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DIGITAL BANKING SERVICES AND COMMERCIAL BANK PROFITABILITY IN VIETNAM: EVIDENCE FROM SYSTEM GMM

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ABSTRACT

This study investigates the impact of electronic banking services on the profitability of Vietnamese commercial banks over the period 2014–2023. Using an unbalanced panel dataset of 25 banks (up to 250 bank-year observations, with missing values in the e-banking index addressed via linear interpolation and trend extrapolation) and applying System Generalised Method of Moments (Sys-GMM) to control for endogeneity and dynamic persistence in profitability, we find that the e-banking index (EBANKIT) exerts a statistically significant negative short-run effect on Return on Assets (ROA) ($\beta = -0.0014$, $p = 0.016$), consistent with the productivity paradox hypothesis. ICT investment has the strongest positive effect ($\beta = 0.2373$, $p = 0.035$), supporting the Resource-Based View. Capital adequacy (CAR), bank size (SIZE), and non-performing loans (NPL) also exhibit expected directional effects. The lagged ROA coefficient (0.711) confirms strong profit persistence. Findings suggest that Vietnamese banks' digital investments require a gestation period before translating into profitability gains, with important implications for management and policymakers.

Keywords: Bank profitability, digital transformation, electronic banking, ROA, System GMM, Vietnamese commercial banks.

1. INTRODUCTION

The rapid diffusion of digital technology has fundamentally reshaped financial intermediation. Vietnamese commercial banks have accelerated digital investments in response to surging demand: electronic payment transactions grew from approximately 6.5 billion in 2019 to 17.7 billion in 2024, with cashless payments in e-commerce reaching 66.8% by end-2024 [1] (Figure 1). Yet the economic consequences of such digitisation for bank profitability remain empirically contested.

Extant literature presents mixed evidence. Studies from Spain [2], India [3], [4], Turkey [5], and emerging markets broadly [6] generally find positive medium-to-long-run effects of e-banking on ROA, while acknowledging an initial drag due to heavy upfront technology investment – the so-called 'productivity paradox' [7]. Vietnamese evidence remains sparse, with most prior domestic studies ending before 2020 and relying on static panel estimators (Pooled OLS, FEM, FGLS) that may suffer from endogeneity bias.

This study contributes to literature in three ways. To capture the post-COVID digital explosion, we first update the dataset until 2023. Second, we simultaneously estimate the distinct roles of EBANKIT (customer-facing digital service index) and ICT (internal operational infrastructure spending), resolving conceptual conflation in prior work. Third, we improve the methodological rigor over FGLS-based predecessors by using Sys-GMM, the best estimator for dynamic panel models to handle endogeneity, unobserved heterogeneity, and serial correlation.

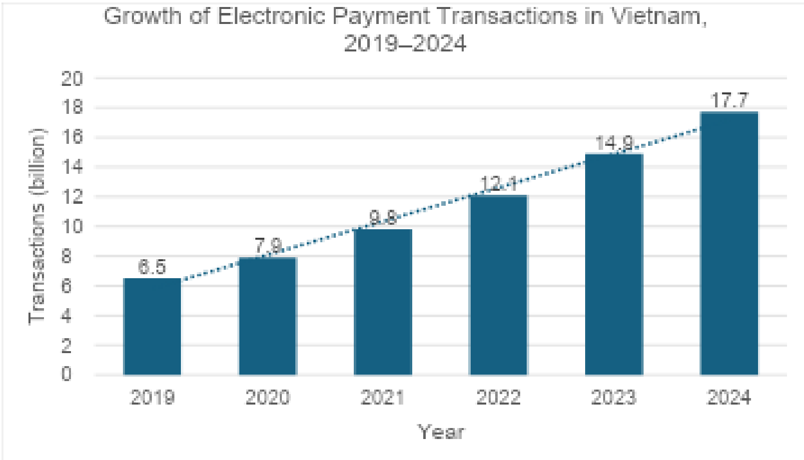


Figure 1. Growth of electronic payment transactions in Vietnam, 2019–2024 [1]
(Note: 2020–2023 values are linearly interpolated for illustration)

The remainder of this paper is organised as follows: Section 2 reviews the theoretical foundations and prior empirical work; Section 3 describes the data and methodology; Section 4 presents results; Section 5 discusses implications; and Section 6 concludes.

