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Posted Date: 3 June 2026

doi: 10.20944/preprints202606.0199.v1

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On the Impact of FinTech Adoption on the Profitability and Competitiveness of Banks in Qatar: A Two-Decade Panel Analysis (2005–2024)

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Abstract

This paper examines the impacts of the financial technology (FinTech) on the profitability of the Qatari commercial banks using panel data over two decades (2005–2024). The analysis is rooted in the two structural breaks that frame its duration: the regulatory phase in 2017, in which the Qatar Central Bank (QCB) formed its FinTech task force, the regulatory sandbox and the centralized eKYC framework; and the digital-acceleration phase in 2020, triggering by the COVID-19 pandemic and the issuance of digital banking license. To gauge the performance of banks, Return on Assets (ROA) and Return on Equity (ROE) are used, while controlling for bank size (log of total assets), and age and type (Islamic vs. conventional). Fixed-effects (FE) panel regressions with cluster-robust standard errors are estimated using an unbalanced panel of 125 bank-year observations, in combination with Hausman and Breusch–Pagan diagnostics. The results show that in general, the post-2017 reforms have led to marginally significant enhancements in ROE ($\beta = 0.031$; $p \approx 0.054$) and not to any significant improvement in ROA. By contrast, the post-2020 phase reveals an effect on ROA that is positive but statistically weak, after controlling for bank size, and muted ROE effects. Interaction terms disapprove any systematic difference between Islamic and conventional banks in both phases. Results indicate an incremental rather than a transformational effect of FinTech adoption in Qatar as well as a greater influence by timing and scale economies and regulatory saturation than by bank type. The study provides empirical evidence specific to Qatar in a literature that tends to offer cross-country averages across the whole GCC and provided nuanced recommendations for bank managers and regulators aiming to deliver digital Qatar through Qatar National Vision 2030/Digital Agenda.

Keywords: FinTech adoption; Qatari banks; bank profitability; return on assets; return on equity; digital transformation; COVID-19; Islamic banking; panel data; fixed-effects estimation

JEL Classification: G21; G28; O33; L86

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1. Introduction

Financial technology (FinTech) is one of the most disruptive forces in modern banking, challenging cost structures, distribution channels and competitive boundaries (Vives, 2019; Boot et al., 2021; Philippon, 2020). Recently, the uptake of artificial intelligence (AI), of blockchain and open-banking platforms has gradually replaced traditional intermediation models in advanced economies (Arner et al., 2016). Adoption has not been as consistent across the Gulf Cooperation Council (GCC); regulatory precautions, existing infrastructure and cybersecurity concerns have hindered adoption in comparison to the United States, China and parts of Southeast Asia (Morshed, 2025, Khan & Al-Harby, 2022). The State of Qatar sits in this regional mosaic in a key yet little researched location.

The Qatar Central Bank (QCB) has placed digital finance at the heart of the national economic diversification agenda, under the Qatar National Vision 2030. In 2017, a national FinTech task force was established, followed by the regulatory 'sandbox' and in 2019 formed Qatar FinTech Hub and recently the Third Financial Sector Strategy 2024-2030 represents a thoughtful effort to establish Doha as a node of digital-finance in the region (Qatar Central Bank, 2024; SDK Finance, 2024; The FinTech Times, 2024). With the onset of the COVID-19 pandemic, this path was speeding up and the process of transitioning to digital, which had been planned for years and years, got cut short to just 2 years. But the economic impact of the regulatory and pandemic shocks to banks in Qatar is scantily quantified.

Previous empirical studies on FinTech and bank performances in the GCC have either been cross-country (Abu Khalaf et al., 2025), (Afzal et al., 2025), (Alshouha et al., 2025), (AlShouha et al., 2024) or adopted cross-sectional design (AlHares et al., 2022). Pooled estimates might overlook country-specific dynamics as Qatar's banking sector is small, concentrated and dominated by conventional and Islamic banks. Furthermore, some country-specific findings seem to contradict each other, as Al-Kubaisi and Abu Khalaf (2023) found a negative relationship between mobile banking and profitability in Qatari banks compared with the positive relationship found in the regional studies (Alafeef et al., 2024). This dissonance is an indication for necessity to provide evidence with respect to the institutional context of Qatar.

This study addresses that gap. It evaluates how two policy-defined episodes (the regulatory reform phase of 2017 and the digital-acceleration phase of 2020) affected the profitability of banks in Qatar. The analysis is first conducted along with a 20-year sample from nine commercial banks collected from Refinitiv Eikon, exploiting the difference in the levels of the phases between banks within the same group. Also, it examines if there was a difference in the response of Islamic and conventional banks keeping in view the dual influence of Shariah-compliance constraints and the influence of Islamic banking over conventional banking in the domestic banking market (Abdul Rahman et al., 2023; Aysan et al., 2022).

This is a threefold contribution. The paper offers one of the first country specific, multi-decade, econometric studies of FinTech and bank performance in Qatar, as well as pooled countries, with within-country evidence. Second, it distinguishes between two policy episodes which are often lumped together and demonstrates that they have different effects in terms of size, sign and profitability indicator. Third, the paper contributes directly to the policy debate on Vision 2030 by providing specific recommendations for the QCB and bank managers in the new digital licensing environment.

The rest of the paper is organized follows: The review of the literature is done in section 2 and then the hypotheses are developed. In section 3 the data, variables and estimation strategy are described. The descriptive and regression analyses results are presented in Section 4. Section 5 discusses the findings in the light of the wider literature, and Section 6 concludes with implications for theory, management practice and regulatory design.

