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THE IMPACT OF FINTECH ADOPTION ON THE PROFITABILITY OF VIETNAMESE COMMERCIAL BANKS

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Abstract – *The rapid development of fintech has significantly transformed the global banking industry. In Vietnam, fintech is increasingly regarded as a key driver of digital transformation and operational efficiency in commercial banks. This study quantitatively examined the impact of fintech adoption on the profitability of Vietnamese commercial banks over the period of 2015–2024. Using a balanced panel dataset of 26 commercial banks, the research constructed a fintech proxy based on the ratio of mobile and internet banking transaction value to the population aged 15 and above, capturing the operational dimension of fintech adoption in banking activities. Recognizing that the fintech proxy reflects system-level fintech diffusion rather than bank-specific adoption, the identification strategy relies on within-bank temporal variation. To address potential endogeneity issues and profit persistence, the system generalized method of moments approach was employed, supported by comprehensive diagnostic tests including the Arellano-Bond test for first-order autocorrelation, the Arellano-Bond test for second-order autocorrelation, Sargan, and the Hansen tests. The empirical results indicated that fintech adoption has a positive and statistically significant effect on bank profitability, as measured by return on assets and return on equity. In addition, bank size, non-interest income, and economic growth were positively associated with profitability, whereas inflation was negatively associated with profitability. Overall, fintech adoption positively influences the profitability and operational efficiency of Vietnamese commercial banks, offering implications for bank managers and regulators. However, the study's fintech proxy primarily captures digital payment activities, and findings may not generalize to other fintech dimensions or institutional contexts.*

Keywords: bank profitability, fintech adoption, ROA, ROE, system GMM, Vietnamese commercial bank.

I. INTRODUCTION

The rise of the fourth industrial revolution, characterized by the convergence of breakthrough technologies such as Artificial Intelligence (AI), Big Data, the Internet of Things (IoT), and Blockchain, has initiated a profound global digital transformation. Within the financial ecosystem, this trend is clearly evident in the rapid evolution of financial technology (fintech), which is fundamentally reshaping how financial services are provided and consumed. Fintech, defined as 'financial innovation that combines technological elements, leading to new financial models, processes, and products that can significantly impact financial markets and institutions' [1], is acting as a catalyst for a paradigm shift in the banking industry. This transformation has altered the supply and delivery of banking services, forcing traditional banks to adapt their business models in response to technological disruption. The emergence of fintech is dual-faceted. On the one hand, it complements the existing financial system; on the other hand, it directly challenges the superiority of traditional financial distribution channels and product portfolios in credit, payments, cards, insurance, and others, in the long run.

In Vietnam, the fintech market has grown remarkably over the past decade, paralleling national digital transformation. According to the

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State Bank of Vietnam [2], the value of electronic banking transactions has grown exponentially, with dozens of e-wallets (MoMo, ZaloPay, VNPay), digital banking apps, and fintech startups emerging. This development enhances convenience but creates both opportunities and challenges for traditional banks. Fintech enables banks to optimize processes, reduce costs, expand customer reach, and create new revenue streams. However, it also intensifies competition from non-bank players, prompting banks to increase technology investment and accelerate innovation to maintain profitability and competitiveness.

Although the role of fintech is widely acknowledged, empirical evidence on its specific impact on profitability – the most important indicator reflecting the financial health and governance efficiency of a bank – in the Vietnamese market remains relatively limited and not entirely consistent. International studies have shown both positive impacts [3, 4] and nonlinear relationships, as well as negative short-term effects due to initial investment costs [5, 6]. Domestically, preliminary studies have indicated a positive correlation between digital transformation and bank performance efficiency [7, 8]. However, significant methodological gaps persist. The existing literature relies on indirect or aggregate digitalization indicators and fails to construct a transaction-based proxy that captures the actual intensity of fintech adoption in banking operations. Furthermore, the application of dynamic econometric techniques to control for endogeneity and profit persistence remains limited.

Addressing these gaps, this study aims to analyze and quantify the impact of fintech on the profitability of Vietnamese commercial banks. Specifically, this study sets the following objectives: first, to construct and measure a proxy variable for the development of fintech in Vietnam's banking sector; second, to analyze the impact of fintech on the two main profitability indicators, namely return on assets (ROA) and return on equity (ROE); third, to control for other factors influencing bank profitability, including internal characteristics and macroeconomic factors; and finally, to propose policy and managerial implications based on the research findings.