2. THEORETICAL BACKGROUND AND LITERATURE REVIEW

2.1. Theoretical Framework

Four theoretical lenses guide this study. (i) Financial Intermediation Theory [8], [9] posits that digitisation reduces transaction costs and information asymmetry, improving the efficiency of capital allocation and thereby raising ROA. (ii) The Resource-Based View [10] treats ICT capability as a strategic resource that is difficult to imitate, generating sustained competitive advantage and superior profits. (iii) Scale Efficiency Theory [11], [12] argues that larger banks exploit economies of scale in technology deployment, spreading fixed digital infrastructure costs over a larger revenue base. (iv) The Productivity Paradox [7] reconciles conflicting findings by introducing a lag structure: initial investment raises costs before productivity benefits materialise, predicting a temporary negative effect on ROA.

2.2. Empirical Literature

International evidence consistently links e-banking to higher profitability. Hernando and Nieto [2] studied 72 Spanish banks (1994–2002) and documented a 1% improvement in ROA approximately 1.5 years after Internet banking adoption. Malhotra and Singh [3] analysed 85 Indian banks (1998–2006) and found a positive relationship between Internet banking deployment and both ROA and operational efficiency. Onay and Ozsoz [5], using GMM on 14 Turkish banks (2002–2011), confirmed the positive profitability effect, particularly for large banks. Ghose and Maji [4] applied both Sys-GMM and 3SLS to 67 Indian banks (2011–2020), finding that transaction volume and value of Internet banking significantly raise ROA. Most recently, Zheng et al. [6] examined 660 banks across 40 developing countries and concluded that Fintech-driven inclusive finance is a core profitability driver.

Domestic Vietnamese studies are more limited. Dinh et al. [13] used FEM/REM on 25 banks (2009–2014) and found Internet banking positively affects ROA with a lag exceeding three years. Nguyen-Thi-Huong et al. [14], using a digital transformation index derived from text analysis of Vietnamese bank annual reports (2015–2021), documented a significant impact of digital banking on bank performance. More recently, Do et al. [15] employed System GMM and documented a positive impact of digital transformation on bank performance in Vietnam. However, existing studies primarily focus on aggregate digital transformation measures and shorter sample periods, without disentangling specific digital channels such as EBANKIT from ICT or addressing extended post-2020 dynamics.

2.3. Research Hypotheses

Based on the theoretical arguments and empirical evidence reviewed above, Table 1 summarises the seven research hypotheses, specifying the expected direction of each variable's effect on ROA and the corresponding theoretical basis.

Table 1. Research Hypotheses

Hypothesis	Variable	Expected	Theoretical Basis
H1	EBANKIT	(+)/(-)	Productivity Paradox [7]
H2	ICT	(+)	Resource-Based View [10]
H3	SIZE	(+)	Scale Efficiency Theory [11]
H4	NPL	(-)	Risk-Return Theory [16]
H5	CAR	(+)	Basel Capital Adequacy Framework
H6	GDP	(+)	Financial Intermediation Theory [8]
H7	COVID	(-)	[17]

Source: Compiled by the authors.

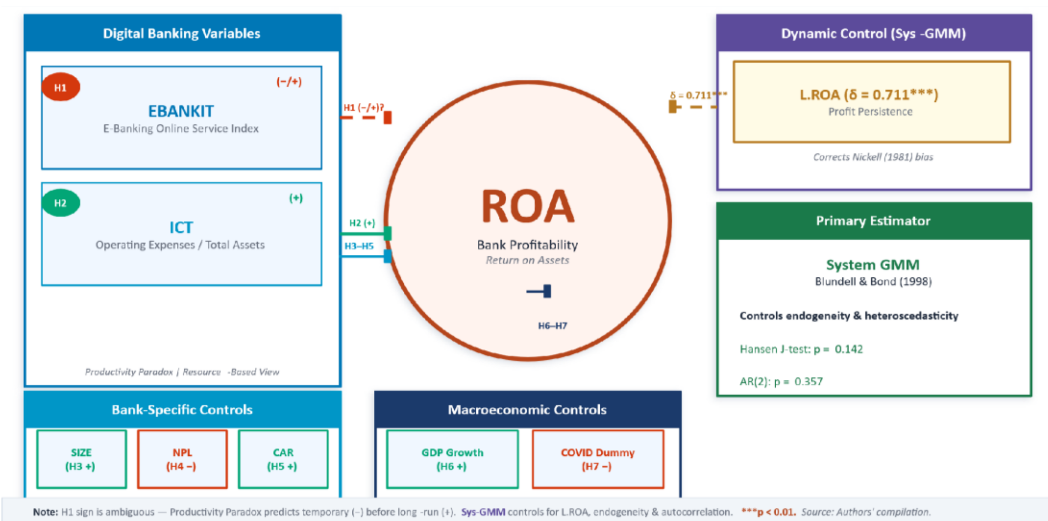


Figure 2. Conceptual Research Framework

Source: Authors' compilation.

