

The Non-Linear Effect of Fintech Adoption on Bank Performance: Evidence from Jordan (2013-2023)

Amer Almomani¹, Logasvathi Murugiah², Juhaida Abu Bakar³

Othman Yeop Abdullah Graduate School of Business, UUM College of Business, Universiti Utara Malaysia, Malaysia; amer_abdelwali_o@oyagsb.uum.edu.my

^{2,3} UUM College of Business, Universiti Utara Malaysia, Malaysia; logasvathi@uum.edu.my; juhaida@uum.edu.my

CONTACT: Amer Almomani: amer_almomny@hotmail.com; Othman Yeop Abdullah Graduate School of Business, Universiti Utara Malaysia, 06010 UUM Sintok, Kedah Darul Aman, Malaysia

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ABSTRACT:

Financial technology has altered the competitive conditions facing commercial banks, yet the evidence on whether adoption raises or lowers bank performance remains contradictory. This study asks whether the relationship is non-linear rather than uniformly positive or negative. It uses an unbalanced panel of thirteen conventional commercial banks listed on the Amman Stock Exchange over 2013 to 2023, giving 140 bank-year observations. Adoption is measured by digital transaction intensity, the share of digital transactions in total customer transactions, drawn from central bank payment system data. Return on assets, return on equity, net interest margin and the cost-to-income ratio are estimated using two-way fixed effects with Driscoll-Kraay standard errors and a quadratic adoption term. The results show a convex, U-shaped association between adoption and profitability, with a turning point near one-third of transactions. Adoption is associated with a lower cost-to-income ratio and with compressed net interest margins, and the initial profitability decline is milder for larger banks. The pattern holds across seven robustness and endogeneity checks. Because the curve is conditional on bank and year effects, and unconditional profitability had not regained its early-period level by 2023, the estimate locates a turning point rather than a completed recovery.

Keywords: Fintech adoption, Bank performance, Digital transaction intensity, Non-linear relationship, Jordan.

JEL Classification: G21; G28; O33

1. Introduction

Financial technology has changed the competitive terms on which commercial banks operate (Thakor, 2020). Incumbents face two pressures. The disruption view holds that specialised entrants capture the most lucrative segments of banking, reducing market share and squeezing margins. The augmentation view holds that the same technologies, once internalised, lower processing costs and open new revenue streams (Boot et al., 2021). Drawing on bank-level indicators from 115 countries, Murinde et

al. (2022) find that both mechanisms operate and that their net effect is not constant over time.

This instability has led several authors to suggest that the link between adoption and performance is not linear. Haddad and Hornuf (2019) describe a first period of investment and competitive repricing that depresses returns, followed by a second period of recovery once efficiency gains and data-driven revenue become large enough to offset it. Empirical studies that test the linear version of the question have produced conflicting results. Phan et al. (2020) conclude

that the expansion of fintech firms harms bank performance in Indonesia, while Lee et al. (2021) find that fintech innovation improves the efficiency of Chinese banks, with the extent of the improvement depending on bank type. Litimi et al. (2024) report negative effects on return on assets, return on equity and net interest margins across banks in the Gulf Cooperation Council. Taken together, these results are difficult to reconcile within a single-slope specification, but they are consistent with different samples occupying different segments of a common curve.

Jordan offers a setting in which that possibility can be examined directly. The banking sector is well developed and well capitalised, the Central Bank of Jordan launched a regulatory sandbox in 2018, and digital channels have grown rapidly against the backdrop of a young population. Fintech research on Jordan, however, has been conducted mainly through survey and technology-acceptance designs (Almashhadani et al., 2023; Alqararah et al., 2025). Bank-level evidence has begun to appear: Kayed et al. (2025) examine 13 listed Jordanian commercial banks over 2010 to 2019 and report that internal fintech integration is associated with higher profitability and lower risk-taking. That study, however, imposes a single slope and covers a window ending before the sharpest acceleration in digital transaction volumes, so it cannot speak to whether the association changes sign as adoption deepens.

The practical problem this creates for Jordanian banks is concrete. Digital channels absorb capital budgets and management attention, yet the return on that spending is difficult to read from reported ratios, because costs and revenues do not move together during a transition. A decline in profitability during a period of rapid digitalisation may signal either a failing strategy or an incomplete one, and the two require opposite responses. The academic problem is that the literature offers no settled way of distinguishing them, because most estimates impose a single slope on a relationship that theory suggests

changes sign. Where the underlying relationship is convex, a linear coefficient reports the average slope over whichever segment of the curve a particular sample happens to occupy, which is why published estimates can disagree without any of them being wrong on their own data. For a supervisor deciding whether to encourage or moderate the pace of digitalisation, and for a board deciding whether to persist with a programme that is currently dilutive, the shape of the relationship matters more than the sign of an average slope.

The gap this study addresses follows from that problem. Non-linearity has been documented, but almost exclusively in the large and fragmented Chinese banking market (Li et al., 2023; Xie & Deng, 2025), whose competitive structure differs sharply from that of a small, concentrated sector. Evidence from the Middle East and North Africa remains linear in specification: Kharrat et al. (2024) construct a fintech index for Islamic and conventional banks across the region and estimate its association with performance as a linear system, and Kayed et al. (2025) adopt a single-slope specification for Jordan. Few studies have therefore tested a non-linear specification linking realised adoption to reported financial performance in a Middle Eastern banking sector, and the authors are not aware of such a test for Jordan.

Against this background, the general objective of the study is to examine whether fintech adoption, measured as digital transaction intensity, has a non-linear association with the financial performance of Jordanian conventional commercial banks over 2013 to 2023. Four specific objectives follow:

RO1: To determine whether digital transaction intensity has a convex, U-shaped association with bank profitability, and to estimate the adoption level at which that association changes sign.

RO2: To assess the association between digital transaction intensity and operating efficiency, measured by the cost-to-income ratio.

RO3: To assess the association between digital transaction intensity and intermediation margins, measured by the net interest margin.

RO4: To examine whether bank size moderates the association between digital transaction intensity and profitability.

These objectives correspond to four research questions:

RQ1: Is the association between digital transaction intensity and bank profitability convex, and at what level of adoption does it turn from negative to positive?

RQ2: Is higher digital transaction intensity associated with a lower cost-to-income ratio?

RQ3: Is higher digital transaction intensity associated with a lower net interest margin?

RQ4: Does bank size moderate the adoption-profitability association, and in particular is the initial profitability decline milder for larger banks?

