

What drives Bank Profitability in Pakistan? Evidence across the Profitability Distribution

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Abstract

Banks provide most of the credit in Pakistan, and their profitability affects how well the financial system can absorb economic shocks. Between 2011 and 2023 Pakistani banks faced the phased adoption of Basel rules, high inflation and sharp interest rate swings, and their performance became very uneven. The present study examines the internal and external determinants of bank profitability in Pakistan and asks whether these determinants affect low- and high-profit banks in the same way. A balanced panel of 29 listed banks (24 private and 5 public) over 2011–2023, giving 377 bank-year observations, was used, with return on assets (ROA) and return on equity (ROE) as measures of profitability. The Method of Moments Quantile Regression (MMQR) of Machado and Santos Silva (2019) was applied to estimate the effects across the profitability distribution, and Instrumental Variables Quantile Regression (IVQR) was used to address endogeneity. The results show that credit risk and the cost-to-income ratio reduce profitability, with the largest effect on the least profitable banks. Revenue diversification, deposit funding and the interest rate raise profitability, mainly for the most profitable banks, while economic growth and money supply growth benefit low-profit banks more. Private banks are more profitable than public banks, although the gap narrows at the top of the distribution, and bank size has little effect. The study suggests that the State Bank of Pakistan should target asset-quality and cost reviews at banks in the lower tail of the profitability distribution.

Keywords: bank profitability, quantile regression, MMQR; IVQR, credit risk, Pakistan

JEL classification: G21, G28, C23, E44

Introduction

The banking sector is the backbone of Pakistan's financial system. Banks mobilise most of the country's savings, provide the bulk of credit to firms and households and pass the monetary policy of the State Bank of Pakistan (SBP) on to the real economy. At the end of 2024 the assets of the banking sector stood at Rs 53,693 billion, after growth of 15.8 percent in a single year, and its after-tax profit reached Rs 644 billion (State Bank of Pakistan, 2025). A profitable banking sector builds capital, absorbs losses and keeps credit flowing in a slowdown, whereas a loss-making one cuts lending and transmits its stress to the rest of the economy (Tabari, Ahmadi, & Emami, 2013).

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For this reason bank profitability has long been read as a barometer of financial stability (Athanasoglou, Brissimis, & Delis, 2008).

Pakistan's banking sector has changed a great deal over the last two decades. At the start of the 2000s it was dominated by state-owned banks with weak governance, high costs and large stocks of non-performing loans. Privatisation, mergers, the freeing of interest rates and stronger supervision by the SBP turned it into a mostly private and more competitive industry, and the SBP adopted the Basel capital framework in phases. The years from 2011 to 2023 then tested this system. The economy went through recurring political instability, wide fiscal deficits, pressure on the exchange rate and inflation that at its peak exceeded 25 percent (Ministry of Finance [MoF], 2023). Because about 55 percent of bank assets are held in investments, mostly government securities, bank income is closely tied to the interest rate cycle (SBP, 2025). Even in 2024, sector return on equity (ROE) fell from 27.1 to 21.5 percent and return on assets (ROA) from 1.6 to 1.3 percent, although total profit was almost unchanged (SBP, 2025).

These shocks did not fall evenly across banks. Most private banks earned small but steady positive returns throughout the period, while a few public and specialised banks recorded heavy losses, with ROA falling to about -0.11 and ROE to nearly -50 in their worst years. The result is a sector in which a stable core sits next to a thin tail of distressed banks. In our sample the kurtosis of ROA exceeds 20 and that of ROE exceeds 250.

The literature explains bank profitability through internal factors, which management controls, and external factors, which it does not (Athanasoglou et al., 2008; Dietrich & Wanzenried, 2011). Internal factors include capital, credit risk, liquidity, cost efficiency, income diversification, funding structure and size, while external factors include economic growth, inflation, interest rates and money supply. For several of these factors theory predicts opposite effects. Higher capital can lower funding costs and raise profit through the expected bankruptcy cost and signalling channels, or it can reduce leverage and lower the return to shareholders (Berger, 1995). Lending out a larger share of deposits raises interest income but leaves a thinner liquidity buffer (Diamond & Dybvig, 1983). Inflation raises profit when banks anticipate it and lowers profit when they do not (Perry, 1992). Not surprisingly, the empirical results are mixed, and studies on Pakistan reach different conclusions on liquidity, inflation and interest rates (Ali, Akhtar, & Ahmed, 2011; Kanwal & Nadeem, 2013; Luft & Omarkhil, 2018; Sultan, Ahmed, Ameen, & Singh, 2020). This ambiguity gives a reason to revisit the determinants of bank profitability in Pakistan with recent data and with a method that suits the shape of the data.

Most existing studies estimate the effect of each factor on the average bank, using pooled OLS, fixed effects or GMM. In a sector as uneven as Pakistan's this can mislead. A factor that hurts weak banks badly and strong banks only slightly will produce an average effect that describes neither group. Studies outside Pakistan have started to use quantile methods for this reason (Bortoluzzo, Ciganda, & Bortoluzzo, 2024; Altaee, Ghani, Azeez, & Abdulwahab, 2024), but the only quantile study for Pakistan, by Haris, Yao, and Fatima (2024), covers 2018–2021 and looks only at credit and liquidity risk.

Several questions therefore remain open. Do internal and external factors affect weak and strong Pakistani banks in the same way? Is the damage from credit risk and high costs larger for banks with low profits? Do income diversification, deposit funding and higher interest rates benefit the most profitable banks more than the rest? And do these patterns hold once we allow for the possibility that capital, credit risk and liquidity are decided together with profit?

This paper answers these questions with a balanced panel of 29 listed banks, 24 private and 5 public, observed from 2011 to 2023. Profitability is measured by ROA and ROE. We apply the Method of Moments Quantile Regression (MMQR) of Machado and Santos Silva (2019), which allows for bank fixed effects and estimates the effect of each factor at the 10th, 25th, 50th, 75th and 90th percentiles of profitability. Since capital, credit risk and liquidity may be endogenous, we test for endogeneity and re-estimate every model with the Instrumental Variables Quantile Regression (IVQR) of Chernozhukov and Hansen (2008). The findings can help bank managers decide where to direct their effort and help the SBP design supervision for banks whose performance differs so widely.

Our study contributes to the literature in two ways. First, it gives recent evidence for Pakistan that covers the full Basel III period up to 2023 and the full set of internal and external determinants. Second, it shows how the effect of each determinant changes across the profitability distribution and checks these patterns against endogeneity, which helps explain why earlier studies based on the average bank disagree. The rest of the paper is organised as follows. Section 2 reviews the literature, Section 3 describes the data, Section 4 sets out the method, Section 5 presents the results, Section 6 discusses them and Section 7 concludes.

Literature review

There are two broad views on what drives the profitability of banks. The first stresses factors inside the bank, such as capital, asset quality, liquidity and cost control, which reflect management decisions. The second stresses the economic environment, such as growth, inflation and interest rates, which banks cannot control. Most studies now combine the two. Early cross-country work by Bourke (1989) on banks in Europe, North America and Australia linked profit to concentration, capital and liquidity, while Molyneux and Thornton (1992) found for European banks that liquidity lowered profit. Demirgüç-Kunt and Huizinga (1999) extended the analysis to 80 countries and showed that bank characteristics, macroeconomic conditions, taxation and regulation all affect margins and profits. Athanasoglou et al. (2008) gave the literature its standard structure by grouping the determinants of Greek bank profitability over 1985–2001 into bank-specific, industry-specific and macroeconomic factors, and found that profits persist over time. Dietrich and Wanzenried (2011) applied the same approach to Swiss banks and found that some effects changed during the global financial crisis.

Most of these studies measure profitability by ROA, and many also use ROE. ROA alone is used by, among others, Al Zaidanin and Al Zaidanin (2021), Yuan, Gazi, Harymawan, Dhar, and Hossain (2022) and Altaee et al. (2024), and ROE alone by Goddard, Molyneux, and Wilson (2004) and Boahene, Dasah, and Agyei (2012). Both measures are used by Athanasoglou et al. (2008), Trujillo-Ponce (2013), Kanwal and Nadeem (2013), De Leon (2020) and Abdelaziz, Rim,

and Helmi (2022), while Dietrich and Wanzenried (2011), Noman, Pervin, Chowdhury, and Banna (2015) and Haris et al. (2024) also report the net interest margin.

Among the internal factors, credit risk has received the most attention. Berger and DeYoung (1997) argue that problem loans and poor cost control go together, either because outside shocks create bad loans that raise costs (“bad luck”) or because weak managers both screen loans badly and run costly operations (“bad management”). Most studies find a negative effect. Noman et al. (2015) found that non-performing loans and loan-loss reserves reduced ROA, ROE and NIM for banks in Bangladesh, and Petria, Capraru, and Ihnatov (2015), Ekinici and Poyraz (2019) and Saleh and Abu Afifa (2020) reported similar results for the European Union, Turkey and Jordan. Boahene et al. (2012) are an exception, with a positive link between credit risk and ROE in Ghana. The evidence on liquidity is more divided. Abbas, Iqbal, and Aziz (2019) found that liquidity raised profit for Asian banks but lowered it for US banks, Abu Khalaf and Awad (2024) found that liquidity risk raised ROE in the MENA region, and Abdelaziz et al. (2022) found that both credit and liquidity risk lowered ROA and ROE. Cost efficiency gives the most consistent results, as a higher cost-to-income ratio lowers profit in nearly every study (Dietrich & Wanzenried, 2011; Trujillo-Ponce, 2013; Al Zaidanin & Al Zaidanin, 2021). Income diversification raised profit for Italian banks (Chiorazzo, Milani, & Salvini, 2008) and for banks in emerging markets (Sanya & Wolfe, 2011), although Stiroh and Rumble (2006) found that the gains from non-interest income were offset by its volatility. For capital, most studies report a positive effect (Athanasoglou et al., 2008; Nguyen, 2020), but Goddard et al. (2004) found weaker results and Bortoluzzo et al. (2024) a negative one. Results for size are also mixed, positive in Dietrich and Wanzenried (2011) and negative in Batten and Vo (2019).

The macroeconomic evidence is less consistent. Economic growth raised profit in Athanasoglou et al. (2008) and in Yuan et al. (2022) for Bangladesh and India, but lowered it for ASEAN banks (De Leon, 2020). Inflation raised profit for ASEAN banks (De Leon, 2020) but lowered it in Nigeria (Owoputi, Olawale, & Adeyefa, 2014), a difference that Perry (1992) links to whether inflation is anticipated. Higher interest rates widen margins when deposit rates adjust slowly (Saunders & Schumacher, 2000), and Borio, Gambacorta, and Hofmann (2017) showed that higher short-term rates raise the profits of large international banks. On ownership, state-owned banks tend to earn less than private banks because they pursue policy goals and carry legacy bad loans (La Porta, López-de-Silanes, & Shleifer, 2002; Micco, Panizza, & Yañez, 2007).

Studies on Pakistan point in the same broad direction but disagree on the details. Ali et al. (2011) found that both bank-specific and macroeconomic factors affected the profitability of Pakistani commercial banks. Arif and Anees (2012) found that liquidity risk lowered profit for 22 banks over 2004–2009. Kanwal and Nadeem (2013) found, for 18 listed banks over 2002–2011, that the real interest rate raised ROA and ROE, inflation lowered them and GDP had little effect, whereas Luft and Omarkhil (2018) found that inflation and growth raised profit and the interest rate had no effect. Sultan et al. (2020) found that GDP growth raised profit while inflation and capital adequacy lowered it. Haris et al. (2024) found, for 37 banks over 2018–2021, that liquidity risk raised and credit risk lowered ROA, ROE and NIM.

