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Research Article

Mobile Banking Adoption and the Performance of Mid-Tier Indonesian Banks: A Google Play Store-Based Timing Approach

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Abstract
Digital transformation has reshaped bank-customer interaction, yet the performance effects of mobile banking adoption among Indonesia's mid-tier commercial banks remain untested, as prior studies treat bank size as a broad control rather than isolating this segment. This study examines whether mobile banking adoption affects the performance of mid-tier Indonesian banks from 2012–2024. Its novelty lies in constructing the adoption timing variable from Google Play Store release dates, an approach not previously applied in Indonesia. A two-way fixed effects panel regression is estimated for three outcomes: return on assets, return on equity, and operational efficiency (BOPO), with standard errors clustered by bank. The Post coefficient carries the theoretically expected sign across all outcomes positive for return on assets and return on equity and negative for BOPO but none is statistically significant, as confidence intervals remain wide enough that a null effect cannot be ruled out. Non-performing loans remain the most significant predictor of performance overall. These findings suggest a directionally consistent but statistically inconclusive pattern, indicating that bank management should treat mobile banking investment as a medium-term capability rather than an immediate profitability driver while maintaining credit risk discipline as the dominant performance lever.

Keywords: Bank Performance, KBMI 2-3, Mobile Banking Adoption, Panel Data, Two-Way Fixed Effects

JEL Classification: G21; O33

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1. Introduction
Digital transformation in the banking industry has evolved beyond automating internal processes to fundamentally reshaping how banks deliver services and interact with customers. Murinde, Rizopoulos, & Zachariadis (2022) argue that the financial technology revolution has altered the global landscape of financial intermediation, compelling traditional banks to build digital capabilities to retain market share against financial technology entrants.

Within this broader shift, mobile banking stands out as the most visible and directly experienced form of digital transformation, serving as the primary channel through which customers conduct daily transactions, make payments, and access financial products (Mogaji, 2023).

Mobile banking's effect on bank performance operates through several distinct channels rather than a single mechanism. Li (2026) provides direct empirical evidence for this multi-channel structure, showing that digital technology adoption improves bank profitability through reduced operating costs, increased non-interest income, and expanded mobile banking usage. Podder & Ghosh (2025), studying 32 commercial banks listed on Indian stock exchanges from 2016 to 2021, confirm a related timing pattern directly. Digital transformation raises costs for a short initial period before those costs are significantly reduced, and bank size, bank age, and customer technological literacy all moderate the strength of the eventual positive effect on performance. Uddin & Barai (2026), investigating 85 banks across nine Asian economies, including Indonesia, from 2014 to 2024, find that fintech adoption's effect on operational efficiency varies by economic tier. In large economies, including Indonesia, China and India, the relationship with efficiency is statistically insignificant. In contrast, in smaller emerging economies it is significantly negative, consistent with short-term implementation costs outweighing efficiency gains during the adjustment period.

This channel structure has a further implication that single-country, large-bank samples often overlook. The balance between these channels is unlikely to be identical for every bank, even within one country. A bank's capacity to convert mobile banking investment into cost savings depends on how much of its existing branch and staffing cost base it can restructure, which in turn depends on scale, consistent with the economies-of-scale argument used by Setiawan & Prakoso (2024) to explain why bank size moderates the digitalization-performance relationship in the Indonesian context specifically, and with Podder & Ghosh (2025) direct finding that bank size moderates this same relationship in an emerging Asian economy.

In Indonesia, banks are classified by OJK (Otoritas Jasa Keuangan) into four tiers by core capital under POJK No. 12/POJK.03/2021 concerning Commercial Banks (Peraturan Otoritas Jasa Keuangan, 2021). KBMI 1 covers core capital up to IDR 6 trillion, KBMI 2 covers above IDR 6 trillion up to IDR 14 trillion, KBMI 3 covers above IDR 14 trillion up to IDR 70 trillion, and KBMI 4 covers above IDR 70 trillion. Banks in the KBMI 2-3 tier face the same competitive pressure to digitalize as the largest KBMI 4 banks, yet without comparable scale to absorb digital infrastructure costs (Mogaji, 2023; Setiawan & Prakoso, 2024). Existing evidence on mobile banking's performance effects in Indonesia tends to treat bank size as a broad category rather than isolating the KBMI tier structure. Saktiawan, Dewi, Risfandy, & Setiyono (2026), studying Indonesian commercial banks from 2014 to 2023, find that the effect of digital transformation on bank performance is significantly heterogeneous for small and medium-sized banks compared to larger institutions, but their heterogeneity test groups small and medium-sized banks together rather than separating KBMI 2 from KBMI 3 specifically.

