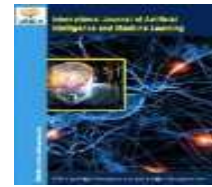




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Fintech Adoption and Bank Profitability: Market-Conditional Evidence from Egypt and Jordan

Amer Almomani¹, Logasvathi Murugiah², Juhaida Abu Baker³

¹Othman Yeop Abdullah Graduate School of Business, UUM College of Business, Universiti Utara Malaysia, 06010 UUM Sintok, Kedah Darul Aman, Malaysia. E-mail: Amer_abdelwali_o@oyagsb.uum.edu.my

²UUM College of Business, Universiti Utara Malaysia, 06010 UUM Sintok, Kedah Darul Aman, Malaysia. E-mail: logasvathi@uum.edu.my

³UUM College of Business, Universiti Utara Malaysia, 06010 UUM Sintok, Kedah Darul Aman, Malaysia. E-mail: juhaida@uum.edu.my

ABSTRACT

There is mixed evidence as to whether digital channels boost bank profitability, which is typically explained by the different ways of measuring them. This study examines if the return is instead dependent on the phase of market expansion in which these channels are used. An unbalanced panel of 30 commercial banks in Egypt and Jordan over 2013–2024 (333 bank-year observations) is estimated with bank fixed effects and Driscoll–Kraay standard errors. Adoption is measured by a three-channel FinTech Index validated by principal component analysis, and the cross-market difference is tested through an interaction term rather than inferred from subsample coefficients. The study found in the pooled panel the index carries no significant association with return on assets. the slope is 0.815 percentage points higher in Egypt than in Jordan ($p < 0.001$), the unrestricted Egyptian estimate being 0.448 ($p < 0.01$) against a Jordanian estimate that is negative but not significant. The divergence survives year fixed effects, winsorisation, sub-period estimation and bank-clustered inference, and is absent for the loan-to-deposit ratio. The study concluded that digital channels should be evaluated in light of the growth of the target market; when the customer base is already served, adoption is a cost to maintain competitive parity, not an investment in growth. Therefore, the difference between markets in the tendency for fintech performance is estimated as a testable metric, and the risks of variation are documented, as the variation between countries can appear as a moderating factor at the firm level.

Keywords FinTech adoption, Bank profitability, Digital banking, Financial inclusion, Egypt, Jordan

1. Introduction

Two decades of investment in digital delivery have left banking with an unresolved question: whether the money paid for mobile applications, internet portals and payment wallets earns a return for the bank. The published record points in both directions. Early internet banking adopters among United States community banks earned better profitability (DeYoung et al., 2007), while listed Chinese banks report the opposite in the short run (Li, 2025). Evidence on the SWIFT network finds positive effects that grow with the number of adopters (Scott et al., 2017; Geetanjali & Singh, 2025), whereas European evidence finds gains arriving indirectly (Di Febo and Angelini, 2022). Thakor (2020) attributes the disagreement to how adoption is measured.

This paper tests a different explanation. There may be no single parameter to estimate, because the return to a digital channel depends on whether it reaches demand the bank could not otherwise serve. Where a large share of the population is entering the formal financial system, the channel extends the market; If the market is mature and competitors are using the same channels, the same investment is cost without an increase in the addressable base. Each individual coefficient then only represents the sampled market.

This can be tested only by comparing two banking systems that are similar in institutional structure and regulation and disclosure, but different in market development. Egypt and Jordan meet that requirement. According to the Central Bank of Egypt (2024), the financial inclusion rate in Egypt in 2023 was 70.7% of adults, and the average loan-to-deposit ratio was 48.4%, which indicates that there are deposits that have not been used for loans. while the financial inclusion rate in Jordan increased from 42% in 2021 to around 50% in 2023 (Central Bank of Jordan, 2023), and the average loan-to-deposit ratio was 82.4%. The difference is not the degree of penetration, but the growth rate of the addressable market.

The study quantifies the relationship between adoption and profitability in each market, compares the two relationships as a single parameter, and determines if any difference is limited to earnings or also impacts the funding position of the bank. The paper makes four contributions. First, it tests market conditionality directly:

studies reporting divergent country results typically compare subsample coefficients, which cannot establish that the difference is distinguishable from zero, whereas here it is a single parameter significant at the 1% level. Second, it separates digital technology from physical delivery infrastructure on dimensionality evidence rather than by assertion. Third, it documents a compositional hazard, since an interaction between adoption and intangible asset intensity that is close to significance in the pooled panel falls to approximately zero once the cross-market divergence is modelled. Fourth, it marks the boundary of the effect, which appears in the return on assets but not in the loan-to-deposit ratio.

Section 2 reviews the evidence and develops the hypotheses, Section 3 describes the sample, variables and estimation strategy, Section 4 reports the results, Section 5 discusses them and Section 6 concludes.

2. Literature Review and Hypothesis Development

2.1 Divergent Evidence on FinTech and Bank Performance

Research on the performance consequences of digital adoption in banking divides into three groups by result, not by method.