Two gaps stand out. First, almost all of these studies estimate the effect on the average bank, which may explain part of the disagreement if a factor affects weak and strong banks differently. Quantile regression (Koenker & Bassett, 1978) addresses this, but its use in banking is recent. Bortoluzzo et al. (2024) found, for 1,200 banks in 101 countries, that the effects of credit risk and inflation depend on a bank's position in the profit distribution, and Altaee et al. (2024) used MMQR for nine Iraqi banks. Second, the Pakistani evidence mostly ends before the Basel III period and the recent inflation and interest rate shocks. To our knowledge, no study applies MMQR with an IVQR check to the full set of determinants for Pakistani banks over 2011–2023.

Data and variables

Sample

Our sample covers 29 scheduled banks listed in Pakistan, observed annually from 2011 to 2023: 24 privately owned and 5 public, including both conventional and Islamic institutions. Only from 2011, after the SBP had begun phasing in Basel capital rules, are capital and risk items reported consistently across all banks.

Bank-level figures are taken from audited annual reports and financial databases. Rather than rely on reported ratios, we build each one from the underlying balance-sheet and income-statement items so that definitions match across banks and years. Macroeconomic data come from the World Development Indicators (WDI) and the SBP. Table 1 defines the variables and gives the expected signs.

Table 1. Variables, definitions and expected signs

Variable	Definition	Source	Expected sign
ROA	Net income / total assets	Annual reports	Dependent
ROE	Net income / shareholders' equity	Annual reports	Dependent
CA	Total equity / total assets	Annual reports	+/-
CR	Loan-loss reserves / total loans	Annual reports	–
LR	Total loans / total deposits	Annual reports	+/-
RD	Non-interest income / total operating income	Annual reports	+/-
OE	Operating cost / operating income	Annual reports	–
BS	Natural log of total assets	Annual reports	+/-
FS	Customer deposits / total liabilities	Annual reports	+
EG	Real GDP growth (%)	WDI	+
INF	GDP deflator inflation (%)	WDI	+/-
IR	Deposit interest rate (%)	SBP	+/-
MSG	Broad money (M2) growth (%)	SBP	+
DUM	1 = private bank, 0 = public bank	Annual reports	+/-

Note. WDI = World Development Indicators; SBP = State Bank of Pakistan.

Variables

Profitability is measured in two ways. ROA, net income over total assets, shows how well a bank uses its assets. It is not affected by leverage, which makes it the most common single measure (Athanasoglou et al., 2008; Dietrich & Wanzenried, 2011). ROE, net income over equity, shows the return to shareholders. It reflects both operating results and leverage (Goddard et al., 2004). Using both helps, because each covers a weakness of the other. ROA can understate the return to owners, and ROE can flatter a bank with little equity (Dietrich & Wanzenried, 2011).

The internal drivers are capital adequacy (CA, equity over total assets), credit risk (CR, loan-loss reserves over total loans), the loans-to-deposits ratio (LR), revenue diversification (RD, non-interest income over total operating income), cost efficiency (OE, operating cost over operating income), bank size (BS, the log of total assets) and funding structure (FS, customer deposits over total liabilities). A higher LR means the bank lends out more of its deposits and holds a smaller liquid buffer, so it carries more liquidity risk. A higher OE means a less efficient bank. The external drivers are real GDP growth (EG), inflation measured by the GDP deflator (INF), the deposit rate (IR) and broad money growth (MSG). A dummy (DUM) equals 1 for private banks and 0 for public banks.

Method

Model

We write profitability as a function of internal and external drivers:

$$\pi_{it} = f(BSF_{it}, MEF_t) \quad (1)$$

where π_{it} is the profitability of bank i in year t , BSF_{it} is the vector of bank-specific factors and MEF_t is the vector of macroeconomic factors common to all banks. In linear form:

$$PROF_{it} = \beta_0 + \sum_k \beta_k INT_{k,it} + \sum_m \gamma_m EXT_{m,t} + \theta DUM_i + \mu_i + \varepsilon_{it} \quad (2)$$

$PROF_{it}$ is the profitability proxy (alternately ROA or ROE); $INT_{k,it}$ denotes the k -th internal determinant; $EXT_{m,t}$ the m -th external determinant; μ_i the unobserved bank-specific effect; and ε_{it} the idiosyncratic error term. DUM_i is the ownership dummy, equal to 1 for private banks.

We estimate four models. Models 1A and 1B relate the two profitability measures to internal factors only:

$$ROA_{it} = \beta_0 + \beta_1 CA_{it} + \beta_2 CR_{it} + \beta_3 LR_{it} + \beta_4 RD_{it} + \beta_5 OE_{it} + \beta_6 BS_{it} + \beta_7 FS_{it} + \theta DUM_i + \mu_i + \varepsilon_{it} \quad (3)$$

$$ROE_{it} = \beta_0 + \beta_1 CA_{it} + \beta_2 CR_{it} + \dots + \beta_7 FS_{it} + \theta DUM_i + \mu_i + \varepsilon_{it} \quad (4)$$

Models 1C and 1D extend Models 1A and 1B by appending the external macroeconomic vector:

$$ROA_{it} = \beta_0 + \sum_k \beta_k INT_{k,it} + \gamma_1 EG_t + \gamma_2 INF_t + \gamma_3 IR_t + \gamma_4 MSG_t + \theta DUM_i + \mu_i + \varepsilon_{it} \quad (5)$$

$$ROE_{it} = \beta_0 + \sum_k \beta_k INT_{k,it} + \sum_m \gamma_m EXT_{m,t} + \theta DUM_i + \mu_i + \varepsilon_{it} \quad (6)$$

Comparing Models 1A and 1B with Models 1C and 1D shows whether the bank-level results change once the economic environment is controlled for.

Diagnostic tests

We begin with descriptive statistics and the Jarque–Bera normality test. Heavy tails in the profit series would make mean estimators unrepresentative. Banks in one country face the same shocks, such as monetary policy, regulation and the business cycle, so their errors are unlikely to be independent. We test for cross-sectional dependence with the CD test of Pesaran (2021). Because dependence is present, we test for unit roots with the cross-sectionally augmented IPS (CIPS) test of Pesaran (2007), which adds cross-sectional averages to each bank's Dickey–Fuller regression. For the national macroeconomic series, which are the same for all banks, we use the standard ADF test.

We test whether the slope coefficients are equal across banks with the delta and adjusted delta statistics of Pesaran and Yamagata (2008). If slopes differ, a pooled estimator is biased and an estimator that allows for heterogeneity is preferred. Finally, we test for cointegration with the error-correction tests of Westerlund (2007) and the residual-based tests of Pedroni (1999, 2004) and Kao (1999), to rule out a spurious relationship among the non-stationary series.

Method of Moments Quantile Regression

Standard quantile regression (Koenker & Bassett, 1978) does not handle fixed effects well in short panels. MMQR solves this with a location-scale model:

$$Y_{it} = \alpha_i + X_{it}'\beta + (\delta_i + Z_{it}'\gamma) U_{it} \quad (7)$$

where X_{it} holds the regressors, Z_{it} is a known function of X_{it} , α_i and δ_i are bank effects, and U_{it} is an error independent of X_{it} . The conditional quantile τ of Y is then:

$$Q_Y(\tau | X_{it}) = (\alpha_i + \delta_i q(\tau)) + X_{it}'\beta + Z_{it}'\gamma q(\tau) \quad (8)$$

The term $(\alpha_i + \delta_i q(\tau))$ is the bank fixed effect at quantile τ . The location parameters β come from a regression of Y on the regressors, the scale parameters γ come from a regression of the absolute residuals, and $q(\tau)$ is estimated from the standardised residuals. We report the location and scale estimates and the coefficients at $\tau = 0.10, 0.25, 0.50, 0.75$ and 0.90 . MMQR suits our data because it allows bank effects to shift the whole distribution, handles the slope differences found by the diagnostic tests, and is less sensitive to outliers than mean estimators.

Endogeneity and IVQR

Capital, credit risk and liquidity may be decided together with profit. A bank with weak profits may let bad loans build up, and a bank with strong profits can add to its capital (Berger, 1995; Berger & DeYoung, 1997). We test whether CA, CR and LR are exogenous with the Durbin and Wu–Hausman tests (Durbin, 1954; Wu, 1973; Hausman, 1978). Each suspect variable is regressed on the instruments and the exogenous variables, and the residuals are added to the profit equation. A significant Durbin χ^2 or Wu–Hausman F statistic means the variables are endogenous.

We then re-estimate all four models with the IVQR estimator of Chernozhukov and Hansen (2008). The structural quantile function is:

$$Q_Y(\tau | D, X) = D'\alpha(\tau) + X'\beta(\tau) \quad (9)$$

where D holds the endogenous regressors and X the exogenous ones. The estimator uses the condition that, at the true parameters, the instruments are unrelated to whether the outcome lies below its quantile. The instruments are the second lags of CA, CR and LR.

Results

Descriptive statistics and correlations

Table 2 reports the descriptive statistics. The mean ROA is 0.006 and the median is 0.008. ROA ranges from −0.109 to 0.183, with a skewness of −0.525 and a kurtosis of 20.1. ROE is far more extreme. Its mean is −0.101 but its median is 0.122, which shows that a few very large losses pull the mean down. Its kurtosis is 253.9. Credit risk has a mean of 0.169 and a median of 0.096, so a few banks carry very high credit risk. The loans-to-deposits ratio has a mean of 1.929 but a median of 0.582, again driven by a few extreme values. Bank size is close to normal, with a kurtosis of 3.0. Among the macroeconomic series, mean growth is 3.7 percent, mean inflation is 9.5 percent and the mean deposit rate is 7.6 percent. The Jarque–Bera test rejects normality for every variable. These heavy tails support the use of quantile methods.

Table 2. Descriptive statistics

Variable	Mean	Median	Max	Min	SD	Skewness	Kurtosis	Jarque–Bera
ROA	0.006	0.008	0.183	-0.109	0.023	-0.525	20.147	4635.658
ROE	-0.101	0.122	3.360	-49.785	2.865	-15.415	253.915	1003902.000
CA	-0.133	0.065	0.741	-7.210	1.149	-5.073	27.093	10735.060
CR	0.169	0.096	0.999	0.000	0.219	2.532	8.927	954.614
LR	1.929	0.582	41.489	-0.185	6.483	5.568	32.970	16057.200
RD	0.135	0.117	0.863	-0.058	0.113	3.402	17.640	4094.043
OE	0.341	0.293	1.448	-0.371	0.210	2.299	11.610	1496.592
BS	8.419	8.496	9.823	6.579	0.717	-0.670	3.027	28.204

Variable	Mean	Median	Max	Min	SD	Skewness	Kurtosis	Jarque–Bera
FS	0.742	0.801	0.959	0.005	0.199	-2.203	8.059	707.123
EG	3.667	4.218	6.574	-1.274	2.313	-0.786	2.847	39.224
INF	9.489	9.036	26.016	0.922	6.285	1.186	4.225	111.934
IR	7.578	7.265	13.000	4.478	2.497	0.875	2.887	48.265
MSG	12.447	12.181	17.395	7.412	2.712	0.155	2.376	7.621

Table 3 reports the correlations. ROA is positively correlated with LR (0.443), RD (0.490) and BS (0.170), and negatively correlated with OE (−0.569), CR (−0.134) and FS (−0.219). ROE is only weakly correlated with most variables. Among the internal drivers, CA is strongly correlated with LR (−0.910) and RD (−0.836), CR is correlated with LR (0.678), and LR is correlated with RD (0.832). Among the macroeconomic series, INF and IR are correlated at 0.861, and both are negatively correlated with EG. We keep these variables because each has a separate economic role, but we read the CA coefficient with care.