The KBMI 2 and 3 tier also occupies a structurally distinct position that parallels a broader pattern documented in international banking research. Maingi (2026), studying the United States regional banking sector following the 2023 regional bank panic, argues that midsize banks represent an important but understudied segment of the banking system, structurally different from both the largest globally systemic banks and the smallest community institutions, yet frequently overlooked in research that treats bank size as a simple control variable rather than a defining characteristic. This pattern holds in Indonesia as well. Industry data reported by OJK indicate that KBMI 3 banks alone account for roughly 27 percent of national banking assets, credit, and third-party funds, a share that places this tier well above marginal relevance despite receiving comparatively little dedicated academic attention relative to the four KBMI 4 banks that dominate published research on Indonesian banking performance (Irawati, 2026). Several KBMI 2 and 3 banks additionally occupy specific market niches, such as housing finance, Islamic banking, or middle market corporate lending, that differ from the diversified, scale-driven business models of the largest banks, suggesting their financial resilience carries distinct economic and financial inclusion implications rather than simply representing a smaller version of the large bank story already documented in the literature. However, despite this structural distinctiveness and economic weight, no existing study has directly tested whether mobile banking adoption yields a measurable performance effect specifically for KBMI 2-3 banks in Indonesia. This study therefore asks whether, and to what extent, adoption timing is associated with profitability and operational efficiency in this understudied mid-tier segment.

Two gaps in the existing literature motivate this study. Internationally, midsize banks remain a structurally distinct but comparatively understudied segment (Maingi, 2026). Domestically, existing Indonesian studies group small and medium-sized banks together without separating KBMI 2 from KBMI 3 specifically (Saktiawan, Dewi, Risfandy, & Setiyono, 2026). Therefore, this study's novelty is twofold. First, it isolates the KBMI 2 and 3 tiers as the specific unit of analysis, rather than treating bank size as a broad control variable or an aggregate cross-tier category. Second, it constructs the mobile banking adoption timing variable directly from verifiable bank-level records of official mobile application launch dates on Google Play, rather than relying on self-reported or approximate adoption indicators commonly used in prior studies. This approach follows Haendler (2022), who hand-collected mobile application rollout dates across United States banks from Google Play and the Apple App Store to construct a similarly precise, staggered adoption timeline. To the authors' knowledge, this app store-based timing approach has not previously been applied to construct a bank adoption panel in the Indonesian banking context, nor specifically to the KBMI 2 and 3 segment. Taken together, these two elements represent the intended contribution of this study, namely providing the first tier-specific, timing-precise evidence on mobile banking's performance effect for Indonesia's mid-tier banks.

This study therefore examines the effect of mobile banking adoption on profitability, measured by ROA and ROE, and operational efficiency, measured by BOPO, among KBMI 2-3 banks in Indonesia over the 2012 to 2024 period, using panel data regression with two-way fixed effects to control for unobserved bank heterogeneity and time-varying macroeconomic conditions common to all banks in a given year.

2. Literature Review and Hypothesis

A large body of empirical work has examined how digital and mobile banking adoption affects bank performance, though findings remain mixed across countries and bank sizes. This section reviews recent evidence through three theoretical lenses that motivate the hypotheses tested here: transaction cost theory as the primary mechanism, the productivity paradox as a counter-narrative, and financial intermediation theory as background context (Ayadi et al., 2025; Khattak et al., 2023).

Transaction cost theory is particularly relevant to KBMI 2–3 banks because they face digitalization pressures similar to those of larger KBMI 4 institutions but have a smaller cost base to restructure. Its prediction that digital channels reduce operating costs relative to operating income can therefore be tested directly using the operating efficiency ratio. Using Transaction Cost Theory, Ayadi et al. (2025) and S. He et al. (2025) find that digitalization improves bank performance mainly by reducing transaction and operating costs, while Chao et al. (2024) show that digital transformation improves profitability among Chinese rural banks specifically by enhancing operating efficiency. Therefore, mobile banking lowers the cost of delivering routine transactions by shifting them from branch-dependent channels to self-service digital channels, directly targeting operating expenses relative to operating income. Recent studies support this cost channel. In Indonesia, Pratiningsih & Wardhani (2024) find a positive digitalization-profitability relationship overall but note smaller banks gain comparatively less than larger peers, motivating this study's focus on the KBMI 2 and 3 tier rather than bank size as a general control.

The relevance of bank size heterogeneity to this mechanism is further supported by evidence on staggered digital adoption. Because banks adopt mobile banking at different points in time, the realized cost effect for any single bank depends on how far along its own adoption timeline it stands, a pattern documented across the staggered mobile banking rollouts observed by Haendler (2022).

