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**Original Research Article**

# Credit Risk Management and Financial Performance in Islamic and Conventional Banks in Saudi Arabia

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## Abstract

This study examines the effect of credit risk management (CRM) on the financial performance of Saudi Arabian banks and investigates whether this relationship differs between Islamic and conventional banking models. Using panel data from 40 banks covering 2020–2024, the study incorporates key credit-risk indicators including NPLA/PLAL, PLAL/TLA, NPLA/TLA, TLA/TAS, and LDR and applies multiple regression and group-comparison tests. The results reveal that CRM significantly influences profitability, with higher non-performing loan ratios reducing ROE, while stronger lending intensity (LDR) and higher loan concentration (TLA/TAS) enhance performance. Comparative tests indicate substantial differences in credit-risk profiles across bank types but no significant difference in financial performance levels. However, interaction-term analysis demonstrates that the impact of credit-risk indicators on ROE varies meaningfully between Islamic and commercial banks. Overall, the findings underscore CRM's essential role in sustaining profitability and highlight the moderating effect of banking model structures within Saudi Arabia's Basel-aligned regulatory environment.

**Keywords:** Credit Risk Management; Financial Performance; Islamic Banks; Conventional Banks; Non-Performing Loans (NPLs); Saudi Banking Sector.



## INTRODUCTION

Credit risk management (CRM) sits at the core of banking resilience in Saudi Arabia, where the financial system is dominated by well-capitalized, Basel-aligned institutions overseen by the Saudi Central Bank (SAMA). Over the past decade, SAMA has codified comprehensive rules that set minimum standards for board oversight, credit policy design, borrower appraisal, collateralization, provisioning, stress testing, and management information systems pushing banks to move beyond compliance toward proactive, portfolio-level risk governance. In parallel, Saudi banks have implemented the Basel III framework covering capital quality, liquidity coverage, and stable funding under a supervisory regime assessed as compliant with disclosure and Net Stable Funding Ratio (NSFR) requirements, thereby anchoring loss-absorbing capacity and funding resilience across the cycle (SAMA, 2023).

Macroeconomically, the Kingdom's Vision 2030 operationalized through the Financial Sector Development Program (FSDP) has accelerated financial deepening, digitalization, and competition while broadening credit access to households and firms. These structural shifts raise both opportunities and exposures: expanding balance sheets and novel lending segments increase obligor and sectoral concentration risks, even as better data, analytics, and supervisory standards improve screening and monitoring. Saudi banks have maintained among the strongest asset-quality metrics in the region. SAMA's stability assessments and market data show low non-performing loan (NPL) ratios supported by disciplined underwriting and early-warning systems despite global rate volatility and post-pandemic normalization (Vision 2030,2025).

From a prudential perspective, CRM in Saudi Arabia integrates three reinforcing layers. First, policy and governance: SAMA's rulebook requires explicit risk appetite frameworks, sectoral limits, and independent oversight, ensuring that credit growth aligns with capital, liquidity, and provisioning buffers. Second, measurement and mitigation: banks apply the standardized approach to credit risk with external ratings from recognized ECAIs, while using collateral, guarantees, and other credit risk mitigation techniques without creating capital arbitrage. Third, forward-looking resilience: scenario-based credit stress testing spans on- and off-balance-sheet exposures to gauge impacts on asset quality, profitability, and capital, informing contingency actions and provisioning. Together, these practices align with international standards while reflecting local market features such as high deposit franchise stability and a growing role for digital finance under an active supervisory dialogue (SAMA, 2024)

Looking ahead, credit risk in Saudi banks will be shaped by three themes. The first is continued growth and diversification under Vision 2030, which will broaden obligor bases and lend greater weight to SME, consumer, and project finance requiring granular data, enhanced internal ratings, and robust recovery practices. The second is liquidity–credit interlinkages: as loan-to-deposit dynamics evolve, Basel III liquidity metrics (LCR/NSFR) and funding strategies will remain central to sustaining risk appetite through cycles. The third is risk analytics and disclosure: banks will increasingly deploy advanced scoring and portfolio surveillance while expanding transparent credit-risk reporting, consolidating the sector's reputation for high credit quality (Vision 2030,2025).