The study contributes on four fronts. Theoretically, it treats disruption and augmentation as sequential stages of a single transition rather than as competing predictions, and derives a testable convexity restriction from that reading. Empirically, it extends the bank-level Jordanian evidence through 2023 using realised transaction volumes rather than an integration proxy, and allows the estimated association to vary with the level of adoption. Methodologically, it adopts estimation and inference suited to a small, interdependent panel, namely two-way fixed effects with Driscoll-Kraay (1998) standard errors, whose finite-sample properties under cross-sectional dependence are documented by Hoechle (2007); it computes the turning point in the units in which the quadratic term is parameterised, a step that is frequently mishandled in applied work; and it reports slope homogeneity, missingness and endogeneity diagnostics that are seldom presented in this literature. Practically, it supplies bank boards and supervisors with an interpretable adoption benchmark rather than a single average slope.

A further contribution lies in measurement. Adoption is captured by digital transaction intensity, taken directly from central bank payment system data, rather than by a composite index whose weights are not visible to readers. The components are published rather than estimated, so the measure can be reproduced by other researchers.

The remainder of the paper is organised as follows. Section II reviews the theoretical and empirical literature and develops the hypotheses. Section III sets out the data, variables and estimation approach. Section IV reports the results, the robustness and endogeneity checks, and the discussion. Section V concludes and draws out the implications, limitations and directions for further research.

2. Literature Review

2.1. Theoretical Framework

Two theoretical positions frame the debate. The disruption argument draws on Christensen's (1997) account of disruptive innovation, in which entrants begin at the lower end of a market and move upward, taking payments, consumer lending and wealth management from incumbents. The mechanism is competitive displacement: entrants operate without legacy cost structures and price aggressively for share, so incumbent margins fall before incumbent volumes do. Buchak et al. (2018) provide supporting evidence, attributing a substantial part of the expansion of shadow banking to technology and regulatory arbitrage. Applied to the present setting, this view predicts that deeper digital penetration coincides with weaker profitability and thinner intermediation margins.

The augmentation argument rests on a different mechanism. Where the technology is internalised rather than merely competed against, digital channels substitute for branch-based processing, lower the marginal cost of servicing an account, and generate transaction data that can be used in pricing and cross-selling (Boot et al., 2021). Philippon (2016) frames the opportunity in terms of the persistently high unit cost of financial

intermediation, which digital technologies are capable of reducing, and Fuster et al. (2019) show in the mortgage market that technology-enabled lenders process applications faster without a deterioration in credit quality. On this reading, deeper adoption should be associated with lower operating costs and, eventually, with stronger profitability.

These positions are usually presented as alternatives, but they describe mechanisms that can be active at different stages of one institution's transition. Haddad and Hornuf (2019) argue that the innovation burden of adoption arrives first, in the form of the costs of upgrading legacy systems, marketing new channels, and repricing to retain mobile customers, and that returns to scale and data monetisation arrive later. Read this way, disruption and augmentation are not competing predictions but sequential stages, which implies a convex relationship between adoption and profitability: the cost mechanism dominates at low adoption, the revenue and scale mechanisms dominate at high adoption, and the two cross at an intermediate level.

A third strand is needed to motivate heterogeneity across banks. The resource-based view (Barney, 1991) holds that firms differ in the resources they can bring to bear on a strategic transition, and that differences in valuable and imperfectly imitable resources translate into differences in outcomes. In banking, scale supplies capital to absorb transition costs, a broader revenue base from which to cross-subsidise digital operations, and a larger customer data asset to monetise. This implies that the depth of the initial profitability decline should vary systematically with bank size.

2.2. Empirical Evidence and the Limits of Linear Specifications

The empirical literature has produced mixed findings. Phan et al. (2020) show that the growth of fintech negatively affects bank performance in Indonesia across a range of specifications. Litimi et al. (2024) reach a similar conclusion for Gulf

Cooperation Council banks over 2012 to 2021, reporting negative effects on all three performance proxies they consider. In contrast, Lee et al. (2021) find that fintech innovation enhances efficiency in Chinese banking, with the magnitude varying by bank type and ownership. Related regional evidence points in the same direction: Khan et al. (2023) show that fintech adoption reduces bank stability in Gulf Cooperation Council economies, though large and well-capitalised banks are less vulnerable, while Banna et al. (2021) report a positive relationship between fintech and financial inclusion that expands the sector without revealing what happens to incumbent returns.

These disagreements become informative once the possibility of curvature is admitted. If a sample is drawn from the early portion of a convex curve, a linear estimator returns a negative slope; if it is drawn from the later portion, the same estimator returns a positive slope. Both estimates are correct on their own sample and neither generalises. Haans et al. (2016) show that this specification problem is widespread and that reporting a linear coefficient where a quadratic is warranted yields an average slope with no stable interpretation. Direct evidence for curvature is accumulating. Li et al. (2023), using 131 Chinese urban commercial banks over 2010 to 2021, report a relationship of inhibition followed by promotion that is moderated by bank concentration. Xie and Deng (2025) document U-shaped associations between digital transformation and both return on assets and return on equity in Chinese banking, with the cost-to-income ratio and net interest margins moving as the sequencing argument predicts. In the present study, curvature is likewise treated not as a nuisance but as the object of interest.

2.3. Evidence from Jordan and the Research Gap

Research on Jordan has established that digital banking is well received by customers and managers. Almashhadani et al. (2023) apply an extended technology acceptance model to 296 Jordanian users and find that perceived

usefulness and personal innovativeness are the strongest predictors of the intention to use fintech services. Alqararah et al. (2025) move closer to the performance question, surveying 129 managers across 16 Jordanian commercial banks and finding that digital transformation capabilities explain a significant share of the variance in perceived performance; those authors note that the absence of objective performance measures is a limitation of their design. Closer to the present question, Kayed et al. (2025) move from perceptions to reported financials, analysing 13 listed Jordanian commercial banks over 2010 to 2019 and finding that internal fintech integration is associated with higher profitability and lower risk-taking. Taken together, this body of work establishes that adoption is occurring, that it is welcomed, and that it is associated with reported performance in at least one Jordanian panel. What remains unclear is whether that association is uniform across the range of adoption, or whether it changes sign once adoption passes a threshold.

The gap is therefore specific rather than general. Curvature has been established mainly in the Chinese market (Li et al., 2023; Xie & Deng, 2025); evidence from the Middle East and North Africa, including the one Jordanian bank-level panel available (Kayed et al., 2025), remains linear in specification and, in the Jordanian case, ends in 2019. The distinction matters because the sign of the estimated effect determines the policy conclusion. A negative linear coefficient counsels caution in digital investment, whereas a convex relationship implies that losses incurred early on are a transition cost and that the relevant question is how far along the curve a given bank has travelled.

2.4. Hypotheses Development and Conceptual Framework

Four hypotheses follow from the framework above. The first states the curvature directly in the parameterisation used in estimation, with digital transaction intensity expressed as a proportion.