Evidence from emerging market banking further suggests these cost effects are not uniform across economic tiers. Uddin & Barai (2026) find that fintech adoption's effect on operational efficiency varies by economic tier across nine Asian economies, while Khattak et al. (2023) find that digital transformation is associated with short-run cost pressure before efficiency gains materialize. This heterogeneity by bank size is echoed in recent evidence from China, where Xu et al. (2025) find the risk-reducing effect of digital transformation to be stronger for small and medium-sized banks, and in MENA emerging markets, where Khanchel et al. (2026) find technology adoption's risk-mitigating effect to instead be stronger for larger banks operating in deeper financial systems, underscoring that the direction and magnitude of the cost effect may vary not only by segment but also by the institutional context in which banks operate.

Meanwhile, the productivity paradox defines a contradictory version (Setiawan & Prakoso, 2024). This theory tempers these expectations by explaining why cost savings may not appear immediately in financial ratios. Zhang (2026) finds that digital transformation has not improved profitability for most Chinese banks and, in fact, reduces ROA and NIM, while Citterio et al. (2024) find that profitability gains among European banks are nonlinear and take time to materialize. (Shanti et al., 2023) find a clear U-shaped pattern among Indonesia's digital business model banks, where profitability falls in the short run before improving later. Financial intermediation theory, originating with Diamond (1984), is also considered as theoretical background. This is because Omarini (2024) and Broby (2021) both argue that financial technology has rechanneled rather than displaced banks' delegated monitoring function, meaning digitalization changes the delivery channel but not the core intermediation role.

Although situational differences may cause the impact of mobile banking adoption to vary, this study draws on transaction cost theory to propose the following hypotheses:
H1: Mobile banking adoption has a positive effect on BOPO, reflecting improved operational efficiency (Ayadi et al., 2025; Chao et al., 2024; S. He et al., 2025; Pratiningsih & Wardhani, 2024)
H2a: Mobile banking adoption has a positive effect on ROA (Citterio et al., 2024; D. He et al., 2020; Setiawan & Prakoso, 2024; Zhang, 2026)
H2b: Mobile banking adoption has a positive effect on ROE (Citterio et al., 2024; D. He et al., 2020; Setiawan & Prakoso, 2024; Shanti et al., 2023)

3. Data and Methodology

Research Design

This study uses a quantitative panel data design with panel least squares and two-way fixed effects to examine the effect of mobile banking adoption on bank profitability. This two-way fixed effects model uses two sets of dummy variables: are for each bank and one for each year (Pan et al., 2026). This approach aligns with recent studies on digital adoption and bank performance in Indonesia, which similarly use panel regression frameworks to assess the effect of digital banking variables on ROA, ROE, and related indicators (Akbary et al., 2025; Aswan et al., 2026).

Model selection follows three sequential steps. First, the Common Effect Model (CEM, also known as Pooled Ordinary Least Squares), the Fixed Effect Model (FEM), and the Random Effect Model (REM) are each estimated as candidate specifications for panel data combining cross-sectional units (banks) with time-series observations (years). Second, the Chow test compares CEM against FEM through an F-test on the joint significance of bank-specific intercepts. Third, the Hausman test compares FEM against REM by testing whether bank-specific effects are correlated with the regressors. These two tests indicate that the model is retained for each of the three outcome variables.

Data and Sample

Data are drawn from annual bank financial statements published on the official website of Indonesia's Financial Services Authority (Otoritas Jasa Keuangan/OJK). Mobile banking adoption years are identified from the launch date of each bank's official mobile banking application on the Google Play Store. The observation period covers 2012 to 2024.

The study population is Indonesian commercial banks classified under Bank Core Capital Group (KBMI) 2 and 3, following OJK's core Tier 1 capital thresholds. KBMI 2 covers banks with core capital of Rp6 to 14 trillion, and KBMI 3 covers banks with core capital of Rp14 to 70 trillion. Foreign bank branch offices are excluded, as they are not separately incorporated under Indonesian law and do not report core capital in a form comparable to domestically incorporated banks. Based on this classification, we identified 33 KBMI 2 to 3 banks, of which 32 have verifiable mobile banking adoption year data and are retained in the final estimation sample.

We determine bank classification into KBMI 2 or 3 using each bank's core capital position as of 2024, the most recent year in the observation window, and apply it uniformly to that bank across the entire 2012 to 2024 period. This cross-sectional classification approach aligns with how OJK and industry publications typically refer to a bank's KBMI tier (Peraturan Otoritas Jasa Keuangan, 2021), as a current standing rather than a year-by-year designation. One implication of this choice is that some banks in the sample had core capital below the KBMI 2 threshold in the earlier years of the observation window and only reached KBMI 2 or 3 status later, meaning the sample reflects banks that are presently classified as mid-tier rather than banks that were mid-tier throughout the entire study period. This is stated explicitly as a scope condition rather than a hidden limitation.