Table 3. Correlation matrix

	ROA	ROE	CA	CR	LR	RD	OE	BS	FS	EG	INF	IR	MSG
ROA	1.000												
ROE	0.326	1.000											
CA	-0.379	0.004	1.000										
CR	-0.134	-0.189	-0.728	1.000									
LR	0.443	0.006	-0.910	0.678	1.000								
RD	0.490	0.004	-0.836	0.560	0.832	1.000							
OE	-0.569	-0.259	-0.034	0.460	0.057	-0.047	1.000						
BS	0.170	0.139	0.455	-0.642	-0.477	-0.307	-0.622	1.000					
FS	-0.219	0.044	0.675	-0.653	-0.710	-0.569	-0.197	0.483	1.000				
EG	0.005	-0.094	0.002	-0.039	0.006	0.126	0.161	-0.048	0.038	1.000			
INF	-0.021	0.062	-0.005	0.059	-0.013	-0.204	-0.212	0.093	-0.088	-0.623	1.000		
IR	-0.033	0.075	-0.008	0.053	-0.005	-0.206	-0.218	0.109	-0.080	-0.563	0.861	1.000	
MSG	0.036	0.049	0.006	0.024	-0.022	-0.008	-0.077	-0.070	0.035	-0.615	0.289	0.156	1.000

Note. Pearson correlation coefficients.

Diagnostic tests

Table 4 shows that every variable has strong cross-sectional dependence, with all CD statistics significant at 1%. Bank size (56.2) and the cost-to-income ratio (32.9) show the strongest dependence among the bank-level variables. The four macroeconomic series share the same value (72.65), as they are common to all banks. The CIPS test shows that most bank-level variables have a unit root in levels. FS is stationary at 1%. Table 5 shows that EG, IR and MSG are I(1). INF is not stationary even after first differencing, so we read the inflation results with care.

Table 4. Cross-sectional dependence and CIPS unit root tests

Variable	Pesaran CD	CIPS (levels)	CIPS decision
ROA	8.825***	-1.842	Unit root
ROE	9.138***	-1.558	Unit root
CA	26.234***	-1.818	Unit root
CR	7.980***	-1.893	Unit root
LR	12.762***	-1.937	Unit root
RD	27.839***	-2.087	Unit root
OE	32.949***	-1.120	Unit root
BS	56.223***	-1.724	Unit root
FS	15.122***	-2.939	I(0) at 1%
EG	72.650***		
INF	72.650***		
IR	72.650***		
MSG	72.650***		

Note. *** $p < .01$. CIPS is applied to bank-level series only; the macroeconomic series are common to all banks and are tested with the ADF test (Table 5). Critical values follow Pesaran (2007).

Table 5. ADF unit root tests for the macroeconomic series

Variable	ADF level	p	ADF first difference	first p	Order
EG	-1.035	.252	-5.162	.001	I(1)
INF	1.493	.955	-0.433	.468	Above I(1)
IR	0.396	.770	-3.311	.004	I(1)
MSG	-0.613	.404	-5.457	.001	I(1)

Note. ADF tests on the annual national series.

Table 6 shows that the slope homogeneity test rejects equal slopes in all four models at the 1% level. The adjusted delta statistics are 4.184 (Model 1A), -12.392 (1B), -10.763 (1C) and -12.136 (1D). The effect of each driver differs across banks.

Table 6. Slope homogeneity tests

Model	Dependent	Regressors	Delta	p	Adj. Delta	p
1A	ROA	7	2.321	.020	4.184	.000
1B	ROE	7	-6.874	.000	-12.392	.000
1C	ROA	11	-9.772	.000	-10.763	.000
1D	ROE	11	-10.501	.000	-12.136	.000

Note. Pesaran and Yamagata (2008) test. H0: slope coefficients are homogeneous across banks.

Table 7 reports the cointegration tests. The Westerlund Pt statistic is significant in every model, though some group statistics are not. All Kao statistics reject the null of no cointegration, as do most of the Pedroni statistics. Taken together, the tests point to a long-run relationship in each model. The mix of cross-sectional dependence, unit roots and slope differences supports an estimator that allows for heterogeneity, such as MMQR.

Table 7. Panel cointegration tests

Model	W: Gt	W: Ga	W: Pt	W: Pa	Kao: MDF	Kao: ADF	P: MPP	P: PP	P: ADF
1A	-1.156 (.177)	-2.870 (.865)	-10.416 (.000)	-3.619 (.000)	-1.639 (.050)	-3.454 (.000)	9.109 (.000)	-11.041 (.000)	-6.884 (.000)
1B	-2.203 (.000)	-2.673 (.000)	-9.437 (.001)	-2.303 (.585)	-7.760 (.000)	-8.138 (.000)	9.334 (.000)	-12.790 (.000)	-8.568 (.000)
1C	-2.529 (.000)	-3.115 (.000)	-9.046 (.001)	-3.366 (.000)	-2.279 (.011)	-3.857 (.000)	9.911 (.000)	2.370 (.008)	0.468 (.319)
1D	-0.802 (.901)	-1.905 (.988)	-8.249 (.000)	-4.103 (.000)	-7.947 (.000)	-8.112 (.000)	9.871 (.000)	2.504 (.006)	-0.127 (.449)

Note. W = Westerlund (2007); Kao = Kao (1999); P = Pedroni (1999, 2004). MDF = modified Dickey–Fuller; MPP = modified Phillips–Perron; PP = Phillips–Perron. p-values in parentheses. H0: no cointegration.

MMQR results with internal drivers

Table 8 and Figure 1 report Model 1A. Credit risk lowers ROA at every quantile. The coefficient is -0.102 at Q0.10 and -0.027 at Q0.90, so the effect at the bottom is almost four times the effect at the top. The cost-to-income ratio also lowers ROA at every quantile, from -3.335 at Q0.10 to -2.411 at Q0.90. Both drivers hurt low-profit banks more than high-profit banks.

Revenue diversification raises ROA, and its effect grows from 3.438 at Q0.10 to 4.078 at Q0.90. Funding structure raises ROA only in the upper half of the distribution. It is not significant at Q0.10 and Q0.25 but is 1.412 at the median, 1.859 at Q0.75 and 2.255 at Q0.90. LR has a small positive effect that declines across quantiles, from 0.00226 to 0.00108. Capital is only weakly significant, at Q0.10 (0.598). Size is not significant at any quantile. Private ownership carries a positive coefficient throughout the distribution.

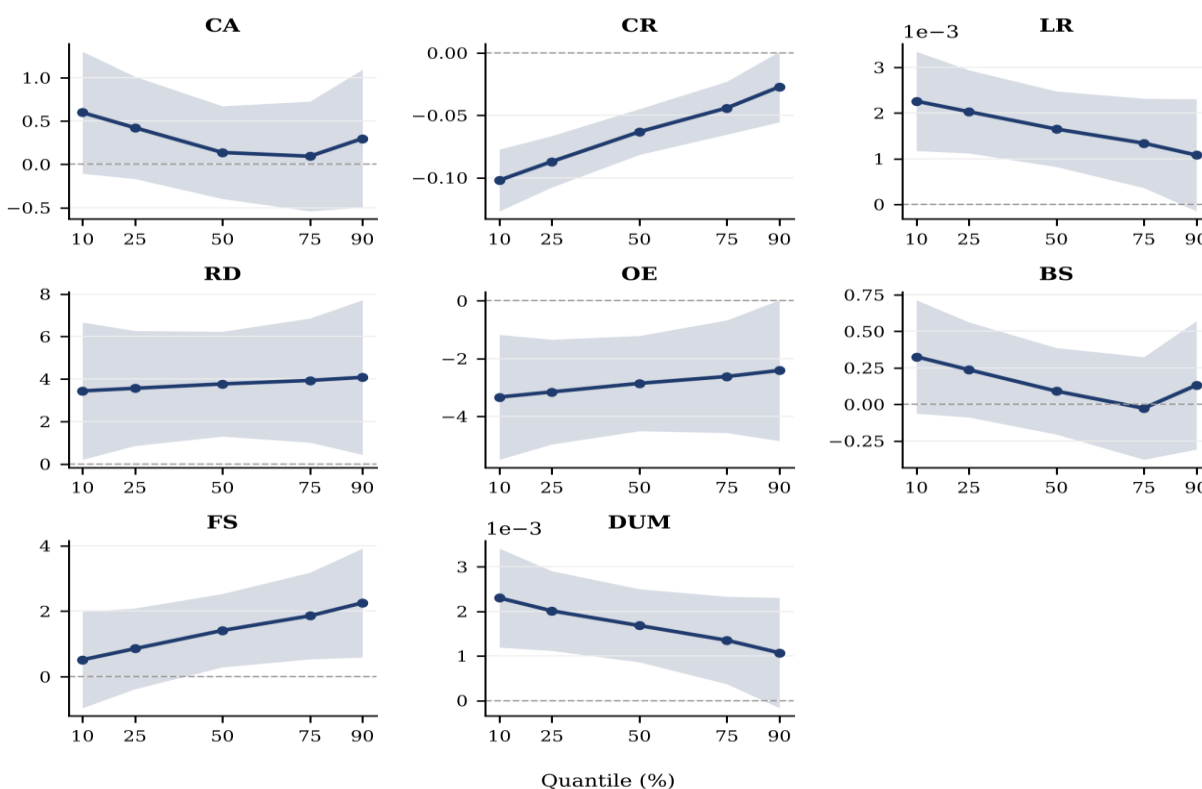
Table 8. MMQR estimates, Model 1A (ROA, internal factors)

Variable	Location	Scale	Q0.10	Q0.25	Q0.50	Q0.75	Q0.90
CA	0.133 (0.274)	0.299* (0.178)	0.598* (0.359)	0.423 (0.301)	0.137 (0.273)	0.0934 (0.323)	0.298 (0.406)
CR	-0.0629*** (0.00934)	-0.0248*** (0.00607)	-0.102*** (0.0126)	-0.0870*** (0.0105)	-0.0632*** (0.00933)	-0.0441*** (0.0108)	-0.0272* (0.0144)
LR	0.00164***	0.000394	0.00226***	0.00203***	0.00165***	0.00134***	0.00108*

Variable	Location	Scale	Q0.10	Q0.25	Q0.50	Q0.75	Q0.90
	(0.000423)	(0.000275)	(0.000554)	(0.000464)	(0.000422)	(0.000499)	(0.000626)
RD	3.770***	0.213	3.438**	3.563***	3.767***	3.932***	4.078**
	(1.259)	(0.819)	(1.646)	(1.380)	(1.258)	(1.489)	(1.855)
OE	-2.855***	-0.308	-3.335***	-3.155***	-2.859***	-2.621***	-2.411*
	(0.843)	(0.548)	(1.103)	(0.925)	(0.841)	(0.995)	(1.244)
BS	0.0887	0.152	0.326	0.237	0.0907	-0.0266	0.131
	(0.151)	(0.0983)	(0.198)	(0.166)	(0.151)	(0.179)	(0.224)
FS	1.420**	0.580	0.517	0.856	1.412**	1.859***	2.255***
	(0.572)	(0.372)	(0.751)	(0.629)	(0.572)	(0.675)	(0.848)
DUM	0.00164***	0.000394	0.00230***	0.00201***	0.00168***	0.00135***	0.00107*
	(0.000421)	(0.000275)	(0.000566)	(0.000455)	(0.000418)	(0.000500)	(0.000631)
Constant	2.076	2.006**	-1.049	0.125	2.049	3.596*	4.967**
	(1.574)	(1.023)	(2.067)	(1.730)	(1.577)	(1.865)	(2.333)
Observations	377	377	377	377	377	377	377

Note. Standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .10$. DUM = 1 for private banks.