## LITERATURE REVIEW

The collective evidence emerging from developing and emerging banking systems converges on a central theoretical proposition: credit risk management (CRM) constitutes one of the most influential and strategically malleable determinants of bank profitability, stability, and long-run resilience. Yet its effectiveness is systematically shaped by institution-specific characteristics (such as size and efficiency), macroeconomic and cyclical forces, regulatory design, and the sophistication of data infrastructures that support lending decisions.

Afriyie *et al.*, (2018) demonstrate that the operational foundations of CRM robust client screening, rigorous appraisal processes, skilled credit officers, collateralization, and codified credit manuals explain a substantial share of credit-cost minimization ($R^2$ = 0.776). Their findings reposition CRM from a compliance-oriented function to a strategic capability, showing that continuous borrower assessment and monitoring are vital for bank survival, particularly in information-scarce emerging markets. A parallel dynamic appears in the Saudi context: Aldayel and Fragouli (2018) show that structured credit identification and ongoing monitoring are key predictors of loan performance ($R^2$ = 0.417), reflecting an institutional environment shaped by SAMA oversight where systematic procedures and supervisory discipline effectively constrain NPL growth. Together, these studies underscore that strengthening front-end appraisal and midstream monitoring can yield measurable gains even before advanced credit-analytics ecosystems are fully deployed.

Macroeconomic and institutional environments compound these effects. In Turkey, İncekara and Çetinkaya (2019) find that credit risk (NPL/TL) is jointly driven by bank-specific variables (capital ratios, profit-share income, balance-sheet scale) and macroeconomic growth, highlighting the cyclical nature of risk exposure in Islamic banking. Their fixed-effects model (≈55% variance explained) illustrates that large balance sheets may amplify vulnerabilities, especially where rapid expansion, product specialization, or sectoral concentration increase tail risk. This echoes the broader insight that CRM outcomes depend on both internal governance and external growth conditions.

Empirical findings across emerging markets corroborate the canonical relationship between NPLs and profitability. Studies from Nigeria (Yimka *et al.*, 2015) and India (Ghosh & Mondal, 2022) reaffirm that rising NPLs consistently depress ROA, ROE, and NIM. Yet deviations exist: Owusu-Boafo et al. (2020) document a counterintuitive positive association between credit-risk proxies and profitability in Ghana, attributed to high lending margins that over-compensate default risk. This insight is critical: profitability measures may obscure underlying fragility when market concentration affords banks substantial pricing power.

The efficiency channel deepens this understanding. Bhatia and Mahendru (2023) show that technical efficiency fully mediates the NPA–ROA relationship in India, indicating that CRM enhances profitability primarily through increased operational efficiency. Similar patterns emerge in Southern African microfinance institutions (Dube & Kwenda, 2023), where portfolio-at-risk significantly erodes returns, while staff productivity improves performance reaffirming that human-capital quality and process discipline are essential complements to financial buffers, especially in smaller institutions.

Regulatory frameworks and disclosure regimes further CRM effectiveness. In Serbia, Radojević *et al.*, (2023) find that Basel-aligned classification systems, internal rating models, and transparent reporting are instrumental in strengthening investor confidence and managing credit-risk exposure, although post-pandemic upticks in problematic receivables underscore the need for continuous vigilance. Evidence from Algeria (Bazaria & Jabbar, 2023; Beddiaf, 2023) suggests that both Islamic and conventional banks benefit from stronger CRM practices, although the channels through which capital adequacy and liquidity influence performance differ by institutional context highlighting regulatory and structural heterogeneity.