The sample combines both conventional commercial banks and Islamic commercial banks; several financial ratios carry different labels across the two bank types despite measuring functionally equivalent concepts. In conventional banks, the Non-Performing Loan ratio measures credit quality. In contrast, Islamic banks use the Non-Performing Financing ratio as the equivalent measure, reflecting that they extend financing through sharia-compliant contracts such as murabahah, mudharabah, and musyarakah rather than interest-bearing loans (Muhammad et al., 2020). Similarly, the Loan-to-Deposit Ratio in conventional banks and the Financing to Deposit Ratio in Islamic banks are calculated identically in structure, as total funds disbursed to customers divided by total third-party funds, and differ only in whether the numerator represents interest-based loans or sharia-compliant financing (Muhammad et al., 2020). This terminology distinction reflects contractual form rather than differences in economic function, and prior panel studies combining Islamic and conventional banks in a single regression framework have treated these ratio pairs as directly comparable measures within the same model (Abduh et al., 2013). Following this convention, this study treats NPL and NPF as a single harmonized variable and treats LDR and FDR also as a single harmonized variable.

Model Specification and Operational Variable
Equation (1) is the model specification that we use in this study:

$$Y_{it} = \beta\, Post_{it} + \delta_1 LnAsset_{it} + \delta_2 CAR_{it} + \delta_3 NPL/NPF_{it} + \delta_4 LDR/FDR_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \qquad (1)$$

Where Y_{it} denotes the dependent variable, ROA, ROE, or BOPO, for bank i in year t, three separate regressions are estimated using this identical specification, allowing the mobile banking effect to be compared across profitability, measured by ROA and ROE, and operational efficiency, measured by BOPO. Meanwhile, $Post_{it}$, $LnAsset_{it}$, CAR_{it}, and NPL/NPF_{it} and LDR/FDR_{it} are the independent variables. $Post_{it}$ is the main independent variable of interest. Its coefficient β captures the average change in the dependent variable associated with adoption of mobile banking. $Post_{it}$ is operationalized as a dummy variable. This binary indicator equals 1 in the year bank i launched its official mobile banking application and in every year thereafter, and 0 in all years prior to that point. Other independent variables are control variables for this study. Table 1 shows the operational variables, including measurements and sources for each variable. As noted above, bank classification into KBMI 2 or 3 is fixed at each bank's 2024 core capital position and applied uniformly across the 2012–2024 period. This scope condition is disclosed explicitly rather than treated as a hidden limitation, and its implications for interpretation are discussed further in the Limitations section.

Table 1. Operational Variable

Classification	Variable	Measurement	Reference	Source
Dependent	ROA	Net income after tax divided by total assets, multiplied by 100%	Antonio, Ebelin, & Matilde (2026)	www.ojk.go.id
Dependent	ROE	Net income after tax divided by total equity, multiplied by 100 percent	Aswan, Fauzi, & Ermawati (2026)	www.ojk.go.id
Dependent	BOPO	Operating expenses divided by operating income, multiplied by 100 percent	Setiawan & Prakoso (2024)	www.ojk.go.id
Main independent variables	Post	Binary indicator equal to 1 from the year of mobile banking launch onward, 0 before	Haendler (2022)	Google Play Store application launch date
Control variables	LnAsset	Natural logarithm of total asset	Akbary, Trunugroho, Risfandy, Pamungkas (2025)	www.ojk.go.id
Control variable	CAR	Tier 1 capital plus Tier 2 capital divided by risk-weighted assets, multiplied by 100 percent	D. He, Ho, & Xu (2020)	www.ojk.go.id
Control variable	LDR/FDR	Total loans disbursed divided by total third-party funds, multiplied by 100 percent	Mardhika & Marpaung (2025)	www.ojk.go.id
Control variable	NPL/NPF	Non-performing loans divided by total loans, multiplied by 100 percent	Uddin & Barai (2026)	www.ojk.go.id

4. Results

Mobile Banking Adoption Timing

As shown in Table 2. mobile banking adoption among the 32 sample banks with verifiable release dates spans nearly twelve years, from PT Bank CIMB Niaga's OCTO Mobile in June 2012 to PT BPD Jawa Barat dan Banten's DIGI bank BJB in April 2024. Adoption is uneven across the sample period. Eleven banks, roughly one third of the sample, adopted mobile banking between 2012 and 2016, a period led by PT Bank CIMB Niaga as the earliest mover, followed by a cluster of six banks releasing their applications within a narrow window in 2016 alone. Adoption activity slowed between 2017 and 2020, with only seven banks entering during this four-year window, before accelerating sharply in the most recent period, with fourteen banks, close to half the sample, adopting between 2021 and 2024. The mean adoption year across the sample is 2019, with a median of 2020, indicating the sample is weighted toward relatively recent adopters despite early movers dating back to 2012.