Figure 1. MMQR estimates, Model 1A (ROA, internal factors)



Note. Solid line: quantile coefficient. Shaded area: 95% confidence band. Source: Authors' calculations.

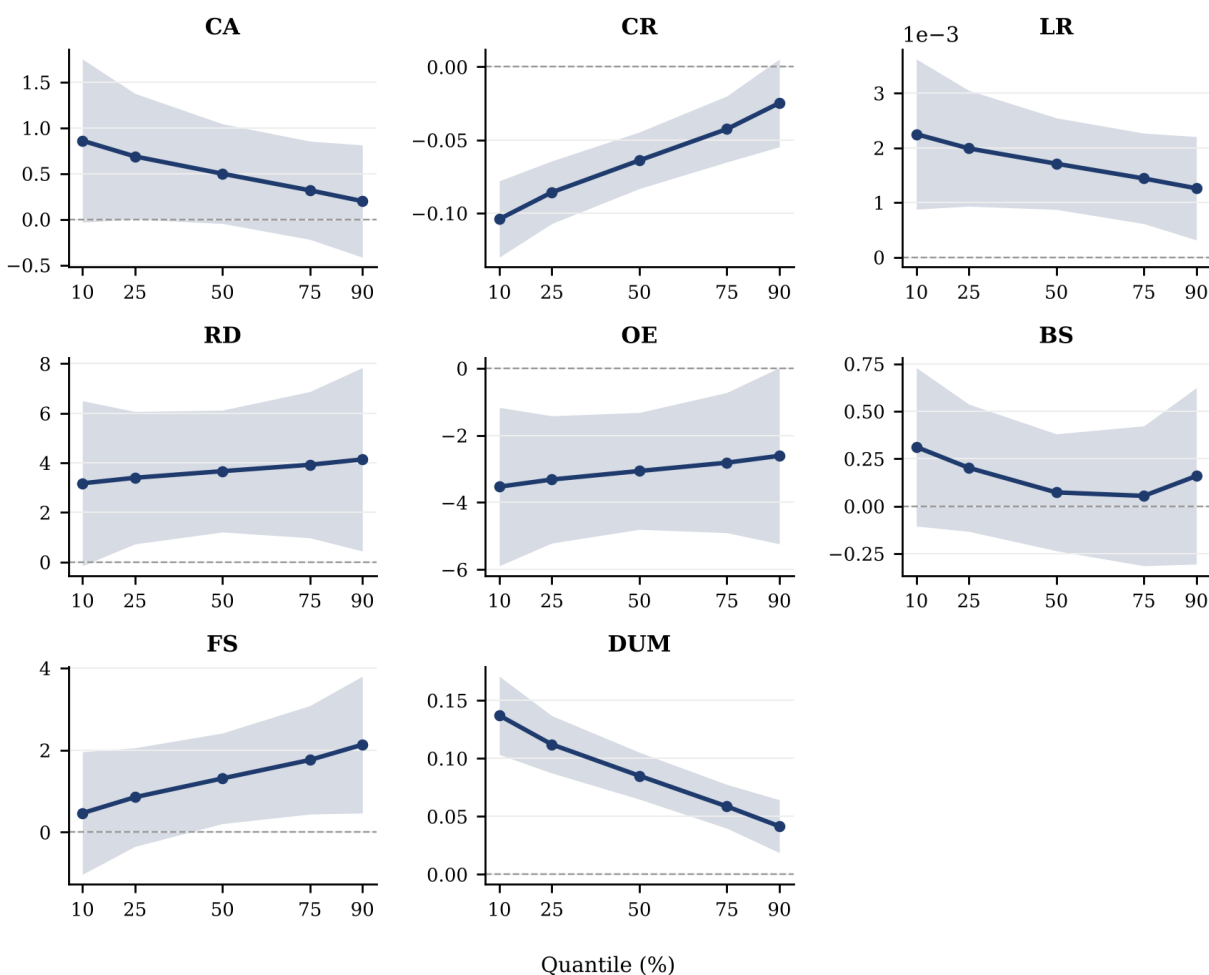
Model 1B, with ROE as the outcome (Table 9 and Figure 2), gives much the same picture. The credit risk coefficient moves from -0.104 at Q0.10 to -0.025 at Q0.90 and loses significance at the top. Costs bite throughout, with coefficients between -3.530 and -2.609 . Revenue diversification and funding structure are positive and grow across quantiles. Capital matters only in the lower half (0.860 , 0.688 and 0.499 from Q0.10 to Q0.50), and the private-bank premium shrinks from 0.137 at Q0.10 to 0.042 at Q0.90.

Table 9. MMQR estimates, Model 1B (ROE, internal factors)

Variable	Location	Scale	Q0.10	Q0.25	Q0.50	Q0.75	Q0.90
CA	0.490*	0.223	0.860*	0.688**	0.499*	0.317	0.199
	(0.275)	(0.179)	(0.455)	(0.351)	(0.278)	(0.274)	(0.313)
CR	-	-	-0.104^{***}	-	-	-	-0.0247
	0.0616^{***}	0.0255^{**}		0.0857^{***}	0.0639^{***}	0.0425^{***}	
	(0.00988)	(0.00645)	(0.0133)	(0.0109)	(0.00985)	(0.0115)	(0.0153)
LR	0.00170^{**}	0.000334	0.00225^{**}	0.00199^{**}	0.00171^{**}	0.00144^{**}	0.00126^{**}
	*		*	*	*	*	*
	(0.000424)	(0.000275)	(0.000700)	(0.000540)	(0.000427)	(0.000422)	(0.000482)
RD	3.692^{***}	0.310	3.175^{*}	3.399^{**}	3.665^{***}	3.924^{***}	4.139^{**}
	(1.264)	(0.825)	(1.697)	(1.362)	(1.253)	(1.504)	(1.886)
OE	-3.036^{***}	-0.296	-3.530^{***}	-3.316^{***}	-3.062^{***}	-2.814^{***}	-2.609^{*}
	(0.897)	(0.586)	(1.204)	(0.968)	(0.889)	(1.066)	(1.340)
BS	0.0590	0.151	0.312	0.202	0.0726	0.0541	0.159
	(0.158)	(0.103)	(0.213)	(0.171)	(0.157)	(0.188)	(0.237)
FS	1.361^{**}	0.535	0.466	0.854	1.312^{**}	1.762^{***}	2.134^{**}
	(0.567)	(0.370)	(0.762)	(0.613)	(0.563)	(0.674)	(0.850)
DUM	0.0838^{***}	0.0323^{**}	0.137^{***}	0.112^{***}	0.0850^{***}	0.0586^{***}	0.0415^{***}
		*					
	(0.0100)	(0.00652)	(0.0172)	(0.0126)	(0.0103)	(0.00963)	(0.0116)
Constant	1.012^{***}	0.481^{***}	0.213	0.586^{***}	0.994^{***}	1.386^{***}	1.641^{***}
	(0.171)	(0.111)	(0.287)	(0.220)	(0.175)	(0.172)	(0.197)
Observations	377	377	377	377	377	377	377

Note. Standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .10$. DUM = 1 for private banks.

Figure 2. MMQR estimates, Model 1B (ROE, internal factors)



Note. Solid line: quantile coefficient. Shaded area: 95% confidence band. Source: Authors' calculations.

MMQR results with internal and external drivers

Adding the four macroeconomic variables (Tables 10 and 11; Figures 3 and 4) leaves the bank-level picture largely intact, so the earlier results are not simply picking up the business cycle.

For ROA (Table 10), credit risk stays negative at every quantile, from -0.101 at Q0.10 to -0.032 at Q0.90. The cost-to-income ratio is significant up to Q0.75 but not at Q0.90. Diversification now matters only from the median up, where its coefficient climbs from 3.146 to 5.443, and funding structure behaves in a similar way. Size, insignificant before, now enters positively at Q0.10 (0.514) and Q0.25 (0.359).

The macroeconomic variables fall into two groups. Growth raises ROA everywhere but most at the bottom (0.100 at Q0.10), and money supply growth is likewise strongest at Q0.10 (4.067) and insignificant by Q0.90. The interest rate runs the other way, from an insignificant 0.220 at Q0.10 to 5.323 at Q0.90. Inflation is positive and fades across quantiles, while the private-bank dummy is significant only between Q0.10 and Q0.50.

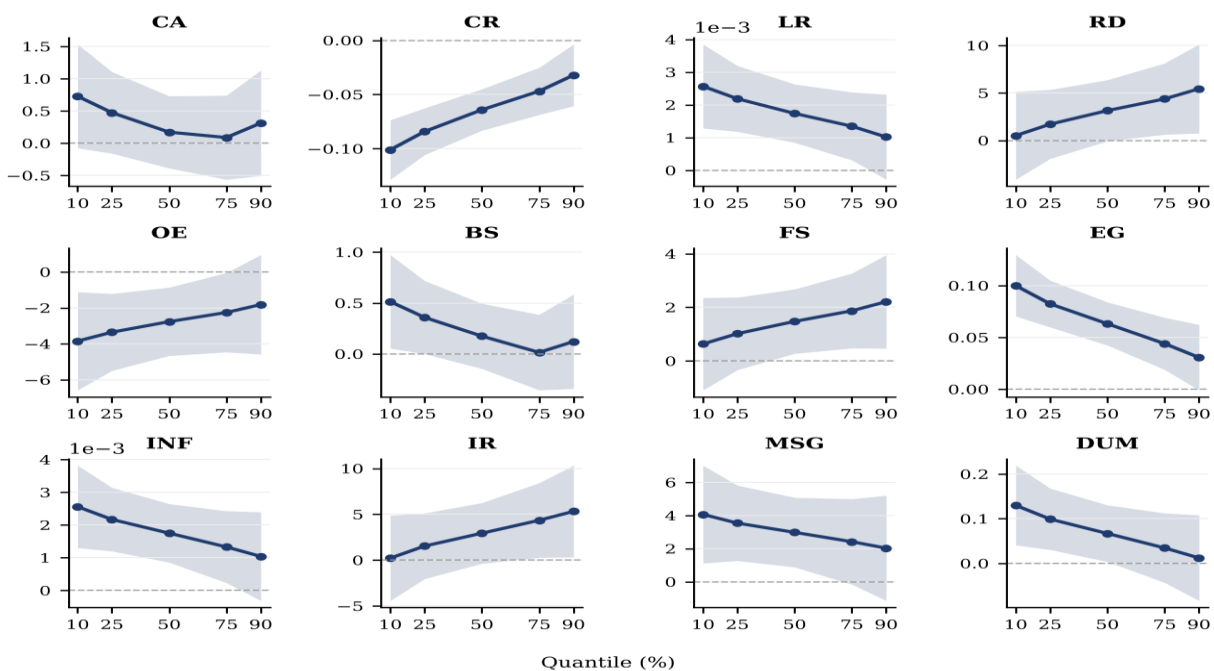
Table 10. MMQR estimates, Model 1C (ROA, internal and external factors)