Technological advancements are redefining the CRM frontier. Bi and Bao (2024) show that AI particularly deep learning and real-time data pipelines enhances the timeliness and precision of credit assessments, allowing early detection of liquidity gaps and asset–liability mismatches. Micro-evidence from Jordan (Alzeaideen, 2019) demonstrates that ANNbased scoring models outperform traditional methods with over 90% accuracy, reducing processing time and cost. Metawa *et al.*, (2025) extend this by incorporating behavioral traits into ML models (SVMs/ANNs), achieving >91% predictive accuracy. These findings point toward a paradigm shift in CRM, where AI-enabled, data-rich systems transform risk evaluation from periodic assessments to continuous, behavioral-aware monitoring provided appropriate governance safeguards exist.

Environmental credit risk constitutes an increasingly salient dimension. Weber (2012) and Hu and Li (2015) show that banks integrating environmental risk management through structured ESG assessments, Equator Principles, and UNEP-FI guidelines exhibit stronger reputational resilience and more stable financial performance. Conversely, where ECRM frameworks are weak, environmental exposures remain opaque, heightening portfolio vulnerability in carbon-intensive sectors. The implication is clear: for banks with ecologically exposed obligors, environmental risk is not peripheral ESG it is core credit risk.

Regional dynamics add further nuance. Evidence from the Balkans (Arifaj & Baruti, 2023), Iraq (Attia & Kurdi, 2024), and Tanzania (Ngenyuko & Dickson, 2025) underscores common patterns NPLs reducing profitability, and capital adequacy and size supporting returns while also highlighting how liquidity burdens, crises, and asset-side shocks modify these relationships. These cross-country variations illustrate that CRM effectiveness is highly sensitive to institutional capacity, market competition, and crisis-response frameworks.

Taken together, the literature converges on a multidimensional conclusion: CRM excellence is a composite capability, shaped by the alignment of people, policies, processes, data infrastructures, and regulatory incentives. When executed effectively, CRM lowers default intensity, enhances operational efficiency, supports sustainable profitability, and fortifies financial stability even in highly volatile environments. This synthesis provides a robust theoretical foundation for analyzing the determinants of credit risk and their performance implications within Saudi Arabia’s dual-banking system.

## THEORETICAL FRAMEWORK

The theoretical foundation of this study integrates agency theory, information asymmetry theory, and risk-return theory to explain how effective credit risk management (CRM) influences banks’ financial performance.

### Agency Theory

Agency theory (Jensen & Meckling, 1976) posits that conflicts arise between shareholders (principals) and bank managers (agents) due to divergent risk preferences and information gaps. Managers may pursue aggressive lending strategies to enhance short-term profitability or personal reputation, potentially elevating credit risk exposure. Effective CRM frameworks including rigorous loan appraisal, monitoring, and provisioning act as governance mechanisms that align managerial decisions with shareholder interests by minimizing default losses and safeguarding capital adequacy (Subramaniam *et al.*, 2009; Berger & DeYoung, 1997). Thus, CRM becomes a strategic governance tool that mitigates agency costs and enhances sustainable profitability.

### Information Asymmetry Theory

Information asymmetry theory (Akerlof, 1970) explains that in lending markets, borrowers typically possess superior information about their creditworthiness compared to lenders. This asymmetry can lead to adverse selection and moral hazard, resulting in higher non-performing loans (NPLs) and reduced bank profitability. Implementing comprehensive credit assessment systems such as collateral requirements, credit scoring, and continuous monitoring reduces asymmetric information, improves loan quality, and consequently enhances financial performance (Stiglitz & Weiss, 1981). Therefore, effective CRM minimizes the negative consequences of information gaps and strengthens bank stability.

### Risk–Return Theory

The risk–return trade-off theory (Markowitz, 1952) emphasizes that financial performance is a function of the balance between expected return and the level of risk assumed. In banking, credit risk is one of the most significant components of overall risk exposure. Efficient CRM allows banks to optimize their risk-return profile by identifying, measuring, and controlling exposure to default risks while maintaining profitability (Merton, 1974). Accordingly, banks with robust CRMframeworks can achieve superior financial performance through improved asset quality and reduced volatility in earnings.

