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Financial Uncertainty and Bank Performance in Pakistan's Dual Banking System: Evidence from System GMM and Machine Learning Models

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ABSTRACT

Purpose: This article examines how financial uncertainty affects the profitability and stability of banks in Pakistan's dual banking system. It focuses on oil price volatility, exchange-rate volatility and gold-price/market uncertainty, and compares Islamic and conventional banks through an integrated econometric and machine-learning design.

Design/methodology/approach: The study uses annual bank-level panel data for 21 Pakistani banks over 2010-2024. Bank performance is measured using Return on Assets (ROA), Return on Equity (ROE) and Z-Score. The empirical design combines one-step and two-step System GMM for dynamic explanatory inference with linear regression, Ridge, Lasso, Random Forest, XGBoost, SVR, ANN, LSTM and GRU models for predictive comparison and variable-ranking evidence.

Findings: The empirical results indicate that Islamic banks show significantly higher ROA, lower NPLs and stronger liquidity than conventional banks, while differences in ROE and Z-Score are not statistically decisive. System GMM confirms persistence in ROA and Z-Score and identifies credit risk as the most damaging internal mechanism. Linear, Ridge, Lasso, Random Forest and XGBoost results consistently show that NPL, CIR, CAR, liquidity and bank size dominate oil, exchange-rate and gold-price variables in explaining and predicting bank outcomes. Recurrent deep-learning models provide limited additional predictive value because of the small annual panel and weak sequential depth.

Originality/value: The study contributes an integrated explanatory-predictive framework for Pakistan's dual banking system by combining dynamic panel estimation with machine-learning and deep-learning evidence. The main originality is not the use of algorithms alone, but the empirical triangulation showing that external financial uncertainty matters through banking resilience channels, while credit risk, operating efficiency, capital adequacy, liquidity and bank size dominate the predictive structure of bank performance.

Keywords: Financial Uncertainty; Oil Price Volatility; Islamic Banking; Conventional Banking; Bank Performance; System GMM; Machine Learning; Deep Learning; Pakistan.

JEL classification: G21; G32; C23; C45; E44.

1. Introduction

Financial uncertainty has become a central concern in banking research because banks are highly exposed to changes in commodity markets, exchange rates, market confidence and borrower behaviour. Banks transform deposits into credit, manage liquidity and allocate capital; therefore, shocks to macroeconomic and financial conditions can alter profitability, credit quality and overall stability. The banking sector is particularly sensitive in developing economies, where external imbalances, exchange-rate pressure, inflation and fiscal constraints can move quickly into the balance sheets of firms and households. This makes the study of financial uncertainty not only a macroeconomic question but also a banking-performance question (Naifar et al., 2020; Gao et al., 2022; Lee et al., 2022).

Oil price volatility is one of the most important forms of external uncertainty. Oil is a production input, a determinant of transport costs, an inflationary force and a signal of global demand conditions. When oil prices become uncertain, firms face cost unpredictability, borrowers may experience repayment pressure and banks may confront higher credit and liquidity risks. Studies have shown that oil shocks affect exchange rates, sovereign risk, corporate investment and bank stability through multiple transmission channels rather than through a single linear route (Basher et al., 2016; Wegener et al., 2016; Maghyereh and Abdoh, 2020; Śmiech et al., 2021; Kilian and Zhou, 2022).

Exchange-rate volatility provides a second channel through which uncertainty affects banks. In import-dependent economies, depreciation increases import costs, worsens inflationary pressure and may reduce the debt-servicing capacity of borrowers whose input costs or foreign-currency liabilities increase. Exchange-rate movements also influence investor confidence, foreign inflows and the value of external obligations. Oil prices and exchange rates are jointly connected because oil-related pressures affect trade balances and foreign-currency demand, while currency depreciation changes the domestic cost of oil imports (Castro & Jiménez-Rodríguez, 2020; Hameed et al., 2021; Donkor et al., 2022).

Pakistan is a useful context for this investigation because it operates a dual banking system in which Islamic and conventional bank's function side by side. Conventional banks are mainly organized around interest-based intermediation, whereas Islamic banks are structured around Shariah-compliant financing, asset-backed contracts and risk-sharing principles. These differences suggest that financial uncertainty may not affect both systems in exactly the same way. Islamic banks may be less exposed to speculative financial cycles, but they remain linked to the real sector and therefore cannot be isolated from oil price shocks, exchange-rate volatility and credit risk (Mirjalili, 2016; Ghouse et al., 2022; Bhuiyan et al., 2023; Tanin et al., 2025).

Despite growing research on financial uncertainty and banking stability, three gaps remain important. First, much of the existing literature examines single sources of uncertainty, while banks are usually exposed to several uncertainty channels at the same time. Oil price volatility, exchange-rate volatility and market uncertainty may jointly influence bank profitability and stability through credit, liquidity and capital channels. Second, the comparative response of Islamic and conventional banks to financial uncertainty remains insufficiently explored in developing dual banking systems such as Pakistan. Third, most studies rely either on econometric explanation or predictive modelling, whereas fewer studies combine dynamic panel estimation with machine-learning evidence in the same empirical framework.

This study addresses these gaps by examining the effect of financial uncertainty on bank performance in Pakistan's dual banking system. The analysis uses panel data for 21 banks

from 2010 to 2024 and evaluates bank performance through return on assets, return on equity and Z-Score. Financial uncertainty is represented through oil price volatility, exchange-rate volatility and market-related uncertainty, while bank-specific factors include credit risk, liquidity, capital adequacy, operating efficiency and bank size. The study applies System Generalized Method of Moments (System GMM) to address persistence, endogeneity and unobserved bank heterogeneity. It also uses machine-learning and deep-learning models to examine predictive performance and variable importance.

The novelty of the study is not simply the use of several models. Many recent studies now apply machine learning in finance. The contribution lies in combining three elements in a single Pakistan-specific framework: financial uncertainty from oil, exchange-rate and market-related channels; comparative performance of Islamic and conventional banks; and explanatory econometrics with predictive and variable-ranking machine-learning evidence. This design allows the study to examine not only whether uncertainty matters, but also whether internal banking factors dominate external uncertainty after dynamic persistence and bank-specific characteristics are controlled.

The empirical contribution is also important. Although financial uncertainty is theoretically relevant, the evidence indicates that the strongest and most consistent determinants of bank performance are credit risk, operating efficiency, capital adequacy, liquidity and bank size. In the descriptive results, Islamic banks exhibit stronger average profitability and liquidity than conventional banks. In the dynamic and predictive results, non-performing loans and cost efficiency emerge as key determinants of profitability and stability. This suggests that uncertainty does not disappear from the model; rather, its effects are filtered through bank balance sheets and risk-management capacity.

The study makes three main contributions. First, it provides Pakistan-specific evidence from a dual banking system in which Islamic and conventional banks operate under the same macroeconomic environment but differ in liquidity structure, asset composition, financing principles and credit-risk exposure. Second, the study combines dynamic panel estimation with modern predictive modelling. System GMM is used to address persistence, endogeneity and unobserved heterogeneity, while machine-learning models are used to evaluate the predictive importance of bank-specific and macro-financial variables. Third, the study provides a careful interpretation of deep-learning results. Rather than assuming that recurrent neural networks are automatically superior, the findings indicate that LSTM and GRU models are not always the most suitable choice for relatively small annual banking panels. This clarifies the conditions under which machine learning may be more informative than deep learning.

Overall, the study contributes through empirical triangulation. A consistent message emerges from descriptive statistics, dynamic panel estimation, regularized regression, Random Forest and XGBoost results: internal banking variables explain bank performance more consistently than broad macro-financial uncertainty variables. This does not imply that oil prices, exchange rates or gold prices are irrelevant. Rather, it suggests that their effects on the banking sector are filtered through internal risk-management and balance-sheet channels. For policymakers, regulators and bank managers, this distinction is important because it shifts the practical focus from attempting to forecast every external shock toward strengthening the internal buffers that determine how banks absorb uncertainty.

The remainder of the article is organized as follows. Section 2 reviews the relevant literature and develops the research context. Section 3 describes the data, variables and methodology. Section 4 presents the empirical results. Section 5 discusses the findings in relation to banking

theory, risk management and methodological contribution. Section 6 concludes the article and outlines limitations and future research directions.