Table 2. Mobile Banking Applications and Play Store Release Date

No	Bank	KBMI	Mobile Banking Name	Launching date in Play Store
1	PT Bank CIMB Niaga Tbk	3	OCTO Mobile by CIMB Niaga	21 June 2012
2	PT Bank Sinarmas Tbk	2	SimobiPlus Mobile Banking	17 November 2014
3	PT Bank China Construction Bank Indonesia Tbk	2	CCB Indonesia Mobile	12 July 2015
4	PT Bank ICBC Indonesia	2	ICBC Mobile Banking	17 October 2015

5	PT Bank Pan Indonesia Tbk	3	MobilePanin	21 April 2016
6	PT Bank Keb Hana Indonesia	2	MyHana Mobile Banking	21 July 2016
7	PT Bank Woori Saudara Indonesia 1906 Tbk	2	BWS Mobile	09 August 2016
8	PT Bank Tabungan Pensiunan Nasional Tbk	3	Jenius	10 August 2016
9	PT BPD Jawa Timur Tbk	2	Jconnect Mobile	02 September 2016
10	PT Bank ANZ Indonesia	2	DBS Digibank Indonesia	22 November 2016
11	PT Bank DBS Indonesia	2	DBS Digibank Indonesia	22 November 2016
12	PT Bank OCBC Nisp Tbk	3	OCBC Mobile Indonesia	29 January 2017
13	PT Bank Syariah Indonesia Tbk	3	BSI Mobile	12 April 2018
14	PT Bank Permata Tbk	3	Permata ME	28 April 2018
15	PT Bank Maybank Indonesia Tbk	3	M2U ID APP	14 August 2019
16	PT Bank UOB Indonesia	3	UOB TMRW Indonesia	08 January 2020
17	Pt Bank Mega Tbk	3	M-Smile (Mega Smart Mobile)	30 March 2020
18	Pt Bpd Jawa Tengah	2	Bima Mobile	30 September 2020
19	PT Bank Jago Tbk	2	Bank Jago/Jago Syariah	13 April 2021
20	PT Bank Danamon Indonesia Tbk	3	D-Bank PRO	07 May 2021
21	PT Bank BTPN Syariah Tbk	2	Tepat Mobile	08 October 2021
22	PT Bank Mandiri Taspen	2	Movin by Mantap Mobile	13 December 2021
23	PT Allo Bank Indonesia Tbk	2	Allo Bank	14 March 2022
24	PT BPD DKI	2	JackOne Mobile	14 July 2022
25	PT Bank Tabungan Negara (Persero) Tbk	3	Bale by BTN	19 October 2022
26	PT Bank HSBC Indonesia	3	HSBC Indonesia Mobile Banking	03 January 2023
27	PT BPD Kalimantan Timur Dan Kalimantan Utara	2	DG By Bankaltimtara	08 February 2023
28	PT Bank Capital Indonesia Tbk	2	Capital Flex	05 September 2023
29	PT Bank Jasa Jakarta	2	Bank Saqu	11 October 2023
30	PT Bank Mayapada International Tbk	2	My Mobile Mayapada	15 November 2023
31	PT Bank Maspion Indonesia Tbk	2	MEB (Maspion Electronic Banking)	28 March 2024
32	PT BPD Jawa Barat Dan Banten Tbk	2	DIGI bank bjb	05 April 2024

Descriptive Statistics

Table 3. presents descriptive statistics for the full sample of 32 KBMI 2-3 banks over 2012-2024, yielding 416 bank-year observations with no missing values across variables after data cleaning.