2. Literature Review and Hypothesis Development

2.1. Theoretical Foundations

This study integrates three complementary theoretical lenses. The Technology Acceptance Model (TAM) (Davis, 1989) suggests that perceived usefulness and perceived ease of use are the two factors that explain technology adoption. Recent findings in the banking industry indicate that trust, performance expectancy, and facilitating conditions are all key factors influencing FinTech adoption. Thus, TAM will help understand why banks with more robust IT infrastructure and more apparent benefits are more engaged with digital platforms (Galeone et al., 2024), and hence it is relevant to understand the heterogeneity among Qatari banks.

How innovations (new ideas, products, services, and frameworks) diffuse through a social system can be modelled by the Diffusion of Innovation theory (Rogers, 2003). Among other friction points for the adoption of FinTech in GCC, institutional barriers, customer inertia and limited FinTech literacy persist. Large banks like QNB and CBQ are early adopters in Qatar, while small

 doi:10.20944/preprints202606.0199.v1

banks are laggards, which aligns with DOI's prediction of differential diffusion (Khan & Al-Harby, 2022).

According to the Resource-Based View (RBV; Barney, 1991) sustained competitive advantage stems from valuable, rare, inimitable, and non-substitutable (VRIN) resources. Proprietary IT infrastructure, data-analytics capability and digitally-skilled staff are keys to successful FinTech deployment in the banking environment. RBV therefore posits that the FinTech–performance association will be moderated by the scale economies and the depth of resources which is straightforwardly incorporated into the empirical specification using the control for bank size.

2.2. FinTech and Bank Performance: Global and Regional Evidence

There is an emerging global literature that highlights that the impact of FinTech on the performance of banks is context dependent. Vives (2019) explains that incremental rather than transformative improvements are likely to occur during the early adoption, and Philippon (2020) and Boot et al. (2021) claim there is a delay from an investment to bottom line improvement. Frost (2023) captures greater ROA increases in other Asian emerging markets, however with a caveat depending on customer adoption and competition levels.

The latest reports from panel studies in the MENA and GCC region suggest that the relationship between FinTech intensity in the MENA and GCC region and profitability is positive but weak or moderately positive. An increase in ROA and ROE is linked to more FinTech adoption in MENA banks, whereas Afzal et al. (2025) demonstrate that FinTech improves the stability indicators. In the ME region, Alafeef et al. (2024) present cost-efficiency improvements for all banks, but recognize that profitability benefits are reduced as core technologies become common. Providing nuanced evidence, Alshouha et al. (2025) demonstrate that FinTech lowers liquidity risk in GCC banks and contingent on bank size, whereas Khan et al. (2022) illustrate the FinTech–stability relationship is relative to the regulating environment. Lamey et al. (2024) and Thakur et al. (2023) continue the discussion by looking at the non-financial and ICT aspects of bank performance.

2.3. FinTech in Qatar and the Research Gap

Empirical work focused on Qatar itself is sparse. Khan Al-Harby (2022), meanwhile, rank Qatar fourth overall within the GCC in terms of digital financial access measures including mobile payments and debit-card penetration, trailing the UAE, Saudi Arabia and Bahrain. Khan et al (2022) discuss the legal systems in place of regional sandboxes, including that of Qatar, but does not attempt to measure performance implications. At the institutional level, conflicting findings appear: positive relationships are found between digitalisation and profitability in regional studies (AlShouha et al., 2024), while a negative connection between the specific Mobile Banking initiatives and Profitability of Qatari Banks was found (Al-Kubaisi and Abu Khalaf, 2023). These paradoxes indicate that aggregating the GCC estimates could obscure responses at the country-level.

There are two other characteristics that set Qatar's banking sector apart. Firstly, Islamic banks hold and manage substantial assets within the system, and their FinTech solutions are influenced by Shariah-compliance factors as highlighted by Abdul Rahman et al. (2023) and Aysan et al. (2022). Second, there is a high degree of concentration in the sector with a few big firms determining patterns of system-wide adoption. These characteristics justify a country-based and multi-period treatment as is done in this paper.

2.4. Hypotheses and Conceptual Model

Drawing on the literature, this study formulates three hypotheses corresponding to two policy episodes and one cross-sectional contrast:

- H1a/H1b: The post-2017 regulatory reform phase is associated with higher ROA (H1a) and ROE (H1b) in Qatari banks.

 doi:10.20944/preprints202606.0199.v1

- H2a/H2b: The post-2020 digital-acceleration phase is associated with higher ROA (H2a) and ROE (H2b).
- H3: The post-period performance effects differ between Islamic and conventional banks.

Figure 1 summarises the conceptual model. Two policy dummies and an interaction with bank type drive bank profitability, while bank size, age and type act as controls.