Variable	Location	Scale	Q0.10	Q0.25	Q0.50	Q0.75	Q0.90
CA	0.157 (0.286)	0.326* (0.186)	0.729* (0.410)	0.474 (0.322)	0.172 (0.285)	0.0887 (0.332)	0.313 (0.416)
CR	-0.0631*** (0.00973)	-0.0215*** (0.00633)	-0.101*** (0.0140)	-0.0841*** (0.0110)	-0.0641*** (0.00974)	-0.0469*** (0.0111)	-0.0321** (0.0145)
LR	0.00172*** (0.000456)	0.000484 (0.000296)	0.00257*** (0.000654)	0.00219*** (0.000513)	0.00174*** (0.000455)	0.00135** (0.000529)	0.00102 (0.000663)
RD	3.219* (1.647)	1.540 (1.071)	0.514 (2.362)	1.716 (1.852)	3.146* (1.645)	4.380** (1.914)	5.443** (2.390)
OE	-2.733*** (0.972)	0.634 (0.632)	-3.847*** (1.392)	-3.352*** (1.092)	-2.763*** (0.969)	-2.255** (1.126)	-1.817 (1.410)
BS	0.165 (0.163)	0.199* (0.106)	0.514** (0.234)	0.359** (0.183)	0.175 (0.163)	0.0154 (0.189)	0.122 (0.236)
FS	1.500** (0.614)	0.493 (0.399)	0.635 (0.879)	1.019 (0.690)	1.477** (0.612)	1.872*** (0.712)	2.212** (0.890)
EG	0.0616*** (0.0106)	0.0219*** (0.00711)	0.100*** (0.0151)	0.0824*** (0.0115)	0.0632*** (0.0106)	0.0440*** (0.0128)	0.0307* (0.0161)
INF	0.00172*** (0.000459)	0.000480 (0.000307)	0.00256*** (0.000642)	0.00217*** (0.000495)	0.00175*** (0.000456)	0.00133** (0.000560)	0.00104 (0.000691)

Variable	Location	Scale	Q0.10	Q0.25	Q0.50	Q0.75	Q0.90
IR	3.059*	1.607	0.220	1.539	2.939*	4.348**	5.323**
	(1.698)	(1.134)	(2.371)	(1.827)	(1.687)	(2.076)	(2.552)
MSG	2.935***	0.641	4.067***	3.541***	2.983***	2.421*	2.032
	(1.078)	(0.720)	(1.503)	(1.159)	(1.069)	(1.314)	(1.617)
DUM	0.0642**	-0.0370*	0.130***	0.0992***	0.0670**	0.0346	0.0122
	(0.0325)	(0.0217)	(0.0455)	(0.0350)	(0.0323)	(0.0397)	(0.0489)
Constant	0.660	2.408*	-3.569	-1.690	0.546	2.476	4.137
	(1.903)	(1.237)	(2.733)	(2.141)	(1.904)	(2.216)	(2.766)
Observations	377	377	377	377	377	377	377

Note. Standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .10$. DUM = 1 for private banks.

Figure 3. MMQR estimates, Model 1C (ROA, internal and external factors)



Note. Solid line: quantile coefficient. Shaded area: 95% confidence band. Source: Authors' calculations.

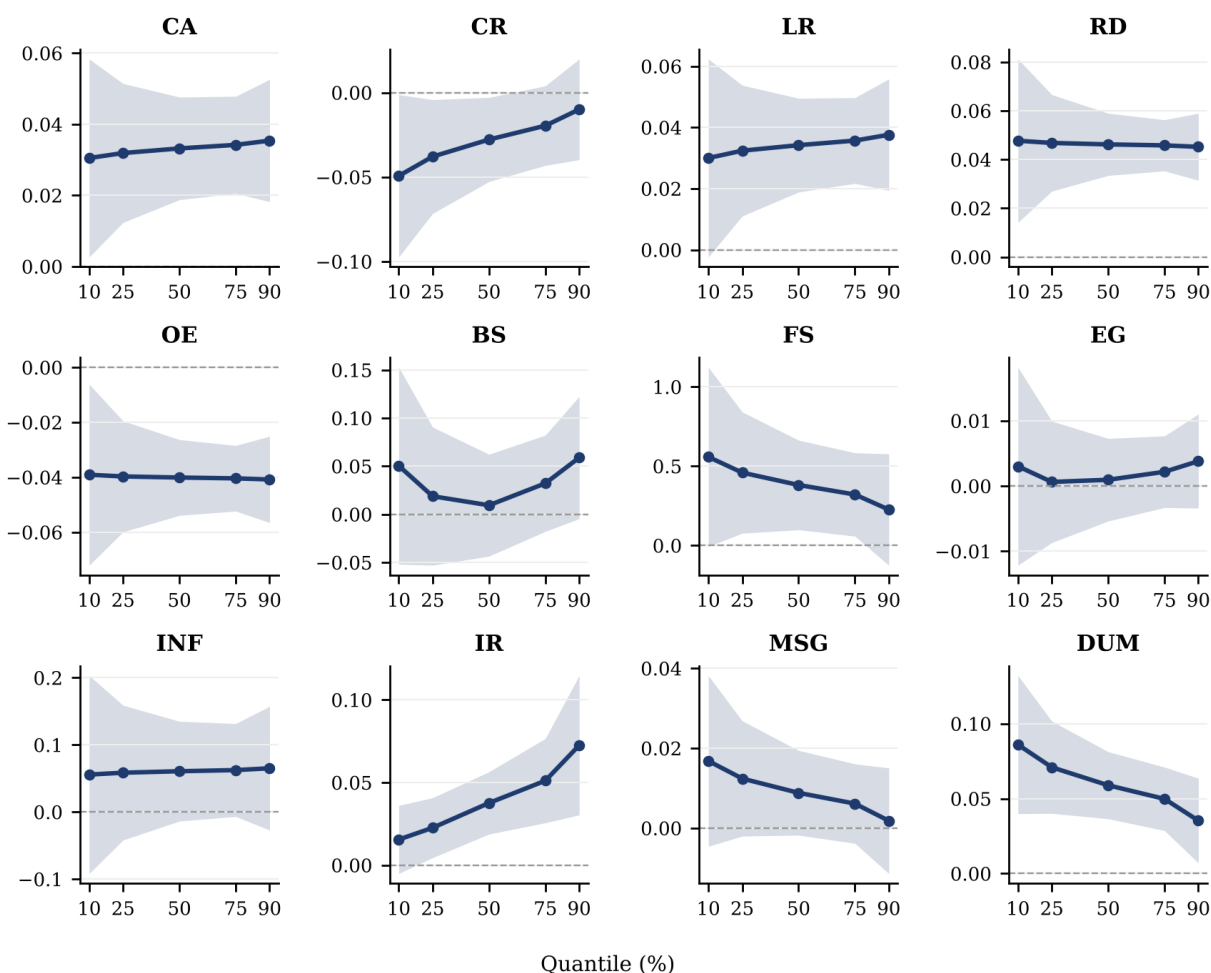
In the ROE model (Table 11), capital is positive and significant at every quantile, and its coefficient rises slightly from 0.031 to 0.035. Credit risk is negative and significant from Q0.10 to Q0.50 only. Revenue diversification and the cost-to-income ratio are stable across quantiles. The interest rate is the main external driver of ROE. It rises from 0.016 (not significant) at Q0.10 to 0.073 at Q0.90. Economic growth has no effect on ROE. Inflation is weakly significant only at Q0.75, and money supply growth only at Q0.25.

Table 11. MMQR estimates, Model 1D (ROE, internal and external factors)

Variable	Location	Scale	Q0.10	Q0.25	Q0.50	Q0.75	Q0.90
CA	0.0329*** (0.00774)	0.00169 (0.00606)	0.0305** (0.0142)	0.0319*** (0.00997)	0.0332*** (0.00736)	0.0342*** (0.00696)	0.0354*** (0.00877)
CR	-0.0299** (0.0134)	-0.0134 (0.0105)	-0.0493** (0.0245)	-0.0379** (0.0172)	-0.0278** (0.0127)	-0.0196 (0.0120)	-0.00995 (0.0152)
LR	0.0339*** (0.00828)	0.00246 (0.00671)	0.0300* (0.0165)	0.0324*** (0.0109)	0.0342*** (0.00781)	0.0357*** (0.00715)	0.0376*** (0.00929)
RD	0.0464*** (0.00779)	0.000868 (0.00740)	0.0477*** (0.0171)	0.0468*** (0.0101)	0.0462*** (0.00651)	0.0458*** (0.00535)	0.0452*** (0.00702)
OE	-0.0399*** (0.00791)	-0.000558 (0.00697)	-0.0391** (0.0168)	-0.0397*** (0.0103)	-0.0401*** (0.00703)	-0.0404*** (0.00609)	-0.0408*** (0.00801)
BS	0.00363 (0.0285)	0.0372* (0.0223)	0.0504 (0.0522)	0.0188 (0.0366)	0.00940 (0.0270)	0.0322 (0.0255)	0.0589* (0.0324)
FS	0.393*** (0.150)	-0.0938 (0.105)	0.558* (0.288)	0.459** (0.195)	0.381*** (0.144)	0.321** (0.134)	0.226 (0.179)
EG	0.000452 (0.00364)	0.00228 (0.00321)	0.00302 (0.00774)	0.000625 (0.00475)	0.000954 (0.00323)	0.00218 (0.00280)	0.00381 (0.00368)
INF	0.0604 (0.0394)	0.00268 (0.0276)	0.0557 (0.0752)	0.0585 (0.0512)	0.0607 (0.0379)	0.0624* (0.0353)	0.0651 (0.0470)
IR	0.0415*** (0.0106)	0.0204** (0.00903)	0.0155 (0.0105)	0.0226** (0.00924)	0.0376*** (0.00961)	0.0511*** (0.0130)	0.0725*** (0.0215)
MSG	0.00938* (0.00564)	0.00424 (0.00395)	0.0168 (0.0109)	0.0124* (0.00736)	0.00882 (0.00541)	0.00612 (0.00507)	0.00183 (0.00674)
DUM	0.0608*** (0.0119)	0.0144* (0.00837)	0.0860*** (0.0235)	0.0709*** (0.0157)	0.0589*** (0.0114)	0.0498*** (0.0108)	0.0353** (0.0144)
Constant	-1.214 (1.515)	3.165*** (1.062)	-6.770** (3.125)	-3.432* (2.030)	-0.793 (1.456)	1.221 (1.408)	4.416** (1.856)
Observations	377	377	377	377	377	377	377

Note. Standard errors in parentheses. *** p < .01, ** p < .05, * p < .10. DUM = 1 for private banks.

Figure 4. MMQR estimates, Model 1D (ROE, internal and external factors)



Note. Solid line: quantile coefficient. Shaded area: 95% confidence band. Source: Authors' calculations.