Table 3. Descriptive Statistics

Variable	N	Mean	SD	Min	Max
ROA (%)	416	1.639	2.049	-15.890	13.580
ROE (%)	416	9.732	10.324	-89.030	68.090
BOPO (%)	416	83.585	20.424	0.800	261.100
NPL/NPF (%)	416	2.571	1.712	0.000	10.360
LDR/FDR (%)	416	87.678	23.771	0.820	171.320
CAR (%)	416	24.819	18.557	0.180	184.610
Log Total Assets	416	17.619	1.401	12.610	19.967

Table 3. Shows that average ROA across the sample is 1.64%, while average ROE is 9.73%. The negative minimum values for both ROA and ROE indicate that some banks experienced substantial losses during the study period. The operational efficiency ratio (BOPO) averages 83.6%, with a standard deviation of 20.4%, and ranges from 0.8% to 261.1%. This wide range reflects the inclusion of banks undergoing significant business model transitions during the sample period. Asset quality, measured by NPL/NPF, averages 2.6% with a standard deviation of 1.7%, indicating generally sound credit portfolios across the sample. LDR averages 87.7%, close to OJK's preferred range of 78% to 92%, while CAR averages 24.8%, well above the regulatory minimum of 8%. The wide range in BOPO, from 0.8% to 261.1%, reflects a small number of banks in

transitional business phases, including newly reclassified digital banks with atypically low operating expenses relative to income in early years, and banks undergoing restructuring with temporarily elevated cost ratios.

Regression Result

As a multicollinearity test, Table 4. presents the pairwise correlation matrix for the independent variables. All correlation coefficients fall well below the conventional threshold of 0.80 used to flag serious multicollinearity concerns, with the highest observed correlation at 0.357 between Post and log assets. This indicates that multicollinearity is not a material concern for regression estimation.

Table 4. Correlation Matrix

	Post	Log Assets	CAR/KPMM	LDR	NPL
Post	1.000				
LnAssets	0.357***	1.000			
CAR	0.160***	-0.254***	1.000		
LDR/FDR	0.133***	-0.053	0.104**	1.000	
NPL/NPF	-0.023	0.071	-0.141***	-0.070	1.000

Notes: * p<0.10, ** p<0.05, *** p<0.01.

Table 6. displays panel regression results. All regression models use standard errors clustered at the bank level. This corrects for two violations of the classical OLS assumptions, which are serial correlation of errors within each bank over time and heteroskedasticity across banks of differing size within the KBMI 2-3 classification. Cluster-robust standard errors (Cameron & Miller, 2015) address both issues simultaneously. Table 5. summarizes the Chow and Hausman test statistics underlying model selection for each outcome. The Chow (F) test rejects CEM in favor of the fixed-effects specification for all three outcome models, confirming significant bank-level heterogeneity. Hausman tests comparing FEM and REM estimators show mixed results across outcomes. For ROA and ROE, the Hausman test rejects the null of no systematic difference between FE and RE coefficients, supporting the use of FE. For BOPO, the test fails to reject the null. Given that the theoretical rationale for FEM, namely the likely correlation between unobserved bank characteristics such as management quality and innovation culture and both the timing of mobile banking adoption and subsequent performance, applies equally across all three outcomes, and to preserve comparability of the Post coefficient across models, the two-way fixed effects specification is retained for all three outcomes.

Table 5. Model Selection Test (Chow and Hausman)

Outcome	Chow test (CEM vs FEM)	Hausman test (FEM vs REM)	Model selected
ROA	$F(31,367)=17.04$, $p<0.001$	$\chi^2=17.63$, $p=0.0034$	FEM
ROE	$F(31,367)=9.66$, $p<0.001$	$\chi^2=14.89$, $p=0.0108$	FEM
BOPO	$F(31,367)=5.53$, $p<0.001$	$\chi^2=5.22$, $p=0.3899$	FEM retained for comparability (see text)

Table 6. Panel Regression Result

Variable	ROA	ROE	BOPO
Post	0.218	0.902	-6.095
	(0.301)	(1.375)	(4.199)
LnAssets	1.081**	5.291***	-6.087*
	(0.511)	(1.196)	(3.584)
CAR	-0.027	-0.143	0.391**
	(0.018)	(0.089)	(0.164)
LDR/FDR	0.016*	0.101*	0.140
	(0.009)	(0.055)	(0.114)
NPL/NPF	-0.206*	-1.320**	3.682***

	(0.102)	(0.499)	(1.311)
Constant	-17.673*	-85.778***	162.171**
	(8.725)	(20.750)	(66.834)
Within R-squared	0.243	0.256	0.242
F-statistic	3.54***	10.03***	6.36***

Notes: Standard errors clustered by bank in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

The Post coefficient carries the theoretically expected sign in all three models, though it does not reach conventional levels of statistical significance in any of them.