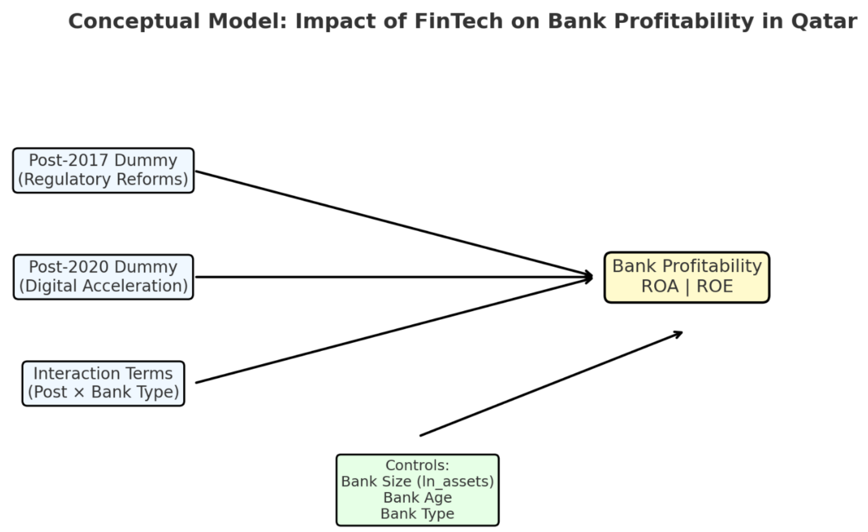

Figure 1. Conceptual model: drivers of bank profitability in Qatar (2005–2024). The model relates the two policy-defined episodes (post-2017 regulatory reform, post-2020 digital acceleration) and their interaction with bank type to ROA and ROE, controlling for bank size, age and type.

3. Data and Methodology

3.1. Sample, Period and Data Source

The sample comprises nine commercial banks operating in Qatar between fiscal years 2005 and 2024, yielding an unbalanced panel of 125 bank-year observations. The 20-year horizon brackets the two structural breaks of interest: the 2017 regulatory phase (QCB FinTech task force, sandbox and eKYC framework) and the 2020 digital-acceleration phase (COVID-19 and the Qatar FinTech Strategy roll-out) (SDK Finance, 2024; The FinTech Times, 2024). Commercial and Islamic banks, as defined by QCB, are included if they have: (i) been in continuous operation in Qatar in the sample window period; (ii) audited annual reports that are available during the sample period. They have chosen the institutions listed in Table 1.

Table 1. Qatari commercial banks included in the analysis.

No.	Bank Name
1	Qatar National Bank QPSC
2	Qatar International Islamic Bank QPSC
3	Qatar Islamic Bank QPSC
4	Ahli Bank QPSC
5	Doha Bank QPSC
6	Commercial Bank PSQC
7	Masraf Al Rayan QPSC

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8	Lesha Bank LLC (Public)
9	Dukhan Bank QPSC

Source: Authors' compilation from Refinitiv Eikon.

The financial information is all taken from Refinitiv Eikon where financial data can be standardised, audited and regulator-approved to facilitate comparison across institutions and over time (Prasophyllaki & Zhang, 2021; Alafeef et al., 2024; Alnsour, 2023). Both for the longitudinal panel design and for the reduction of measurement error, they use one high-quality source.

3.2. Variables

The dependent variables are two profitability ratios commonly used in the banking literature: Return on Assets (ROA = net income ÷ total assets) capturing operational profitability, and Return on Equity (ROE = net income ÷ shareholders' equity) capturing shareholder returns. Two binary policy variables drive the analysis: *post2017* (= 1 for years ≥ 2017) and *post2020* (= 1 for years ≥ 2020). Three controls are in line with the literature: for banks of any kind (bank size), total assets, measured in the natural log (*ln_assets*); bank age, the number of years since the bank was established; and bank type, a dummy equal to one for Islamic banks and zero for conventional banks. The interaction dummy terms between policy and bank type tests for bank specific policy effects.

3.3. Estimation Strategy

The study employs a fixed-effects (FE) panel data approach to control for time-invariant, bank-specific characteristics such as governance culture, risk appetite and ownership structure. The baseline specification is:\

$$Yit = \alpha i + \beta_1 \,\mathrm{Post}t + \beta_2 \ln(\mathrm{Assets})it + \beta_3 \,\mathrm{Age}it + \varepsilon it \quad (1)$$

where Yit is ROA or ROE for bank i in year t, αi is the bank-level fixed effect, Post$t$ is either the *post2017* or *post2020* dummy, and εit is the idiosyncratic error. A second specification adds the interaction term Post$t$ × BankType$i$ to test H3.

Model selection follows standard panel diagnostics. The Hausman test compares FE against a random-effects (RE) alternative, while the Breusch–Pagan Lagrange Multiplier test compares RE against pooled OLS. In both phases, the Hausman statistic strongly rejects RE consistency, justifying FE estimation (Section 4). Cluster-robust standard errors at the bank level correct for heteroskedasticity and within-bank serial correlation, in line with Wooldridge (2010). Estimation is carried out in R using the plm package; lmtest and sandwich provide the robust inference.

In accordance with Gujarati & Porter (2009) and Hair et al. (2019), asset size is log transformed to mitigate skewness, while Shapiro–Wilk tests are additionally reported to supplement the descriptive statistics. For explanatory ability, within-r^2 is reported and for statistical inference, p-values.

4. Empirical Results

4.1. Descriptive Statistics and Diagnostics

The descriptive statistics have been presented in Table 2. The distribution of ROA is positively skewed, leptokurtic with an average value of 2.0%: Most banks fall within a narrow range in terms of profitability and a few produce exceptional returns. ROE is 16.0% on average; it has not been very asymmetric (skewness = 0.18). Total assets have fallen between QAR 1.69 billion and QAR 356.13 billion, which is typical of concentrated banking markets. Following Hair et al. (2019) the log-transformation (*ln_assets*) reduces the skewness to 0.41. The age of the banks ranges from 1 year to 60 years (averaging to 33.9 years), including some old and young banks. There is evidence of a lack of

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normality (rejecting the sample normality at 0.001 levels) for all variables; Gujarati and Porter (2009) found that financial ratios often are non-normal.

Table 2. Descriptive statistics for key variables (2005–2024).