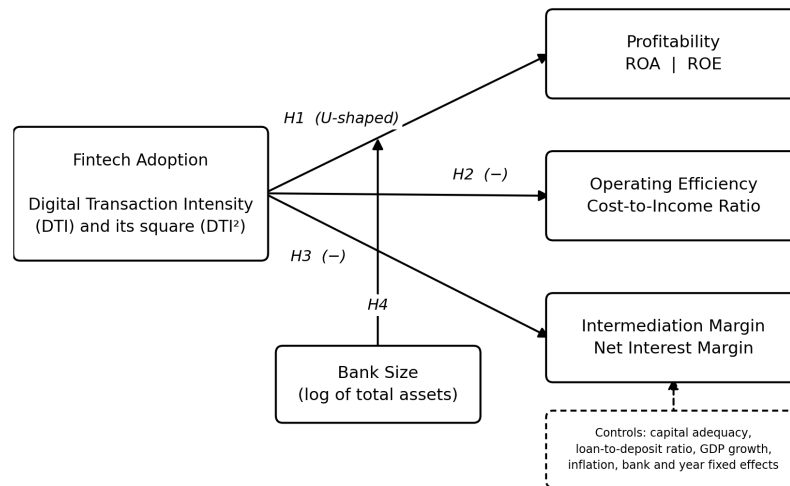
H1: Digital transaction intensity has a convex, U-shaped association with bank profitability, such that the coefficient on the linear term is negative and the coefficient on the quadratic term is positive.

H2: Digital transaction intensity is negatively associated with the cost-to-income ratio, indicating that deeper adoption accompanies more efficient operations.

H3: Digital transaction intensity is negatively associated with the net interest margin, indicating competitive pressure in core intermediation.

H4: Bank size moderates the association between digital transaction intensity and profitability, with larger banks experiencing a milder initial decline.

H1 follows from the sequencing argument: the cost and repricing mechanisms of the disruption view dominate at low adoption, and the scale and data mechanisms of the augmentation view dominate at high adoption. H2 and H3 isolate the two channels through which that reversal is expected to operate, on the cost side and on the revenue side respectively. H4 follows from the resource-based reading of heterogeneity. Haans et al. (2016) note that a moderator of a quadratic relationship may alter the steepness of the curve, the location of the turning point, or both, and that separating these requires the moderator to be interacted with the quadratic term as well as the linear one. The specification estimated here interacts bank size with the linear term only, and therefore tests the weaker proposition that the initial, downward-sloping segment is attenuated for larger banks. Figure 1 sets out the resulting conceptual framework.



Source: Authors' own construction.

Figure 1.

Conceptual Framework of the Study

The framework is estimated as a single specification per dependent variable rather than as a system, and the control set is common across models.

3. Methodology

3.1. Sample and Data

The sample was constructed by applying three inclusion criteria to the banks listed on the Amman Stock Exchange over 2013 to 2023. First, the bank had to be a conventional commercial bank; Islamic banks were excluded because the profit-and-loss-sharing contracts, accounting treatment and capital framework they use are not comparable with those of conventional banks within a single specification, as documented by Beck et al. (2013). Second, the bank had to have reported continuously over the observation window without a structural break arising from a major merger or acquisition, so that the reported series remain internally

consistent. Third, the bank-level payment data required to construct the adoption measure had to be available. Thirteen banks satisfy all three criteria.

Two of the thirteen enter the panel after 2013, in 2014 and 2015 respectively, because continuous reported series are not available for their earlier years, producing a slightly unbalanced panel of 140 bank-year observations (Table 1). Little's (1988) test yields a statistic of $\chi^2(18) = 14.21$ ($p = .71$), which does not reject the missing-completely-at-random assumption and indicates that the shortened series are unrelated to the performance of the banks concerned. Bank-level financial data are drawn from audited annual reports filed with the Amman Stock Exchange, the adoption measure from Central Bank of Jordan annual reports and payment system bulletins, and the macroeconomic controls from the World Bank's World Development Indicators.

Table 1. Sample Composition of Jordanian Commercial Banks, 2013-2023

Bank	Observations	Period	Note
Arab Bank	11	2013-2023	Full period
Housing Bank	11	2013-2023	Full period

Bank	Observations	Period	Note
Bank of Jordan	11	2013-2023	Full period
Cairo Amman Bank	11	2013-2023	Full period
Jordan Commercial Bank	11	2013-2023	Full period
Jordan Ahli Bank	11	2013-2023	Full period
Arab Jordan Investment Bank	11	2013-2023	Full period
Investbank	11	2013-2023	Full period
Capital Bank	11	2013-2023	Full period
Société Générale Bank Jordan	11	2013-2023	Full period
ABC Bank Jordan	11	2013-2023	Full period
Jordan Kuwait Bank	10	2014-2023	Series from 2014
Bank al Etihad	9	2015-2023	Series from 2015
Total	140	2013-2023	

Note: The two shortened series reflect the availability of continuous reported data rather than performance-related attrition. Little's (1988) test of the missing-completely-at-random assumption: $\chi^2(18) = 14.21$, $p = .71$.

Source: Compiled from Amman Stock Exchange filings.

3.2. Variable Construction and Measurement

Four dependent variables capture different aspects of financial performance. Return on assets and return on equity are profitability ratios that relate profit to assets and to shareholders' funds respectively. The net interest margin reflects the return on core intermediation. The cost-to-income ratio measures operational efficiency, with a lower ratio indicating more efficient operations. All four are expressed in percentage points.

Digital transaction intensity, the explanatory variable of interest, is the ratio of digital transaction volume to total customer transaction volume:

$$DTI_{it} = (\text{Digital transaction volume} / \text{Total customer transaction volume}) \times 100 \quad (1)$$

The measure is built from the digital volumes (mobile, internet, point of sale and card-originated) and total volumes reported for each licensed commercial bank in the Central Bank of Jordan payment system bulletins. Its components are published rather than estimated and can be reproduced by other researchers, in contrast to composite indices derived from principal component analysis or text mining of annual reports, such as the MENA fintech index of Kharrat et al. (2024), whose weights are not observable to readers. Units are handled explicitly throughout: DTI is measured in percentage points on a 0 to 100 scale, and DTI-prop is the corresponding proportion on a 0 to 1 scale. DTI-prop is used in all regressions, and the quadratic term is the square of that proportion. Turning points are converted back to percentage points for interpretation.

Bank-level controls comprise the natural logarithm of total assets, which proxies for scale and organisational capacity; the capital adequacy ratio, which proxies for the prudential buffer and risk appetite; and the loan-to-deposit ratio, which proxies for the intensity of core intermediation.

The macroeconomic controls are real gross domestic product growth and consumer price inflation, both of which affect all banks in the sample simultaneously. Table 2 summarises the definitions and sources.