The first group reports positive associations. DeYoung et al. (2007) find that United States community banks adopting internet banking earned higher deposit service revenues and improved profitability, and Scott et al. (2017), reconstructing SWIFT adoption across 6,848 banks in twenty-nine countries, report long-term effects that grow with the number of adopters. Tunay et al. (2015) report evidence of causality running from internet banking to profitability across thirty European countries, a relationship that holds in the more developed systems only, and Sarker et al. (2024) report positive mobile banking effects among Bangladeshi banks.

The second group reports negative or null associations. Li (2025) finds a negative short-run effect among Chinese listed banks, attributing it to deposit diversion and investment cost, Di Febo and Angelini (2022) find gains arriving indirectly across 3,679 European banks, and Wu et al. (2026) report a negative association with liquidity creation among the 300 largest United States banks.

The third group locates the effect in where the technology originates and which margin it touches. Kharrat et al. (2024) find the relationship holds among MENA banks only when FinTech growth or decline is pronounced, Buchak et al. (2018) locate the effect in reallocation between regulated and shadow institutions. Wu et al. (2023) find that internally developed FinTech alters bank risk-taking in China, while Safiullah and Paramati (2024) report that the growth of FinTech firms is associated with greater bank stability in Malaysia.

2.2 What the Literature Has not Established

The dominant interpretation, stated most directly by Thakor (2020), attributes the disagreement to measurement heterogeneity: studies define adoption differently and examine different margins. The composite-index literature has responded with broader measures (Gomber et al., 2018; Kharrat et al., 2024; Ozili, 2018). That is not the only available explanation, and the alternative has not been tested. If the return depends on the structure of the market into which a channel is deployed, two studies using identical measurement would still obtain different coefficients from different markets. Distinguishing the two accounts requires holding measurement constant and varying the market, which a two-country panel with a common instrument permits.

A recent systematic review identifies the Middle East as an underrepresented setting and cross-country comparative designs as underused (Xu et al., 2025). Three gaps follow. First, no study in the MENA banking literature estimates the cross-market difference in the FinTech-performance slope as a parameter subject to a hypothesis test. Second, composite measures usually settle the treatment of physical delivery infrastructure by assertion, without reference to dimensionality evidence (OECD, 2008). Third, work on innovation investment as a moderator (Albaity et al., 2026; Baig et al., 2025) has not asked whether an apparent firm-level moderator is a compositional artefact of pooling heterogeneous markets.

2.3 Theoretical Framework

The resource-based view holds that a resource generates rent when it is valuable, rare and difficult to imitate (Barney, 1991), and is usually invoked to predict that digital capability improves bank performance. That prediction is incomplete, because two of the three conditions are properties of the market rather than of the resource. A digital channel is valuable when it reaches demand the existing network cannot reach: where a large share of the population is entering the formal financial system it performs that function (Beck et al., 2015), whereas where account ownership is established it merely migrates customers between delivery modes. Rarity is likewise a market property: a channel offered by a minority of banks differentiates, while one offered by every competitor becomes a cost of parity.

The time dimension is given by innovation diffusion theory (Rogers, 2003), which states that the advantage decreases as the number of adopters grows. The average fintech index in this sample increases from 0.086 in 2013 to 0.968 in 2024, indicating that diffusion is highest in the period observed. It is not the bank's adoption

of the technology that is the condition for a positive impact, but the market's lack of acceptance of the technology.

According to financial intermediation theory (Gurley and Shaw, 1960), the functions that a bank can use to earn revenue are customer acquisition and service, borrower screening, and maturity transformation. Digital channels impact the first function, changing the cost of customer acquisition and service, but not the balance sheet maturity structure. This framework assumes that the impact will be seen in the return on assets and not the loan-to-deposit ratio, so profitability effects without funding effects are seen as evidence of the functioning of this technology. Cohen and Levinthal (1990) argue that the capacity to exploit a new technology depends on prior investment in related knowledge, which predicts that banks carrying more capitalised technology convert adoption into performance more effectively.

2.4 Hypothesis Development

The resource-based view predicts a positive return where the channel extends the addressable market. Egyptian inclusion approximately tripled over the sample window, against a mean loan-to-deposit ratio of 48.4% that leaves a substantial part of the deposit base uncommitted to lending.

H1: Digital channel adoption is positively associated with bank profitability in the expanding market (Egypt). Where the customer base is stable and every competitor offers the same channels, the investment buys parity rather than rent, while its costs reach the income statement immediately. Jordanian banks operated at a mean cost-to-income ratio of 50.2%, against 33.5% in Egypt.

H2: Digital channel adoption is not positively associated with bank profitability in the mature market (Jordan). The hypothesis being tested is not that there are two separate variables, but that they are different, which requires direct testing.

H3: The association between digital channel adoption and bank profitability differs significantly between the two markets.

Financial intermediation theory locates digital delivery in customer acquisition rather than maturity transformation.

H4: Digital channel adoption is not associated with the loan-to-deposit ratio in either market, and the cross-market difference found for profitability does not appear for the funding position.

Absorptive capacity predicts that prior technology investment amplifies the return to a new channel, examined here as an auxiliary proposition.

H5: The association between digital channel adoption and bank profitability is stronger at higher levels of intangible asset intensity.