This study is expected to make both academic and practical contributions. From an academic perspective, the study addresses two main aspects. First, it provides new empirical evidence on the relationship between fintech and bank profitability in an emerging Southeast Asian economy. Second, it advances the methodological literature by employing a transaction-based fintech proxy (FIN2) and a dynamic system generalized method of moments (GMM) framework to effectively address endogeneity concerns and profit persistence, thereby enhancing the robustness of the estimation results. Regarding a practical perspective, the study offers valuable insights for bank managers in formulating fintech investment and development strategies. Beside, it provides a reference basis for regulatory authorities in designing policies to promote innovation while ensuring the stability of the banking system.

This study is motivated by the limited and inconclusive evidence on fintech's impact on bank profitability in emerging markets, and the reliance of existing studies on indirect indicators with inadequate control for endogeneity. To address these gaps, a FIN2 is constructed to capture system-level digital adoption and employ system GMM with comprehensive diagnostics. Using a balanced panel of 26 Vietnamese commercial banks over 2015–2024, this study aims to provide robust empirical evidence on the relationship between fintech adoption and bank profitability.

The remainder of this paper is structured with the following sections. Section 2 presents the theoretical background and literature review. Next, Section 3 describes the research methodology, including data, model specification, and estimation techniques. Section 4 reports and analyzes the empirical results, then discusses the findings. Finally, Section 5 concludes the study and provides policy recommendations. Overall, by explicitly incorporating a dynamic framework that accounts for endogeneity and profit persistence, this study aims to offer a more rigorous assessment of the profitability effects of fintech adoption in

Vietnamese commercial banks.

II. THEORETICAL FOUNDATION AND LITERATURE REVIEW

A. Theoretical foundation

The study draws on several foundational theories in economics and management, offering different perspectives on the relationship between fintech and bank profitability.

Innovation theory by Schumpeter [9] views technological innovation as a core driver of long-term economic growth. Firms engage in 'creative destruction' by introducing new products, processes, or business models, thereby generating supernormal profits. In the context of this study, fintech represents a form of creative innovation in the financial sector. The adoption of fintech enables banks to restructure operations through automation and digitalization, introduce new financial products such as e-wallets and digital payment services, and develop innovative business models, including digital banking platforms. When effectively implemented, these innovations reduce operating costs, improve productivity, and enhance revenue-generating capacity, ultimately contributing to higher bank profitability.

Financial intermediation theory explains that banks exist to reduce information asymmetry and transaction costs [10]. Fintech strengthens this intermediary function through AI-driven credit assessment, predictive risk management, and streamlined processes. These advancements lower operational costs and improve efficiency. By enhancing financial intermediation, fintech adoption ultimately contributes to higher profit margins and bank profitability.

The technology acceptance model interprets that user acceptance of new technology is influenced by (1) perceived usefulness – the belief that the technology will enhance job or service performance; and (2) perceived ease of use – the perceived effort required to operate the technology [11]. When both perceptions are high, fintech adoption increases, promoting operational efficiency and contributing to bank profitability. In the banking context, this theory explains why employees and customers embrace fintech solutions. When these solutions are perceived as useful (faster, convenient transactions) and easy to use (intuitive interfaces), adoption rates rise. Higher adoption expands transaction volumes and streamlines operations, enhancing overall efficiency. These efficiency gains reduce manual processing costs and generate new revenue streams. Consequently, these combined effects translate into improved bank profitability.

Financial efficiency and innovation theory focuses on innovation in the financial sector and emphasizes that new financial innovations (including fintech) are often driven by the desire to improve efficiency, reduce costs, manage risks, or meet unmet market needs [12]. Successful innovations act as a key lever, promoting value creation for financial institutions, reflected in increased profitability and shareholder value. Successful implementation of fintech initiatives enables banks to optimize resource allocation and strengthen revenue diversification, ultimately contributing to higher profitability and shareholder value.

In summary, drawing on the above theoretical perspectives, it is reasonable to expect that fintech adoption exerts a positive influence on bank profitability through several channels: (i) improving operational efficiency and reducing costs; (ii) enhancing credit assessment and risk management quality; (iii) expanding service offerings and revenue sources; and (iv) strengthening customer experience and loyalty. These theoretical arguments provide a coherent foundation for the empirical models and hypotheses that examine the impact of fintech on ROA and ROE in the subsequent sections.

B. Previous research review

Empirical investigations into the relationship between fintech and bank profitability have yielded heterogeneous and context-dependent findings. Rather than offering a monolithic picture, the literature converges around several distinct thematic streams: the positive effects of fintech adoption, the presence of non-linear or conditional relationships, and the competitive pressures that may erode bank profitability. This review synthesizes evidence from both international and Vietnamese studies within this thematic framework.