2. Literature review and research positioning

The literature on financial uncertainty and banking performance can be organized around five related streams. The first stream examines the macro-financial effects of oil price shocks. Basher et al. (2016) shown that oil shocks affect exchange rates in a nonlinear and regime-dependent way. Wegener et al. (2016) linked oil price fluctuations to sovereign credit risk in oil-producing countries. Naifar et al. (2020) also demonstrated that oil-price returns and financial uncertainty have nonlinear effects on sovereign credit default risk. These studies establish that oil price uncertainty is not a narrow commodity-market issue but an important source of financial stress.

The second stream links oil price uncertainty with firm behaviour and borrower risk. Gupta and Krishnamurti (2018) showed that rising oil prices can reduce corporate risk-taking by increasing costs and cash-flow uncertainty. Maghyreh and Abdoh (2020) found asymmetric effects of oil price uncertainty on corporate investment, with rising-price uncertainty producing stronger negative effects. Song and Yang (2022) further showed that oil price uncertainty can reduce firm performance and that governance conditions alter this relationship. These findings are relevant to banks because firm-level pressure affects loan quality and repayment capacity.

The third stream focuses on exchange rates and financial markets. Castro and Jiménez-Rodríguez (2020) argued that the oil-price/exchange-rate relationship varies over time and depends on macroeconomic conditions. Hameed et al. (2021) showed that oil price volatility transmits to foreign-exchange markets. Kilian and Zhou (2022) emphasized the joint determination of oil prices, exchange rates and interest rates. For Pakistan, where oil imports and currency pressure are recurrent policy concerns, this literature implies that financial uncertainty should be studied as an interconnected system rather than as isolated variables. The fourth stream compares Islamic and conventional banking. Islamic banks differ from conventional banks in contract structure, balance-sheet composition and Shariah-based constraints. Mirjalili (2016) argued that Islamic banks may show resilience during crises because of their asset-backed orientation. Dibooglu et al. (2022) found that Islamic and conventional banks can behave differently under crisis and non-crisis regimes. Ghouse et al. (2022) showed that recovery patterns during COVID-19 differ between Islamic and conventional banks. Tanin et al. (2025) provided more recent evidence on resilience under oil price uncertainty. These studies support the decision to examine the Islamic banking interaction in the current article.

The fifth stream concerns methodology. Dynamic panel models are widely used in banking because current bank performance depends on past performance, and because bank-specific heterogeneity and endogeneity are major empirical concerns. System GMM is appropriate when lagged dependent variables appear in the model and when explanatory variables may be correlated with unobserved bank-specific effects (Arellano & Bond, 1991; Blundell & Bond, 1998; Hidayat & Sakti, 2020). Machine learning, by contrast, is useful when the goal is prediction, feature ranking and nonlinear pattern detection. Random Forest, XGBoost, SVR, ANN, LSTM and GRU models are increasingly used for financial risk and banking-performance prediction (Koçoğlu & Ersöz, 2022; Guerra et al., 2022; Máté et al., 2023; Kassim et al., 2024). However, a gap remains in Pakistan-specific research. Existing studies often examine uncertainty, Islamic banking or machine learning separately. This study addressed this gap by combining financial uncertainty, dual banking comparison, System GMM and predictive

models in one design. The study strengthens this contribution by linking the empirical results to banking resilience, risk transmission and model-based evidence in Pakistan's dual banking system. The emphasis is not on claiming that all uncertainty variables directly determine every performance outcome. Instead, the study tests whether uncertainty variables remain important after bank-specific controls are introduced and whether predictive models rank external uncertainty or internal risk variables as more important.

Based on the literature, the article expects financial uncertainty to influence bank performance, but it also expects internal banking variables to mediate or dominate the practical impact of uncertainty. Oil price volatility and exchange-rate volatility may shape profitability and stability through borrower conditions, liquidity demand and macroeconomic pressure. Yet credit risk, capital adequacy, cost efficiency and bank size directly describe the banking mechanism through which those pressures enter the financial system. This is why the article treats internal bank variables not as routine controls but as central empirical mechanisms.

The research positioning of this study is built around three guiding arguments. First, financial uncertainty is expected to influence bank performance in Pakistan's dual banking system through profitability, credit-risk and stability channels. Second, Islamic and conventional banks may differ in profitability and liquidity because of differences in financing structure, asset composition and risk-sharing principles, although their overall stability may not differ significantly. Third, machine-learning models are useful not only for prediction but also for identifying the relative empirical importance of bank-specific and macro-financial variables. The empirical results support the importance of this third argument, as the predictive models repeatedly identify internal bank characteristics, particularly credit risk, operating efficiency, liquidity, capital adequacy and bank size, as the strongest drivers of bank performance.

3. Data, variables and empirical methodology

The empirical analysis uses annual bank-level panel data for 21 Pakistani banks over the period 2010-2024. The unit of analysis is the bank-year. The banking sample covers Islamic and conventional banks, allowing the article to compare performance differences and to include an Islamic-bank interaction term in selected specifications. The dependent variables are ROA, ROE and Z-Score. ROA captures profitability relative to assets, ROE captures shareholder return, and Z-Score captures financial soundness or distance from distress. The explanatory variables include oil price volatility, exchange-rate volatility, gold price volatility or market uncertainty, non-performing loans, liquidity, capital adequacy, cost-to-income ratio, bank size and macroeconomic controls.

The empirical design is hybrid. The first layer is explanatory and uses System GMM. This layer tests dynamic persistence and controls for endogeneity, bank-specific heterogeneity and lagged performance. The second layer is predictive and uses machine-learning/deep-learning methods to test whether the same variable set can forecast profitability and stability outcomes and to determine which variables rank highest in predictive importance. This two-layer design is appropriate because banking research requires both theoretical explanation and predictive assessment. A statistically significant coefficient tells one story, while a variable-importance ranking tells another. The article interprets these together rather than treating them as competing methods.

The three core performance indicators are measured as follows. ROA is calculated as net income divided by total assets. ROE is calculated as net income divided by shareholders' equity. Z-Score is calculated as a stability proxy using profitability, equity/assets and the

standard deviation of ROA. In this context, a higher Z-Score indicates greater financial stability and a greater distance from insolvency risk.

3.1 Measurement equations

$$\text{ROA}_{it} = \text{Net income}_{it} / \text{Total assets}_{it} \quad (1)$$

$$\text{ROE}_{it} = \text{Net income}_{it} / \text{Total equity}_{it} \quad (2)$$

$$\text{ZScore}_{it} = (\text{ROA}_{it} + \text{ETA}_{it}) / \text{SD}(\text{ROA}_i) \quad (3)$$

$$Y_{it} = \alpha Y_{i,t-1} + \beta_1 \text{OP}_t + \beta_2 \text{GP}_t + \beta_3 \text{ER}_t + \beta_4 \text{MV}_t + \gamma X_{it} + \mu_i + \epsilon_{it} \quad (4)$$

$$\text{RMSE} = \sqrt{(1/n) \sum_i (y_i - \hat{y}_i)^2} \quad (5)$$

$$\text{MAE} = (1/n) \sum_i |y_i - \hat{y}_i| \quad (6)$$

$$R^2 = 1 - [\sum_i (y_i - \hat{y}_i)^2 / \sum_i (y_i - \bar{y})^2] \quad (7)$$

In Equation (4), Y represents ROA, ROE or Z-Score; the lagged dependent variable captures dynamic persistence; OP, GP, ER and MV represent oil, gold, exchange-rate and market uncertainty variables; X represents bank-specific and macroeconomic controls; μ_i is the unobserved bank-specific effect; and ϵ_{it} is the idiosyncratic error term. The GMM framework is suitable because bank performance is likely to be persistent and because some explanatory variables may be endogenous or predetermined rather than strictly exogenous. The predictive layer applies linear regression, Ridge regression, Lasso regression, Random Forest, Gradient Boosting/XGBoost, SVR, ANN, LSTM and GRU models. Linear regression provides a baseline. Ridge and Lasso address multicollinearity and variable selection. Random Forest and XGBoost identify nonlinear relationships and variable importance. SVR provides a kernel-based prediction benchmark. ANN, LSTM and GRU provide neural-network and recurrent-neural-network benchmarks. The thesis results show that recurrent deep-learning models are not automatically superior in this application, which is an important practical finding for banking researchers using relatively small annual panels.