For ROA, the Post coefficient of 0.218 indicates that, holding bank size, capital, liquidity, and asset quality constant, banks show an average increase of 0.218 percentage points in return on assets following mobile banking adoption (p=0.475, 95 percent confidence interval -0.396 to 0.833). Relative to the sample mean ROA of 1.64%, this represents roughly a 13% increase. However, this result is not statistically significant and should therefore be read as suggestive rather than confirmed. Meanwhile, in ROE, the Post coefficient of 0.902 suggests an average increase of just under one percentage point in return on equity following adoption (p=0.516, 95 percent confidence interval -1.902 to 3.706). Against a sample mean ROE of 9.732 percent, this represents an increase of about 9 percent in relative terms. In BOPO, the Post coefficient of -6.095 indicates an average reduction of just over six percentage points in the BOPO ratio following adoption (p=0.157, 95 percent confidence interval -14.658 to 2.469). A 6.1 percentage point reduction in BOPO represents a decrease of approximately 7% relative to the sample mean of 83.6 percent. Among the control variables, NPL Gross is the most consistent predictor across all three outcomes, and bank size is significantly associated with ROA and ROE.

5. Discussion

Consistent with the hypotheses formulated in Section 2, the discussion below first addresses H1 concerning operational efficiency (BOPO), followed by H2a and H2b concerning profitability (ROA and ROE). Read together, the three points estimates describe a coherent picture in which mobile banking adoption is associated with modest gains in profitability and a more pronounced improvement in operating efficiency, in the direction hypothesized in Section 2, but the precision of the estimates is insufficient to rule out a zero effect at conventional confidence levels The direction of the Post coefficients across all three outcomes is consistent with the hypothesized effects of mobile banking adoption. Adoption is associated with higher ROA, higher ROE, and lower BOPO, exactly the pattern predicted under Transaction Cost Theory, in which digital channels reduce the marginal cost of processing transactions and thereby improve operating efficiency and profitability (Forcadell et al., 2020). The fact that the BOPO coefficient is the largest in relative magnitude and comes closest to significance is itself consistent with this framework, since transaction cost reduction operates most directly on the cost side of bank operations before it is fully reflected in profitability measures such as ROA and ROE.

That the coefficients fail to reach statistical significance while retaining the expected sign and a plausible economic magnitude is itself informative and aligns with a growing body of evidence that the performance effect of digital banking adoption in emerging markets is conditional rather than uniform. Setiawan & Prakoso (2024) find that the profitability effect of digital banking adoption among Indonesian banks depends on bank size, with smaller and mid-tier banks realizing weaker or delayed gains compared to larger institutions, a pattern broadly consistent with the KBMI 2-3 population examined here. Kasri, Indrastomo, Hendranastiti, & Prasetyo (2022) similarly report that the performance implications of digital payment adoption in Indonesia's dual banking system depend on bank-specific balance sheet characteristics rather than operating as a single average effect across all adopters. Under this conditional view, a pooled coefficient across 32 banks with heterogeneous starting positions in capital, liquidity, and asset quality would be expected to average out some of the individual variation in realized gains, producing point estimates that retain the correct sign but lack the precision to achieve significance.

The Productivity Paradox offers a complementary explanation for why the profitability outcomes in particular, ROA and ROE, show smaller and less precisely estimated effects than BOPO. Khattak, Ali, Azmi, & Rizvi (2023) find that digital transformation in banking is associated with short-run cost pressure from investment in platforms, cybersecurity, and staff retraining, with the profitability payoff materializing only after these costs are absorbed. Li (2026) similarly finds that the profitability effect of digital and AI adoption in Chinese banks is conditional on complementary organizational capabilities being in place, rather than following automatically from adoption itself. Both studies support an interpretation in which the positive but insignificant ROA and ROE coefficients found here reflect a genuine but still maturing performance effect, rather than the absence of an effect.

The absence of statistical significance across all three Post coefficients also warrants explicit consideration of statistical power. With 32 banks and 416 bank-year observations, the design has limited power to detect an average treatment effect of the magnitude implied by the point estimates, particularly given that mobile banking adoption in this sample is staggered across a twelve-year window rather than concentrated at a single point in time, which further disperses the identifying variation. This constraint reflects the KBMI 2-3 population size itself, which is fixed by regulatory definition and cannot be expanded through additional data collection within the same segment. The non-significant but directionally consistent results reported here should therefore be interpreted as underpowered to detect the hypothesized effect with precision, rather than as evidence that the effect does not exist. This interpretive stance follows the guidance of the American Statistical Association, which cautions that a p-value does not measure the size or importance of an effect and that smaller p-values do not necessarily imply larger or more important effects, nor do larger p-values imply an absence of effect (Wasserstein & Lazar, 2016). Recent empirical work in bank performance research reflects this same caution in practice. Nasution & Putra (2026) report a marginally significant coefficient in a study of Indonesian bank digital investment, explicitly interpret their result as suggestive rather than conclusive, and do not dismiss it outright, a stance this study adopts for its own non-significant but theoretically consistent Post coefficients.