3. Research Methodology

3.1 Sample and Data

The population comprises commercial banks in Egypt and Jordan. A bank enters the sample if complete annual reports and verifiable technology-adoption information are available for 2013 to 2024, which yields 31 banks and 372 bank-year observations, 19 Egyptian and 12 Jordanian. Four reported cost-to-income ratios below one per cent, all belonging to a single Jordanian bank in 2014–2017. Dropping bank-years missing a value on any model variable then removes 38 observations, concentrated in 2013–2015 and arising mainly from non-disclosure of the cost-to-income ratio and of the automated teller machine count in the earliest reporting years. A bank enters the estimation sample only if it contributes at least four complete bank-years, since a bank observed once or twice cannot contribute to a within estimator. One Egyptian bank, whose automated teller machine series is unavailable in eleven of its twelve years, retains a single complete year and is therefore excluded. This leaves an estimation sample of 30 banks and 333 bank-year observations, 193 Egyptian and 140 Jordanian. No exclusion reflects a selection rule; each follows from a stated criterion applied before estimation. Financial data were collected from annual reports published on banks' websites and central bank publications, and from macroeconomic data series from the World Bank's World Development Indicators (World Bank, 2024) and the two central banks. Balance sheet values were converted to US dollars at the average annual official exchange rate for the period, and each ratio is calculated with the numerator and denominator in the same currency.

3.2 Variable Measurement

Return on assets (ROA) is the most widely used indicator of a bank's ability to generate profits from its assets, and is calculated as net income divided by total assets. The second dependent variable, which is used to test the fourth hypothesis (H4), is the loan-to-deposit ratio (LIQ) defined as net loans divided by total deposits. The direction of this ratio must be clearly identified: the higher the ratio, the more deposits are being used for lending, which means a higher lending intensity and a lower reserve requirement, but not necessarily a better liquidity.

The independent variable of interest is the FinTech Index (FTI), the equally weighted mean of three binary indicators, each equal to one in a year in which the bank offers mobile banking, internet banking or an e-wallet. Bounded on the unit interval, the index can be read as the proportion of digital channels the bank offers. Adoption is used in its institutional sense, distinct from the individual-level construct dominating the mobile banking literature (Shaikh and Karjaluo, 2015), and captures breadth of provision rather than customer uptake, which banks do not disclose consistently.

Equal weighting is validated rather than assumed. Principal component analysis on the 363 bank-year observations with complete channel indicators yields a first component with an eigenvalue of 2.096, accounting for 69.88% of the variance, with loadings of 0.882, 0.888 and 0.729 and a second eigenvalue of 0.628. The three indicators are therefore unidimensional under the Kaiser (1960) criterion, and every loading clears conventional thresholds (Hair et al., 2019). Cronbach's alpha is 0.781 and the Kaiser–Meyer–Olkin statistic 0.646, with the Bartlett (1951) test rejected at the 1% level. A loading-weighted index correlates with the equally weighted mean at 0.999, so the latter is retained for interpretability (OECD, 2008). Adding the automated teller machine network, which restricts the sample to the 347 observations that also report the network, produces a second component with an eigenvalue of 1.132 and a loading of 0.297, while alpha falls to 0.670 and the Kaiser–Meyer–Olkin statistic to 0.603, so the four indicators do not measure a single construct. The network (lnATM) is therefore treated as a separate regressor, a decision reinforced by its near-zero correlations with mobile banking (0.007) and internet banking (0.061). Full diagnostics are reported in Tables S1 and S2 of the supplementary material.

The market indicator, EGYPT, equals one for Egyptian banks and zero for Jordanian banks. It proxies the stage of market expansion documented in Section 1 and Table 2, and the bank fixed effects absorb its main effect.

Table 1 gives definitions and sources for the bank-specific and macroeconomic variables. Two require comment. Credit risk (NPL) is non-performing loans to total loans. Asset quality, credit risk exposure and the non-performing asset position are measured by the same underlying series, so they enter as a single regressor rather than as three, which also avoids near-perfect collinearity. Intangible asset intensity (IAI) is intangible assets to total assets, an accounting-based proxy for technological investment whose link to profitability has been estimated structurally in non-financial settings (Warusawitharana, 2015); research and development expenditure is not disclosed separately by these banks, and capitalised intangibles are largely software, platforms and licences.

Table 1. Variable definitions and measurement

Variable	Symbol	Measurement	Source
Return on assets	ROA	Net income / total assets (%)	Annual reports
Loan-to-deposit ratio	LIQ	Net loans / total deposits (%)	Annual reports
FinTech Index	FTI	Mean of three binary channel indicators (0–1)	Annual reports; central banks
Egypt indicator	EGYPT	1 if Egyptian bank, 0 if Jordanian	Author constructed
ATM network	lnATM	ln(number of ATMs operated)	Annual reports; central banks
Capital adequacy	CAR	Regulatory capital / risk-weighted assets (%)	Annual reports
Credit risk	NPL	Non-performing loans / total loans (%)	Annual reports
Cost-to-income ratio	EFF	Operating expenses / operating income (%)	Annual reports
Bank size	lnTA	ln(total assets, USD billions)	Annual reports; World Bank FX
Bank age	lnBA	ln(observation year – establishment year)	Annual reports
Chief technology officer	CTO	1 if a CTO is in post, 0 otherwise	Governance disclosures
Intangible asset intensity	IAI	Intangible assets / total assets (%)	Annual reports
Inflation	INF	Annual CPI inflation (%)	World Bank WDI
Interest rate	INT	Central bank policy rate (%)	Central banks
GDP growth	GDP	Annual real GDP growth (%)	World Bank WDI
COVID-19	COVID	1 for 2020–2021, 0 otherwise	Author constructed