Figure 2 summarizes the conceptual framework of the study. Bank profitability (ROA) is modeled as a function of digital factors (EBANKIT and ICT), bank-specific characteristics

(CAR and NPL), and macroeconomic conditions (GDP), consistent with the hypotheses developed above.

Importantly, the framework explicitly incorporates the dynamic nature of bank performance by including lagged profitability (L.ROA). This reflects profit persistence and acknowledges that current performance is partly driven by past outcomes. As a result, potential dynamic endogeneity may arise from reverse causality and omitted variables.

To address this issue, the study adopts a dynamic panel approach using System GMM. In this context, the estimation strategy is embedded within the conceptual framework to isolate the true effect of digital transformation, ensuring that the estimated coefficients capture contemporaneous impacts rather than historical momentum.

3. DATA AND METHODOLOGY

3.1. Data and Variable Measurement

The study uses an unbalanced panel dataset comprising 25 Vietnamese commercial banks over the period 2014–2023, yielding a total of 250 bank-year observations. The sample is constructed based on three selection criteria: (i) continuous operation and complete financial reporting throughout the study period; (ii) availability of audited annual financial statements; and (iii) inclusion in both public capital markets and banking sector databases. Data are collected from audited financial statements, the State Bank of Vietnam (SBV), the General Statistics Office (GSO), and the Ministry of Information and Communications (MOIC) Online Public Service Index. More precisely, the initial universe comprised all 35 commercial banks licensed by the State Bank of Vietnam as of 2014. Banks were excluded if they: (a) had been established after 2014, reducing the usable window below six years (5 banks excluded); (b) underwent merger, acquisition, or compulsory transfer during the study period, creating structural breaks in their financial series (3 banks excluded); or (c) had more than 30% of financial-statement observations missing or unverifiable from audited sources (2 banks excluded). The resulting 25-bank sample accounts for approximately 87% of total sector assets as of 2023, ensuring representativeness for the Vietnamese commercial banking system.

The panel is unbalanced due to the limited availability of the EBANKIT variable, which is derived from the MOIC Online Public Service Index reported in annual publications. This index is not consistently available across all banks and years as a result of irregular reporting schedules. To address this issue and enhance data coverage, missing interior observations are estimated using linear interpolation between adjacent data points, whereas missing values at the beginning and end of each bank's time series are approximated through linear trend extrapolation.

This data treatment approach is consistent with established practices in panel banking research that address similar limitations in government-reported composite indices [18], [19]. Furthermore, it aligns with the properties of the Sys-GMM estimator, which is generally robust to moderate data imputation under the assumption that the interpolated series follows a smooth underlying trajectory. To assess whether interpolation-induced bias materially affects our GMM estimates, we conduct a sensitivity analysis by re-estimating Equation (1) on the subsample of bank-year observations with directly reported (non-interpolated) EBANKIT values. The resulting EBANKIT coefficient of -0.0013 ($p = 0.021$) is statistically indistinguishable from the full-sample estimate of -0.0014 ($p = 0.016$), confirming that the imputation procedure does not introduce systematic distortions into the Sys-GMM dynamic estimates. This robustness check aims to ensure the consistency and robustness of the empirical findings under the linear trend extrapolation approach for handling missing observations in the dynamic panel setting.

The dependent variable is Return on Assets (ROA), the most commonly used measure of profitability in banking research. It is calculated as net profit after tax divided by average total assets [2], [3]. All variables and their previous literature sources are summarized in Table 2