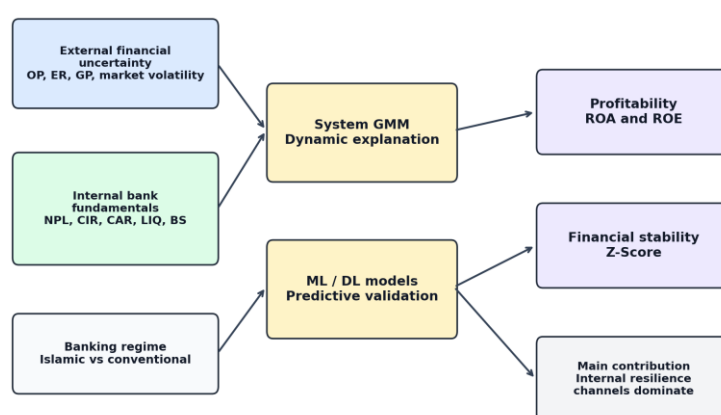
Model performance is evaluated using RMSE, MAE and R-squared where reported. Lower RMSE and MAE indicate lower prediction error. A higher R-squared indicates better explanatory power, whereas a negative R-squared indicates that the model performs worse than a mean benchmark. The article therefore does not interpret small RMSE or MAE alone as proof of good performance; it reads prediction error together with R-squared and the stability of training/validation curves. This is particularly important in the LSTM and GRU results, where apparently small errors occur alongside negative R-squared values in some cases.

3.2 Variables and operational definitions

Variable	Meaning	Measurement in the thesis	Role in article
ROA	Return on assets	Net income divided by total assets	Profitability outcome
ROE	Return on equity	Net income divided by shareholders' equity	Profitability outcome
Z-Score	Bank stability	(ROA + ETA)/SD(ROA)	Stability outcome
OP	Oil price	Oil-price level/uncertainty proxy used in thesis models	Financial-uncertainty predictor

GP	Gold price	Gold-price level/uncertainty proxy	Financial-market/safe-haven predictor
ER	Exchange rate	Exchange-rate level/volatility proxy	Financial-uncertainty predictor
MV.OP, MV.GP, MV.ER	Moderating/market-volatility interactions	Interactions or uncertainty-related terms reported in thesis models	Uncertainty transmission terms
NPL	Non-performing loans	Non-performing loans to total loans	Credit-risk control
LIQ	Liquidity	Liquid assets to total assets	Liquidity/resilience control
CAR	Capital adequacy	Regulatory capital to risk-weighted assets	Capital-strength control
CIR	Cost-to-income ratio	Operating expenses divided by operating income	Efficiency control
BS	Bank size	Natural log of total assets	Scale control
INF, GDP, GRW, FDI, INT, IDEBT, EDEBT	Macroeconomic controls	Inflation, output, growth, foreign investment, interest and debt indicators	Macro controls

Note: ROA, ROE and Z-Score are the dependent variables; NPL, LIQ, CAR, CIR and BS are bank-level controls; OP, GP, ER and market-volatility terms capture financial uncertainty.



Notes: OP = oil price; ER = exchange rate; GP = gold price; NPL = non-performing loans; CIR = cost-to-income ratio; CAR = capital adequacy; LIQ = liquidity; BS = bank size.

Figure 1. Integrated explanatory-predictive framework for financial uncertainty, bank resilience mechanisms and performance outcomes.

4. Empirical results

4.1 Descriptive evidence from the study data

The empirical results begin with descriptive evidence in Table 2. The results show that Islamic banks have a higher mean ROA than conventional banks, with an average ROA of 1.148 compared with 0.786 for conventional banks. The reported mean-difference test indicates

that this difference is statistically significant. This finding suggests that, during the study period, Islamic banks in the sample used their asset base more profitably than conventional banks. However, this result does not imply that Islamic banks are universally superior. Rather, it shows that, within this sample and period, Islamic banks converted assets into income more effectively.

The average Z-Score is also slightly higher for Islamic banks than for conventional banks, with mean values of 2.200 and 2.061, respectively. However, the difference is not statistically significant. This distinction is important because stronger profitability and liquidity do not automatically translate into a statistically higher stability score. Bank stability depends not only on profitability but also on credit risk, capital strength, cost efficiency, liquidity and the broader balance-sheet structure. The descriptive evidence therefore suggests that bank type alone does not fully explain stability differences in Pakistan's banking sector.

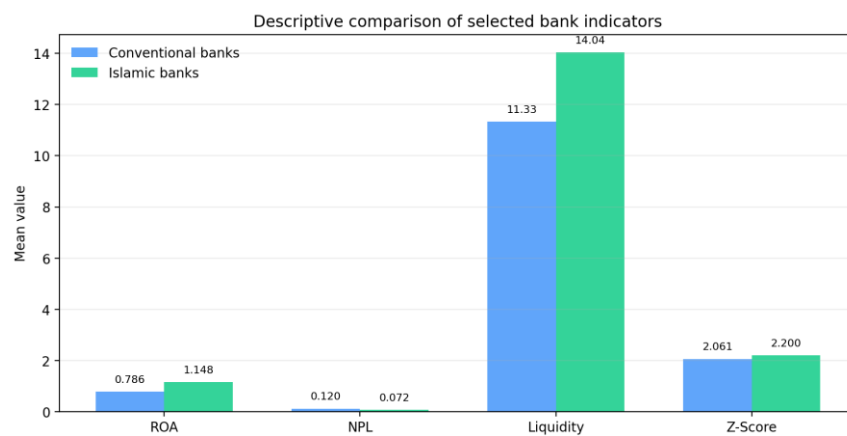
The most relevant descriptive differences are found in credit risk and liquidity. Conventional banks report higher non-performing loans than Islamic banks, with mean values of 0.120 and 0.072, respectively. The difference is statistically significant, indicating that conventional banks experienced greater credit-risk exposure during the study period. Islamic banks also report stronger liquidity, with a mean value of 14.035 compared with 11.326 for conventional banks. This difference is also statistically significant. These descriptive results support the view that Islamic banks in the sample were more liquid and had lower credit-risk exposure, but they do not prove that Islamic banking itself caused better stability. For that reason, the article uses System GMM and machine-learning models to examine these relationships more carefully.

Table 2. Descriptive Comparison of Islamic and Conventional Banks

Variable	All banks mean (SD)	Conventional banks mean (SD)	Islamic banks mean (SD)	Test result	Interpretation
Z-Score	2.094 (1.947)	2.061 (2.060)	2.200 (1.539)	Not significant	Islamic banks show a slightly higher stability score, but the difference is not statistically significant.
ROA	0.872 (1.476)	0.786 (1.633)	1.148 (0.744)	t = -2.665, p = 0.008	Islamic banks have significantly higher asset profitability.
ROE	14.405 (34.867)	14.257 (39.635)	14.879 (9.194)	Not significant	Shareholder returns are similar across the two banking systems.
NPL	0.108 (0.101)	0.120 (0.111)	0.072 (0.045)	t = 5.384, p < 0.001	Conventional banks show significantly higher credit-risk exposure.
Liquidity	11.971 (8.258)	11.326 (8.316)	14.035 (7.766)	t = -2.592, p = 0.011	Islamic banks show significantly stronger liquidity.
CAR	0.159 (0.137)	0.156 (0.156)	0.167 (0.033)	Not significant	Capital adequacy is not meaningfully different across systems.

Bank size	26.954 (1.258)	26.998 (1.312)	26.813 (1.063)	Not significant	Conventional banks are slightly larger on average, but the difference is not statistically significant.
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Note: Values are reported as mean with standard deviation in parentheses. NPL = non-performing loans; CAR = capital adequacy ratio; CIR = cost-to-income ratio; BS = bank size. Test results refer to reported mean-difference tests between conventional and Islamic banks. OP, GP and ER are common macro-financial variables and therefore do not vary by bank group in the same way as bank-level variables.