Variable	Mean	SD	Median	Skew	Kurtosis	Min	Max
ROA	0.0200	0.0100	0.0200	2.07	5.29	0.000	0.080
ROE	0.1600	0.0600	0.1500	0.18	0.28	0.020	0.310
Assets (QAR bn)	48.88	73.85	25.67	2.80	7.05	1.69	356.13
ln_assets	23.97	1.07	23.97	0.41	0.40	21.25	26.60
Bank age (yr)	33.89	13.01	35.00	−0.42	−0.10	1	60

N = 125 bank-year observations, 9 banks, 20 years. *Source: Refinitiv Eikon; authors' calculations.*

The distribution of ROA and ROE are given in figure 2. The right tail of ROA is heavier than would be consistent with the high kurtosis statistic, whereas ROE seems to be broadly symmetric with a double mode. The correlation matrix is shown in figure 3. Concentrating on the relations among the groups, as expected, ROA and ROE are very closely linked (r = 0.74) and both are negatively correlated with bank size (ROA–ln_assets r = −0.54) and bank age (ROA–age r = −0.42). This trend confirms the findings of Demirgüç-Kunt and Huizinga (2010), according to whom the smaller a bank's size and the younger it is, the more likely it is to detect high profits.

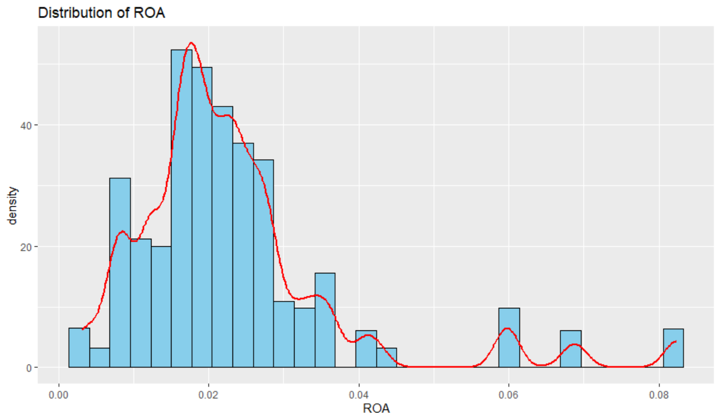

Figure 2. a. Distribution of ROA (right-skewed, leptokurtic).

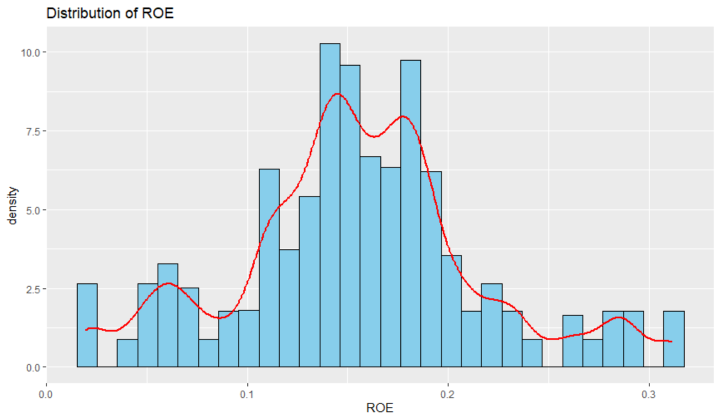

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Figure 2. b. Distribution of ROE (approximately symmetric, bimodal).

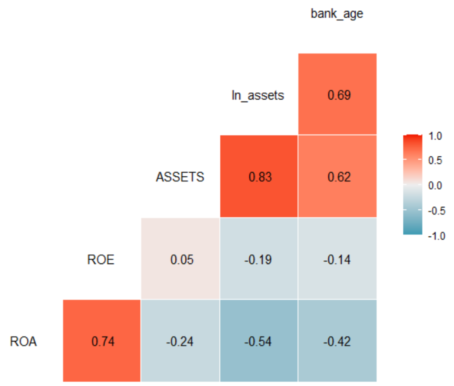

Figure 3. Correlation matrix of the key variables. ROA and ROE are strongly positively correlated (r = 0.74); both correlate negatively with bank size and bank age.

4.2. The Post-2017 Regulatory Phase

Table 3 reports the FE estimates for the post-2017 specification. The Hausman test shows that RE consistency is rejected strongly, as shown by $\chi^2(3) = 138.94$ with $p<0.001$, and also the Breusch–Pagan LM test confirms that there are significant panel effects, as seen in the Appendix Figure A1 with $\chi^2(1) = 6.28$ and $p = 0.012$. Based on this, the most suitable estimator is FE. ROA is practically unchanged since 2017 ($\beta = -0.00058$; $p = 0.868$), meaning that there was little observed in terms of differential asset-based profitability after the regulation changes. The size of the bank ($\beta = -0.0173$, $p < 0.001$) is significant and negative, as discussed in Demirgüç-Kunt and Huizinga (2010), supporting the agility advantage of smaller banks. The within-R^2 is quite large at 0.587.

For ROE, the picture is different: *post2017* carries a positive coefficient of 0.0306 with $p \approx 0.054$, marginally significant at the 10% level. The value of the point estimate suggests that, on average, ROE rose by about three percentage points over the years following the QCB reforms, after accounting for size and age. The ROE model does not consider the size or age of the bank. Results of the heterogeneity test along the dimension of Bank Type (the last column of the Table 3) yield an insignificant interaction term ($\beta = -0.00424$, $p = 0.336$); meaning that there is no systematic differential impact of Islamic banks and conventional ones.

Table 3. Fixed-effects panel regressions for the post-2017 phase.