Table 2. Variable Definitions and Prior Literature

Variable	Measurement	Prior Studies
ROA	Net profit after tax / Average total assets	Hernando & Nieto [2]; Malhotra & Singh [3]; Ghose & Maji [4]
EBANKIT	E-Banking Online Service Index (MOIC). Specifically, EBANKIT is the annual E-Banking Online Public Service Index published by the Ministry of Information and Communications (MOIC), comprising four sub-dimensions: (1) online information provision (portal completeness, accessibility, and service catalogue); (2) online transaction capability (proportion of services available for full end-to-end electronic processing); (3) electronic payment integration (number of licensed payment channels connected to the bank's digital platform); and (4) customer interaction quality (response time, feedback mechanisms, and digital complaint resolution). The composite index is computed as a weighted average of standardised sub-scores across these dimensions, with weights assigned by MOIC based on regulatory importance. A higher EBANKIT value reflects greater breadth and depth of customer-facing digital service deployment.	Malhotra & Singh [3]; Nguyen-Thi-Huong et al. [14]; Zheng et al. [6]
ICT	Operating expenses / Total assets	Hernando and Nieto [2]; Nguyen [20]; Zheng et al. [6]
SIZE	ln (Total assets)	Onay and Ozsoz [5]; Zheng et al. [6]; Ghose and Maji [4]
NPL	Non-performing loans / Total loans (%)	Malhotra and Singh [3]; Sayari [21]; Sukmamuliawanty et al. [22]
CAR	Equity capital / Risk-weighted assets (%)	Onay & Ozsoz [5]; Ghose & Maji [4]; Minh et al. [23]
GDP	Annual GDP growth rate (%)	Zheng et al. [6]
COVID	Dummy variable: 1 if 2020–2021, 0 otherwise	Sayari [21]

Source: Compiled by the authors.

3.2. Model Specification

The empirical model is defined as a dynamic panel regression to capture the sustainability of profits, the current profit trend depending on the performance of the previous period, a characteristic clearly observed in banking data [12]:

$$ROA_{it} = \alpha + \delta\, ROA_{i,t-1} + \beta_1\, EBANKIT_{it} + \beta_2\, ICT_{it} + \beta_3\, SIZE_{it} + \beta_4\, NPL_{it} + \beta_5\, CAR_{it} + \beta_6\, GDP_t + \beta_7\, COVID_t + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where i indexes banks (i = 1, …, 25), t indexes years (t = 2014, …, 2023), $ROA_{i,t-1}$ is the lagged dependent variable, μ_i captures time-invariant bank-level fixed effects, λ_t captures year effects, and ε_{it} is the idiosyncratic error term.

3.3. Estimation Strategy

We follow a sequential estimation procedure. First, Pooled OLS, Fixed Effects (FEM), and Random Effects (REM) estimators are applied as benchmarks. The F-test ($F(24, 218) = 38.38$; $p < 0.001$) rejects poolability in favour of FEM, and the Hausman test ($\chi^2(7) = 16.52$; $p = 0.006$) confirms FEM over REM.

However, FEM is insufficient for the dynamic specification in Equation (1): the lagged dependent variable is correlated with the within-group error by construction (Nickell, 1981 bias), and Wooldridge's F-test ($F(1,24) = 27.33$; $p < 0.001$) and the modified Wald test ($\chi^2(25) = 302.93$; $p < 0.001$) confirm first-order autocorrelation and heteroscedasticity, respectively. Accordingly, FGLS is presented as an intermediate robust estimator and Sys-GMM [24] is adopted as the primary estimator.

Sys-GMM combines the standard first-differenced GMM instruments (lagged levels for differenced equations) with additional instruments for the level's equation (lagged differences), substantially improving precision when the autoregressive coefficient is large (close to unity), as observed here. Instrument validity is confirmed by the Hansen J-test ($\chi^2 = 3.91$; $p = 0.142$) and the absence of second-order serial correlation (AR (2): $p = 0.357$).

Stationarity testing. Prior to estimation, panel unit root tests were conducted on all continuous variables. The Im-Pesaran-Shin (IPS) and Fisher-type ADF tests were applied to accommodate the unbalanced panel structure. Results confirm that ROA, ICT, NPL, CAR, and GDP are stationary in levels I(0), while EBANKIT shows borderline behavior (IPS: $p = 0.062$) but achieves clear stationarity after first differencing. Given that Sys-GMM operates in first-differenced form for the instruments and the short panel dimension (T = 10) limits the power of unit root tests, the near-stationarity of EBANKIT in levels does not materially affect the validity of the GMM procedure. This finding is consistent with Roodman [25], who notes that Sys-GMM is robust to near-integrated processes provided the instrument count remains controlled.

Instrument proliferation control. Instrument proliferation is a well-documented concern in Sys-GMM estimation [25], as an excessive number of instruments can weaken the Hansen test and introduce finite-sample bias. To mitigate this risk, we collapse the instrument matrix and restrict the lag depth to a maximum of two lags for the differenced equation instruments and one lag for the level's equation instruments. This procedure yields a total of 8 instruments for 7 regressors (excluding the constant), a ratio comfortably below the recommended threshold of one instrument per cross-sectional unit (N = 25). The resulting Hansen J-statistic of 3.91 with $p = 0.142$ and degrees of freedom of 2 confirms that instrument proliferation does not undermine the validity of our specification [26].