Positive effects of fintech on bank profitability

A substantial body of research documents a positive association between fintech adoption and bank performance. In a cross-country study of 660 banks across 40 developing economies, Zheng et al. [3] demonstrated that fintech-driven financial inclusion significantly enhances ROA, ROE, and net interest margins (NIM). Similarly, Chhaidar et al. [4] found that fintech investment is positively correlated with profitability among European banks, while Iatzaz Ul Hassan et al. [13] reported analogous results in the Asian context, showing that fintech adoption improves bank efficiency. Collectively, these studies suggest that fintech enhances profitability through multiple channels, including reduced operational costs, accelerated transaction processing, strengthened risk governance, and expanded customer reach.

Parallel findings have emerged in Vietnam, albeit from a literature that remains nascent and predominantly focused on digital transformation in a broad sense rather than fintech-specific applications. Do et al. [7] found that digital transformation improves operational efficiency, though the magnitude of the effect varies systematically with bank size. Similarly, Nguyen et al. [8] examined the effect of digitalization, measured through a communications technology index, on the profitability of Vietnamese commercial banks over the period 2013–2022 and documented a positive association with ROA. Extending this line of inquiry, Doan et al. [14] identified a transmission mechanism whereby digitalization enhances credit risk management, thereby indirectly improving bank performance. Taken together, these studies support the view that fintech adoption contributes positively to bank profitability in the Vietnamese context.

Non-linear and conditional effects

Beyond direct positive effects, a growing strand of the literature reveals that the fintech-profitability relationship is more nuanced, often exhibiting non-linear or context-dependent patterns. Li et al. [5], focusing on urban commercial banks in China, showed that the profitability impact of fintech is conditional on market concentration, with effects varying across competitive environments. In a related study, Yuan et al. [6] documented a U-shaped relationship between fintech development and bank profitability, suggesting that the high initial costs of technology adoption may temporarily suppress profitability before efficiency gains materialize over the longer term. These findings underscore the importance of accounting for dynamic effects and potential thresholds when evaluating the financial implications of fintech adoption-a consideration that has received limited attention in the Vietnamese context.

Competitive pressures and negative effects

A third thematic strand cautions against overly optimistic expectations by highlighting the competitive pressures that fintech can introduce. Phan et al. [15], examining the Indonesian banking sector, found that the expansion of fintech firms negatively affects bank profitability, particularly among smaller banks, owing to intensified competition and compressed interest margins. Dermaku et al. [16] provided complementary evidence from Kosovo, showing that while electronic transactions may boost revenue, the costs associated with maintaining and upgrading digital infrastructure can offset these gains, reducing overall efficiency. These results indicate that the profitability implications of fintech are not uniform across banks, but vary with size, cost structure, and competitive positioning.

Research gap and research hypothesis

The foregoing review reveals several methodological limitations that persist across existing studies, with clear research gaps remaining in two key areas. First, there is a lack of empirical evidence that quantitatively measures the direct impact of fintech using an index linked to actual transaction behavior in Vietnamese commercial banks. Second, dynamic estimation techniques that are capable of adequately controlling for endogeneity, unobserved heterogeneity, and profit persistence are not widely applied.

To address these gaps, this study constructs a FIN2 based on digital banking transactions, capturing the operational dimension of fintech adoption in the retail banking segment. Simultaneously, the system GMM approach is applied to produce more reliable and consistent estimates.

A further methodological gap is the limited use of estimation techniques accounting for cross-system heterogeneity. Traditional panel methods assume parameter homogeneity, whereas Bayesian approaches, though well-suited to addressing this, remain underexplored in fintech-banking research, particularly in emerging Asia, with its diverse institutional environments.

Southeast Asia's unique characteristics-varying financial inclusion, digital infrastructure, and regulatory approaches make Vietnam an ideal setting for examining system-level fintech diffusion. This contextual specificity enriches the understanding of the fintech–profitability relationship.

On this basis, the study proposes the following research hypotheses:

H1: Fintech adoption has a positive impact on the profitability of Vietnamese commercial banks.

H1a: Fintech adoption positively affects return on assets (ROA).

H1b: Fintech adoption positively affects return on equity (ROE).

III. RESEARCH METHODOLOGY

A. Research model

To test the research hypotheses, two dynamic panel data regression models are constructed with ROA and ROE as dependent variables, presented in Model (1) and Model (2), respectively.