3.3 Model Specification

The baseline model is estimated for each dependent variable:

$$Y_{it} = \alpha + \beta_1 FTI_{it} + \beta_2 IAI_{it} + \beta_3 (FTI_{it} \times IAI_{it}) + \beta_4 \ln ATM_{it} + \beta_5 CAR_{it} + \beta_6 NPL_{it} + \beta_7 EFF_{it} + \beta_8 \ln BA_{it} + \beta_9 \ln TA_{it} + \beta_{10} CTO_{it} + \beta_{11} INF_{ct} + \beta_{12} INT_{ct} + \beta_{13} GDP_{ct} + \beta_{14} COVID_t + \eta_i + \varepsilon_{it} \quad (1)$$

The test of H3 augments equation (1) with the product of the FinTech Index and the market indicator:

$$Y_{it} = \dots + \beta_{15} (FTI_{it} \times EGYPT_i) + \eta_i + \varepsilon_{it} \quad (2)$$

The main effect of the market indicator is absorbed by the bank fixed effects, since no bank changes country. The coefficient β_{15} is the difference between the two market slopes: the Jordanian slope is read from β_1 and the Egyptian slope from $\beta_1 + \beta_{15}$, with the standard error of the sum obtained from the full covariance matrix. The FinTech Index and intangible asset intensity are mean-centred before the interactions are formed, which removes non-essential collinearity, and the automated teller machine network, bank age and total assets enter in natural logarithms. Equation (2) constrains every coefficient other than that on the FinTech Index to be equal across markets, and subsample estimates relaxing that constraint are reported alongside it. The timing of channel launches reduces synchronization but does not establish externality, so transactions are partial correlations based on intrabank variance so it is not claim of causal identification is made

3.4 Estimation Strategy

The valuation process is plagued by three problems: the imperceptible heterogeneity of banks, the possible synchronization between investment in technology and performance, and the fact that the residuals are usually sequentially linked, common-shock, and heterogeneous in variance. The within transformation handles the first, and the Breusch–Pagan test rejects the null of no bank-level effects in both equations (LM = 348.9 and 655.1, $p < 0.001$). Fixed effects are preferred to random effects because the estimator remains consistent whether or not the bank effects are correlated with the regressors (Baltagi, 2021), and because ownership structure, risk appetite and branch footprint would violate the orthogonality condition.

Residual diagnostics determine the inference procedure. The modified Wald test (Baum, 2001) rejects a common error variance across banks in both equations ($\chi^2(30) = 1,103.4$ and $9,964.3$, $p < 0.001$). The Wooldridge (2010) test rejects the absence of serial correlation in the profitability equation, $F(1, 29) = 61.01$, $p < 0.001$, and in the liquidity equation, $F(1, 29) = 5.40$, $p = 0.027$. The Pesaran (2015) test rejects cross-sectional independence in the profitability equation ($CD = 5.47$, $p < 0.001$) but not in the liquidity equation ($CD = -0.67$, $p = 0.504$). Driscoll–Kraay standard errors (Driscoll and Kraay, 1998; Hoechle, 2007) with a Bartlett kernel of bandwidth two remain valid under all three conditions, and bank-clustered errors are reported in Section 4.5. Fisher-type panel unit root tests (Maddala and Wu, 1999) reject the unit root null for all series except intangible asset intensity, the automated teller machine network, the cost-to-income ratio and the policy rate. The test has little power with twelve annual observations, so possible non-stationarity is recorded among the limitations.

4. Results

4.1 Descriptive Statistics

Table 2 reports descriptive statistics for the sample and by market.

Table 2. Descriptive statistics

Variable	Full sample mean (SD)	Egypt (n = 193) mean (SD)	Jordan (n = 140) mean (SD)
ROA (%)	1.863 (1.180)	2.412 (1.213)	1.106 (0.547)
LIQ (%)	62.927 (28.997)	48.376 (14.310)	82.988 (32.033)
FTI	0.551 (0.399)	0.529 (0.432)	0.581 (0.347)
IAI (%)	0.176 (0.221)	0.105 (0.102)	0.275 (0.292)
lnATM	5.293 (1.183)	5.723 (1.287)	4.701 (0.669)
CAR (%)	17.604 (4.250)	17.950 (5.060)	17.127 (2.715)
NPL (%)	5.157 (3.111)	4.999 (3.468)	5.376 (2.533)
EFF (%)	41.072 (14.419)	33.450 (11.561)	51.581 (10.956)
lnBA	3.739 (0.515)	3.712 (0.594)	3.777 (0.379)
lnTA	1.812 (1.066)	1.994 (1.164)	1.562 (0.857)
CTO	0.474 (0.500)	0.456 (0.499)	0.500 (0.502)
GDP growth (%)	3.374 (1.518)	4.144 (1.239)	2.314 (1.196)
Inflation (%)	10.052 (10.153)	15.862 (9.745)	2.043 (1.879)

Variable	Full sample mean (SD)	Egypt (n = 193) mean (SD)	Jordan (n = 140) mean (SD)
Interest rate (%)	10.282 (6.752)	14.576 (5.742)	4.361 (1.559)

Notes: Standard deviations in parentheses. Variable definitions are given in Table 1.