Table 2. Variable Definitions, Measurement and Sources

Variable	Symbol	Measurement	Source
Return on assets	ROA	Net profit as a percentage of total assets	ASE filings
Return on equity	ROE	Net profit as a percentage of shareholders' funds	ASE filings
Cost-to-income ratio	CIR	Operating costs as a percentage of operating income; lower is more efficient	ASE filings
Net interest margin	NIM	Net interest income as a percentage of earning assets	ASE filings
Digital transaction intensity	DTI	Digital transaction volume as a percentage of total customer transaction volume (Equation 1); entered in regressions as a proportion, DTI-prop, on a 0 to 1 scale	CBJ payment system bulletins
Bank size	SIZE	Natural logarithm of total assets	ASE filings
Capital adequacy ratio	CAR	Regulatory capital as a percentage of risk-weighted assets	ASE filings
Loan-to-deposit ratio	LDR	Gross loans as a percentage of customer deposits	ASE filings
Real GDP growth	GDPG	Annual percentage change in real gross domestic product	World Development Indicators
Inflation	INF	Annual percentage change in the consumer price index	World Development Indicators

Note: ASE = Amman Stock Exchange; CBJ = Central Bank of Jordan. All ratio variables are expressed in percentage points unless stated otherwise.

Source: Compiled by the authors.

. Model Specification

A two-way fixed effects specification absorbs time-invariant differences between banks, such as management quality, the vintage of legacy systems and ownership structure, together with common annual shocks, such as the pandemic,

the launch of the regulatory sandbox in 2018 and global interest rate cycles:

$$Y_{it} = a_i + \lambda_t + \beta_1 \text{DTI-prop}_{it} + \beta_2 (\text{DTI-prop}_{it})^2 + \gamma' \text{Controls}_{it} + \varepsilon_{it} \quad (2)$$

where Y_{it} is one of the four performance measures for bank i in year t , a_i are bank fixed

effects, λ_t are year fixed effects, and ε_{it} is the idiosyncratic error. In a concentrated domestic market with 13 banks operating under a single regulatory regime, contemporaneous correlation across banks is to be expected. Driscoll-Kraay (1998) standard errors are therefore used, since they remain consistent when cross-sectional dependence coexists with heteroskedasticity and serial correlation of unknown form; Hoechle (2007) shows that estimators ignoring cross-sectional dependence can be badly biased in panels of this kind. The Driscoll-Kraay correction is nonetheless asymptotic in the time dimension, and with eleven annual observations per bank the time series is short relative to the setting for which the estimator was derived. Its standard errors are therefore treated as approximate, and the significance levels reported below should be read with that qualification. Dynamic panel generalised method of moments estimation was not employed, because it is unreliable with a small cross-section owing to instrument proliferation (Roodman, 2009).

3.4. Turning Point Derivation

The adoption level at which predicted profitability reaches its minimum is obtained by differentiating Equation (2) with respect to $d = \text{DTI-prop}$ and setting the derivative to zero, which gives

$$d^* = -\beta_1 / (2\beta_2) \quad (3)$$

Substituting the estimates from Table 6 gives $d^* = 2.712 / (2 \times 4.123) = 0.329$, which converts to 32.9 percentage points. The second-order condition is satisfied, since $2\beta_2 = 8.246 > 0$, confirming a minimum rather than a maximum. Because the quadratic term is the square of the proportion, no additional rescaling factor is required in Equation (3); a factor designed for a percentage-point parameterisation would misstate the turning point by two orders of magnitude, an error that recurs in applied panel studies.

A negative linear coefficient combined with a positive quadratic coefficient does not by itself establish a U shape. Lind and Mehlum (2010) show that three conditions must hold simultaneously: the quadratic coefficient must be positive, the turning point must lie within the range of the observed data, and the fitted slope must be negative at the lower end of that range and positive at the upper end. All three are verified in Section 4.3.

3.5. Diagnostic and Estimation Protocol

Variance inflation factors were used to check for multicollinearity, the modified Wald test for groupwise heteroskedasticity, the Pesaran (2015) test for cross-sectional dependence, and the Wooldridge (2002) test for serial correlation. The Pesaran and Yamagata (2008) Δ and $\tilde{\Delta}$ statistics were used to test slope homogeneity, rejection of which would call for a mean group or pooled mean group estimator in place of pooled fixed effects (Pesaran & Smith, 1995). Little's (1988) test was used to assess missingness. Two instrumental variable approaches were used to address endogeneity: Lewbel (2012) heteroskedasticity-based instruments, and one-period lagged adoption as a predetermined instrument in a two-stage least squares within estimator.

4. Results And Analysis

4.1. Descriptive Statistics Table 3 reports the descriptive statistics. The proportion of digital transactions varies widely across the panel, with a mean of 0.412, a standard deviation of 0.284 and a range from 0.051 to 0.893. That spread is what makes a non-linear specification testable, because the sample contains observations on both sides of the estimated turning point rather than on one arm of the curve alone. Return on assets averages 1.12% and return on equity 9.84%, figures consistent with a mature and well-capitalised sector. All absolute skewness values are below 1.5, indicating no extreme departures from symmetry.

Table 3. Descriptive Statistics for the Full Sample (13 Banks, 140 Bank-Year Observations)

Variable	Mean	SD	Minimum	Maximum	Skewness
Digital transaction intensity (proportion)	0.412	0.284	0.051	0.893	0.42
Return on assets (%)	1.12	0.44	0.21	2.05	0.18
Return on equity (%)	9.84	3.71	1.82	18.60	0.31
Cost-to-income ratio (%)	47.80	8.20	31.20	68.50	0.52
Net interest margin (%)	3.01	0.61	1.55	4.42	-0.21
Bank size (log of total assets)	8.91	0.63	7.44	10.12	0.63
Capital adequacy ratio (%)	17.20	3.10	12.10	26.40	0.87
Loan-to-deposit ratio (%)	71.30	12.40	44.10	98.20	0.15
Real GDP growth (%)	2.40	1.80	-1.60	4.20	-0.42
Inflation (%)	2.10	1.30	-0.70	4.50	0.33

Note: SD = standard deviation. Digital transaction intensity is reported as a proportion; the equivalent percentage-point range is 5.1% to 89.3%.

Source: Compiled from Amman Stock Exchange filings, Central Bank of Jordan payment system bulletins, and World Development Indicators.