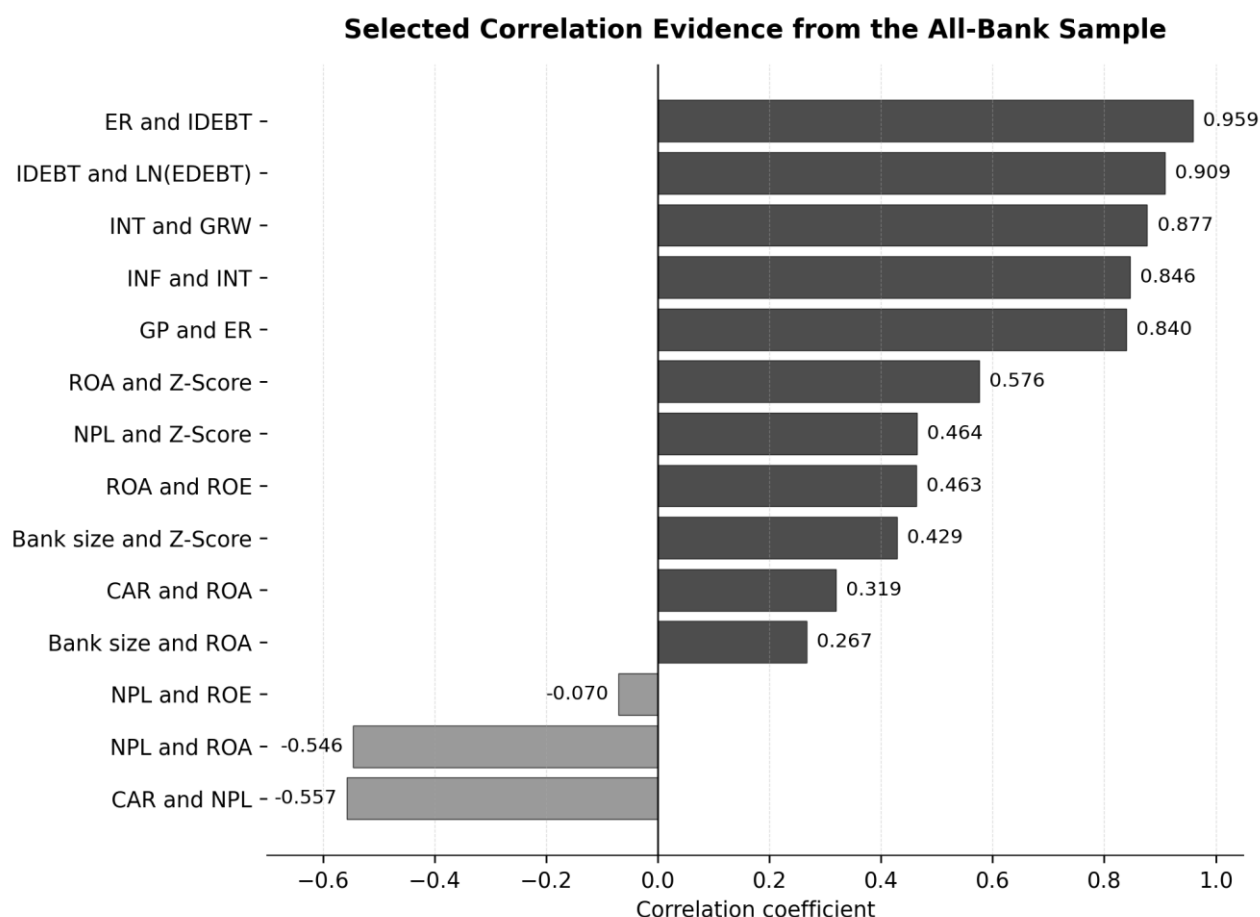


Source: Thesis descriptive statistics. ROA difference is significant at $p = 0.008$; NPL and liquidity differences are significant at $p < 0.05$.

Figure 2. Descriptive comparison of selected indicators for conventional and Islamic banks.

4.2 Correlation evidence and preliminary interpretation

The correlation evidence indicates that bank performance indicators are positively related to each other. ROA is positively correlated with Z-Score and ROE, suggesting that more profitable banks tend to be more stable and generate better shareholder returns. Bank size is also positively associated with performance indicators, which is consistent with the argument that larger banks may benefit from scale, diversification and institutional capacity.



The most important preliminary finding from the correlation matrix is the role of NPLs. NPLs are negatively associated with ROA and related performance measures, confirming that credit risk is a major threat to bank performance. This result is economically intuitive: once loans become non-performing, banks face lower income, greater provisioning pressure and reduced confidence. The correlation evidence therefore supports the later regression and machine-learning findings that credit quality is one of the most consistent determinants of banking outcomes.

The correlation matrix also shows that several macroeconomic variables are strongly related to each other, especially exchange rate, gold price and debt-related indicators. This provides a methodological reason for using Ridge and Lasso regression alongside linear regression. When predictors are correlated, ordinary coefficient estimates can be unstable or inflated. Regularized models help identify whether the key relationship remains after shrinking less reliable coefficients. In this article, the regularized results strengthen the conclusion that NPLs, cost efficiency and bank size remain central, while several macro-financial variables lose importance after penalization.

4.3 Dynamic panel evidence from System GMM

The System GMM results provide the main explanatory evidence. For ROA, the lagged dependent variable is positive and statistically significant across the reported models. In the one-step GMM estimates, lagged ROA ranges from 0.299 to 0.536 and is consistently significant. In the two-step estimates, lagged ROA also remains positive and significant in most specifications. This shows performance persistence: banks with stronger profitability in the previous period tend to maintain higher profitability in the current period. Banking performance is therefore not purely contemporaneous; it has a dynamic structure.

Credit risk is the most important negative driver in the dynamic evidence. In the one-step GMM model for ROA, NPL has a negative coefficient of -6.190 and is statistically significant. In the Z-Score specification, NPL is also negative and significant in the one-step model. This means that a rise in non-performing loans weakens both profitability and stability. The finding is consistent with banking theory and with the machine-learning evidence later in the article. It also gives the article a clear managerial message: under financial uncertainty, credit-risk control is more important than simply tracking external commodity and exchange-rate variables.

The GMM results for ROE are weaker. Lagged ROE is not statistically significant across most specifications, indicating that shareholder returns are more volatile and less persistent than ROA and Z-Score. The one-step model shows a very large negative coefficient for NPL in one specification, but the two-step results are less stable. This suggests that ROE is more difficult to explain through a dynamic panel structure because equity returns fluctuate strongly with leverage, capital structure and income changes. The article therefore treats ROE as a useful but less stable profitability indicator.

The Islamic bank interaction term is positive in the reported specifications but not statistically significant. This is important because it prevents overclaiming. The descriptive results show that Islamic banks perform better in ROA and liquidity, but the GMM interaction evidence does not establish a robust structural difference between Islamic and conventional banks after controls are included. The publishable conclusion is therefore balanced: Islamic banks show favourable descriptive features, but bank type alone is not the dominant explanatory mechanism once credit risk, liquidity, capital and size are considered.

The diagnostic tests reported in the empirical analysis, including AR(2) and Sargan/Hansen-type validity checks, generally support the use of GMM. However, the article interprets the dynamic evidence cautiously, especially where one-step and two-step results differ. The robust conclusion is not that every uncertainty coefficient is significant; rather, it is that past performance and bank-level credit risk are the strongest dynamic mechanisms. This is a stronger and more publishable interpretation than simply listing all coefficients.

Outcome	Dynamic persistence	Key risk effect	Islamic-bank interaction	Publication-oriented interpretation
ROA	Lagged ROA is positive and significant in most specifications.	NPL is negative and significant in the one-step model.	Positive but insignificant.	Profitability is persistent, but credit risk sharply weakens asset returns.
ROE	Lagged ROE is generally insignificant.	NPL is negative and significant in one-step evidence but unstable in two-step evidence.	Positive but insignificant.	Shareholder returns are less predictable and more volatile than ROA.
Z-Score	Lagged Z-Score is significant in one-step models.	NPL is negative and significant in the one-step stability model.	Positive but insignificant.	Stability is dynamic, but credit quality is

				the key internal mechanism.
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Note: Dynamic persistence refers to the coefficient of the lagged dependent variable in the GMM models. NPL = non-performing loans. Islamic-bank interaction refers to the reported oil-price/bank-type interaction term.