Three features bear directly on the argument. Average adoption is similar across markets, 0.529 in Egypt and 0.581 in Jordan, so the divergence reported below is not a difference in how much technology was deployed. The funding positions differ sharply, 48.4% against 83.0%. Egyptian banks also operate at lower cost-to-income ratios, 33.5% against 51.6%, and earn more, 2.412% of assets against 1.106%, in an environment of markedly higher inflation and policy rates. That macroeconomic contrast is the principal confounding threat, and Section 4.5 addresses it.

4.2 Correlations and Multicollinearity

Pairwise correlations, reported in full in Table S3 of the supplementary material, show that profitability is negatively correlated with the cost-to-income ratio (−0.58) and positively with the policy rate (0.61) and inflation (0.57), while the FinTech Index is only weakly correlated with the two dependent variables, at 0.07 and 0.07.

Two pairs of variables have a correlation coefficient greater than 0.70: inflation and the base interest rate (0.91) and bank size and ATM network (0.73). The inflation coefficients of variation (Table S4) are high (8.92 for base interest rate and 6.69 for inflation) but not above 10 (Gujarati and Porter, 2009). All other independent variables are below 4.4, and the interaction limits are 1.57 and 4.14, which confirms that mean-centering has removed the non-essential collinearity an uncentred product would introduce.

4.3 Main Results

Table 3 reports the fixed effects estimates for the return on assets.

Table 3. Fixed effects estimates, return on assets

Variable	(1) Baseline	(2) With FTI × IAI	(3) With FTI × EGYPT	(4) Bank and year FE
FTI	0.214 (0.218)	0.201 (0.217)	−0.391** (0.169)	−0.370 (0.278)
FTI × EGYPT	–	–	0.815*** (0.189)	0.902*** (0.276)
IAI	0.147 (0.155)	0.062 (0.154)	0.090 (0.171)	0.220 (0.207)
FTI × IAI	–	−0.552 (0.348)	0.009 (0.274)	0.351 (0.278)
lnATM	−0.062 (0.181)	−0.062 (0.177)	−0.073 (0.178)	0.141 (0.239)
CAR	0.035** (0.014)	0.034** (0.013)	0.022* (0.012)	0.026** (0.012)
NPL	−0.024 (0.016)	−0.025 (0.016)	−0.023 (0.015)	−0.018 (0.014)
EFF	−0.027*** (0.005)	−0.026*** (0.005)	−0.025*** (0.005)	−0.027*** (0.005)
lnBA	−0.272 (0.395)	−0.224 (0.400)	−0.034 (0.450)	–
lnTA	0.047 (0.106)	0.061 (0.106)	0.080 (0.120)	0.014 (0.115)
CTO	−0.192 (0.121)	−0.195* (0.114)	−0.160 (0.126)	0.007 (0.046)
GDP growth	−0.055 (0.064)	−0.053 (0.064)	−0.063 (0.063)	–
Inflation	0.001 (0.011)	0.003 (0.010)	−0.001 (0.009)	–
Interest rate	0.054** (0.023)	0.052** (0.022)	0.055*** (0.018)	–
COVID-19	−0.314 (0.194)	−0.321 (0.196)	−0.322* (0.191)	–
Constant	3.489 (1.882)	3.298 (1.934)	2.776 (2.184)	1.845 (1.222)
Observations	333	333	333	333
Banks	30	30	30	30
Within R ²	0.440	0.443	0.470	0.259

Notes: Driscoll–Kraay standard errors in parentheses, Bartlett kernel of bandwidth two. Bank fixed effects in all columns; column (4) adds year fixed effects and drops the four macroeconomic controls, which vary by country as well as by year; bank age is absorbed. FTI and IAI are mean-centred. Variable definitions are given in Table 1. Significance is indicated by ***, ** and * at the 1%, 5% and 10% levels respectively.

The pooled null that motivates the paper is reproduced in column (1). The FinTech Index has a coefficient of 0.214 and a standard error of 0.218, well beyond the typical significance thresholds, which on its own means that there is no relationship between adoption and profitability. The interaction with intangible asset intensity is added in column (2) and is negative at −0.552 with a p-value of 0.114. That's close enough to conventional

significance to warrant interpretation as a dampening mechanism, but it only increases the within R^2 by a small amount, from 0.440 to 0.443.