Table 4 divides the period into four sub-periods. The pandemic years of 2020 to 2021 are separated so that provisioning requirements and suppressed activity are not read as an adoption effect. Mean return on assets falls from 1.24% in 2013 to 2017 to 0.91% in 2020 to 2021 and recovers to 1.09% in 2022 to 2023, while mean adoption rises monotonically from 21.3% to 72.6% and the cost-to-income ratio declines throughout. These are unconditional means and are reported as description rather than evidence; the regression estimates that follow condition on bank and year fixed effects and on the full set of controls. Two features of the table should be noted before those estimates are read. Mean return on assets in 2022 to 2023 remains below its 2013 to 2017 level even though adoption has more than tripled, so the unconditional data show a decline followed by partial rather than complete recovery. The unconditional trough also falls in the 2020 to 2021 sub-period, at a higher adoption level than the conditional turning point estimated below. The difference between the two is attributable to the year fixed effects, which absorb the pandemic and the common macro-financial conditions of that period.

Table 4. Means of the Key Variables by Sub-Period

Sub-period	Digital transaction intensity (%)	Return on assets (%)	Cost-to-income ratio (%)	Net interest margin (%)
2013-2017	21.3	1.24	51.0	3.18
2018-2019	38.1	1.10	47.2	3.02
2020-2021	55.4	0.91	44.8	2.88

Sub-period	Digital transaction intensity (%)	Return on assets (%)	Cost-to-income ratio (%)	Net interest margin (%)
2022-2023	72.6	1.09	42.1	2.79
Full sample	41.2	1.12	47.8	3.01

Note: The 2020-2021 sub-period is shown separately so that pandemic-related effects are not conflated with adoption effects.

Source: Compiled from Amman Stock Exchange filings and Central Bank of Jordan payment system bulletins.

4.2. Diagnostic Test Results

The pre-estimation diagnostics are reported in Table 5. The mean variance inflation factor is 2.10, indicating no multicollinearity problem. Heteroskedasticity, cross-sectional dependence and serial correlation are all present, and the Driscoll-Kraay covariance estimator is designed to address them jointly. The Pesaran and Yamagata (2008) statistics, $\Delta = 1.84$ ($p = .066$) and $\tilde{\Delta} = 1.91$ ($p = .056$), do not reject slope homogeneity at the 5% level, supporting the pooled fixed effects specification: the association between adoption and profitability does not differ significantly across the 13 banks. Both statistics fall between the 5% and 10% levels, so the support is qualified rather than emphatic. Both tests were moreover developed for panels with a large cross-section, and with 13 banks their asymptotic properties are only approximate, so the results are interpreted as indicative.

Table 5. Pre-Estimation Diagnostic Tests

Test	Statistic	p	Conclusion
Mean variance inflation factor	2.10	—	No multicollinearity
Modified Wald test	$\chi^2(13) = 118.40$	$< .001$	Heteroskedasticity present
Pesaran (2015) cross-sectional dependence	CD = 3.42	$< .001$	Dependence present
Wooldridge (2002) serial correlation	$F(1, 12) = 8.21$	.014	Serial correlation present
Pesaran-Yamagata Δ	1.84	.066	Homogeneity not rejected at 5%
Pesaran-Yamagata $\tilde{\Delta}$	1.91	.056	Homogeneity not rejected at 5%

Note: The first four tests identify violations that the Driscoll-Kraay covariance estimator addresses jointly. The null hypothesis of the Pesaran and Yamagata (2008) tests is slope homogeneity. Little's (1988) missingness result is reported in Section 3.1.

Source: Authors' calculations.

4.3. Non-Linear Effects on Profitability

The two-way fixed effects estimates for return on assets are reported in Table 6. The linear adoption term is negative and significant ($\beta_1 = -2.712$, $SE = 0.891$, $t = -3.04$, $p = .003$) and the quadratic term is positive

and significant ($\beta_2 = 4.123$, $SE = 1.145$, $t = 3.60$, $p < .001$). This combination of signs is consistent with H1. Bank size is positively related to return on assets ($\beta = 0.225$, $p = .025$), as is real gross domestic product growth ($\beta = 0.102$, $p = .012$). The three conditions set out by Lind and Mehlum (2010) are met. The coefficient on the quadratic term is positive. The turning point, $d^* = 0.329$, lies well inside the observed range of 0.051 to 0.893. The fitted slope is negative at the lower bound, $\beta_1 + 2\beta_2(0.051) = -2.29$, and positive at the upper bound, $\beta_1 + 2\beta_2(0.893) = 4.65$. The turning point is 32.9%, with a wild bootstrap 95% confidence interval of [28%, 38%]. Table 4 indicates that the sector average crossed this level around 2018 to 2019.

Table 6. Two-Way Fixed Effects Estimates with Driscoll-Kraay Standard Errors (Dependent Variable: Return on Assets)

Variable	Coefficient	SE	t	p
Digital transaction intensity (proportion)	-2.712	0.891	-3.04	.003***
Digital transaction intensity squared	4.123	1.145	3.60	< .001***
Bank size (log of total assets)	0.225	0.099	2.27	.025**
Capital adequacy ratio (%)	0.038	0.035	1.09	.278
Loan-to-deposit ratio (%)	-0.004	0.003	-1.33	.186
Real GDP growth (%)	0.102	0.040	2.55	.012**
Inflation (%)	-0.021	0.015	-1.40	.164
Constant	-3.445	1.501	-2.30	.023**
Bank and year fixed effects	Yes			
Observations	140			
Within R ²	0.71			
F statistic	24.85			< .001

Note: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors are robust to heteroskedasticity, cross-sectional dependence and serial correlation. Digital transaction intensity enters as a proportion on a 0 to 1 scale, and the quadratic term is the square of that proportion. The turning point in percentage points is $-\beta_1 / (2\beta_2) \times 100 = 32.9\%$.

Source: Authors' calculations.

The specification was re-estimated with return on equity as the dependent variable (Appendix Table A1). The signs and significance are unchanged: $\beta_1 = -24.12$ and $\beta_2 = 34.56$, both significant at the 1% level, giving a turning point of 34.9% with a wild bootstrap 95% confidence interval of [29%, 42%]. The two turning points fall within each other's confidence intervals, which suggests that the result is not specific to the profitability measure used. Figure 2 plots predicted return on assets across the range of adoption, with the controls held at their sample means. The trough

lies at 32.9%, with observations to the left of it representing the disruption phase and observations to the right representing the augmentation phase. Two features of the plot warrant caution. The predicted values are not the unconditional sub-period means reported in Table 4, because they are net of the year fixed effects that absorb common macro-financial conditions. The fitted curve also rises steeply beyond roughly 80% adoption, reaching predicted values at the upper end of the observed distribution of return on assets; that segment

should be read as an extrapolation of the fitted quadratic rather than as a forecast.