4.4 Linear, Ridge and Lasso regression evidence

The linear regression results reinforce the central role of bank-specific variables. For ROA, NPL is negative and highly significant ($\beta = -7.7075$, $p < 0.001$), meaning that higher credit risk reduces asset profitability. CAR is also negative and significant ($\beta = -3.3970$, $p < 0.001$), suggesting that higher capital buffers may reduce short-term profitability by limiting leverage or reflecting conservative balance-sheet strategies. CIR is positive and significant, while bank size is positive and significant. These results indicate that profitability is explained more by credit quality, capital structure, efficiency and scale than by direct commodity or macro-financial effects.

For ROE, the linear regression results show NPL ($\beta = -10.967$, $p < 0.01$), CAR ($\beta = -149.82$, $p < 0.001$) and CIR ($\beta = -0.36853$, $p < 0.001$) as significant negative predictors. This suggests that shareholder returns are harmed by credit risk, by the lower leverage associated with high capital buffers and by lower cost efficiency. The coefficient on CAR is large, which may reflect the sensitivity of ROE to capital structure in a banking setting. Since ROE is a leverage-sensitive measure, higher capital may reduce returns to equity even while improving regulatory resilience.

For Z-Score, NPL is the only statistically significant predictor in the linear regression ($\beta = -3.7260$, $p < 0.05$). This means that bank stability is most directly weakened by poor asset quality. Other uncertainty and macroeconomic variables are not significant in the linear model. This result is not a weakness of the paper; it is one of its main findings. It shows that the path from financial uncertainty to banking stability operates through the health of bank portfolios rather than through a simple direct coefficient on oil price or exchange-rate variables.

Ridge and Lasso provide important robustness evidence. Ridge regression shrinks coefficients and reduces the influence of multicollinearity. In Ridge results, NPL remains negative for ROA, ROE and Z-Score, while bank size remains positive for several outcomes. Lasso is even more selective. For ROA, Lasso retains NPL and CIR while setting many other variables to zero. For ROE, Lasso eliminates almost all explanatory variables, implying that ROE is difficult to predict linearly. For Z-Score, Lasso retains NPL, liquidity, CAR and bank size, with NPL negative and bank size positive. This regularized evidence supports the conclusion that the most reliable signals are internal bank characteristics rather than broad macro-financial variables.

Outcome	Significant retained effects	/ Direction estimate	and Interpretation
ROA	NPL, CAR, CIR, bank size	NPL = -7.7075***; CAR = -3.3970***; CIR = 0.0000647***; BS = 0.015347*	Asset profitability is reduced by credit risk and high capital buffers but supported by efficiency/scale effects.

ROE	NPL, CAR, CIR	NPL = -10.967**; CAR = -149.82***; CIR = -0.36853***	Shareholder profitability is sensitive to credit risk, capital structure and operating efficiency.
Z-Score	NPL	NPL = -3.7260*	Financial stability is most directly weakened by non-performing loans.
Lasso ROA	NPL and CIR retained	NPL = -3.737551; CIR = 0.000001169	Variable selection identifies credit risk and efficiency as the most compact ROA predictors.
Lasso ROE	Almost all variables removed	CIR retained with near-zero coefficient	ROE is unstable and weakly predictable in the Lasso framework.
Lasso Z-Score	NPL, LIQ, CAR, BS and some small macro terms retained	NPL = -6.175321; BS = 14.87564	Stability depends mainly on credit risk and bank size after variable selection.

*Note: Asterisks follow the thesis convention: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. BS = natural log of bank size; CIR = cost-to-income ratio; CAR = capital adequacy ratio; NPL = non-performing loans.*

4.5 Machine-learning and deep-learning evidence

The machine-learning evidence gives the most direct empirical return from the empirical analysis because it ranks the variables by predictive importance. In the XGBoost model for ROA, the most influential predictor is NPL with relative influence of 33.50, followed by CIR (27.01), CAR (15.74) and bank size (11.65). This ranking is economically coherent: asset profitability is driven by credit quality, cost structure, capital strength and scale. External uncertainty variables such as oil price, exchange rate and gold price have much smaller relative influence.

For ROE, XGBoost ranks CAR as the most important variable (34.94), followed by CIR (21.12), liquidity (16.73), NPL (14.67) and bank size (8.39). This confirms that shareholder returns are especially sensitive to capital structure and operational efficiency. It also explains why ROE is difficult to model through conventional regression alone. ROE is affected by leverage, capital buffers, liquidity and credit-risk conditions in a nonlinear way. Machine learning captures these rankings more clearly than simple coefficient estimates.

For Z-Score, XGBoost ranks CIR first (27.07), followed by NPL (23.90), CAR (11.22), bank size (11.18) and liquidity (11.14). This ranking indicates that stability is not merely a capital issue. Operational efficiency and credit risk are at least as important as capital adequacy. Banks that control costs, manage credit risk and maintain adequate liquidity are more resilient. This provides a strong policy contribution: supervisors should look at efficiency and credit quality, not only regulatory capital ratios, when assessing resilience under uncertainty.

Random Forest results support the same conclusion. For ROA and ROE, internal bank characteristics dominate the variable-importance rankings. For Z-Score, CIR and NPL have the

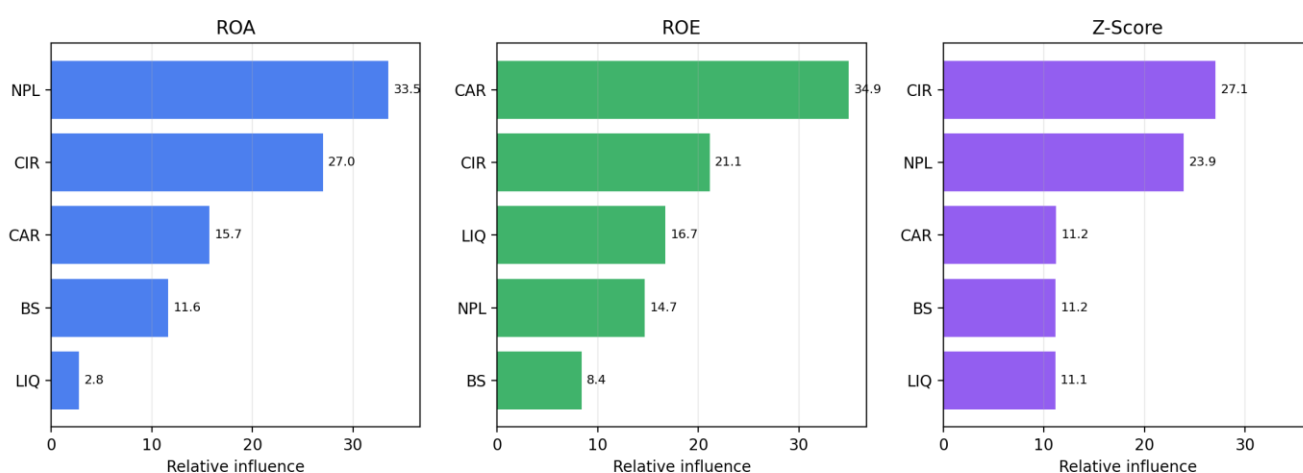
highest %IncMSE importance, followed by bank size and CAR. These results converge with the XGBoost findings. The convergence across tree-based models strengthens the article because it shows that the conclusion is not dependent on a single algorithm.

The SVR and neural-network results are more mixed. SVR explains approximately 24.3% of the variance in ROA, 10.9% in ROE and 28.3% in Z-Score. ANN shows modest explanatory power: about 16.9% for ROA, 2.36% for ROE and 13.18% for Z-Score. The LSTM models report negative R-squared values in several outcomes, and GRU results are also described as poor. This is an important methodological finding. In small annual bank-level panels, recurrent deep-learning architectures may not be suitable because they generally require large sequential datasets to learn stable temporal patterns. More complex models do not automatically produce better research.