	(1) ROA	**(2) ROE**	**(3) ROA – Interaction**
post2017	−0.00058	0.0306†	–
	(0.00345)	(0.0157)	–
ln_assets	−0.0173***	−0.0125	−0.0138
	(0.00304)	(0.0219)	(0.0107)
bank_age	0.00045	−0.00680	–
	(0.00054)	(0.00411)	–
post2017 × bank_type	–	–	−0.00424

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			(0.00439)
Bank fixed effects	Yes	Yes	Yes
Cluster-robust SE	Yes	Yes	Yes
Within R^2	0.587	0.434	0.119
Observations (N)	125	125	125
Banks (n)	8	8	8

Cluster-robust standard errors at the bank level in parentheses. Hausman $\chi^2(3) = 138.94$, $p < 0.001$; Breusch–Pagan LM $\chi^2(1) = 6.28$, $p = 0.012$. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, † $p < 0.10$. Source: Refinitiv Eikon; author's estimation in R (plm).

4.3. The Post-2020 Digital-Acceleration Phase

Table 4 reports the corresponding FE estimates for the post-2020 phase. Diagnostics again favour FE (Hausman $\chi^2(3) = 1697$, $p < 0.001$; Breusch–Pagan LM $\chi^2(1) = 18.667$, $p < 0.001$). The *post2020* coefficient in ROA is positive but is not significantly different than zero ($\beta = 0.00218$, $p = 0.539$). Bank size is strongly negative ($\beta = -0.0160$, $p \approx 0.05$), however, and remains so in every specification: larger banks systematically achieve lower ROA, consistent with a case of diseconomies in asset utilisation among the large banks in Qatar.

In the ROE model, the *post2020* coefficient is positive but not significant (at level $\beta = 0.0224$, $p = 0.150$). Bank age, on the other hand, is significantly negative ($\beta = -0.00613$, $p = 0.017$), indicating deteriorating shareholder returns for older banks during the pandemic/ post-pandemic year. Within R^2 for ROE is 0.425, which is slight lower as compared to ROA (0.588).

Again, interaction effects fail to live up to the expectations. A small and not significant interaction coefficient ($\beta = -0.00051$, $p = 0.914$) emerges, and bank size has a strong negative effect ($\beta = -0.0144$, $p < 0.001$) in the ROA model with Post2020 × BankType. The same applies to ROE with the same interaction (column 4); while bank size has again a more pronounced (negative) impact ($\beta = -0.0469$, $p = 0.0026$), the effect of the interaction term is not significant ($\beta = 0.00956$, $p = 0.709$) either. Across all four columns, H3 finds no support: Qatari Islamic and conventional banks did not respond differentially to the post-2020 shock.

Table 4. Fixed-effects panel regressions for the post-2020 phase.

	(1) ROA	**(2) ROA – Inter.**	**(3) ROE**	**(4) ROE – Inter.**
post2020	0.00218	–	0.0224	–
	(0.00354)	–	(0.0154)	–
ln_assets	−0.0160*	−0.0144***	−0.0103	−0.0469***
	(0.00812)	(0.00386)	(0.0151)	(0.0153)
bank_age	0.00012	–	−0.00613**	–
	(0.00096)	–	(0.00254)	–
post2020 × bank_type	–	−0.00051	–	0.00956

 doi:10.20944/preprints202606.0199.v1

		(0.00467)		(0.0256)
Bank fixed effects	Yes	Yes	Yes	Yes
Cluster-robust SE	Yes	Yes	Yes	Yes
Within R^2	0.588	0.583	0.425	0.396
Observations (N)	125	125	125	125
Banks (n)	8	8	8	8

Cluster-robust standard errors at the bank level in parentheses. Hausman $\chi^2(3) = 1697$, $p < 0.001$; Breusch–Pagan LM $\chi^2(1) = 18.667$, $p < 0.001$. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Source: Refinitiv Eikon; author's estimation in R (plm).

4.4. Hypothesis Testing Summary

The results of the hypotheses are summarised in Table 5. H1a is rejected: the effect ROA post-2017 is not significant. H1b is partially accepted: ROE shows a marginally significant uplift after the 2017 reforms. Both H2a and H2b are disconfirmed—the post-2020 coefficients of ROA and ROE have both positive signs but are statistically testing insignificant. H3 is rejected in both intervals and there is no evidence of differential Islamic as compared to conventional dynamics.

Table 5. Hypothesis outcomes.

Hypothesis	Empirical finding	Decision
H1a: Post-2017 → ↑ ROA	$\beta = -0.00058$, $p = 0.868$	Rejected
H1b: Post-2017 → ↑ ROE	$\beta = 0.0306$, $p \approx 0.054$	Partially accepted
H2a: Post-2020 → ↑ ROA	$\beta = 0.00218$, $p = 0.539$	Rejected
H2b: Post-2020 → ↑ ROE	$\beta = 0.0224$, $p = 0.150$	Rejected
H3: Islamic ≠ Conventional response	All interaction terms insignificant	Rejected

There are two patterns of crossing that merit emphasis. First, the kind of indicator of profitability that moves varies from episode to episode: ROE moves (weakly) with the 2017 regulatory phase; ROA and ROE do not move clearly with the 2020 regulatory phase. Second, in every specification, bank size is the most robust indicator of profitability, with a negative sign. These findings seem to suggest that the quarters in which policies took effect have less of a direct contribution to the FinTech–performance nexus in Qatar, as opposed to structural factors within the banks: scale, specifically.