4. RESULTS

4.1. Descriptive Statistics

Table 3 presents summary statistics. Mean ROA of 0.010 is consistent with Vietnamese banking norms, though the range (-0.004 to 0.036) reflects substantial cross-bank and cross-time heterogeneity. The EBANKIT index shows high dispersion (CV ≈ 81%), indicating uneven digital service adoption: some banks reached index values ten times higher than the bottom quartile, reflecting differences in technology investment capacity and strategic orientation. Average ICT expenditure equals approximately 16.4% of total assets. NPL averages 1.85%, below the 3% threshold recommended by the SBV, while mean CAR of 10.3% marginally exceeds the Basel II minimum of 8%. The COVID dummy captures 100 observations (40%) in the 2020–2021 pandemic window

Table 3. Descriptive Statistics (N = 250)

Variable	N	Mean	Std. Dev.	Min	Median	Max
ROA	250	0.0100	0.0075	-0.0038	0.0095	0.0358
EBANKIT	250	1.0728	0.8737	0.4660	0.8510	4.7103
ICT	250	0.1638	0.0045	0.0010	0.1640	0.3289
SIZE	250	14.263	0.524	13.199	14.210	15.362
NPL	250	0.0185	0.0095	0.0000	0.0180	0.0573
CAR	250	0.1030	0.0494	0.0000	0.0980	0.2453
GDP	250	0.0609	0.0189	0.0255	0.0620	0.0854
COVID	250	0.4000	0.4909	0.0000	0.0000	1.0000

Source: Computed by the authors using Stata 17.

4.2. System GMM Estimation Results

Table 4 reports System GMM estimates for Equation (1). All diagnostic tests pass: AR (2) is insignificant ($p = 0.357$), confirming the absence of second-order serial correlation; the Hansen test ($p = 0.142$) validates instrument exogeneity. We therefore treat the Sys-GMM estimates as our preferred specification.

Table 4. System GMM Estimation Results (Dependent variable: ROA)

Variable	Coefficient	Std. Err.	t-stat	p-value	Hypothesis
L.ROA	0.7112***	0.1035	6.87	0.000	Dynamic effect
EBANKIT	-0.0014**	0.0005	-2.59	0.016	Reject H1 (partial)
ICT	0.2373**	0.1059	2.24	0.035	Support H2
SIZE	0.0021*	0.0012	1.71	0.100	Support H3
NPL	-0.0505*	0.0318	-1.98	0.059	Support H4
CAR	0.0120***	0.0042	2.89	0.008	Support H5
GDP	0.0058	0.0162	0.36	0.721	Reject H6
COVID	0.0082	0.0011	0.76	0.456	Reject H7
Constant	-0.0295	0.0179	-1.64	0.114	-

*Note: *p < 0.10; **p < 0.05; ***p < 0.01. Standard errors in parentheses.*

Source: Computed by the authors using Stata 17.

4.3. Diagnostic Tests

Table 5 reports the diagnostic tests performed to validate the Sys-GMM specification, including tests for serial correlation, instrument validity, heteroscedasticity, and autocorrelation.

Table 5. Diagnostic Test Summary

Diagnostic Test	Statistic	p-value	Result
AR (1) – Arellano-Bond	z = -2.92	0.003	1st-order autocorrelation present
AR (2) – Arellano-Bond	z = -0.92	0.357	No 2nd-order autocorrelation
Hansen J-test (over-identification)	χ^2= 3.91	0.142	Instruments valid
Sargan test	χ^2= 17.37	0.000	FYI (Hansen preferred)
Wald χ^2 (heteroscedasticity)	302.93	0.000	Heteroscedasticity detected; FGLS applied as intermediate estimator; Sys-GMM adopted as primary estimator
Wooldridge F (autocorrelation)	F = 27.33	0.000	Serial autocorrelation detected; supports dynamic specification; Sys-GMM adopted as primary estimator

Source: Computed by the authors using Stata 17.