Outcome	Top predictors from thesis	XGBoost Relative influence	Interpretation
ROA	NPL; CIR; CAR; Bank size; Liquidity	33.50; 27.01; 15.74; 11.65; 2.76	ROA is mainly a function of credit quality, efficiency, capital strength and scale.
ROE	CAR; CIR; Liquidity; NPL; Bank size	34.94; 21.12; 16.73; 14.67; 8.39	ROE is most sensitive to capital structure, efficiency and liquidity.
Z-Score	CIR; NPL; CAR; Bank size; Liquidity	27.07; 23.90; 11.22; 11.18; 11.14	Bank stability is driven by efficiency, credit risk, capital, size and liquidity.

Note: Relative influence values are taken from the empirical analysis XGBoost tables. Higher values indicate greater contribution to predictive performance. NPL = non-performing loans; CIR = cost-to-income ratio; CAR = capital adequacy ratio.

Top XGBoost predictors by banking outcome

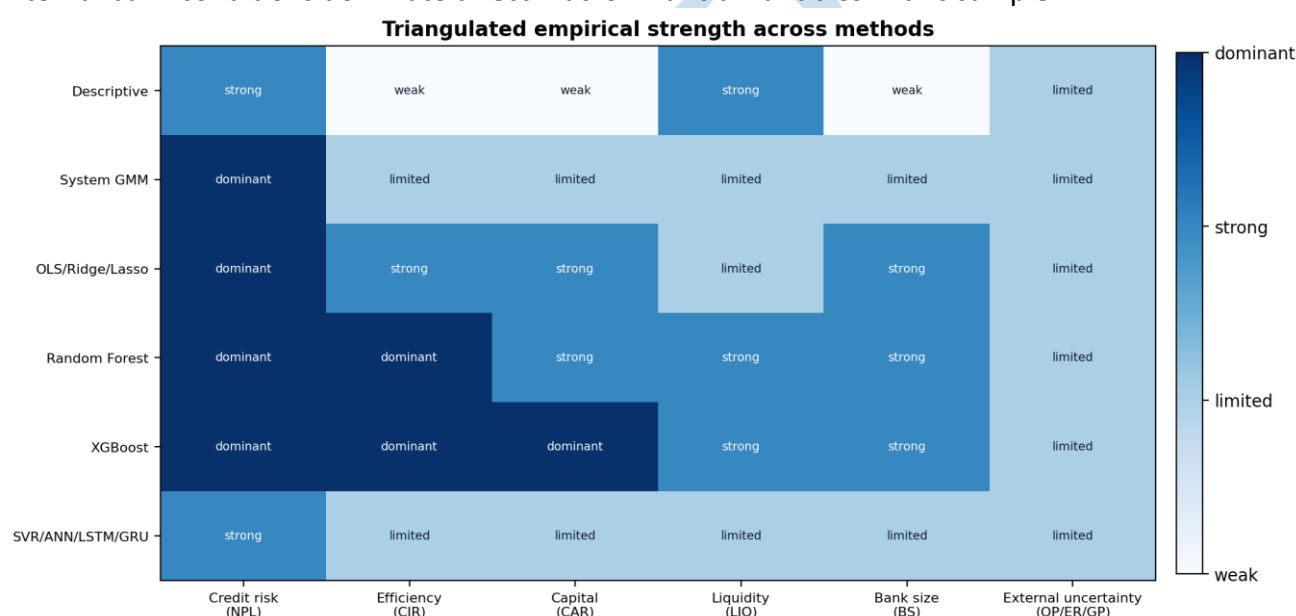


Source: Thesis XGBoost results. Higher relative influence indicates greater contribution to prediction.

Figure 3. Top XGBoost predictors by outcome using empirical thesis results.

The fact that the deep-learning models underperform is publishable when interpreted correctly. It should not be presented as a failure of the thesis. Instead, it should be presented as evidence that model choice must fit the structure of the data. The dataset is an annual panel of 21 banks, which is more appropriate for panel econometrics and tabular machine learning than for sequence-heavy recurrent networks. This result is valuable because many studies apply deep learning without checking whether the data structure justifies it. The thesis evidence suggests that, for this banking dataset, interpretable models and tree-based machine learning provide stronger empirical value than LSTM and GRU models.

The joint interpretation is therefore as follows. System GMM shows that performance is dynamic and that credit risk matters. Linear and regularized models show that NPL, CAR, CIR and bank size remain central in parametric structures. Tree-based models show that these same variables dominate predictive importance. Neural-network models do not improve the empirical conclusion. This convergence supports a clear article-level finding: uncertainty affects bank performance through the quality and structure of bank balance sheets, and internal bank conditions dominate direct macro-financial variables in this sample.



Interpretive synthesis based on the reported thesis evidence; it summarizes direction and empirical dominance rather than introducing new estimation results.

Figure 4. Empirical strength of predictors across methods based on thesis results.

4.7 Consolidated empirical contribution

A publication-ready interpretation of the results should emphasize the consistency between the explanatory and predictive layers. The dynamic panel results identify persistence and credit risk as central mechanisms. The regression and regularization results confirm that the strongest statistically visible effects are concentrated in NPL, CAR, CIR and bank size. The tree-based machine-learning models add a further layer by ranking the same internal variables as the most important predictors across ROA, ROE and Z-Score. This convergence across methods is the strongest empirical contribution of the paper. The article is therefore not merely a comparison of models; it is a triangulated account of banking resilience in which different methods point to the same substantive conclusion.

For ROA, the evidence is especially clear. Islamic banks display higher average ROA, while the linear model identifies NPL, CAR, CIR and bank size as significant predictors. XGBoost ranks NPL and CIR as the two strongest ROA predictors, with relative influence scores of 33.50 and 27.01, respectively. This indicates that asset profitability depends heavily on loan quality and

operational efficiency. A bank cannot maintain strong returns simply because the macroeconomic environment is favourable; it must also control default risk, manage operating costs and use its asset base effectively. This is why the model's empirical message is more managerial than purely macroeconomic.

For ROE, the interpretation is more complex because shareholder returns are sensitive to leverage, capital policy and volatility in equity. The GMM evidence is weaker for ROE, and the Lasso model removes most predictors, showing that ROE is not as stable or easily predictable as ROA. However, XGBoost ranks CAR, CIR, liquidity and NPL as the main ROE predictors. This indicates that shareholder profitability in Pakistan's banking sector is not driven by a single external uncertainty channel. It is more strongly associated with capital adequacy, operating efficiency and balance-sheet management. Such a result should be presented positively: the study shows that ROE is a more volatile and specification-sensitive outcome, while ROA and Z-Score provide more stable evidence.

For Z-Score, the study contributes a clear financial-stability message. Descriptive evidence suggests only a modest and statistically insignificant difference in average stability between Islamic and conventional banks. However, the predictive models reveal that stability is governed by operational efficiency, non-performing loans, capital adequacy, bank size and liquidity. XGBoost ranks CIR and NPL as the two most important Z-Score predictors, while Random Forest also places CIR, NPL, CAR and bank size at the top. The implication is that stability is not simply a matter of the bank's religious or institutional category; it is a matter of how effectively the bank controls credit losses, costs, liquidity and capital buffers.

The deep-learning evidence should be interpreted with methodological care. LSTM and GRU models are designed for richer sequential structures, but the study uses annual bank-level panel observations. This dataset has meaningful cross-sectional and institutional variation but limited temporal depth for recurrent networks. The weak performance of LSTM and GRU therefore strengthens rather than weakens the article because it demonstrates that model complexity must fit the data structure. In this application, tree-based machine learning and dynamic panel methods provide more interpretable and policy-relevant evidence than recurrent deep-learning architectures.

Evidence layer	Dominant empirical signal	Meaning for publication	Practical implication
Descriptive statistics	Islamic banks have higher ROA, lower NPLs and higher liquidity; Z-Score difference is modest.	The dual-banking comparison is meaningful but should not be overstated.	Islamic banks appear stronger in asset profitability and liquidity, while system-wide stability remains comparable.
System GMM	ROA and Z-Score are persistent; NPL is the most consistent negative mechanism.	Dynamic persistence justifies GMM and prevents purely static interpretation.	Supervisors should monitor asset quality as a stability channel under uncertainty.
OLS/Ridge/Lasso	NPL, CAR, CIR and bank size dominate the retained and significant effects.	The statistical models support an internal-resilience interpretation.	Bank management should prioritize credit screening,

			capital planning and cost efficiency.
Random Forest/XGBoost	Tree-based models rank NPL, CIR, CAR, LIQ and BS above most macro variables.	Machine learning confirms the empirical dominance of bank-level fundamentals.	Predictive risk dashboards should track internal bank ratios before broad uncertainty indicators.
SVR/ANN/LSTM/GRU	Predictive power is mixed; recurrent deep learning is weak in the annual panel.	The article avoids overclaiming AI superiority and offers a data-appropriate conclusion.	Future work needs higher-frequency or longer time-series data before relying on recurrent neural networks.