Endogeneity tests and IVQR results

Table 12 reports the Durbin–Wu–Hausman tests. The null that CA, CR and LR are exogenous is rejected in all four models. The Durbin χ^2 statistics range from 16.97 to 19.74, and the Wu–Hausman F statistics range from 20.18 to 23.61, all with p-values below .001. We therefore re-estimate the four models with IVQR.

Table 12. Durbin–Wu–Hausman endogeneity tests

Model	Endogenous regressors	Durbin χ^2	p	Wu–Hausman F	p
1A	CA, CR, LR	18.62	.000	21.84	.000
1B	CA, CR, LR	16.97	.000	20.18	.000

1C	CA, CR, LR	19.74	.000	23.61	.000
1D	CA, CR, LR	17.83	.000	21.06	.000

Note. Instruments are the second lags of the endogenous regressors. H0: the regressors are exogenous.

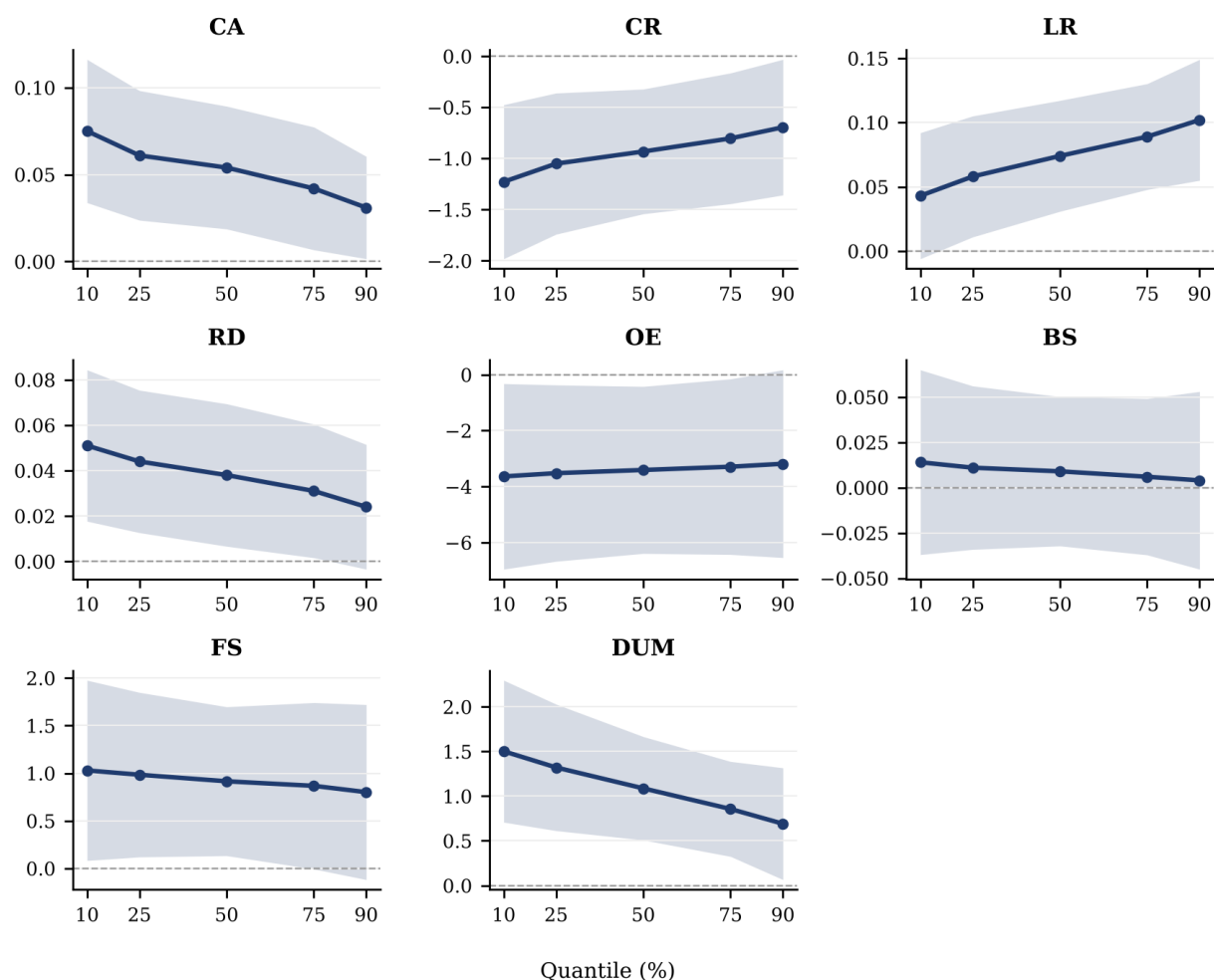
Tables 13 and 14 and Figures 5 and 6 report the IVQR results for the two internal-factor models. The sign of every driver matches the MMQR results, and capital and funding structure are significant at more quantiles under IVQR. Capital is positive and its effect falls from 0.075 at Q0.10 to 0.031 at Q0.90 in the ROA model. Credit risk is negative at every quantile and its effect shrinks from -1.228 to -0.695 . The cost-to-income ratio is negative and stable near -3.3 , funding structure is positive and size is not significant. Two differences stand out. The coefficients on credit risk and liquidity are much larger than in the MMQR results. Part of this gap may come from removing simultaneity bias, but its size means the magnitudes in these two models should be read with caution. The gradients of LR and RD also run the other way: under IVQR the LR effect rises across quantiles and the RD effect falls. The ROE model in Table 14 shows the same pattern.

Table 13. IVQR estimates, Model 1A (ROA, internal factors)

Variable	Q0.10	Q0.25	Q0.50	Q0.75	Q0.90
CA	0.075*** (0.021)	0.061*** (0.019)	0.054*** (0.018)	0.042** (0.018)	0.031** (0.015)
CR	-1.228*** (0.384)	-1.051*** (0.352)	-0.932*** (0.311)	-0.804** (0.326)	-0.695** (0.338)
LR	0.043* (0.025)	0.058** (0.024)	0.074*** (0.022)	0.089*** (0.021)	0.102*** (0.024)
RD	0.051*** (0.017)	0.044*** (0.016)	0.038** (0.016)	0.031** (0.015)	0.024* (0.014)
OE	-3.638** (1.692)	-3.521** (1.608)	-3.407** (1.523)	-3.291** (1.601)	-3.185* (1.712)
BS	0.014 (0.026)	0.011 (0.023)	0.009 (0.021)	0.006 (0.022)	0.004 (0.025)
FS	1.029** (0.483)	0.984** (0.441)	0.915** (0.399)	0.867* (0.446)	0.801* (0.469)
DUM	1.502*** (0.405)	1.321*** (0.361)	1.087*** (0.295)	0.856*** (0.271)	0.691** (0.319)
Constant	10.923*** (3.921)	10.851*** (3.714)	10.776*** (3.562)	10.742*** (3.781)	10.705*** (4.015)

Note. Standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .10$. Instruments are the second lags of CA, CR and LR.

Figure 5. IVQR estimates, Model 1A (ROA, internal factors)



Note. Solid line: quantile coefficient. Shaded area: 95% confidence band. Source: Authors' calculations.

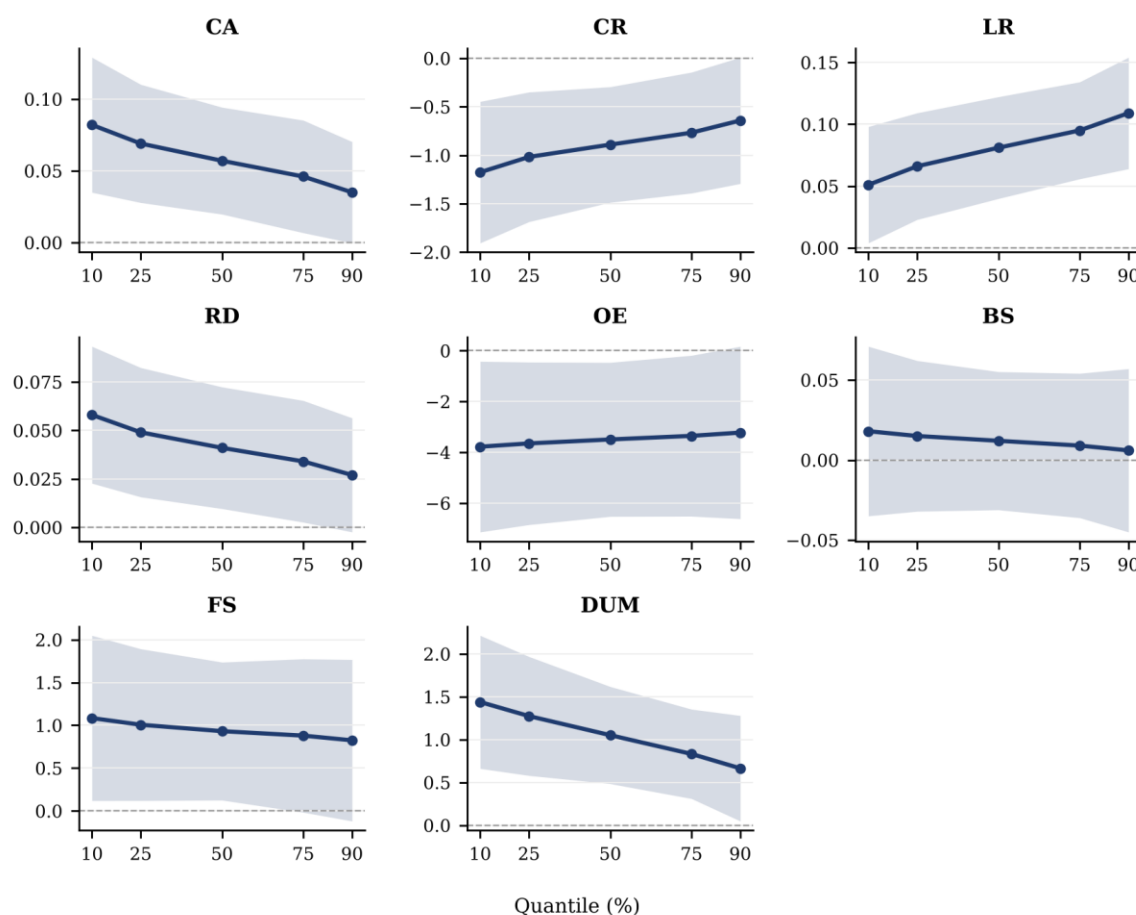
Table 14. IVQR estimates, Model 1B (ROE, internal factors)

Variable	Q0.10	Q0.25	Q0.50	Q0.75	Q0.90
CA	0.082*** (0.024)	0.069*** (0.021)	0.057*** (0.019)	0.046** (0.020)	0.035** (0.018)
CR	-1.176*** (0.372)	-1.018*** (0.341)	-0.891*** (0.304)	-0.768** (0.318)	-0.642** (0.332)
LR	0.051** (0.024)	0.066*** (0.022)	0.081*** (0.021)	0.095*** (0.020)	0.109*** (0.023)
RD	0.058*** (0.018)	0.049*** (0.017)	0.041** (0.016)	0.034** (0.016)	0.027* (0.015)
OE	-3.781**	-3.652**	-3.496**	-3.354**	-3.226*

	(1.714)	(1.633)	(1.547)	(1.615)	(1.731)
BS	0.018	0.015	0.012	0.009	0.006
	(0.027)	(0.024)	(0.022)	(0.023)	(0.026)
FS	1.084***	1.006**	0.931**	0.879*	0.824*
	(0.492)	(0.452)	(0.411)	(0.457)	(0.481)
DUM	1.438***	1.274***	1.051***	0.832***	0.664**
	(0.396)	(0.354)	(0.289)	(0.266)	(0.314)
Constant	11.147***	10.963***	10.801***	10.635***	10.512***
	(3.847)	(3.641)	(3.488)	(3.692)	(3.931)

Note. Standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .10$. Instruments are the second lags of CA, CR and LR.