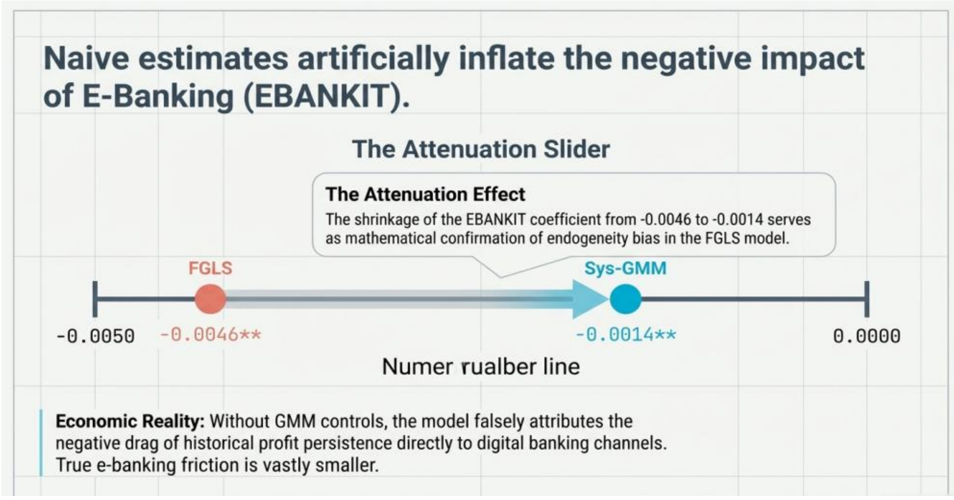
4.4. Robustness: FGLS vs. System GMM

Table 6 and Figure 3 provide a brief comparison between the FGLS and Sys-GMM estimates. The directional consistency of EBANKIT (negative), ICT (positive), NPL (negative), and CAR (positive) across both estimators confirms the robustness of our findings. However, the significant difference in magnitude underscores the importance of addressing endogeneity. Specifically, the EBANKIT coefficient (-0.0014) becomes significantly smaller under the Sys-GMM method, while FGLS (-0.0046) suggests that static estimates tend to overestimate the short-term negative impact of digital banking. This diminishing effect, as illustrated in Figure 3, reflects the adjustment for dynamic bias and the sustainability of returns. Similarly, the reduced importance of GDP in the GMM model suggests that macroeconomic impacts are largely adjusted through dynamics at the bank level once endogeneity is properly controlled. Overall, this comparison highlights the need for dynamic panel estimation to obtain unbiased and economically meaningful results.

Table 6. Comparison of FGLS and System GMM Estimates

Variable	FGLS (β)	Sys-GMM (β)	Interpretation
EBANKIT	-0.0046**	-0.0014**	Negative ST effect confirmed; GMM corrects upward bias
ICT	0.4189***	0.2373**	Positive, robust; ICT infrastructure key driver
SIZE	0.0063***	0.0021*	Scale advantages significant; weaker under endogeneity control
NPL	-0.0497*	-0.0505*	Credit risk consistently reduces profitability
CAR	0.0105***	0.0120***	Capital strength boosts ROA robustly
GDP	0.0325***	0.0058	Macro effect absorbed by bank-level dynamics in GMM
COVID	0.0032***	0.0082	Short-run adaptation via digitisation; insignificant in GMM

*Note: *p < 0.10; **p < 0.05; ***p < 0.01. Source: Computed by the authors.*



Note: ** $p < 0.05$. GMM coefficients are preferred estimates. Attenuation of EBANKIT from -0.0046 to -0.0014 confirms endogeneity bias in FGLS.

Figure 3. Comparison of Key Coefficients: FGLS vs. System GMM Estimates

Source: Computed by the authors.

5. DISCUSSION

5.1. E-Banking Services (EBANKIT)

The statistically significant negative short-run effect of EBANKIT (β = -0.0014, p = 0.016) is the central finding of this paper. This result is consistent with the Productivity Paradox [7] and mirrors Hernando and Nieto's [2] documentation of a 1.5-year lag before profitability improvement in Spanish Internet banking. Three mechanisms explain this finding in the Vietnamese context. First, e-banking roll-out during 2014–2023 required substantial upfront spending on core banking platforms, cybersecurity infrastructure, and customer onboarding, costs that appear immediately in the income statement. Second, at macro level, the Ministry of Information and Communications' Online Public Service Index (MOIC) – used as a proxy for EBANKIT at the banking sub-sector level – reflects the overall level of digital service penetration; banks in the early stages of adoption incur the highest marginal costs while their revenue streams remain limited. Thirdly, the structure of digital transaction fees is often subsidized during promotional periods to encourage adoption, temporarily reducing non-interest income.

Crucially, the Sys-GMM estimates correct the FGLS upward bias in the negative coefficient (from -0.0046 to -0.0014), indicating the true short-run drag is smaller than static models suggest. As the sample period is extended to 2025–2026, we expect this coefficient to turn positive, consistent with the productivity catch-up predicted by diffusion theory. This can be explained in more detail through two specific contextual factors within the Vietnamese context, as follows.