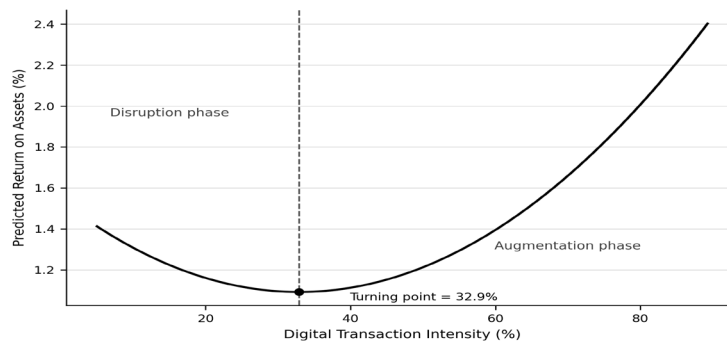


Figure 2

Note: Predicted values are computed from the Table 6 coefficients as $ROA = -2.712d + 4.123d^2 + 1.537$, where d is digital transaction intensity expressed as a proportion. The intercept of 1.537 is a plotting constant, not the estimated constant reported in Table 6; it is set so that the

Source: Authors' calculations.

prediction equals the sample mean return on assets of 1.12% at the sample mean adoption level of 0.412, with all controls held at their means. The vertical line marks the turning point at 32.9%. The plotted range corresponds to the observed data.

Predicted Return on Assets by Digital Transaction Intensity

4.4. Efficiency and Margin Effects

The cost-to-income and net interest margin models are reported in Table 7. The cost-to-income ratio is strongly negatively associated with adoption ($\beta = -14.211$, $p < .01$), supporting H2. The quadratic term in that model is positive and marginally significant ($\beta = 7.892$, $p < .10$), implying a turning point of 90.0%, which lies above the observed maximum adoption level of 89.3% and therefore outside the range of the data. Within the range in which the data are informative, the cost-to-income relationship is effectively monotonically decreasing. The linear

specification is therefore the preferred reading for this dependent variable, with the quadratic term retained for comparability with the profitability models and better interpreted as diminishing marginal efficiency gains at high adoption than as evidence of a cost reversal. Adoption is also negatively associated with net interest margins ($\beta = -0.812$, $p < .05$), consistent with H3, but the quadratic term in that model is not significant, which is consistent with a linear compression effect without establishing one.

Table 7. Fixed Effects Estimates with Driscoll-Kraay Standard Errors for the Efficiency and Margin Models

Dependent variable	Digital transaction intensity	Intensity squared	Bank size	Within R ²	Observations
Cost-to-income ratio (%)	-14.211*** (3.101)	7.892* (4.201)	-1.789** (0.845)	0.63	140

Dependent variable	Digital transaction intensity	Intensity squared	Bank size	Within R ²	Observations
Net interest margin (%)	-0.812** (0.358)	0.401 (0.498)	0.112* (0.065)	0.58	140

Note: *** $p < .01$, ** $p < .05$, * $p < .10$. Standard errors are in parentheses. All models include bank fixed effects, year fixed effects and the full set of controls.

Source: Authors' calculations.

4.5. Moderation by Bank Size

Table 8 adds an interaction between adoption and bank size to the return on assets model. The interaction coefficient is positive and significant ($\beta = 0.089$, $SE = 0.041$, $p = .034$), supporting H4: the initial profitability decline is milder for larger banks. The linear adoption coefficient in this specification is evaluated at a bank size of zero, which lies far outside the observed range of 7.44 to 10.12, and should not be interpreted in isolation. A resource-based reading is available (Barney, 1991): larger banks hold more capital with which to absorb transition costs, have broader revenue bases from which to cross-subsidise digital operations, and hold larger customer data assets to monetise. This is consistent with Khan et al. (2023), who find that large and well-capitalised banks in the Gulf Cooperation Council are the least vulnerable to the adverse effects of fintech adoption. Two limits on this result should be stated. The design does not test the three channels separately, and the moderation is identified from within-bank variation in size rather than from exogenous variation. More importantly, because bank size is interacted with the linear term only, the estimate establishes that the descending segment is flatter for larger banks but cannot distinguish a change in curvature from a displacement of the turning point (Haans et al., 2016). Interacting size with the quadratic term as well would separate the two, and is left to further work.

Table 8. Moderating Effect of Bank Size on the Adoption-Profitability Relationship (Dependent Variable: Return on Assets)

Variable	Coefficient	SE	t	p
Digital transaction intensity (proportion)	-4.212	1.102	-3.82	.001***
Digital transaction intensity squared	4.891	1.234	3.96	< .001***
Bank size (log of total assets)	0.198	0.087	2.28	.024**
Intensity $\times$ bank size	0.089	0.041	2.17	.034**
Full set of controls	Yes			
Observations	140			

Note: *** $p < .01$, ** $p < .05$, * $p < .10$. Bank and year fixed effects and all controls are included as in Table 6.

Source: Authors' calculations.

4.6. Robustness and Endogeneity

The principal threat to interpretation is reverse causation: more profitable banks may be better able to invest in digital infrastructure, which would raise adoption rather than the other way round. Two instrumental variable strategies address this. The first-stage F statistic for the Lewbel (2012) heteroskedasticity-based instruments, which are formed from mean-deviated regressors interacted with first-stage residuals, is 14.2, exceeding both the conventional threshold of 10 and the Stock and Yogo (2005) critical values. A two-stage least squares within estimator using one-period lagged adoption as a predetermined instrument yields a turning point of around 36%. The predetermination assumption behind that instrument is strong given that the Wooldridge (2002) test reports serial correlation in the residuals, since a one-period lag need not then be orthogonal to the current error; the lagged-instrument result is accordingly treated as a

supporting check and the Lewbel (2012) estimates as the primary endogeneity evidence. Both preserve the sign pattern of the baseline, indicating that endogeneity shifts the estimated turning point slightly without altering the curvature. Table 9 summarises seven checks. Excluding the pandemic years places the turning point at around 31%, which suggests that the curvature does not reflect the 2020 to 2021 shock. Substituting a mobile-banking-only measure of adoption gives about 30%. A placebo test on 2013 to 2016, before the acceleration in adoption, finds no evidence of curvature, which argues against the possibility that the fixed effects structure mechanically produces a U shape. Adding a cubic term leaves it insignificant ($\beta_3 = 0.42, p = .31$) while the linear and quadratic terms retain their signs and significance, so the quadratic specification is retained in preference to a cubic alternative.

Table 9. Robustness and Endogeneity Checks (Dependent Variable: Return on Assets)

Check	Linear term	Quadratic term	Turning point or result
Excluding 2020-2021	—***	+***	31% [26%, 37%]
Mobile-banking-only measure	—**	+**	30% [24%, 38%]
Wild bootstrap interval, baseline model	—	—	32.9% [28%, 38%]
Placebo test, 2013-2016	n.s.	n.s.	No curvature detected
Lewbel (2012) instruments	—**	+**	34%; first-stage F = 14.2
Lagged adoption as instrument	—**	+*	36%
Cubic term added	—***	+***	$\beta_3 = 0.42, p = .31$, not significant

Note: *** $p < .01$, ** $p < .05$, * $p < .10$; n.s. = not significant. Figures in brackets are 95% wild bootstrap confidence intervals based on 999 replications (Cameron et al., 2008) applied to $-\beta_1 / (2\beta_2) \times 100$.