The central result is in column (3). Including the interaction between the FinTech Index and the market indicator, the difference in slopes is 0.815 (SE 0.189), significant at the 1% level ($t = 4.31$, $p < 0.0001$), and the within R^2 increases to 0.470. Moving from none of the three channels to all three is associated with a return on assets 0.815 percentage points higher in Egypt than in Jordan, an economically large gap relative to the sample mean of 1.863%. Read from the FinTech Index coefficient, the Jordanian slope is -0.391 (SE 0.169) and significant at the 5% level, and the implied Egyptian slope is 0.424. The interaction with intangible asset intensity falls to 0.009 ($p = 0.973$), a point taken up in Section 5.3. Column (4) replaces the macroeconomic controls with year fixed effects: the market difference is 0.902 (SE 0.276) and remains significant at the 1% level, so the result is not produced by the way the macroeconomic environment is modelled.

The remaining coefficients replicate the established determinants of profitability. Most precisely estimated is the cost-to-income ratio, at -0.025 with $p < 0.001$ in column (3). Capital adequacy enters positively and non-performing loans negatively (Athanasoglou et al., 2008; Berger and Bouwman, 2013; Berger and DeYoung, 1997; Ghosh, 2015), and the policy rate is positive and significant.

4.4 Market-specific Estimates

Table 4 relaxes the cross-market restrictions entirely by estimating the full specification separately on each subsample.

Table 4. Market-specific fixed effects estimates

Variable	Egypt: ROA	Jordan: ROA	Egypt: LIQ	Jordan: LIQ
FTI	0.448*** (0.169)	-0.156 (0.149)	-2.909 (2.362)	1.711 (8.381)
IAI	0.067 (0.393)	0.005 (0.172)	6.686* (3.548)	7.915*** (2.613)
FTI $\times$ IAI	1.155 (1.117)	-0.320 (0.316)	-13.712 (15.266)	21.039 (14.724)
lnATM	-0.034 (0.266)	0.106 (0.093)	9.547*** (1.745)	-3.246 (2.336)
CAR	0.026** (0.010)	0.021 (0.038)	-0.130 (0.182)	0.394 (1.325)
NPL	-0.026 (0.018)	-0.009 (0.022)	-0.324* (0.156)	-0.583* (0.341)
EFF	-0.021** (0.008)	-0.025*** (0.003)	0.166*** (0.053)	0.320 (0.245)
lnBA	0.764 (0.656)	-0.811 (0.809)	-9.286 (6.761)	40.751 (31.792)
lnTA	0.089 (0.146)	0.240 (0.155)	-0.243 (0.772)	-34.644*** (9.531)
CTO	-0.073 (0.100)	-0.187 (0.117)	0.432 (1.906)	5.886** (2.640)
GDP growth	-0.202** (0.074)	0.078*** (0.014)	-0.620** (0.240)	0.660*** (0.225)
Inflation	-0.012** (0.005)	0.004 (0.018)	0.116 (0.069)	-0.461 (0.970)
Interest rate	0.049** (0.017)	-0.024 (0.039)	-0.083 (0.077)	0.478 (1.356)
COVID-19	-0.771*** (0.226)	-0.322*** (0.088)	1.625 (1.594)	-3.810 (4.007)
Observations	193	140	193	140
Banks	18	12	18	12
Within R^2	0.513	0.528	0.172	0.184

Notes: Driscoll–Kraay standard errors in parentheses. Bank fixed effects in all columns. In the pooled loan-to-deposit specification corresponding to equation (2), the market interaction is 5.926 (SE 6.620, $p = 0.371$). Variable definitions are given in Table 1. ***, ** and * denote significance at the 1%, 5% and 10% levels respectively.

Without cross-market restrictions the Egyptian slope is 0.448 (SE 0.169), significant at the 1% level, roughly a fifth of the Egyptian mean return of 2.412%. The Jordanian slope is -0.156 (SE 0.149) and does not reach conventional significance. The two specifications therefore differ in what they establish about Jordan: under the cross-market restrictions of equation (2) the Jordanian slope is -0.391 and significant at the 5% level, while the unrestricted subsample estimate is negative but indistinguishable from zero. H1 is supported and H2, which states that adoption is not positively associated with profitability in the mature market, is supported under both. The interaction test in Table 3 supports H3.

The loan-to-deposit columns support H4. The FinTech Index is insignificant in both markets, at -2.909 and 1.711 against standard errors of 2.362 and 8.381, and the pooled market interaction is 5.926 (SE 6.620, $p = 0.371$). The divergence that is sharp for earnings is therefore absent for the funding position. Two secondary results reinforce the separation of physical from digital infrastructure: the automated teller machine network

is positively associated with the loan-to-deposit ratio in Egypt (9.547, $p < 0.001$) and insignificant in Jordan, and intangible asset intensity is positively associated with it in Jordan (7.915, $p < 0.01$).

H5 is not supported. The interaction between adoption and intangible asset intensity is negative rather than positive in column (2) of Table 3, at -0.552 ($p = 0.114$), and drops to 0.009 ($p = 0.973$) once the market divergence is modelled. In the market-specific estimates it carries opposite signs, 1.155 in Egypt and -0.320 in Jordan, and is significant in neither.

4.5 Robustness Checks

The market difference was re-estimated under ten alternative treatments of the sample, the fixed effects structure and the inference procedure. Full results appear in Tables S5 to S7 of the supplementary material.

