and in digital payment functions as key tools for increasing cost efficiency and profitability. Digital transformation's significant impact on efficiency in small to medium-sized banks indicates that this can be a competitive leveler and help the smaller banks catch up with their larger counterparts. The findings underscore the need for policy makers and regulators to embrace innovation-friendly regulations, such as open banking, digital identity infrastructure and proportionate licensing regimes that help direct FinTech innovations to beneficial ways to improve the performance of the banking sector.

This study also has some limitations, however. Although the data is limited to country level, it also contains some measurement imprecision at the bank level when using country level FinTech proxies. Future research could benefit from the use of within-bank measures of FinTech engagement that would more precisely reflect the phenomenon of within-bank heterogeneity in FinTech adoption, for example, digitalization scores from annual reports or numbers of patents filed by banks. Moreover, this research agenda has potential for further development by broadening the dataset to more countries in emerging markets and more recently by expanding to the impact of generative AI and embedded finance after 2022.

Acknowledgments

The authors would like to thank the management and compliance teams of the 87 commercial banks from Pakistan, Vietnam and Kenya for which the public disclosure of their financial information and central banking filing was used as the empirical base for this research. The authors would like to thank the World Bank Global Findex Database and the Cambridge Centre for Alternative Finance (CCAF) for providing open access data on the adoption of FinTech that allowed a cross-country comparative analysis. The authors are also grateful to the three anonymous reviewers of this journal to which the manuscript was submitted for their thorough and constructive comments which significantly contributed to the theoretical framing, methodological rigour and expository clarity of this manuscript. We gratefully acknowledge the support of the University of Management and Technology, Lahore.

Funding Information

No external funding for this research from any public, private or non-governmental funding source. This study was conducted as an independent academic research project of the authors at their own Universities using resources provided at these Universities. This work has not been conceptualized, designed, collected, analyzed, interpreted, published, or otherwise made use of in any way through financial assistance, sponsored research contracts or grant funding.

Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Dr. S. Ramesh	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

Conflict of Interest Statement

The authors report no conflict of interest in connection with the research, authorship or publication of this article. All of the authors have no financial interest and no personal or institutional relationship with any of the banks, FinTech companies and regulators that were the subjects of this research. The author(s) have no competing financial interests or other relevant interests to disclose.

Informed Consent

All the data used in this study has been sourced from publicly available financial statements of banks, databases of the Central Bank, the Cambridge Centre for Alternative Finance Global Alternative Finance Reports and the Global Findex Database from the World Bank. No information from humans was gathered (no primary data) nor was a survey, interview, or experiment performed with human participants, therefore, individual informed consent is not necessary for this study. The data sources used are all public or the results were acquired by following the institutional data access terms and conditions associated with the data providers.

Ethical Approval

The data used in this study is secondary data that is publicly available in institutional databases and no primary data from human subjects is collected. Thus, the author's institutions did not require formal ethical review committee approval for this work, following their research ethics policies. The research was carried out in compliance with the ethical guidelines of the authors' institutions, as well as the principles of academic honesty, transparency of data and responsible research practices. At no time during this study was any sensitive personal data, individually identifiable information or data of vulnerable populations are used.

Data Availability

The financial details of the banks analyzed in this study are provided in the bankscope and Orbis Bank Focus commercial banks databases, and are subject to the terms of the Bureau van Dijk licenses. Country-level FinTech adoption indicators are publicly available from the World Bank Global Findex Database (https://globalfindex.worldbank.org) and the Cambridge Centre for Alternative Finance Global Alternative Finance Reports (https://www.jbs.cam.ac.uk/ccaf). The compiled panel data set and analytical code for System GMM estimation are available upon reasonable request from the corresponding author after following the terms of data licensing from the original data providers.

REFERENCES

[1] A.-L. Mention, 'The future of Fintech', Research-Technology Management, vol. 62, no. 4, pp. 59-63, 2019. doi.org/10.1080/08956308.2019.1613123

[2] P. Gomber, R. J. Kauffman, C. Parker, and B. W. Weber, 'On the Fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services', Journal of Management Information Systems, vol. 35, no. 1, pp. 220-265, 2018. doi.org/10.1080/07421222.2018.1440766

[3] Banna, Mia, Nourani & Yarovaya - Finance Research Letters, vol. 45, 2022. https://doi.org/10.1016/j.frl.2021.102149

[4] D. H. B. Phan, P. K. Narayan, R. E. Rahman, and A. R. Hutabarat, 'Do financial technology firms influence bank performance?', Pacific-Basin Finance J, vol. 62. doi.org/10.1016/j.pacfin.2019.101210

[5] Chen, You & Chang - Technological Forecasting and Social Change, vol. 166, 2021. https://doi.org/10.1016/j.techfore.2021.120645