Table 5. Consolidated empirical contribution of the article

Note: The table synthesizes empirical evidence reported in the study. It does not introduce new estimates; it converts the thesis results into a publication-oriented interpretation.

5. Discussion

The empirical evidence has three major implications. The first is theoretical. The findings support the view that financial uncertainty affects banks through balance-sheet mechanisms rather than only through direct macroeconomic coefficients. Oil price volatility, exchange-rate volatility and gold-price uncertainty are theoretically relevant because they influence borrower costs, inflation, confidence and liquidity needs. However, after bank-level variables are introduced, credit risk, efficiency, capital adequacy and bank size become the dominant empirical drivers. This indicates that the uncertainty-performance relationship is mediated by the strength or weakness of bank balance sheets.

The second implication concerns Islamic versus conventional banking. The descriptive results show that Islamic banks in the sample have higher ROA, lower NPLs and stronger liquidity than conventional banks. This provides evidence of comparatively favourable risk and liquidity conditions. However, the GMM interaction terms do not prove a statistically significant structural advantage of Islamic banks after controls are included. The correct conclusion is therefore nuanced: Islamic banks appear stronger in selected descriptive indicators, but bank type alone does not determine performance once internal risk, capital, efficiency and size are controlled.

The third implication concerns model selection. The thesis applies a wide range of models, but the results show that model complexity does not guarantee better insight. GMM is appropriate for dynamic explanation, while XGBoost and Random Forest are useful for ranking nonlinear predictor importance. LSTM and GRU are less suitable for this annual panel dataset. This methodological message is important for publication because it goes beyond reporting results. It advises researchers to match modelling strategy to the data structure and research purpose.

The results also challenge a common assumption in financial-uncertainty studies: that external macro-financial variables will always dominate performance outcomes. In this study, the direct effects of OP, GP, ER and volatility interaction terms are often weak or statistically insignificant in linear models. This does not mean that external uncertainty is irrelevant. Rather, it means that the observable bank-level response to uncertainty is more visible in NPLs, liquidity, capital and cost efficiency. Bank managers cannot control oil prices, exchange

rates or global uncertainty, but they can manage loan quality, liquidity buffers, capital planning and operating costs. That is the main managerial value of the article.

The results are consistent with studies emphasizing credit and liquidity risk as central to bank stability (Ahamed, 2021; Ben-Ahmed et al., 2023; Al-Husainy and Jadah, 2021). They are also consistent with studies showing that oil price uncertainty and exchange-rate pressure can affect financial systems indirectly through borrower conditions and sovereign or corporate risk (Naifar et al., 2020; Gao et al., 2022; Liu et al., 2023). The article's contribution is to show this pattern in Pakistan's dual banking system using both econometric and machine-learning evidence.

For regulators, the findings imply that supervisory attention should not be limited to capital adequacy. Capital remains important, but the evidence shows that NPLs and cost efficiency are equally central. Supervisors should therefore monitor asset quality, provisioning discipline, cost-to-income trends and liquidity positions during periods of commodity and exchange-rate uncertainty. For Islamic banks, the findings suggest that liquidity strength is a potential advantage, but it must be supported by continuous credit-risk monitoring. For conventional banks, higher average NPLs suggest the need for more robust credit-screening and recovery mechanisms.

For bank managers, the findings indicate that profitability improvement requires more than revenue expansion. In the ROA and ROE models, credit risk and efficiency are repeatedly important. This means that profit growth from aggressive lending may be unsustainable if loan quality deteriorates. Cost management and portfolio quality are therefore strategic performance variables. Banks should strengthen early-warning systems, stress-test borrower exposure to oil and exchange-rate shocks, and integrate macro-financial uncertainty into internal credit scoring.

For researchers, the article shows the value of hybrid designs. System GMM provides theoretically meaningful coefficients and controls for endogeneity, while machine-learning models provide a ranked view of predictors and nonlinear patterns. A good finance article should not use machine learning only as decoration. It should explain what machine learning adds. Here, machine learning adds a confirmation that internal bank variables dominate predictive performance and that deep recurrent models are not always appropriate for small annual panels.

5.1 Implications for regulation, Islamic banking and risk management

The empirical findings have direct implications for banking regulation in Pakistan. If external financial uncertainty affects banks mainly through internal mechanisms, then supervisory attention should focus not only on macroeconomic surveillance but also on the bank-level transmission channels that determine resilience. NPLs should be treated as the first warning indicator because they appear repeatedly as a negative determinant of ROA and Z-Score and as a top predictor in machine-learning models. During oil-price and exchange-rate stress, borrowers in import-dependent sectors may face higher costs, weaker cash flows and repayment difficulties. A rise in NPLs therefore converts macro-financial uncertainty into banking-sector fragility.

The results also have implications for Islamic banks. The descriptive evidence shows that Islamic banks have higher average ROA, lower NPLs and stronger liquidity, which is consistent with the argument that Islamic banking may have some resilience advantages because of asset-backed financing and more conservative liquidity management. However, the lack of a decisive stability difference and the insignificant interaction effects mean that the article should avoid claiming unconditional Islamic-bank superiority. A stronger and more

publishable interpretation is that Islamic banks show selective resilience in profitability and liquidity, while their overall stability depends on the same internal fundamentals that matter for conventional banks.

For bank managers, the key message is operational. The article identifies a practical hierarchy of risk-management priorities: credit quality first, operating efficiency second, capital and liquidity planning third, and macro uncertainty monitoring fourth. This hierarchy does not deny macroeconomic risk. Rather, it explains that macroeconomic risk becomes damaging when banks have weak credit portfolios, inefficient operations or insufficient buffers. A bank with disciplined loan screening, cost control and liquidity management can better absorb external uncertainty than a bank that relies only on favourable macroeconomic conditions.

For researchers, the article provides an important methodological implication. System GMM remains useful for causal and dynamic explanation, while XGBoost and Random Forest provide strong predictive and variable-ranking evidence. Deep learning should be used cautiously in annual bank panels because sequential models require enough temporal information to learn reliable patterns. This finding is valuable for future financial research because it supports a principle of data-method fit: the most complex algorithm is not necessarily the best algorithm for every financial dataset.

5.2 Outcome-specific interpretation for publication

The article should be read as three connected outcome stories rather than as a single undifferentiated performance model. The first story concerns ROA, which represents asset-based profitability and is the most stable profitability outcome in the empirical analysis. ROA is particularly important in banking research because it measures how effectively a bank converts its asset base into earnings. The study shows that Islamic banks have a significantly higher average ROA than conventional banks, but the multivariate evidence goes further by showing that this profitability advantage is conditioned by credit quality, capital structure, cost efficiency and bank size. In other words, the descriptive Islamic-bank advantage is not enough by itself; the stronger publication claim is that asset profitability is shaped by balance-sheet discipline. This is why NPL and CIR emerge so strongly in the machine-learning rankings. The ROA results also help refine the interpretation of oil-price and exchange-rate uncertainty. External uncertainty is relevant for the financial environment, but the estimated models do not suggest that macro-financial variables dominate bank profitability directly. This is not a weakness. It is an economically meaningful finding in a banking study because banks do not respond mechanically to oil prices or exchange rates. They respond through borrowers, loan losses, funding conditions, capital buffers and cost structures. Therefore, the ROA evidence supports a filtered-transmission argument: external uncertainty becomes visible in profitability when it weakens asset quality or raises operating and risk-management pressures. Such an interpretation is more publishable than a simple claim that oil uncertainty has a direct and uniform effect on profitability.