With bank-clustered errors in place of the Driscoll–Kraay procedure, the market difference is 0.815 (SE 0.207) and remains significant at the 1% level. The principal remaining threat is that the two markets differ in macroeconomic trajectory as well as in stage of expansion, so that the FinTech Index may be proxying for the Egyptian inflation and interest rate cycle. Year fixed effects raise the difference to 0.902 ($p < 0.01$). Country-year fixed effects absorb the entire macroeconomic path of each market, identifying the coefficients only from variation across banks within the same country and year. The difference falls to 0.457 , with implied slopes of 0.440 in Egypt and -0.017 in Jordan. It remains significant at the 1% level under Driscoll–Kraay inference, but not under bank-clustered inference with 30 clusters ($p = 0.247$). The point estimate is nonetheless positive and sizeable across every specification, from 0.457 to 0.902 , so what weakens under the most demanding treatment is the precision of the estimate rather than its magnitude.

Winsorising the cost-to-income ratio at the first and ninety-ninth percentiles leaves the difference at 0.815 , and winsorising all six accounting ratios leaves it at 0.849 . Excluding 2024 reduces it to 0.654 while retaining significance at the 1% level, and restricting the sample to 2016–2024 raises it to 0.923 . No sample restriction reverses the finding.

Two further checks qualify the controls. Because inflation and the policy rate correlate at 0.91 , the model was re-estimated with each entered singly. Alone, both are positive, the policy rate at the 1% level and inflation at the 10% level; entered together, the policy rate is unchanged and inflation falls to approximately zero. This is the signature of two jointly but not separately identified regressors, so the inflation coefficient in Table 3 is not evidence that inflation is unrelated to profitability. A quadratic policy rate term is not reported, because the two rate distributions barely overlap and the quadratic is close to a market indicator in disguise. Dynamic panel estimation was also examined, since the generalised method of moments is the estimator most common in this literature (Xu et al., 2025). In every workable specification the lagged dependent variable fell outside the credibility interval bounded by the fixed effects and pooled estimates (Bond, 2002). The Arellano–Bond family suits panels with many units over few periods, and this panel has the opposite shape.

5. Discussion

5.1 A Null that Combines Two Opposing Effects

The central result is that a pooled coefficient of 0.214 (SE 0.218), which any reader would classify as a null, combines two associations of opposite sign. Under the restricted specification of equation (2) the Jordanian slope is -0.391 and the implied Egyptian slope is 0.424 , and the difference between them, 0.815 percentage points, is significant at the 1% level with a t -statistic of 4.31 . When the cross-market restrictions are relaxed entirely, the Egyptian estimate is 0.448 and significant at the 1% level, while the Jordanian estimate is -0.156 and not significant. What the design identifies with precision is therefore the difference between the two markets rather than the Jordanian slope on its own.

This bears on how the literature should be read. Its disagreements have been attributed principally to measurement heterogeneity (Thakor, 2020), yet here two banking systems in the same region produce coefficients of opposite sign under the same indicators, estimator and controls. A study reporting either in isolation would describe its own market accurately and estimate a general parameter misleadingly.

5.2 Why the Direction Reverses

In Section 2.3, it was suggested that a digital channel should be rented out where it adds value to the addressable market and not rented out where it does not. There are three aspects of the data that support that reading. The difference is not in the intensity of treatment, as adoption levels are nearly the same (0.529 in Egypt and 0.581 in Jordan). The difference lies in context: Egyptian inclusion tripled in the observation window (Central Bank of Egypt, 2024), and Jordanian inclusion rose from 42% to approximately 50% in 2021–2023 (Central Bank of Jordan, 2023). A channel placed in the first environment will be able to reach customers who were not bankable, while in the second environment, it will be able to reach customers who already have accounts. The funding positions (48.4% vs. 83.0%) indicate a difference in the ability to monetise new relationships, and the cost structures differ in the same direction, with a mean cost-to-income ratio of 33.5%

in Egypt and 51.6% in Jordan. When the revenue base doesn't grow, the expenses of a digital channel are on the income statement with no revenue offset.

This is consistent with the diffusion account (Rogers, 2003) and with the network-effect evidence of Scott et al. (2017). It also has implications for Tunay et al. (2015), whose contingency is in the other direction, implying that it is not the level of development per se that is the conditioning variable, but the growth of the addressable market.

There is one qualification required. The Egypt indicator captures all of this at once, as it is a summary of all the differences between the two systems, including regulation, market size, speed of inclusion, competitive structure and macroeconomic environment. The country-year specification eliminates the last of these and retains the pattern, which reduces the number of candidate explanations without excluding market expansion. Market expansion is thus an interpretation, not a parameter estimated by this design, but one that is described.

5.3 A Moderating Effect that was not There

In the pooled panel the interaction between adoption and intangible asset intensity is -0.552 with a p-value of 0.114 . That is close enough to conventional thresholds that under a slightly different sample or control set it could cross them and be reported as a firm-level dampening mechanism. Once the market divergence is included it falls to 0.009 ($p = 0.973$). The apparent moderator was absorbing cross-market heterogeneity: Jordanian banks carry higher intangible intensity, 0.275% against 0.105% of assets, and Jordan is where the FinTech slope is negative, so the adoption–intangibles interaction partly identifies the same variation as an adoption–market interaction. In multi-country panels, a firm-level interaction whose moderating variable differs systematically in level across countries is not identified separately from cross-country heterogeneity unless that heterogeneity is modelled.