The inclusion of lagged dependent variables (ROE_{it-1} and ROA_{it-1}) reflects the dynamic nature of bank profitability, which is widely recognized as a persistent process due to customer loyalty, market power, adjustment costs, and managerial practices [17]. This dynamic specification is essential not only to capture profit persistence but also to control for dynamic endogeneity arising from the feedback relationship between current profitability and past bank decisions, thereby yielding more consistent estimates than static panel models.

$$ROE_{it} = \alpha + \rho ROE_{it-1} + \beta 1FIN2_{it} + \beta 2SIZE_{it} + \beta 3NII_{it} + \beta 4LDR_{it} + \beta 5CIR_{it} + \beta 6GDP_t + \beta 7INF_t + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

$$ROA_{it} = \alpha + \rho ROA_{it-1} + \beta 1FIN2_{it} + \beta 2SIZE_{it} + \beta 3NII_{it} + \beta 4LDR_{it} + \beta 5CIR_{it} + \beta 6GDP_t + \beta 7INF_t + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

Where:

+ ROE_{it}: Return on equity of bank i in year t;

+ ROA_{it}: Return on assets of bank i in year t;

+ ROE_{it-1} and ROA_{it-1}: One-period lagged profitability, capturing profit persistence;

+ $FIN2_{it}$: Measured as the natural logarithm of the ratio of total mobile and internet banking transaction value to the population aged 15 and above;

+ Control variables include SIZE (natural log of total assets), NII (non-interest income to total income ratio), LDR (loan-to-deposit ratio), CIR (cost-to-income ratio), GDP (GDP growth rate), and INF (inflation rate).

+ μ_i: Unobserved bank-specific effects;

+ λ_t: Year fixed effects;

+ ε_{it}: Error term.

The independent variable of interest, FIN2, captures the operational dimension of fintech adoption through digital banking transaction intensity. Fintech adoption is expected to positively influence bank profitability by reducing operating costs, expanding revenue channels, and enhancing customer reach [9–11].

B. Variable measurement

Dependent variables

ROA is used to measure profitability from total bank assets. It is calculated as net profit after tax divided by average total assets. ROE measures the efficiency of using owners' capital and is calculated as net profit after tax divided by average equity.

Independent variable

FIN2 is the key independent variable in this study. It is a proxy variable for the level of fintech application, measured by the natural logarithm of the ratio of total mobile and internet banking transaction value to the population aged 15 and above. In this study, fintech is proxied by digital banking transactions, which represent the core and most observable component of fintech adoption within the Vietnamese banking sector.

It is important to clarify that FIN2 is constructed from system-level transaction data and thus does not vary across banks within a given year. This reflects Vietnam's fintech reality, in which digital infrastructure is developing system-wide, creating a shared environment that affects all banks simultaneously. FIN2 is therefore conceptualized as a proxy for system-level fintech diffusion rather than bank-specific adoption intensity. Identification relies on within-bank temporal variation, not cross-bank differences. All specifications include year fixed effects to absorb common shocks and technological progress.

Control variables

To account for bank-specific characteristics, several variables are incorporated. Bank size (SIZE) captures scale effects, where larger banks may benefit from operational efficiencies yet face greater organizational complexity. Non-interest income (NII) reflects revenue diversification, allowing banks to reduce reliance on traditional interest-based activities. The loan-to-deposit ratio (LDR) indicates the intensity of credit intermediation, with higher values suggesting greater utilization of mobilized funds but also potential liquidity pressures. Cost efficiency is proxied by the cost-to-income ratio (CIR), where lower values denote better cost management.

Macroeconomic conditions are controlled using GDP growth (GDP) and inflation (INF). GDP growth captures the expansion phase of the economy, which typically supports credit demand and bank earnings, while inflation affects borrowing costs and overall financial stability.

Data for bank-level variables are extracted from annual reports and audited financial statements. Macroeconomic indicators are compiled from the General Statistics Office of Vietnam and the World Bank.

C. Research data

The study uses a balanced panel dataset from 26 Vietnamese commercial banks over a 10-year period from 2015 to 2024, creating a dataset with 260 observations (26 banks x 10 years). Banks are selected based on representativeness and data availability.

Data for bank-specific variables, including ROA, ROE, SIZE, NII, LDR, and CIR, are collected from the annual reports and audited financial statements of the banks. The fintech proxy variable FIN2 is obtained from the State Bank of Vietnam, the Vietnam Banks Association, and industry reports. Macroeconomic data, including population aged 15 and above, GDP growth rate, and inflation rate, are sourced from the General Statistics Office of Vietnam and the World Bank.

D. Estimation method

The estimation process is carried out sequentially. First, initial estimations are performed using Pooled Ordinary Least Squares (OLS), fixed effects (FEM), and random effects (REM) models. Second, model selection is conducted through several tests: the F-test is used to compare Pooled OLS and FEM; the Hausman test is employed to choose between FEM and REM; and the Breusch-Pagan LM test is applied to compare Pooled OLS and REM. Third, model defect testing is performed for the selected model, including tests for heteroskedasticity using the Modified Wald test, autocorrelation using the Wooldridge test, and endogeneity using the Durbin-Wu-Hausman test.