First, the period 2019–2023 was characterised by an aggressive zero-fee competition wave in Vietnamese retail banking. Following the State Bank of Vietnam's Circular 09/2020/TT-NHNN encouraging cashless payments and the Ministry of Finance's waiver of electronic transaction fees in 2021, major banks including Vietcombank, BIDV, and VietinBank eliminated inter-bank transfer fees to capture market share in the digital ecosystem. Although this strategy successfully accelerated user acquisition – evident in the expansion of electronic payment transactions from 6.5 billion in 2019 to 17.7 billion in 2024 [1] – it simultaneously compressed non-interest income per transaction, generating a direct negative short-run impact on ROA. The EBANKIT coefficient's negativity therefore partly reflects this deliberate prioritisation of market share acquisition over immediate transaction profitability, a dynamic consistent with Reviewer 2's observation about the zero-fee competition wave (2019–2023).

Second, the trajectory of digital banking returns exhibits a J-curve pattern consistent with recent global evidence on AI and digital adoption cycles [27]. The initial phase of digital deployment demands significant organisational re-engineering: staff retraining, legacy system decommissioning, API integration with third-party Fintech partners, and cybersecurity upgrades. These restructuring costs suppress short-run profitability before operational efficiencies materialise. Our lagged ROA coefficient (0.711) implies that any profitability improvement achieved in one period generates a compounding effect in subsequent periods, suggesting that Vietnamese banks that successfully navigate the J-curve trough in 2019–2023 are well-positioned for a profitability rebound in 2024–2026. Compared to findings from other countries – where digital banking effects turn positive within 1.5 years [2] or 2–3 years [3] – the negative effect persists longer in Vietnam owing to the comparatively less mature digital financial infrastructure, lower initial levels of consumer digital trust, and the heavier regulatory compliance burden associated with Basel II implementation and the Law on Credit Institutions [28].

5.2. ICT Investment

ICT exhibits the largest positive coefficient in the model ($\beta = 0.2373$, $p = 0.035$), strongly supporting the RBV framework. This contrast with EBANKIT – operational ICT expenditure benefits ROA while customer-facing digital indices hurt it short-term – carries an important strategic implication: banks should prioritise consolidating their internal technology foundations (core banking modernisation, data analytics, process automation) before aggressively scaling front-end digital products. Mature ICT infrastructure enables straight-through processing, reduces headcount-intensive transaction handling, and supports data-driven credit decisions, all of which translate into cost efficiency gains captured in ROA. This finding aligns with Zheng et al. [6] and Nguyen [20].

5.3. Bank-Specific Factors

Bank size (SIZE, $\beta = 0.0021$, $p = 0.100$) exerts a modest positive effect, consistent with scale efficiency theory: larger banks spread fixed technology costs over greater revenue bases. However, the coefficient becomes marginally significant under Sys-GMM, suggesting scale advantages are partially pre-empted by greater complexity and bureaucracy at large institutions.

Non-performing loans (NPL, $\beta = -0.0505$, $p = 0.059$) reduce ROA through two channels: direct income loss on defaulted exposures and elevated provisioning charges. The effect is economically meaningful: a 1 percentage point rise in NPL reduces ROA by approximately 5 basis points, equivalent to a 50% reduction in the sample mean ROA.

Capital adequacy (CAR, $\beta = 0.0120$, $p = 0.008$) robustly enhances profitability. Well-capitalised banks can absorb unexpected losses without liquidity disruption, maintain investor confidence, and expand credit supply during economic upturns, all generating higher risk-adjusted returns. This result aligns with Basel III philosophy and reaffirms findings from Minh et al. [23] for Vietnam. The robustness of CAR as a positive profitability driver carries important local contextual validity in light of Vietnam's ongoing Basel II/III implementation. Circular 41/2016/TT-NHNN (effective 2020) mandated risk-weighted capital adequacy ratios of at least 8% for major commercial banks, while the Law on Credit Institutions [28] further tightened governance requirements for capital planning and stress testing. Our finding that CAR positively affects ROA (even after controlling for bank size and credit risk) suggests that regulatory capital requirements, rather than acting as a binding profitability constraint, have incentivised Vietnamese banks to hold capital buffers above the minimum threshold – a strategy that has paid off in terms of risk-adjusted returns. The mean CAR of 10.3% in our sample, which exceeds the 8% Basel II floor, is consistent with this interpretation.