Figure 6. IVQR estimates, Model 1B (ROE, internal factors)



Note. Solid line: quantile coefficient. Shaded area: 95% confidence band. Source: Authors' calculations.

Tables 15 and 16 and Figures 7 and 8 report the IVQR results for the full models, which are very close to the MMQR results. In the ROA model, credit risk is negative at every quantile and its

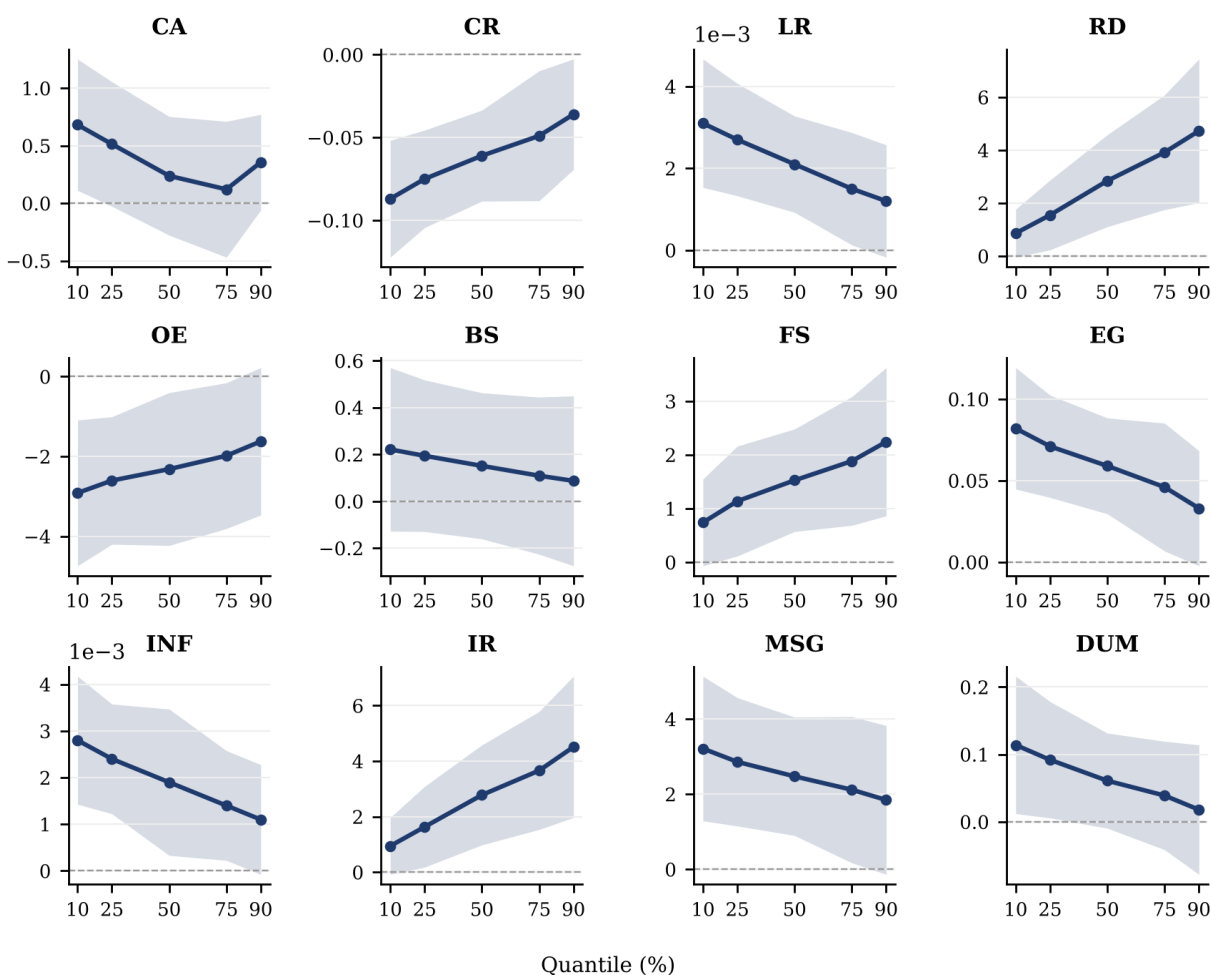
effect shrinks from -0.087 at Q0.10 to -0.036 at Q0.90, against -0.101 and -0.032 under MMQR. The cost-to-income ratio falls in absolute size from -2.914 to -1.623 . Revenue diversification, funding structure and the interest rate rise across quantiles, while economic growth, inflation and money supply growth decline. In the ROE model, capital rises from 0.029 to 0.036 , credit risk weakens from -0.046 to -0.011 and is not significant at Q0.90, and the interest rate rises from 0.018 to 0.075 .

Table 15. IVQR estimates, Model 1C (ROA, internal and external factors)

Variable	Q0.10	Q0.25	Q0.50	Q0.75	Q0.90
CA	0.682** (0.291)	0.514* (0.276)	0.238 (0.263)	0.121 (0.301)	0.356* (0.212)
CR	-0.087*** (0.018)	-0.075*** (0.015)	-0.061*** (0.014)	-0.049** (0.020)	-0.036** (0.017)
LR	0.0031*** (0.0008)	0.0027*** (0.0007)	0.0021*** (0.0006)	0.0015** (0.0007)	0.0012* (0.0007)
RD	0.864* (0.462)	1.552** (0.671)	2.843*** (0.884)	3.917*** (1.104)	4.726*** (1.382)
OE	-2.914*** (0.931)	-2.604*** (0.814)	-2.317** (0.976)	-1.982** (0.931)	-1.623* (0.941)
BS	0.221 (0.178)	0.194 (0.165)	0.151 (0.159)	0.109 (0.171)	0.087 (0.185)
FS	0.741* (0.412)	1.138** (0.522)	1.526*** (0.487)	1.884*** (0.611)	2.243*** (0.704)
EG	0.082*** (0.019)	0.071*** (0.016)	0.059*** (0.015)	0.046** (0.020)	0.033* (0.018)
INF	0.0028*** (0.0007)	0.0024*** (0.0006)	0.0019** (0.0008)	0.0014** (0.0006)	0.0011* (0.0006)
IR	0.945* (0.522)	1.634** (0.741)	2.782*** (0.918)	3.661*** (1.083)	4.512*** (1.297)
MSG	3.214*** (0.982)	2.861*** (0.871)	2.475*** (0.804)	2.119** (0.993)	1.846* (1.011)
DUM	0.114** (0.052)	0.092** (0.044)	0.061* (0.036)	0.039 (0.041)	0.018 (0.049)
Constant	-2.846 (2.431)	-1.574 (2.018)	0.814 (1.902)	2.136 (2.221)	3.987* (2.354)

Note. Standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .10$. Instruments are the second lags of CA, CR and LR.

Figure 7. IVQR estimates, Model 1C (ROA, internal and external factors)



Note. Solid line: quantile coefficient. Shaded area: 95% confidence band. Source: Authors' calculations.

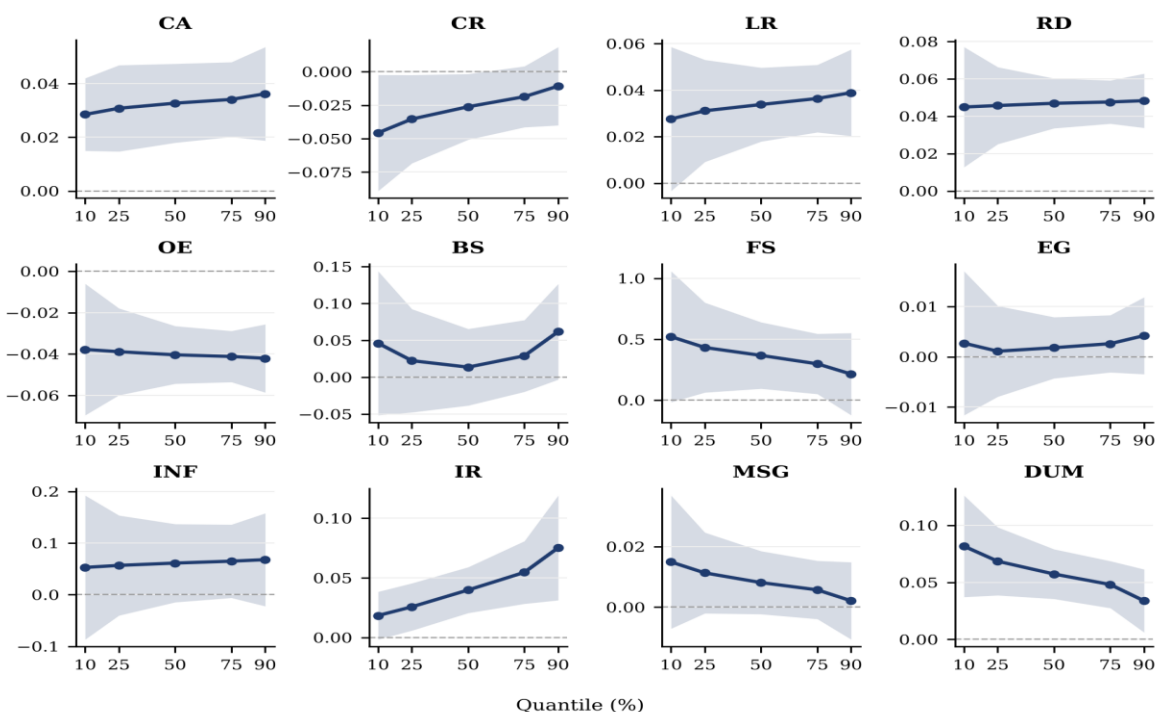
Table 16. IVQR estimates, Model 1D (ROE, internal and external factors)

Variable	Q0.10	Q0.25	Q0.50	Q0.75	Q0.90
CA	0.0285*** (0.0069)	0.0308*** (0.0082)	0.0327*** (0.0075)	0.0341*** (0.0071)	0.0362*** (0.0089)
CR	-0.0457** (0.0221)	-0.0354** (0.0168)	-0.0262** (0.0125)	-0.0187* (0.0116)	-0.0108 (0.0149)
LR	0.0276* (0.0158)	0.0311*** (0.0112)	0.0338*** (0.0081)	0.0364*** (0.0074)	0.0389*** (0.0095)
RD	0.0449*** (0.0164)	0.0457*** (0.0105)	0.0469*** (0.0068)	0.0476*** (0.0059)	0.0483*** (0.0074)
OE	-0.0378**	-0.0389***	-0.0404***	-0.0412***	-0.0421***

	(0.0162)	(0.0107)	(0.0071)	(0.0063)	(0.0084)
BS	0.0461	0.0224	0.0136	0.0289	0.0617*
	(0.0498)	(0.0357)	(0.0265)	(0.0248)	(0.0331)
FS	0.521*	0.432**	0.367***	0.298**	0.214
	(0.274)	(0.188)	(0.139)	(0.126)	(0.172)
EG	0.0027	0.0011	0.0018	0.0026	0.0042
	(0.0073)	(0.0046)	(0.0031)	(0.0029)	(0.0039)
INF	0.0528	0.0567	0.0612	0.0649*	0.0678
	(0.0711)	(0.0494)	(0.0386)	(0.0362)	(0.0459)
IR	0.0184*	0.0257**	0.0398***	0.0546***	0.0752***
	(0.0102)	(0.0101)	(0.0098)	(0.0134)	(0.0224)
MSG	0.0149	0.0113*	0.0081	0.0057	0.0021
	(0.0112)	(0.0068)	(0.0053)	(0.0049)	(0.0065)
DUM	0.0817***	0.0685***	0.0573***	0.0481***	0.0338**
	(0.0227)	(0.0152)	(0.0111)	(0.0105)	(0.0141)
Constant	-5.842**	-3.121*	-0.962	1.354	4.627**
	(2.914)	(1.986)	(1.482)	(1.593)	(1.921)

Note. Standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .10$. Instruments are the second lags of CA, CR and LR.