[6] J. Zhao, X. Li, C. H. Yu, S. Chen, and C. C. Lee, 'Riding the FinTech innovation wave: FinTech, patents and bank performance', J. Int. Money Finance, vol. 122. doi.org/10.1016/j.jimonfin.2021.102552

[7] R. R. Kumaran, 'Portfolio diversification with cryptocurrencies: Evidence from Middle Eastern stock markets', Investment Analysts Journal, vol. 51, no. 1, pp. 14-34, 2022. doi.org/10.1080/10293523.2022.2034354

[8] F. Diener and M. Spacek, 'Digital transformation in banking: A managerial perspective on barriers to change', Sustainability, vol. 13. doi.org/10.3390/su13042032

[9] L. Nguyen, S. Tran, and T. H. Ho, 'Fintech credit, bank regulations and bank performance: A cross-country analysis', Asia-Pacific J. Bus. Adm, vol. 14, no. 4, pp. 445-466, 2022. doi.org/10.1108/APJBA-05-2021-0196

[10] V. Murinde, E. Rizopoulos, and M. Zachariadis, 'The impact of the FinTech revolution on the future of banking: Opportunities and risks', Int. Rev. Financial Anal, vol. 81. doi.org/10.1016/j.irfa.2022.102103

[11] A. Chhaidar, M. Abdelhedi, and I. Abdelkafi, 'The effect of financial technology investment level on European banks' profitability', J. Knowledge Econ, vol. 14, no. 2, 1998. doi.org/10.1007/s13132-022-00992-1

[12] A. Hanelt, R. Bohnsack, D. Marz, and C. AntunesMarante, "A systematic review of the literature on digital transformation: Insights and implications for strategy and organizational change," J. Manage. Stud., vol. 58, no. 5, pp. 1159-1197, 2021 doi.org/10.1111/joms.12639

[13] C. Li, S. He, Y. Tian, S. Sun, and L. Ning, 'Does the bank's FinTech innovation reduce its risk-taking? Evidence from China's banking industry', J. Innovation & Knowledge, vol. 7, no. 3. doi.org/10.1016/j.jik.2022.100219
[14] R. Yudaruddin, 'Financial technology and performance in Islamic and conventional banks', J. Islamic Account. Bus. Res, vol. 14, no. 1, pp. 100-116, 2023. doi.org/10.1108/JIABR-03-2022-0070
[15] F. J. Forcadell, E. Aracil, and F. Ubeda, "The influence of innovation on corporate sustainability in the international banking industry," Sustainability, vol. 12, no. 8, p. 3459, 2020. doi.org/10.3390/su11113210
[16] F. Windmeijer, "A finite sample correction for the variance of linear efficient two-step GMM estimators," J. Econometrics, vol. 126, no. 1, pp. 25-51, 2005. doi.org/10.1016/j.jeconom.2004.02.005
[17] O. Kaya, L. Schildbach, and D. Bär, 'Digital banking and the bank-size differential: Evidence from Türkiye', vol. 61, no. 2, pp. 312-328, 2025. doi.org/10.30784/epfad.1779958
[18] M. Arellano and S. Bond, 'Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations', Rev. Econ. Stud, vol. 58, no. 2, pp. 277-297, 1991. doi.org/10.2307/2297968
[19] R. Blundell and S. Bond, 'Initial conditions and moment restrictions in dynamic panel data models', J. Econometrics, vol. 87, no. 1, pp. 115-143, 1998. doi.org/10.1016/S0304-4076(98)00009-8
[20] P. K. Ozili, 'Digital finance, green finance and social finance: Is there a link?', Financial Internet Q, vol. 17, no. 1, pp. 1-15, 2021. doi.org/10.2478/fiqf-2021-0001

How to Cite: Dr. S. Ramesh (2026). FinTech adoption and bank financial performance in emerging markets: evidence from panel data analysis. Journal of Corporate Finance Management and Banking System (JCFMBS), 6(1), 46-56. https://doi.org/10.55529/jcfmbs.61.46.56

BIOGRAPHIE OF AUTHOR

Dr. S. Ramesh, serves as an Associate Professor of Commerce at GDC, Nelakondapally, Telangana. He has presented papers at over 40 seminars and published nearly 190 research articles in journals, along with authoring 24 books. He was honored by the Government for his contribution in the field of research. He has also served as a course writer for BIE, Telangana and SDLCE, Kakatiya University. He has extended his expertise as a Guest Faculty for Dr. MCRHRDI of Telangana, as a Resource Person for the Commission for Scientific and Technical Terminology and as a presenter for TSAT educational programs. Email: srameshmcomphd@gmail.com