5. Discussion

5.1. Interpreting the Post-2017 Effects

The slight improvement in ROE following the 2017 reforms is consistent with Vives's (2019) and Philippon's (2020) incrementalist argument. The QCB's task force and eKYC (electronic Know Your Customer) framework lowered compliance frictions on the early FinTech initiatives, which may have been a catalyst for increasing shareholder returns because of cost rationalisation and revenues from telecommunications channels. The lack of ROA effect is also in line with the literature, as cost-efficiency benefits may first manifest in ROE, with savings in operating expenses flowing through to

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improve bottom-line profitability more directly than to be added to per-asset productivity (Alafeef et al., 2024; Al-Shari & Lokhande, 2023). The trend is also consistent with Frost (2023), who observes that digitalisation impact on profitability is typically seen first in equity return, in concentrated markets with incumbents having pricing power.

While larger EM studies produced more eye-catching figures, the Qatari one is more subdued. Boot et al. (2021) identify greater immediate ROA increases in less concentrated markets of the world, while AlShouha et al. (2024) find more intensive profitability gains in markets more broadly. Perhaps Qatar's succession of a few large incumbents and a smaller, more concentrated sector simply lacks the opportunity for FinTech to disrupt, and this reinforces much of the need for context-specific evidence.

5.2. Why Post-2020 Effects Are Muted

Three forces appear to dampen the post-2020 signal. First, the COVID-19 pandemic was a distortion, not a clean treatment. Balance sheet provisioning, lending moratoria and capital-conserving provisions did all the reverse they enhanced the balance sheet and suppressed the reported profit, thereby obscuring any gains from FinTech (Naz et al., 2022; Butt & Chamberlain, 2025). Second, it confirmed what Kalai and Toukabri (2024) documented for other international comparisons – that the economic gains from greater efficiency in the short run may have been absorbed by requirements for compliance in the new digital banking framework, as set out by the QCB in 2024. Third, during this time, the FinTech market might be saturated: the growth rate of the marginal returns to further FinTech adoption is expected to diminish once the core mobile and digital services have been mainstreamed, which largely occurred in Qatar by 2021 (Alafeef et al., 2024; AlShouha et al., 2024).

This strong negative association of bank size at each specification makes it difficult to draw an easy conclusion that "larger banks benefit more." Larger Qatari banks, on a per-asset basis, earn less, reflecting those smaller, more troubled banks took on sovereign and corporate exposures that produced lower yields and fewer scale effects came from FinTech rollout costs. This aligns with Alshouha et al. 2025's finding of the moderating effect of bank size in relation to liquidity risk and extends the exhypothesis to profitability.

5.3. Theoretical and Practical Implications

The findings refine TAM, DOI and RBV in the Qatari context. TAM wise, it can be seen that the ROE uplift for 2017 was limited and therefore the shareholder value realization for the perceived usefulness seems to be only at a system utilization level. It is interesting to note that Christian banks and Islamic banks, in terms of DOIs, did not show any significant difference implying that diffusion in the small banking system in Qatar has been more uniform than expected as soon as one such large incumbent bank adopts, others do so more swiftly. The steady negative size coefficient means that VRIN resources in Qatari banks: (ROA, ROE) are not currently creating any kind of differential profitability from a RBV perspective, they may be in other dimensions (resilience, regulatory position) that are not reflected in ROA or ROE.

This means two things to bank managers. Expectations for profitability from Fin Tech adoption are restricted: do not hope for transformational – rather incremental – returns. The value of cybersecurity, data analytics and customer-centric platforms created by long-run digital integration is not short-term ROA enhancements. In the context of Islamic banks, a lack of differential effect implies that Islamic-compliant FinTech, such as blockchain smart contracts and Islamic digital wallets, are not yet providing a competitive advantage over non-Islamic banks (Abdul Rahman et al., 2023).

 doi:10.20944/preprints202606.0199.v1

5.4. Limitations

Three limitations qualify the findings. Firstly, the sample of nine banks represents the entire listed Qatari sector, and thus the external validity is restricted to other GCC markets. Second, using policy defined episode dummies instead of more direct FinTech-intensity measures (e.g., share of digital transaction, IT capex) is a deliberate choice of identification for the sake of granularity. Third, the identification of causal inferences is a matter of the within-bank variation explained by FE and unobserved time-varying shocks may still be a confounder. Future studies should use granular data on digital activity, extend estimates to a cross-GCC panel, and integrate econometric estimates with qualitative case studies on digital transformation in key Qatari banks (Naz et al., 2022; Kalai & Toukabri, 2024).

6. Conclusions

This paper conducted a 20-year panel study across the countries to determine the impact of FinTech adoption on the profitability of commercial banks in Qatar. Two policy-defined episodes were analyzed: the regulatory reform phase in 2017 when Qatar Central Bank created the built-out of its FinTech infrastructure and the digital-acceleration phase in 2020 when COVID-19 accelerated years of digital transition into months. The analysis used a 125-observation bank-year panel with fixed-effects inference design, and found that Return on Equity was marginally significantly related to the post-2017 reforms, which were not significantly related to the Return on Assets. In contrast, the post-2020 stage did not yield any statistically significant impact on either of the profitability variables and bank size turned out to be the most robust variable in all specifications. Differential response rejected in interaction tests, both Islamic and conventional banks.

The implications are subtle. Bank managers may find the findings a bit of a dampener to their hopes of quick and easy profit-intensivity through their FinTech investments. The degree of digital integration, especially around cybersecurity, AI and analytics, and customer experience, will be the key to achieving a lasting competitive edge and not merely FinTech uptake itself. Smaller banks should look at shared digital engagement platforms and collaborative technology to help spread the burden of fixed costs. From the empirical perspective, it is observed that although there is no immediate benefit for Islamic banks on profitability by investing in Shariah-compliant FinTech innovation, financing in this field should be pursued as a strategic differentiator.