The significant role of NPL/NPF across all three models, and to a lesser extent bank size, is consistent with Financial Intermediation Theory as the appropriate background frame for this sample. Larger, better-capitalized banks with lower non-performing loans systematically exhibit better profitability and cost efficiency, independent of mobile banking adoption status, indicating that traditional credit risk management remains a first-order determinant of performance for KBMI 2-3 banks during this period. Murinde, Rizopoulos, & Zachariadis (2022) similarly note that the performance benefits of financial technology adoption in banking tend to be secondary to, and conditioned by, the underlying strength of a bank's core intermediation function, which is consistent with the relative magnitude of the NPL and Post coefficients observed in Table 6. From the authors' perspective, this pattern suggests that for KBMI 2-3 banks specifically, credit risk discipline functions as a precondition rather than a complement to digital transformation. This view is reinforced by Wang et al. (2023), who find that fintech input reduces non-performing loan risk and translates into measurable performance gains only once this risk-reduction effect materializes, typically after a lag of several periods rather than immediately. A bank with weak asset quality is therefore unlikely to convert mobile banking investment into measurable performance gains, regardless of how well the technology is implemented, since NPL erosion offsets efficiency gains on the cost side. This interpretation is further supported by tier-specific evidence from Indonesian banking itself. Nasution & Putra (2026) find that mid-tier KBMI 2 banks bear digital transition costs without offsetting profitability gains, in contrast to the largest KBMI 4 banks, which realize positive returns, suggesting that the capacity to convert digital investment into performance gains scales with a bank's underlying financial strength rather than following automatically from adoption itself.

6. Conclusion

This study examined whether mobile banking adoption affects the financial performance of KBMI 2-3 banks in Indonesia, using a Post treatment indicator constructed from Google Play Store release dates following Haendler (2022), and found that the Post coefficient carries the theoretically expected sign across all three outcomes (positive for ROA and ROE, negative for BOPO) though without reaching conventional statistical significance in a 32-bank sample. This pattern is consistent with Transaction Cost Theory and the Productivity Paradox, under which digital investment costs offset near-term profitability gains before efficiency benefits materialize. In contrast, the consistent significance of NPL/NPF across all three models confirms that credit risk management remains the dominant performance determinant for this tier regardless of digital adoption. For bank management, the results imply that mobile banking should be treated as a medium-term capability rather than a near-term profitability driver, with credit risk discipline maintained as a precondition rather than a substitute for digital investment. These findings are drawn from a fixed population of 32 KBMI 2-3 banks, and the resulting statistical power constrains how precisely the Post effect can be estimated, a limitation addressed further below.

Recommendation

Bank management at KBMI 2-3 institutions should track mobile banking's contribution to performance through specific, measurable indicators rather than expecting an immediate profitability payoff. In the short to medium term, management should monitor the BOPO ratio, active user growth, and the share of transactions migrated from branch to mobile channels as leading indicators of the cost-side effect, since BOPO showed the largest relative magnitude among the three outcomes examined here. Cybersecurity readiness should be built alongside adoption, not after it, because operational risk exposure rises with transaction volume. Digital investment should be paired with continued NPL/NPF discipline, since credit risk remained the strongest performance predictor in this sample regardless of adoption status. For capital-constrained mid-tier banks, a phased rollout prioritizing core transactional features before capital-intensive services such as embedded lending allows efficiency gains to be captured without straining capital adequacy. Management should evaluate mobile banking's profitability contribution over a three- to five-year horizon, and internal monitoring could usefully compare early versus late adopters within the KBMI 2 and 3 population to track whether the direction of the Post effect strengthens as more banks accumulate post-adoption years.

Limitations and Avenue for Future Research

This study has several limitations that define the scope of its conclusions. First, the sample of 32 banks limits the statistical power available to detect the Post effect with precision, and a longer post-adoption observation window, as recent adopters accumulate additional years of data, would allow more precise estimation and a clearer test of whether the coefficient direction strengthens over time. Second, the two-way fixed effects design estimates a single average treatment effect and does not incorporate staggered-adoption robustness checks, event-study diagnostics, or difference-in-differences estimators, which are natural extensions for future work once a longer panel is available. Third, the KBMI classification is applied as a fixed 2024 cross-section rather than a time-varying designation, a scope condition disclosed in the Data and Sample section. Fourth, this study does not separate KBMI 2 from KBMI 3 banks in the estimation, nor does it incorporate app usage intensity, digital transaction volumes, or customer-level adoption data, all of which could sharpen the measurement of mobile banking's effect beyond the binary Post indicator used here. Future studies are encouraged to pursue these extensions, including alternative performance indicators, as more years of post-adoption data and more granular usage data become available.

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