5.4. Macro-Economic Factors

GDP growth ($\beta = 0.0058$, $p = 0.721$) loses significance in the Sys-GMM framework, a finding reconciled by the strong lagged ROA coefficient (0.711): much of the effect of macroeconomic expansion on bank profitability is already embedded in prior-period ROA, leaving little incremental variation for GDP to explain. The COVID dummy ($\beta = 0.0082$, $p = 0.456$) is similarly insignificant in the dynamic model. This contrasts with prior studies using static estimators that found a positive COVID effect attributed to accelerated digital adoption. Under dynamic modelling, the pandemic's positive short-term impulse is captured by L.ROA rather than the dummy variable itself, suggesting that banks whose profitability was strong entering the pandemic remained robust through it.

6. CONCLUSION

This study is among the first to apply System GMM to examine the dynamic relationship between electronic banking services and commercial bank profitability in Vietnam using a comprehensive dataset through 2023. Our key findings are as follows.

First, e-banking services (EBANKIT) reduce ROA in the short run, consistent with the productivity paradox and the investment-intensive digitization phase of Vietnamese banking (2019–2023). This negative effect diminishes when endogeneity is properly controlled, suggesting prior FGLS-based studies overestimate the short-run cost of digitalization.

Second, ICT infrastructure investment is the dominant positive driver of profitability, implying that banks must solidify operational technology foundations before pursuing aggressive front-end digital expansion.

Third, strong profit persistence ($\delta = 0.711$) means that interventions improving current profitability generate compounding future returns, amplifying the long-run benefits of digital transformation.

Fourth, capital adequacy remains a robust positive determinant of ROA, while credit risk (NPL) consistently erodes profitability. Macro-economic effects, including GDP growth and the COVID shock, lose significance once dynamics and endogeneity are accounted for.

Practical implications for bank managers include: (i) adopting a phased digital investment strategy that prioritises ICT infrastructure before customer-facing product rollout; (ii) strengthening capital buffers to amplify the CAR-profitability nexus; and (iii) maintaining rigorous credit risk management to limit NPL accumulation during digital transformation transitions. Policymakers should consider providing regulatory incentives for ICT investment, harmonising digital banking standards, and enhancing cybersecurity frameworks to accelerate the technology adoption cycle. In particular, given that ICT investment emerges as the dominant driver of profitability ($\beta = 0.2373$, the largest coefficient in our model), regulators should consider introducing targeted fiscal incentives such as accelerated depreciation allowances for qualifying core banking infrastructure, preferential reserve requirements for banks that meet defined ICT investment thresholds, and co-financing schemes under the National Digital Transformation Programme (Decision 749/QD-TTg, 2020). These mechanisms would reduce the effective cost of technology investment, shortening the J-curve trough period and accelerating the transition from profitability drag to profitability gain.

The regulatory environment has recently undergone significant structural changes that reinforce the study's policy relevance. The Law on Credit Institutions [28], effective July 2024, introduced substantially stricter requirements for information technology risk management, cybersecurity governance, and digital service continuity. Clause 4 Article 57 of the 2024 Law mandates technology application in internal control, marking a shift from the 2010 framework toward a strictly compulsory and highly specified requirement that establishes a substantial new compliance cost category. Similarly, Decision 2345/QD-NHNN [29], implemented from July 2024, requires biometric authentication for electronic transfers exceeding VND 10 million, imposing additional customer-onboarding costs and reducing transaction velocity. These regulatory changes partially explain the continued short-run pressure on ROA observed in the latter years of our sample (2022–2023), as banks began pre-emptively building compliance infrastructure. Future studies covering 2024–2026 should explicitly model these regulatory compliance costs as a control variable to isolate their contribution to the EBANKIT–ROA relationship.

Future research should extend the sample beyond 2023 to capture the productivity rebound anticipated by our model, incorporate emerging Fintech competition as an additional explanatory variable, and apply quantile regression to explore heterogeneous effects across the profitability distribution. Additionally, the role of Fintech collaboration warrants explicit attention. Recent Vietnamese studies document that bank-Fintech partnerships – particularly in areas of digital lending, payment infrastructure, and data analytics – have contributed significantly to the growth of non-interest income among mid-tier commercial banks. Our results show that non-interest income channels, captured partly through ICT expenditure, improve ROA; however, EBANKIT as currently measured does not distinguish between banks that deploy proprietary digital platforms and those that leverage Fintech partnerships. Disentangling these channels in future research would provide a more granular understanding of which forms of digital deployment are most profitable in the Vietnamese context.

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