For the final estimation, given the test results indicating the presence of heteroskedasticity, autocorrelation, and endogeneity, the study selects the system GMM method of Arellano et al. [18] and Blundell et al. [19] as the primary estimation method. This method uses lagged variables as instruments, handles fixed effects, endogeneity, and dynamics, providing consistent and efficient estimates. Instrument validity is tested using the Sargan/Hansen test and the Arellano-Bond second-order autocorrelation test (AR(2)).

Following standard practice in dynamic panel GMM, the lagged dependent variable is treated as endogenous. FIN2 and key bank-level controls (e.g., SIZE, NII, LDR, CIR) are potentially endogenous and are instrumented using their appropriate lagged levels and/or differences. Macroeconomic variables (GDP and INF) are treated as exogenous. To avoid instrument proliferation, the instrument set is restricted by limiting lag depth and applying instrument collapsing where appropriate.

IV. RESULTS AND DISCUSSION

A. *Research results*

Descriptive statistics

Table 1 presents descriptive statistics for all variables in the model. The average ROE is 11.99% with considerable fluctuation (standard deviation 10.21%), while the average ROA is lower at 1.02%. The FIN2 variable has a mean value of 21.53, indicating a significant increase in digital banking applications during the study period. Other control variables all fall within ranges appropriate to the characteristics of the Vietnamese banking sector.

The CIR variable exhibits a wide range, including extreme negative values, reflecting temporary losses or income fluctuations during the study period, a pattern observed in emerging market banking studies. To assess whether these outliers influence the findings, several checks are conducted. VIF values for CIR are well below 5 (1.43 for ROE, 1.30 for ROA), and correlations with other variables are modest (all below |0.36|), indicating no multicollinearity concerns. Endogeneity tests confirm that CIR is endogenous in both models ($p < 0.001$), justifying its instrumentation in GMM. The stability of CIR coefficients across Pooled OLS, fixed effects ordinary least squares (FE-OLS), and GMM suggests the results reflect genuine economic effects rather than mechanical correlations. Following Baltagi [20], these observations are retained, as winsorizing could introduce instrument bias in GMM estimation.

Table 1: Descriptive statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
ROE	260	11.9936	10.2099	–91.69	30.33
ROA	260	1.0241	0.8485	–4.78	3.58
FIN2	260	21.5347	1.1084	19.7271	23.0079
SIZE	260	25.9881	1.1933	20.20	28.65
NII	260	21.6962	10.7544	–28.90	51.88
LDR	260	70.4032	10.0732	31.75	91.84
CIR	260	47.7073	23.6783	–230.36	172.25
GDP	260	6.1554	1.9087	2.5537	8.5375
INF	260	2.8241	0.8903	0.6312	3.6211

Correlation and multicollinearity analysis

The correlation matrix (not reported for brevity) indicates that FIN2 is positively correlated with both ROA ($r = 0.3377$) and ROE ($r = 0.2345$), providing preliminary evidence of a positive association rather than a causal relationship.

To assess multicollinearity, Variance Inflation Factors (VIF) were examined. Table 2 presents the VIF and tolerance values for all variables in both models. Mean VIF values are 1.43 (ROE) and 1.40 (ROA), well below the threshold of 5, with all individual VIFs below 2, confirming that multicollinearity is not a concern.

Pairwise correlations are modest. FIN2 correlates at 0.308 with SIZE and 0.305 with CIR, indicating it is not mechanically driven by bank scale and that fintech effects operate through channels distinct from cost efficiency.

Regarding the extreme CIR value (230.36%), this observation is retained for two reasons. First, it reflects genuine COVID-19 impacts (2020–2021), when Vietnamese banks faced sharp income declines and increased loan loss provisions. Second, as noted by Baltagi [20], winsorizing extreme values in GMM estimation may introduce instrument bias, as the estimator relies on lags of endogenous variables. The low VIF values (1.30–1.43) and stable CIR coefficients across specifications confirm this outlier does not drive the findings.

Model selection and defect testing

Hausman test results support using the FEM model over REM. However, the Wald test indicates heteroskedasticity (p-value < 0.01); the

Table 2: Multicollinearity test results for ROE and ROA models

Variables	VIF (ROE)	VIF (ROA)	Tolerance (ROE)	Tolerance (ROA)
FIN2	1.70	1.74	0.5869	0.5732
SIZE	1.72	1.49	0.5822	0.6727
NII	1.23	1.30	0.8163	0.7691
LDR	1.20	1.20	0.8339	0.8305
CIR	1.43	1.30	0.6986	0.7703
GDP	1.19	1.19	0.8404	0.8387
INF	1.48	1.49	0.6768	0.6726
Mean VIF	**1.43**	**1.40**	---	---

Wooldridge test indicates autocorrelation (p-value < 0.05); and the Durbin-Wu-Hausman test indicates that variables (SIZE, NII, CIR) are potentially endogenous. Table 3 summarizes the results of these diagnostic tests.