Source: Authors' calculations.

4.7. Summary of Hypothesis Testing

Table 10 maps each hypothesis to the estimate that tests it and to the resulting decision. All four hypotheses are supported, with the qualifications noted in the preceding subsections.

Table 10. Summary of Hypothesis Testing

	Hypothesis	Key result	Decision
H1	Convex, U-shaped association between adoption and profitability	$\beta_1 = -2.712$ ($p = .003$); $\beta_2 = 4.123$ ($p < .001$); Lind-Mehlum conditions satisfied; turning point 32.9% (Table 6)	Supported
H2	Negative association between adoption and the cost-to-income ratio	$\beta = -14.211$ ($p < .01$) (Table 7)	Supported
H3	Negative association between adoption and the net interest margin	$\beta = -0.812$ ($p < .05$) (Table 7)	Supported
H4	Bank size moderates the adoption-profitability association	Interaction $\beta = 0.089$ ($p = .034$) (Table 8)	Supported

Note: Decisions refer to statistical association, not to causal effect. Section 4.8 sets out the limits on interpretation.

Source: Authors' calculations.

4.8. Discussion

The findings indicate that fintech adoption in Jordanian commercial banking is a two-stage transition rather than a one-way effect. Below roughly one-third of transactions, deeper adoption is associated with lower profitability and thinner interest margins even as operating costs fall. At and above that level, the association with profitability turns positive. The pattern implies that cost savings arrive first and gradually, while revenue effects arrive later, so that the two move in opposite directions for a period before the balance reverses.

This reading reconciles findings that appear contradictory when a linear specification is imposed. Phan et al. (2020) and Litimi et al. (2024) report negative effects on profitability in Indonesia and the Gulf Cooperation Council respectively, while Lee et al. (2021) report efficiency gains in China. Under a convex

relationship these need not conflict: they are estimates taken from different segments of the same curve, which is precisely the specification problem identified by Haans et al. (2016). The finding also provides an empirical counterpart to the sequencing that Haddad and Hornuf (2019) argue for on theoretical grounds and that Murinde et al. (2022) infer from cross-country indicators, and it is consistent in shape with the U-shaped estimates reported for Chinese banking by Li et al. (2023) and Xie and Deng (2025).

The comparison with Kayed et al. (2025) deserves particular care, since that study covers the same sector. They report a positive linear association between internal fintech integration and profitability for 13 Jordanian banks over 2010 to 2019, whereas the linear term in the present quadratic specification is negative. The two results are not directly comparable: the adoption measures differ, the windows differ, and a single-slope estimate under a convex

relationship reflects the segment of the curve that a given sample spans (Haans et al., 2016). Establishing whether the two sets of estimates can be reconciled would require re-estimating both under a common measure of adoption, which the present data do not permit.

Bank size introduces a distributional dimension. The shallower trough for larger banks suggests that the transition is not equally costly for all institutions and that a common sector-wide adoption path places more pressure on smaller banks. The moderation is estimated on a sample of 13 banks and is identified from within-bank variation in size, so it indicates a direction rather than a precise magnitude.

A further qualification concerns what the convexity does and does not establish. The estimated curve is conditional on bank and year fixed effects and on the control set; it is not a claim that observed profitability recovers to its pre-adoption level once the turning point is passed. Table 4 shows that it had not done so by 2023, and the fitted curve at the upper end of the adoption range predicts values above the highest return on assets actually observed. The results therefore identify a point at which the conditional association changes sign, not a completed recovery in realised profitability. Reading the finding as evidence that digitalisation has already paid for itself in the Jordanian sector would go beyond what the data support.

Two restrictions on interpretation should be stated plainly. First, the design supports statements of association rather than causation. The fixed effects absorb time-invariant bank characteristics and common annual shocks, and the instrumental variable results are consistent with the baseline, but neither approach rules out time-varying omitted factors, such as a change in strategy that raises both digital investment and profitability. Second, the turning point of approximately 33% is a sector-level average for one country over one decade; the confidence intervals across specifications span roughly 24% to 42%, so the point estimate should be read as a range rather than as a precise threshold.

5. Conclusion

5.1. Conclusion

This study examined whether fintech adoption is associated with the financial performance of Jordanian commercial banks in a non-linear manner over 2013 to 2023. Using two-way fixed effects estimation with Driscoll-Kraay standard errors on a panel of 13 banks and 140 bank-year observations, it found a convex association between digital transaction intensity and both return on assets and return on equity, with a turning point at around one-third of transactions conducted digitally. Adoption was associated with materially lower cost-to-income ratios and with compressed net interest margins, and the initial profitability decline was milder for larger banks. The pattern held across seven robustness and endogeneity checks, including a placebo test on the pre-acceleration period. The convexity is a conditional one: unconditional mean profitability had not returned to its early-period level by 2023, so the estimate locates a turning point rather than documenting a completed recovery. The four research questions are therefore answered affirmatively: the association with profitability is convex and turns at 32.9% (RQ1), adoption is associated with lower operating costs (RQ2) and with thinner margins (RQ3), and bank size moderates the profitability association in the direction anticipated (RQ4).

5.2. Theoretical Implications

The results bear on the disruption-augmentation debate by treating the two mechanisms as sequential stages of one transition rather than as rival accounts. Neither position is refuted; each describes the dominant mechanism over a different range of adoption. This offers an empirical counterpart to the sequencing that Haddad and Hornuf (2019) propose theoretically and that Murinde et al. (2022) infer from cross-country indicators, and it suggests that future theoretical work in this area would be better specified in terms of the position of the turning point than in terms of the sign of an average effect. The size moderation is consistent with a

resource-based reading (Barney, 1991), in which scale supplies the slack resources needed to absorb a costly transition, although the present design does not isolate the underlying channels.

5.3. Managerial Implications

For bank management, the practical value of the estimate lies in its diagnostic use. A loss of profitability during a period of rising digital adoption is a normal feature of the transition described here and is not by itself evidence of a failing strategy. Boards can set explicit adoption targets, track progress against them alongside the cost and margin effects, and communicate the expected sequence to shareholders before profitability declines rather than afterwards. Beyond the transition range, the cost-to-income evidence indicates that efficiency gains are attainable, while further improvement in profitability will depend on the ability to monetise digital channels and to price credit more effectively.