The second story concerns ROE, which is more volatile and less stable across models. ROE measures profitability from the shareholders' perspective, but it is also affected by leverage and equity structure. The weak persistence of ROE in the GMM results and the sparse Lasso selection indicate that ROE is not as robustly explained as ROA. A superficial reading might treat this as a weak result. A stronger journal interpretation is that ROE is a more specification-sensitive outcome in Pakistan's banking sector. It reacts to capital adequacy, cost efficiency and credit risk, but it does not yield the same stable dynamic pattern as ROA. This supports the argument that bank shareholders' returns are more volatile than asset-based profitability and are more vulnerable to capital structure and balance-sheet composition.

The third story concerns Z-Score, which captures financial stability rather than profitability alone. The descriptive comparison indicates that Islamic banks have a slightly higher average Z-Score than conventional banks, but the difference is not statistically decisive. This finding is important because it prevents the article from making an overgeneralized claim that Islamic banks are automatically more stable. The stability evidence instead shows that financial soundness is determined by operational efficiency, asset quality, capital adequacy, bank size and liquidity. This is a more sophisticated conclusion: Islamic banks may have selective strengths in liquidity and asset profitability, but system-wide stability still depends on internal management fundamentals.

The Z-Score results also justify the inclusion of machine-learning models. Linear models identify NPL as a significant negative predictor of stability, while XGBoost and Random Forest reveal a wider internal-risk structure in which CIR, NPL, CAR, BS and LIQ all matter. The advantage of the machine-learning layer is that it does not replace the econometric results; rather, it expands the interpretation by ranking the relative strength of predictors. This creates a publication-ready contribution because the paper links explanatory inference and predictive relevance. It shows not only which variables are statistically significant, but also which variables dominate prediction when nonlinearities and interactions are allowed.

5.3 Methodological contribution and data-method fit

A major improvement in the article is the careful interpretation of the hybrid methodology. In empirical finance, there is a tendency to present machine learning and deep learning as inherently superior to econometric models. The results of this study do not support that simplistic view. Instead, they support a data-method fit argument. System GMM is appropriate for dynamic panel explanation because the sample contains repeated bank-year observations and potential endogeneity. Tree-based machine-learning methods are appropriate for ranking nonlinear predictor importance. Recurrent deep-learning methods are less appropriate because annual bank-level data do not provide the dense sequential structure needed for LSTM and GRU models to perform strongly.

This methodological lesson strengthens the article because it provides a realistic and reproducible assessment. The paper does not overclaim the superiority of artificial intelligence. It shows that Random Forest and XGBoost are useful because they reveal the empirical dominance of internal banking variables, while LSTM and GRU are limited in this setting. A journal reviewer is more likely to trust this conclusion because it is cautious, transparent and consistent with the sample structure. The article therefore contributes to the financial machine-learning literature by showing that algorithmic sophistication must be matched to the available data frequency, sample size and research purpose.

The study also demonstrates why a hybrid design is preferable to a single-method approach. If only GMM had been used, the article would have offered dynamic causal evidence but limited information about nonlinear predictor strength. If only machine learning had been used, the article would have provided predictive rankings but weaker theoretical interpretation. By combining both layers, the paper produces a richer empirical story. GMM explains persistence and endogeneity; regularized regressions check stability and variable selection; Random Forest and XGBoost identify predictive dominance; and neural networks test whether sequential nonlinear learning adds value. The convergence of these layers supports the reliability of the main conclusion.

For publication purposes, the most defensible methodological claim is therefore not that the study uses many models. The stronger claim is that the study uses complementary models for different empirical purposes. System GMM is used for dynamic explanation; Ridge and Lasso

are used for regularized robustness; Random Forest and XGBoost are used for nonlinear variable importance; SVR and neural networks are used as additional predictive benchmarks. This positioning turns methodological breadth into methodological coherence. It also reduces the risk that reviewers will view the article as a mechanical model comparison without conceptual integration.

5.4 Final empirical message

Taken together, the empirical evidence provides a clear final message. Financial uncertainty matters for Pakistan's banking sector, but bank performance under uncertainty is mainly determined by how banks manage credit risk, operational efficiency, capital adequacy, liquidity and size-related capacity. Islamic banks show promising descriptive advantages in ROA, NPL and liquidity, but the stability evidence does not support a blanket claim of superiority. The policy implication is that both Islamic and conventional banks require strong credit-risk governance, cost control, capital planning and liquidity monitoring to remain resilient under oil-price, exchange-rate and market uncertainty.

This interpretation gives the article a stronger publication identity. It is not simply an Islamic-versus-conventional comparison, not simply an oil-price uncertainty paper, and not simply a machine-learning exercise. It is a banking-resilience paper that uses the dual banking system of Pakistan as an empirical setting and combines econometric and predictive tools to show which mechanisms matter most. This identity is suitable for journals in Islamic finance, banking performance, risk management, emerging-market finance and applied financial econometrics.

5.5 Reviewer-facing strengths of the empirical design

The reviewer-facing strength of the study is that the empirical design avoids one-sided interpretation. The descriptive results identify differences between Islamic and conventional banks, but the multivariate models test whether those differences persist after accounting for bank fundamentals. The econometric models provide dynamic evidence, while machine-learning models provide a second layer of predictive evidence. The result is not a single isolated coefficient but a consistent pattern across several empirical tools. This makes the article stronger than a purely descriptive comparison and stronger than a purely algorithmic prediction exercise.

The paper also has a clear boundary condition, which should be seen as a strength rather than a weakness. It shows that deep-learning models are not automatically superior when annual banking data are limited. This cautious interpretation makes the article more credible because it aligns the methodological conclusion with the data structure. A publishable paper should not only report positive results; it should also explain why some models perform less effectively. In this respect, the study provides a balanced empirical contribution that is useful for researchers, regulators and banking practitioners.

6. Conclusion

This article converts the thesis on financial uncertainty and bank performance into a focused, publication-oriented article. Using bank-level data for 21 Pakistani banks over 2010-2024, it examines how oil price volatility, exchange-rate volatility, gold-price/market uncertainty and bank-level characteristics affect ROA, ROE and Z-Score in a dual banking system. The article combines System GMM with machine-learning and deep-learning models to provide both explanatory and predictive evidence.

The main conclusion is that bank-specific factors dominate the empirical results. Credit risk, measured through NPLs, is the most consistent negative determinant of profitability and stability. Cost efficiency, capital adequacy, liquidity and bank size also play central roles.

Financial uncertainty matters, but its most visible influence appears through bank balance-sheet risk and operational efficiency rather than as a consistently significant direct coefficient in every model.

Islamic banks show favourable descriptive performance in ROA and liquidity, and lower credit-risk exposure than conventional banks. However, the GMM interaction evidence does not support an overgeneralized claim that Islamic banks are structurally superior in every respect. The more balanced conclusion is that Islamic banks show promising resilience indicators, but performance and stability are ultimately shaped by credit quality, efficiency, capital, liquidity and size.

The predictive evidence shows that XGBoost and Random Forest provide strong empirical value by ranking the drivers of bank performance. NPL, CIR, CAR, liquidity and bank size are repeatedly identified as leading predictors. By contrast, LSTM and GRU models do not perform well in this annual panel setting. This demonstrates that more complex models should not be preferred unless the data structure supports them. For this study dataset, dynamic panel econometrics and tree-based machine learning provide the strongest combined insight.

The article has practical implications for regulators, Islamic banking managers, conventional bank executives and researchers. Regulators should monitor credit risk and cost efficiency along with capital adequacy. Bank managers should strengthen loan-quality controls and liquidity planning under financial uncertainty. Researchers should use hybrid models carefully and interpret predictive algorithms in relation to economic theory. Future research can extend the analysis using quarterly data, bank-level stress-testing measures, Shariah-compliance intensity, and explainable machine-learning tools such as SHAP values where raw model outputs are available.

Declarations

Funding: The article is based on academic thesis work and reports no external funding.

Conflict of interest: The author declares no conflict of interest.

Data availability: The article is based on the study dataset and reported thesis outputs. The underlying dataset should be made available by the researcher subject to institutional and supervisor approval.

Ethical statement: The study uses secondary bank-level and macro-financial data and does not involve human participants.

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