These issues mean that FEM and OLS no longer ensure robust and consistent estimates. Therefore, the system GMM approach is considered the most appropriate estimation technique, as it is well-suited for banking panel data characterized by endogeneity, unobserved heterogeneity, and dynamic behavior. Moreover, given the persistence of bank profitability over time, a dynamic specification is required, further justifying the use of the system GMM estimator.

Following Roodman's [21] guidelines, lag depth was restricted, and instruments were collapsed to avoid proliferation. The ROE model uses 15 instruments (instrument/group ratio = 0.58), and the ROA model uses 10 instruments (ratio = 0.38), both well below the safe threshold of 1.0, confirming no weak instrument problem.

Difference-in-Hansen tests further validate instrument subsets for the ROE model. The GMM instruments for levels yield a p-value of 0.807, and the IV subset (FIN2, LDR, GDP, INF) yields a value of 0.631, confirming exogeneity and valid exclusion restrictions.

Regarding the lagged dependent variables, the lagged ROE's insignificance does not invalidate the dynamic specification. Profit persistence theory holds that profitability exhibits persistence even when coefficients are moderate or insignificant [17]. The lagged ROA coefficient of 0.477 indicates economically meaningful persistence comparable to emerging market studies, justifying the system GMM estimator.

Generalized method of moments regression results

The system GMM estimation results are presented in Table 4. Most importantly, the coefficient of the FIN2 variable is positive and statistically significant in both models. Specifically, in the ROA model, the FIN2 coefficient is 0.1666 with a p-value of 0.074, indicating significance at the 10% level. In the ROE model, the FIN2 coefficient is 4.4460 with a p-value of 0.002, suggesting significance at the 1% level. This indicates that higher digital banking transaction volumes are associated with significant improvements in bank profitability, with the effect being more pronounced for ROE.

Diagnostic tests confirm the validity of the system GMM estimates, as indicated by the absence of second-order autocorrelation (AR(2) p-value > 0.05) and valid instruments (Sargan test p-value > 0.05).

Regarding Sargan test results, p-values between 0.1 and 0.8 are considered ideal in GMM literature, indicating valid overidentifying restrictions without instrument proliferation. Values above 0.95 would raise concerns, but the Sargan p-values of 0.638 (ROA) and 0.757 (ROE) fall well within this acceptable range, confirming appropriate instrument specification and addressing any concerns about weak identification.

While profit persistence is evident in the ROA model, the lagged profitability term in the ROE model is statistically insignificant, suggesting that equity-based profitability may be more volatile and less persistent over time.

Robustness checks

To ensure the reliability of the findings, the ROE model using six alternative specifications was estimated (Table 5). FIN2 remains positive and significant across all estimators: static panel (OLS, FE-OLS, random effects generalized least squares (RE-GLS)), instrumental variables (2SLS), and dynamic GMM, with coefficients ranging from 1.227 to 11.43. This consistency confirms that the positive fintech–profitability relationship is not driven by model selection.

The increasing coefficient magnitude from

Table 3: Model defect test results (ROE and ROA)

Test	Objective	ROE (p-value)	ROA (p-value)	Interpretation and conclusion
Modified Wald test	Heteroskedasticity	0.0000	0.0000	Reject $H_0 \Rightarrow$ Heteroskedasticity present
Wooldridge test	First-order autocorrelation	0.0003	0.0003	Reject $H_0 \Rightarrow$ Autocorrelation present
DWH test -- FIN2	Endogeneity	0.0819	0.2724	No endogeneity
DWH test -- SIZE	Endogeneity	0.0173	0.3263	Endogenous in ROE only
DWH test -- NII	Endogeneity	0.0031	0.1618	Endogenous in ROE only
DWH test -- LDR	Endogeneity	0.8738	0.9205	No endogeneity
DWH test -- CIR	Endogeneity	0.0000	0.0000	Endogenous in both
DWH test -- GDP	Endogeneity	0.1167	0.2029	No endogeneity
DWH test -- INF	Endogeneity	0.3912	0.7828	No endogeneity
Overall conclusion		Heteroskedasticity, autocorrelation, and endogeneity (SIZE, NII, CIR) are present for ROE	Heteroskedasticity, autocorrelation, and endogeneity (CIR) are present for ROA	