Figure 8. IVQR estimates, Model 1D (ROE, internal and external factors)



Note. Solid line: quantile coefficient. Shaded area: 95% confidence band. Source: Authors' calculations.

Table 17 sums up the comparison. The sign of every driver is the same under both estimators in all four models. In the full models the gradients also match. We conclude that the main MMQR findings are not driven by reverse causality.

Table 17. Summary comparison of MMQR and IVQR estimates

Variable	MMQR sign	MMQR gradient (Q0.10 → Q0.90)	IVQR sign	IVQR gradient (Q0.10 → Q0.90)	Verdict
CA	+	Falls (ROA); flat or rising (full ROE)	+	Falls (internal); rises (full ROE)	Sign confirmed
CR	–	Effect shrinks	–	Effect shrinks	Confirmed
LR	+	Falls (ROA); rises (full ROE)	+	Rises (internal, full ROE); falls (full ROA)	Sign confirmed
RD	+	Rises (flat in full ROE)	+	Falls (internal); rises (full)	Sign confirmed
OE	–	Effect shrinks (ROA)	–	Effect shrinks (ROA)	Confirmed
BS	ns / +	Weak	ns / +	Weak	Confirmed
FS	+	Rises (ROA)	+	Falls (internal); rises (full ROA)	Sign confirmed
EG	+	Falls (ROA)	+	Falls (ROA)	Confirmed
INF	+	Falls (ROA)	+	Falls (ROA)	Confirmed
IR	+	Rises	+	Rises	Confirmed
MSG	+	Falls	+	Falls	Confirmed
DUM	+	Falls	+	Falls	Confirmed

Note. “Gradient” is the direction in which the coefficient moves from the 10th to the 90th percentile. ns = mostly not significant. Internal = Models 1A and 1B; full = Models 1C and 1D.

Discussion

Credit risk

Credit risk is the most consistent driver in our results. It reduces profit in all four models, at nearly every quantile and under both estimators, which supports H1 and fits the bad-management account of Berger and DeYoung (1997). The mechanics are familiar. Provisions for bad loans come straight out of current income, impaired loans stop paying interest while still tying up funding and capital, and a record of poor loans raises a bank’s cost of funds and diverts management from new business (Petria et al., 2015; Saleh & Abu Afifa, 2020).

What the quantile estimates add is a sense of who bears the cost. In the ROA models, a unit increase in credit risk does three to four times as much damage at the 10th percentile as at the 90th. A bank with thin earnings has little room before it makes a loss, whereas a highly profitable bank can absorb the same shock from its ordinary margin. The direction of the effect agrees with Noman et al. (2015), Petria et al. (2015), Ekinici and Poyraz (2019), Saleh and Abu Afifa (2020) and, for

Pakistan, Haris et al. (2024). Boahene et al. (2012) are the exception, and their positive estimate for Ghana may reflect lending rates high enough to cover the extra risk.

Cost efficiency

The cost-to-income ratio also lowers profit in every specification, again in line with H1. Part of this is arithmetic, since every rupee spent on operations is a rupee not kept as profit. Part of it is managerial. Cost overruns tend to accompany weak lending practices (Berger & DeYoung, 1997), and inefficient banks often lack the scale or technology to compete on price (Dietrich & Wanzenried, 2011). In the ROA models the penalty is heaviest at the bottom, where an extra unit of cost is more likely to tip a bank into loss. Dietrich and Wanzenried (2011), Petria et al. (2015) and Al Zaidanin and Al Zaidanin (2021) report the same sign. Read alongside the credit risk results, this suggests that what divides Pakistan's weak banks from its strong ones is, above all, the quality of their loan books and their control of costs.

Revenue diversification and funding structure

Diversification raises profit, consistent with H2. Fee and commission income can smooth earnings, needs less capital than lending and lets a bank sell more to clients it already has (Chiorazzo et al., 2008; Elsas, Hackethal, & Holzhäuser, 2010; Sanya & Wolfe, 2011). The quantile pattern is telling. In Model 1C the effect is insignificant below the median but large at the 75th and 90th percentiles. Running a fee business takes systems, staff and a client base that strong banks have already built, and a weak bank that tries to grow fee income without them gains little. That may be one reason the literature is divided, with Chiorazzo et al. (2008), Sanya and Wolfe (2011) and Meslier, Tacneng, and Tarazi (2014) finding gains and Stiroh and Rumble (2006) finding that they vanish.

Deposit funding shows a similar gradient. Customer deposits are cheaper and more stable than market funding, so they widen the margin and lower rollover risk (Demirgüç-Kunt & Huizinga, 1999; Dietrich & Wanzenried, 2011). In the ROA models the effect grows toward the top. A low-cost deposit base raises profit most when the bank can also lend it out well. For a weak bank, cheap funding alone cannot make up for bad loans and high costs. Our results are in line with Demirgüç-Kunt and Huizinga (1999) and Saona (2016), and differ from Ha (2020), who found a negative effect when deposit costs rose.

Capital, liquidity and size

The results for these three drivers partly support H3. Capital (equity over assets) has a weak and uneven effect on ROA but a positive and significant effect on ROE in the full model. Two reasons can explain the positive effect. First, a higher capital ratio lowers the perceived risk of failure, so depositors and lenders accept a lower return and the bank keeps a wider margin (Berger, 1995). Second, a well-capitalised bank can absorb losses without cutting its lending, so it keeps earning in difficult years when thinly capitalised banks must shrink (Athanasoglou et al., 2008). In Pakistan's unstable setting, a strong capital position also helps a bank keep the confidence of

depositors and hold on to cheap deposits. The CA results should still be read with care because CA is highly correlated with LR and RD.

The loans-to-deposits ratio has a small positive effect on profit. Because a higher ratio means the bank lends out more of its deposits, the positive sign means that banks earn more when they lend more. A large share of Pakistani bank assets is held in government securities (SBP, 2025), so a bank that lends more of its deposits to the private sector may earn a higher margin. In the MMQR results the gain is largest for low-profit banks. Our results match Bourke (1989) and Haris et al. (2024), who also found a positive liquidity risk effect for Pakistan, and differ from Molyneux and Thornton (1992) and Arif and Anees (2012), who found a negative one.

Size has little effect. It matters only at the lower quantiles of the full ROA model. Larger banks can spread fixed costs for technology, compliance and branches over a bigger base, and they may have more market power and cheaper wholesale funding (Mester, 2010; Goddard et al., 2004). Beyond a point, however, the gains from scale fade as large banks become harder to manage. This would explain why size gives some protection to weak banks but adds little for banks that are already highly profitable. Athanasoglou et al. (2008) also found size insignificant, and Bortoluzzo et al. (2024) found a negative size effect.

The economic environment

The macroeconomic results support H4, and the way they change across quantiles is informative. Growth and monetary expansion do most for low-profit banks. In good years demand for loans rises, defaults fall and liquidity is easier to come by (Athanasoglou et al., 2008; Bikker & Hu, 2002), and it is the weaker banks that lean on this outside support, while stronger ones rely more on their own franchise. Monetary expansion works in a similar way. Faster money growth adds to the funds banks can lend and eases their funding costs (Kosmidou, 2008), which matters most for weak banks that find it harder to raise funds on their own. A positive growth effect is also reported by Yuan et al. (2022), Luft and Omarkhil (2018) and Sultan et al. (2020), whereas De Leon (2020) and Islam (2023) find the reverse.

Interest rates show the opposite gradient, with effects on ROA and ROE that rise sharply toward the top. Loans usually reprice faster than deposits, and Pakistani banks hold large portfolios of government securities whose yields follow the policy rate (Borio et al., 2017; Saunders & Schumacher, 2000). A bank with plenty of cheap deposits and good asset and liability management turns a rate rise into a wider margin, while a weak bank keeps little of the gain. Kanwal and Nadeem (2013) found a positive real interest rate effect for Pakistan and Saeed (2014) one for the UK, but Luft and Omarkhil (2018) found none.

The positive inflation coefficient in the ROA models has three possible explanations. First, when inflation is expected, banks raise their lending rates ahead of their funding costs, which widens the margin (Perry, 1992). Second, inflation in Pakistan has moved closely with nominal interest rates (the two are correlated at 0.861 in our data), and higher rates raise interest income on loans and government securities (Demirgüç-Kunt & Huizinga, 1999). Third, inflation lowers the real value of deposits and other fixed-rate liabilities, which transfers value to the bank (Bourke, 1989). De

Leon (2020) and Luft and Omarkhil (2018) report the same sign, and Kanwal and Nadeem (2013) and Sultan et al. (2020) a negative one. Since inflation is not stationary in our sample, we put little weight on the size of the estimate.

Ownership

In most models private banks earn more than public ones. Private owners have sharper incentives to pursue profit and monitor managers, while state banks often serve policy aims and carry inherited problem loans (La Porta et al., 2002; Micco et al., 2007; Cornett, Guo, Khaksari, & Tehranian, 2010). The premium is widest at the bottom of the ROE distribution and less than half as large at the 90th percentile. Among the most profitable banks, ownership seems to matter less, possibly because the best public banks now operate on commercial lines. Among the weakest, private ownership goes with markedly better outcomes. Altunbas, Evans, and Molyneux (2001), by contrast, found little difference by ownership among German banks.

Conclusion

We set out to explain what drives the profitability of 29 Pakistani banks over 2011–2023 and whether the answer differs between weak and strong banks. It does. Under both MMQR and IVQR, credit risk and high costs hurt the least profitable banks most, while diversified income, deposit funding and higher interest rates help the most profitable banks most. Growth and money supply expansion favour weaker banks, and the private-bank advantage narrows at the top.

Several practical points follow. The SBP could direct asset-quality reviews and cost-reduction plans at banks in the lower tail, where these two drivers do the most harm, since a rule applied identically to every bank misses that concentration. Weak banks may get less from expanding fee business than strong ones and would probably do better to repair loan quality and costs first. All banks stand to gain from stronger asset and liability management, both to capture rate rises and to cope with rate cuts. Public banks in the lower tail would also benefit from governance reform and the resolution of legacy problem loans.

The study has limitations. Thirteen years and 29 banks leave few observations in the extreme quantiles. Profitability is measured only with accounting ratios, and several internal drivers are correlated with one another. Market-based measures, frontier efficiency scores, a comparison of Islamic and conventional banks and a longer panel are natural next steps.

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