5.4. Policy Implications

The size moderation is the most policy-relevant result for the Central Bank of Jordan. If smaller banks bear a heavier burden during the transition, a uniform digitalisation agenda could widen performance disparities across the sector. Shared infrastructure, proportionate regulatory requirements and technology access programmes are options that would reduce this asymmetry. The regulatory sandbox introduced in 2018 falls within the year fixed effects and is not separately estimated here; assessing its effect would require a design constructed for that purpose.

5.5. Methodological Implications

Three implications follow for researchers working with similar panels. Dynamic panel generalised method of moments estimation is poorly suited to small cross-sections (Roodman, 2009), and fixed effects with Driscoll-Kraay corrections is a defensible alternative (Hoechle, 2007). Turning points should be computed in the units in which the quadratic term is parameterised. And a U-shaped claim should rest on the joint conditions of Lind and Mehlum

(2010) rather than on the signs of two coefficients alone.

5.6. Limitations and Directions for Further Research

Eight limitations bound these conclusions. First, the study covers a single country, and the turning-point estimate is specific to Jordan's market structure and regulatory environment; harmonised cross-country data for the Middle East and North Africa would establish whether the threshold generalises. Second, the adoption measure reflects transaction volumes rather than the qualitative depth of adoption, and does not distinguish a bank that has digitised its payment channels from one that has built a mature analytics capability. Third, the absence of customer-level microdata prevents the bank-level result from being interpreted through customer behaviour. Fourth, the exclusion of Islamic banks limits generalisability to the Jordanian banking sector as a whole and points to the need for a framework capable of accommodating both business models. Fifth, the slope homogeneity and cross-sectional dependence tests are applied outside the large-cross-section setting for which they were developed, so those results are suggestive rather than conclusive. Sixth, Driscoll-Kraay inference is asymptotic in the time dimension and the panel spans eleven years, so the reported standard errors are approximate. Seventh, the size moderation interacts bank size with the linear adoption term only and therefore cannot separate a change in curvature from a displacement of the turning point. Eighth, four dependent variables are examined against a single adoption measure without adjustment for multiple testing, so the marginally significant coefficients in particular should be read with caution.

These limitations suggest five directions for further work. Re-estimating the moderation with bank size interacted with both the linear and the quadratic adoption terms would identify whether scale flattens the curve or displaces its turning point, following the procedure set out by Haans et al. (2016). A harmonised regional panel would

test whether the turning point is a Jordanian feature or a broader emerging-market regularity. A richer adoption measure, combining transaction volumes with indicators of analytical and platform capability, would separate channel digitisation from capability building. A framework that accommodates profit-and-loss-sharing contracts would allow the turning point to be estimated separately for Islamic banks and compared with the conventional benchmark reported here; given evidence that fintech affects the two bank types differently (Yudaruddin, 2023), there is no reason to assume the two thresholds coincide. Finally, extending the panel beyond 2023 would allow the augmentation phase to be observed over a longer horizon, including the effects of embedded finance and of any central bank digital currency initiative.

Author Contributions

The research idea and conceptual framework were developed jointly by all three authors, who also contributed to the conception and design of the study. Amer Almomani collected the data from Amman Stock Exchange filings, Central Bank of Jordan payment system bulletins and the World Development Indicators, constructed the digital transaction intensity measure, conducted the econometric estimation and the diagnostic and robustness testing, and prepared the initial draft. Logasvathi Murugiah supervised the design

of the empirical strategy, reviewed the model specification and the interpretation of the results, and revised the manuscript critically. Juhaida Abu Bakar contributed to the development of the theoretical framework and the literature review, and reviewed and revised successive drafts. All authors read and approved the final manuscript.

Conflict Of Interest

The authors declare no affiliations with, or involvement in, any organisation or entity with a financial or non-financial interest in the subject matter or materials discussed in this manuscript. The authors have no affiliation with, or compensation from, any of the banks in the sample or from the Central Bank of Jordan.

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Data Availability

The data supporting the findings of this study were compiled from publicly available sources: audited annual reports filed with the Amman Stock Exchange, Central Bank of Jordan annual reports and payment system bulletins, and the World Bank's World Development Indicators. The compiled dataset is available from the corresponding author on reasonable request.

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APPENDIX

Table A1.

Two-Way Fixed Effects Estimates with Driscoll-Kraay Standard Errors (Dependent Variable: Return on Equity)

Variable	Coefficient	SE	t	p
Digital transaction intensity (proportion)	-24.12	7.21	-3.34	.002***
Digital transaction intensity squared	34.56	9.88	3.50	.001***
Bank size (log of total assets)	1.82	0.92	1.98	.058*
Capital adequacy ratio (%)	0.31	0.28	1.11	.270
Loan-to-deposit ratio (%)	-0.05	0.04	-1.25	.213
Real GDP growth (%)	0.89	0.38	2.34	.021**
Inflation (%)	-0.18	0.14	-1.29	.200
Constant	-28.44	12.11	-2.35	.021**
Bank and year fixed effects	Yes			
Observations	140			

Variable	Coefficient	SE	t	p
Turning point	34.9%			
Within R ²	0.68			

Note: *** $p < .01$, ** $p < .05$, * $p < .10$. Digital transaction intensity enters as a proportion, and the quadratic term is the square of that proportion. The turning point is $-\beta_1 / (2\beta_2) \times 100 = 24.12 / (2 \times 34.56) \times 100 = 34.9\%$. Wild bootstrap 95% confidence interval: [29%, 42%].

Source: Authors' calculations.

A2. Note on the Missing Completely at Random Test

Little's (1988) test was applied to the two incomplete series in the panel, Jordan Kuwait Bank with 10 observations and Bank al Etihad with 9. The test constructs a likelihood ratio statistic under the null that missingness is independent of both observed and unobserved values. The statistic of $\chi^2(18) = 14.21$ ($p = .71$) does not reject that null, indicating that the shortened series are unrelated to the performance ratios or adoption levels of the two banks in the missing years, and that the unbalanced structure does not introduce selection bias into the estimates.

A3. Wild Bootstrap Procedure for the Turning-Point Interval

The turning point is a ratio of two estimated coefficients, so its sampling distribution is not well approximated by the delta method in a panel of this size. Confidence intervals were therefore obtained by wild bootstrap following Cameron et al. (2008). For each of 999 replications, residuals from the estimated model were multiplied by Rademacher weights drawn independently at each cross-sectional unit, preserving the within-bank error structure; the dependent variable was reconstructed from the fitted values and the perturbed residuals; the two-way fixed effects model was re-estimated; and the turning point $-\beta_1 / (2\beta_2) \times 100$ was recomputed. The reported intervals are the 2.5th and 97.5th percentiles of the resulting distribution of turning points.