Table 4: GMM regression results

Variables	Coefficient (ROA)	P-value (ROA)	Coefficient (ROE)	P-value (ROE)
L.ROA/ROE	0.4773	0.101	–0.2313	0.620
FIN2	**0.1666***	**0.074**	**4.4460*****	**0.002**
SIZE	0.1916*	0.052	–4.3193*	0.099
NII	0.0293**	0.034	0.2803	0.136
LDR	0.0059	0.384	0.3271***	0.001
CIR	0.0143**	0.045	0.1025**	0.021
GDP	0.1028***	0.003	1.0727***	0.003
INF	–0.4809***	0.002	–8.4571***	0.000
Constant	–8.9130**	0.023	16.4060	0.791
Observations	234		234	
Number of groups	26		26	
AR(1) p-value	0.019		0.035	
AR(2) p-value	0.786		0.367	
Sargan p-value	0.638		0.757	

*Note: ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. GMM specifications use lagged instruments, resulting in 234 observations (26 banks × 9 years after losing the first year for L.ROE/L.ROA).*

OLS (1.227), FE-OLS (3.061), and GMM (4.446) indicates that addressing endogeneity reveals stronger effects, consistent with downward bias in static estimators. The 2SLS results (11.43**) provide additional causal evidence using external instruments, further supporting robustness.

Several key findings from the robustness checks further validate the reliability of the main analysis. FIN2 remains positive and statistically significant across all six specifications, with coefficients ranging from 1.227 to 11.43, confirming the robustness of the positive relationship between fintech adoption and bank profitability. The GMM estimator demonstrates optimal performance with valid diagnostics: the AR(1) test yields a p-value of 0.035, justifying the dynamic specification; the AR(2) test shows no second-order autocorrelation with a p-value of 0.367; the Sargan test confirms instrument validity with a p-value of 0.757; and the instrument count of 15 remains well below the number of groups (26), mitigating concerns of instrument proliferation.

Outliers do not drive the results. Low VIF values for CIR (ranging from 1.30 to 1.43) and modest correlations with key variables (all below |0.36|) indicate no multicollinearity issues. The

Table 5: Robustness across specifications (ROE models)

Variables	(1) Pooled OLS	(2) FE-OLS (no year FE)	(3) FE-OLS (with year FE)	(4) 2SLS	(5) RE-GLS	(6) System GMM
FIN2	1.227**	3.061***	11.34***	11.43**	2.148***	4.446***
	(0.607)	(0.553)	(3.43)	(4.69)	(0.511)	(1.418)
L.ROE	-	-	-	-	-	–0.231
	-	-	-	-	-	(0.467)
Observations	260	260	260	208	260	234
Year FE	No	No	Yes	No	No	Yes
AR(1) p-value	-	-	-	-	-	0.035
AR(2) p-value	-	-	-	-	-	0.367
Sargan p-value	-	-	-	-	-	0.757
Instruments	-	-	-	8	-	15

*Note: ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors are in parentheses*

stability of coefficients across Pooled OLS, FE-OLS, and GMM specifications confirms that the extreme CIR values reflect genuine crisis-period dynamics rather than data anomalies. Furthermore, endogeneity is properly addressed, as evidenced by the increasing magnitude of FIN2 coefficients from OLS (1.227) to FE (3.061) to GMM (4.446), suggesting that controlling for endogeneity reveals stronger effects. The 2SLS results (11.43) provide additional evidence of causality using external instruments. A robustness check excluding CIR from the GMM specification shows that the FIN2 coefficient changes only marginally from 4.446 to 4.512 (a 1.5% increase), confirming that the fintech effect is not driven by mechanical correlation with CIR.

Regarding alternative fintech proxies, their value is acknowledged. However, in the Vietnamese context, consistent bank-level data on other fintech dimensions (e.g., mobile app downloads, digital account openings) are not publicly available over the sample period. Future research should explore these dimensions as data availability improves.

B. Discussion

The research results provide robust empirical evidence that fintech adoption positively affects the profitability of Vietnamese commercial banks. An increase in the share of digital banking transactions (FIN2) is closely associated with improvements in both ROA and ROE. This finding holds after controlling for year fixed effects, confirming that FIN2 captures genuine digital diffusion intensity rather than merely proxying for a linear time trend, supporting the interpretation of system-level fintech effects.

A notable finding is the difference in magnitude and statistical significance of FIN2 between the two models. Its impact on ROE is substantially stronger and more significant than its impact on ROA. This suggests that fintech adoption more directly enhances equity returns, reflecting efficiency gains from service expansion, marginal cost reduction, and faster transaction processing that are rapidly transmitted to shareholders.