The results imply that the next step in the FinTech regulation process should be tiered and ecosystem-centric in the eyes of regulators, especially the QCB. Uniform compliance burdens carry the risk of crowding out smaller institutions, and obsessing over adoption rates (as opposed to outcomes like financial inclusion, resilience, and consumer trust) runs the risk of inducing saturation effects like those noticed in the post-2020 outcomes. But step-up FinTech regulation in line with longer arc Qatar National Vision 2030, e-government, SME finance, regional payment interoperability, would see the harnessing of FinTech as a tool for economic diversification, not just an industry objective.

For the academic literature, the paper contributes one of the first Qatar-specific, multi-decade econometric assessments of FinTech and bank performance, complementing cross-country GCC averages with within-country evidence. Furthermore, it shows an empirical asymmetry between the impacts of policy episodes: the 2017 regulatory period resulted in a change in ROE, whereas the 2020 digital-acceleration period did not unambiguously budge either indicator a finding that should be linked to other small and concentrated markets. Future research would benefit from an expansion to include a multi-country GCC panel, the inclusion of direct proxies of FinTech intensity and the use of quantitative estimates alongside qualitative interviewing to gain deeper insights into the strategic logic of the headline coefficients.

Funding: This research received no external funding.

doi:10.20944/preprints202606.0199.v1

Data Availability Statement: The financial data analysed in this study were obtained from Refinitiv Eikon under an institutional licence. Aggregated descriptive statistics and regression outputs are available from the corresponding author upon reasonable request.

Conflicts of Interest: The author declares no conflict of interest.

Acknowledgments: The author gratefully acknowledges the supervision of Mr. Nodir Karimov at Newcastle Business School and the helpful comments of two anonymous referees.

Abbreviations

AI	Artificial Intelligence	**MENA**	Middle East and North Africa
CBQ	Commercial Bank of Qatar	**QCB**	Qatar Central Bank
FE	Fixed Effects	**QFC**	Qatar Financial Centre
FinTech	Financial Technology	**QNB**	Qatar National Bank
GCC	Gulf Cooperation Council	**RBV**	Resource-Based View
ICT	Information and Communication Technology	**RE**	Random Effects
KYC	Know Your Customer	**ROA**	Return on Assets
LM	Lagrange Multiplier	**ROE**	Return on Equity

Appendix A. Statistical Output Evidence (R plm & sandwich)

This appendix reproduces the raw R console output that underpins the regression results reported in Tables 3 and 4. The estimation environment uses R 4.3 with the plm package for panel estimation and sandwich/lmtest for cluster-robust coefficient testing.

```
> # Breusch-Pagan LM test for RE effects
> plmtest(re_roa_2017, type = "bp")

        Lagrange Multiplier Test - (Breusch-Pagan)

data:  ROA ~ post2017 + ln_assets + bank_type + bank_age
chisq = 6.2751, df = 1, p-value = 0.01224
alternative hypothesis: significant effects
```

Figure A1. Breusch–Pagan Lagrange Multiplier test for random effects in the ROA model. The result ($\chi^2 = 6.275$, $p = 0.0122$) supports the presence of significant panel effects.

```
> (s <- summary(fe_roa_2017))
Oneway (individual) effect Within Model

Call:
plm(formula = ROA ~ post2017 + ln_assets + bank_type + bank_age,
    data = pdat, effect = "individual", model = "within")

Unbalanced Panel: n = 8, T = 2-20, N = 125

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-3.4617e-02 -4.0069e-03  2.8821e-05  4.0553e-03  3.4617e-02

Coefficients:
             Estimate  Std. Error t-value  Pr(>|t|)
post2017   -0.00057685  0.00345030 -0.1672    0.8675
ln_assets  -0.01734321  0.00304089 -5.7033 9.402e-08 ***
bank_age    0.00045074  0.00053775  0.8382    0.4037
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    0.023908
Residual Sum of Squares: 0.0098799
R-Squared:      0.58676
Adj. R-Squared: 0.55051
F-statistic: 53.9556 on 3 and 114 DF, p-value: < 2.22e-16
```

Figure A2. FE summary – ROA, post-2017.

```
> roe_2017_ct

t test of coefficients:

            Estimate Std. Error t value Pr(>|t|)
post2017   0.0305467  0.0156608  1.9505  0.05357 .
ln_assets -0.0125411  0.0219086 -0.5724  0.56816
bank_age  -0.0067967  0.0041148 -1.6518  0.10133
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>
> # Within R^2
> summary(fe_roe_2017)$r.squared["rsq"]
      rsq
0.4336062
```

Figure A3. Cluster-robust coefficients – ROE, post-2017.

```
> roa_2017_tw_ct

t test of coefficients:

                      Estimate Std. Error t value Pr(>|t|)
ln_assets           -0.0137617  0.0106521 -1.2919   0.1995
post2017:bank_type  -0.0042404  0.0043873 -0.9665   0.3362

>
> # Within R^2
> summary(fe_roa_2017_tw)$r.squared["rsq"]
      rsq
0.1186322
```

Figure A4. Heterogeneity test for the post-2017 ROA model with the Post2017 × BankType interaction. The interaction term is insignificant (p = 0.336).