5.4 The Primacy of the Traditional Determinants

Across every specification the cost-to-income ratio is the most precisely estimated determinant of profitability, ranging from -0.025 to -0.027 with p-values below 0.001 , followed by capital adequacy and credit risk. A ten percentage point reduction in the ratio is associated with a 0.25 percentage point gain in the return on assets. The comparison with digital adoption is one of reliability rather than of magnitude: the cost-to-income coefficient is significant at the 1% level in every specification estimated, whereas the FinTech Index is null in the pooled panel and carries opposite signs in the two markets. In two systems whose mean channel provision moved from 0.086 to 0.968 within twelve years, the traditional determinants remained the more dependable, consistent with the bad-management hypothesis of Berger and DeYoung (1997) and the determinants literature (Athanasoglou et al., 2008; Dietrich and Wanzenried, 2011; Petria et al., 2015).

6. Conclusion And Implications

This paper asked whether the profitability return to digital channel adoption is a single parameter. Evidence from 333 bank-year observations covering 30 commercial banks in Egypt and Jordan between 2013 and 2024 indicates that it is not. In the pooled panel the FinTech Index carries no significant association with the return on assets, but that null combines a positive association in Egypt, estimated without cross-market restrictions at 0.448 percentage points, with a negative and insignificant one in Jordan. The difference between the restricted slopes, 0.815 percentage points, is significant at the 1% level and robust to year fixed effects, winsorisation, sub-period restriction and alternative inference, weakening only under country-year fixed effects with cluster-robust inference, where the point estimate remains 0.457 . No corresponding divergence appears in the loan-to-deposit ratio, which places the effect in earnings rather than funding structure. Two secondary findings follow: a marginally negative interaction between adoption and intangible asset intensity disappears once the market divergence is modelled, identifying a compositional hazard in multi-country panel research; and the cost-to-income ratio, capital adequacy and asset quality remain the dominant determinants of profitability.

6.1 Theoretical Implications

The resource-based view is extended by making two of its three rent conditions market-contingent. It is routinely invoked to predict that digital capability improves performance, with value and rarity treated as properties of the resource; here they behave as properties of the market, since the same channel satisfies both conditions in one system and neither in another. Innovation diffusion theory acquires a testable implication: an adoption coefficient depends on the point of the diffusion curve at which the sample is observed. For financial intermediation theory, the evidence bears on where the effect sits, sharp for the return on assets and absent for the loan-to-deposit ratio. There is also a methodological implication for the identification of moderating mechanisms. A firm-level interaction close to conventional significance vanished here once cross-market heterogeneity was modelled, which suggests an inexpensive diagnostic: include the market interaction before interpreting the firm-level one.

6.2 Practical Implications

For bank managers: the return to a digital channel should be evaluated against the growth of the addressable market rather than a general expectation that digital investment pays. In a saturated market, a channel every competitor offers is a cost of remaining in business and should be appraised as an operating expense. The absence of a positive Jordanian coefficient does not argue against adoption, since a bank that fails to match its competitors will lose customers. It argues against expecting the investment to raise the return on assets within a few years. Cost discipline remains the more dependable lever, since the cost-to-income ratio is significantly associated with profitability in every specification estimated while digital adoption is not.

For regulators: the finding qualifies the that digital adoption will lead to greater profitability and stability in the sector. Adoption and earnings go hand in hand where an inclusion strategy increases the number of bankable customers, as in Egypt. If the customer base is already served, a mandate to adopt places a cost on the sector without a revenue impact. It was not technology promotion per se, but the inclusion agenda that brought the market into which technology was introduced.

6.3 Limitations and Future Research

Most importantly, the adoption measure is a measure of provision, not use, as usage data are not reported uniformly in either market. The market indicator is a composite that incorporates all that is different between the two systems. The macroeconomic component is removed by country-year fixed effects, but market expansion is not separated from regulatory, structural and competitive differences, and two markets cannot establish external validity. In addition, the panel it was short and narrow: 30 banks over 12 years is sufficient for the within estimator with Driscoll–Kraay inference, but not for dynamic panel methods, and it is insufficient for cluster-robust inference under demanding fixed effects structures. Non-stationarity cannot be excluded for four series. Four cost-to-income observations were treated as missing because the reported values are not attainable for a commercial bank, and the underlying figures could not be recovered from the bank's disclosures. Finally, the intangible asset intensity proxy is imperfect, because much technology spending in banking is expensed rather than capitalised, so it understates investment by an amount that may itself differ across the markets.

Future research should extend the design to more markets with a continuous conditioning measure such as the growth of account ownership recorded in the Global Findex database (Demirgüç-Kunt et al., 2022), replace institutional adoption with usage intensity, and test whether the compositional hazard documented in Section 5.3 affects other reported moderating mechanisms. The proposed mechanism implies that the Egyptian gain should be visible in fee and commission income and the Jordanian loss in operating expense.

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