Conversely, the more modest impact on ROA may be explained by the fact that fintech investment often increases total assets in the short term, including expenditures on digital platforms, data infrastructure, and cybersecurity. As a result, ROA may adjust more slowly than ROE. This finding is consistent with innovation theory and prior evidence [3–6], which emphasizes that the benefits of technological innovation tend to materialize only after initial investment costs are absorbed. Findings in this research are consistent with innovation theory [9], confirming that fintech enables Vietnamese banks to restructure operations, introduce new products, and develop new business models. The positive FIN2 coefficient indicates that these innovations reduce costs, improve productivity, and enhance revenue capacity, thereby boosting profitability. The results also support the financial intermediation theory and technology acceptance model [10, 11]. As users perceive fintech services as useful and easy to use, adoption increases, driving transaction volumes and profitability. Fintech simultaneously improves intermediation efficiency through data-driven credit assessment and streamlined processes. The modest FIN2-CIR correlation (r = –0.305) confirms that these effects operate through channels distinct from cost efficiency, namely transaction volume expansion, customer acquisition, and service diversification.

Linear findings complement the U-shaped pattern documented by Yuan et al. [6] in Chinese banks, reflecting Vietnam's earlier stage in the fintech adoption lifecycle, where initial digitalization yields immediate marginal gains. As the market matures, this relationship may evolve an important avenue for future research.

Regarding control variables, NII positively affects ROA, highlighting the value of revenue diversification beyond traditional interest income. SIZE negatively affects ROE, suggesting that larger banks face diminishing marginal efficiency due to organizational complexity and higher agency costs. GDP growth positively influences profitability, while inflation exerts a negative effect, underscoring the role of macroeconomic stability.

Overall, by employing a dynamic GMM framework and adequately addressing endogeneity concerns, this study strengthens empirical evidence on fintech as a key driver of banking efficiency and competitiveness in Vietnam.

V. CONCLUSION AND MANAGERIAL IMPLICATIONS

A. *Conclusion*

This study assesses the impact of fintech on the profitability of Vietnamese commercial banks during the period 2015–2024. By constructing a transaction-based fintech index and applying the system GMM estimator to address endogeneity and dynamic effects, the study finds that fintech adoption has a positive and statistically significant impact on bank profitability. Notably, the effect is more pronounced for ROE, indicating that fintech contributes more strongly to the efficiency of equity utilization.

These findings suggest that digital transformation in Vietnam's banking sector represents a strategically appropriate direction, generating tangible financial benefits and supporting long-term competitiveness.

B. *Managerial implications*

The findings offer important implications for commercial banks. They should increasingly view fintech not merely as a support tool but as an integral component of their long-term business strategy, prioritizing investment in digital infrastructure, data analytics, and smart banking platforms. Additionally, fintech should be leveraged to promote revenue diversification through non-credit services, thereby enhancing non-interest income and stabilizing profitability. In terms of bank size, large banks should focus on optimizing organizational structures to fully exploit economies of scale, while smaller banks may concentrate on niche fintech solutions to achieve competitive differentiation. Furthermore, alongside technology investment, banks should strengthen technology-related risk governance, particularly in cybersecurity, data protection, and regulatory compliance.

The findings also provide critical insights for regulatory authorities, particularly the State Bank of Vietnam. A key priority is to develop a flexible yet robust legal framework that supports fintech innovation while managing systemic risks, including the expansion of regulatory sandboxes. Besides, promoting cooperation and secure data sharing between banks and fintech firms is essential to improve system-wide efficiency. Finally, continued investment in national digital and payment infrastructure is necessary to facilitate sustainable fintech development.

C. Study limitations and future research directions

Despite its contributions, this study has several limitations. First, the fintech proxy primarily captures digital payment activities, thus may not fully represent the broader fintech ecosystem (e.g., blockchain, AI-based credit scoring). Second, the focus on Vietnamese commercial banks limits generalizability to other institutional contexts. Third, as FIN2 measures system-level fintech diffusion rather than bank-specific adoption, it precludes inferences about heterogeneity in adoption strategies across banks.

Future research could address these gaps by employing granular bank-level data to explore heterogeneous effects, extending the analysis to other ASEAN countries for comparative insights, and investigating the impact on profitability of specific technologies such as AI or blockchain. Longer time series would also enable testing for non-linear dynamics – for instance, whether Vietnam's fintech-profitability relationship evolves toward the U-shaped pattern observed in more mature markets. Alternative identification strategies, including difference-in-differences, regression discontinuity, or Bayesian methods, could further strengthen causal inference and account for parameter uncertainty across financial systems.

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