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```
> summary(fe_roa_2020)   # For fixed effects model
Oneway (individual) effect Within Model

Call:
plm(formula = ROA ~ post2020 + ln_assets + bank_type + bank_age,
    data = pdat, effect = "individual", model = "within")

Unbalanced Panel: n = 8, T = 2-20, N = 125

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.03447076 -0.00348315  0.00016046  0.00406303  0.03447076

Coefficients:
             Estimate  Std. Error t-value  Pr(>|t|)
post2020   0.00218347  0.00341116  0.6401    0.5234
ln_assets -0.01603278  0.00335162 -4.7836 5.196e-06 ***
bank_age   0.00011764  0.00056201  0.2093    0.8346
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    0.023908
Residual Sum of Squares: 0.0098469
R-Squared:      0.58814
Adj. R-Squared: 0.55201
F-statistic: 54.2635 on 3 and 114 DF, p-value: < 2.22e-16
```

Figure A5. FE summary – ROA, post-2020.

```
> summary(fe_roa_2020_tw) # For interaction term model
Oneway (individual) effect Within Model

Call:
plm(formula = ROA ~ ln_assets + post2020:bank_type, data = pdat,
    effect = "individual", model = "within")

Unbalanced Panel: n = 8, T = 2-20, N = 125

Residuals:
       Min.     1st Qu.      Median     3rd Qu.        Max.
-0.03443675 -0.00422577 -0.00026655  0.00405339  0.03443675

Coefficients:
                      Estimate  Std. Error  t-value Pr(>|t|)
ln_assets          -0.01439652  0.00123241 -11.6816   <2e-16 ***
post2020:bank_type -0.00050537  0.00308552  -0.1638   0.8702
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares:    0.023908
Residual Sum of Squares: 0.0099721
R-Squared:      0.5829
Adj. R-Squared: 0.55026
F-statistic: 80.356 on 2 and 115 DF, p-value: < 2.22e-16
```

Figure A6. ROA with Post2020 × BankType interaction.

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```
> summary(fe_roe_2020)   # For ROE model
Oneway (individual) effect Within Model

Call:
plm(formula = ROE ~ post2020 + ln_assets + bank_type + bank_age,
    data = pdat, effect = "individual", model = "within")

Unbalanced Panel: n = 8, T = 2-20, N = 125

Residuals:
      Min.    1st Qu.     Median    3rd Qu.       Max.
-0.0835366 -0.0265446  0.0027434  0.0271464  0.1069885

Coefficients:
            Estimate Std. Error t-value Pr(>|t|)
post2020   0.0223452  0.0154125  1.4498  0.14986
ln_assets -0.0103189  0.0151435 -0.6814  0.49699
bank_age  -0.0061289  0.0025393 -2.4136  0.01739 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares:    0.34946
Residual Sum of Squares: 0.20102
R-Squared:      0.42477
Adj. R-Squared: 0.37432
F-statistic: 28.061 on 3 and 114 DF, p-value: 1.1564e-13
```

Figure A7. FE summary – ROE, post-2020.

```
> # Within R²
> summary(fe_roe_2020_tw)$r.squared["rsq"]
      rsq
0.3963482
>
> # Output the clustered coefficient table
> roe_2020_tw_ct

t test of coefficients:

                     Estimate Std. Error t value Pr(>|t|)
ln_assets          -0.0469305  0.0152674 -3.0739 0.002639 **
post2020:bank_type  0.0095612  0.0255581  0.3741 0.709022
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure A8. Cluster-robust coefficients – ROE with interaction.

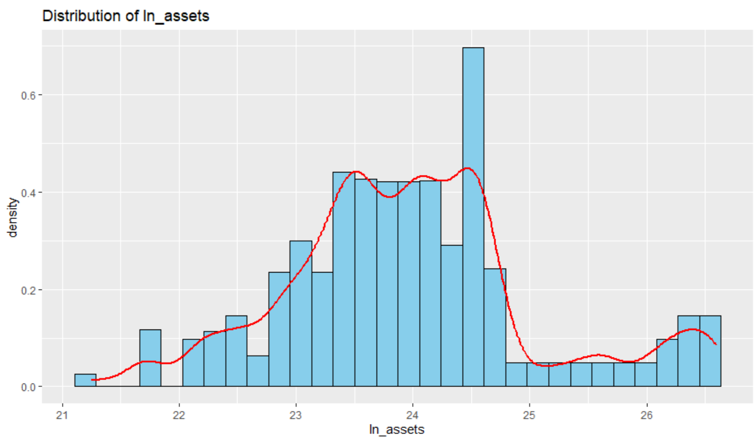

Figure A9. Distribution of ln_assets. Log transformation reduces skewness to 0.41.

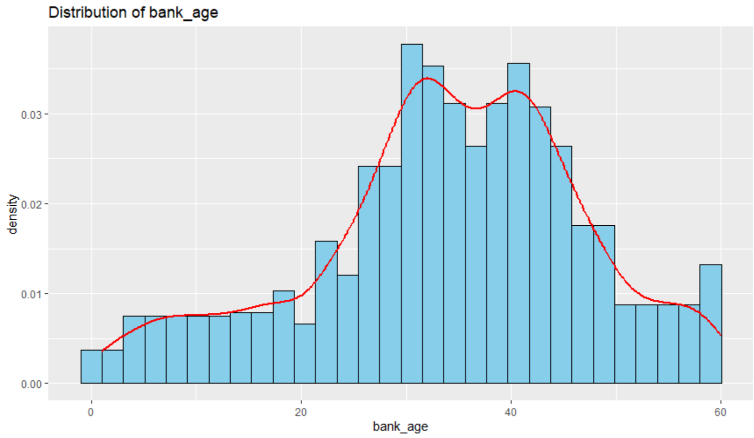

Figure A10. Distribution of bank age.

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