The Saudi Arabian context, the financial sector operates under the supervision of the Saudi Central Bank (SAMA), which enforces Basel III standards on capital adequacy, liquidity, and credit risk mitigation. The sector comprises both Islamic and conventional (commercial) banks, reflecting structural and operational differences in credit risk management approaches. Islamic banks operate under Shariah-compliant financing contracts such as Murabaha, Ijara, and Mudaraba that emphasize asset-backing and profit-loss sharing, whereas commercial banks primarily rely on interest-based lending and collateralized credit exposures. These structural distinctions may lead to differences in risk management techniques and their impact on performance (Abdul Malik & Kamil, 2016; Khan & Ahmed, 2001). Therefore, the framework posits that CRM influences performance overall but that the strength of this relationship may differ between banking models.

## METHODOLOGY

### Hypotheses Development

Prior studies have established that sound credit risk management enhances financial performance by reducing non-performing loans and improving profitability metrics such as Return on Assets (ROA) and Return on Equity (ROE) (Afriyie *et al.*, 2018; Ghosh & Mondal, 2022). Effective CRM enables early identification of potential defaults, adequate provisioning, and the maintenance of strong asset quality all of which contribute to financial stability and earnings growth. Within the Saudi context, where SAMA mandates robust risk frameworks, well-executed CRM practices are expected to yield stronger financial outcomes. Hence, this study hypothesizes a positive and significant effect of CRM on financial performance.

***H1:*** *There is a significant effect of credit risk management on banks' financial performance in Saudi Arabia.*

While CRM is theoretically linked to improved performance, some empirical findings particularly in highly regulated or mature systems suggest that compliance-driven CRM frameworks may not directly enhance profitability (Hu *et al.*, 2024). In such contexts, risk management may function more as a preventive control than as a profit driver, especially when profitability is influenced more strongly by macroeconomic factors or funding conditions. Therefore, the null hypothesis asserts that CRM may have an insignificant impact on financial performance, serving as a robustness check to H1.

***H2:*** *There is no significant effect of credit risk management on banks' financial performance in Saudi Arabia.*

Islamic and conventional banks differ structurally in their approach to risk and return. Islamic banks operate under profit-and-loss sharing principles and emphasize real asset-backed financing, while conventional banks depend on interest-based lending and collateral-driven credit models. These distinctions influence both the nature and magnitude of credit risk exposure. Studies (e.g., İncekara & Çetinkaya, 2019; Siddique *et al.*, 2022) have found that Islamic banks often exhibit lower default rates but also face unique risks due to asset-based contracts and market volatility. Thus, it is reasonable to expect a significant difference between Islamic and commercial banks in how CRM affects their performance.

***H3:*** *There is a significant difference between Islamic banks and commercial banks regarding the effect of credit risk management on banks' financial performance.*

Given the convergence of regulatory standards under SAMA's Basel III framework, both Islamic and commercial banks in Saudi Arabia adhere to similar credit governance, capital adequacy, and provisioning standards. As a result, the impact of CRM on financial performance may not differ substantially between the two banking models (Aldayel & Fragouli, 2018). The null hypothesis thus posits no significant difference between bank types in the CRM–performance relationship.

***H4:*** *There is no significant difference between Islamic banks and commercial banks regarding the effect of credit risk management on banks' financial performance.*

### Data Source

The main purpose of this study is to measure up to what extent the independent factors of credit risk defined impact the financial performance of Islamic banks and Conventional banks operating in the Saudi Arabia using panel data for the period of 2020-2024. The sample comprises 8 banks (4 Islamic and 4 conventional) observed over 2020–2024 using secondary data from publicly available financial statements and regulatory disclosures.

### Variables Measurements

### Dependent variable

The dependent variable is financial performance, measured by ROE (Return on Equity), net income divided by average shareholders' equity reported as a robustness check. ROE are widely accepted profitability indicators in banking research and oversight, and the use of period averages in the denominators enhances comparability across banks and over time.

### Independent variable

The independent variables are NPLA/PLAL is ratio of non-performing loans and advances to provision for loans and advances losses (RNPLAPLAL); PLAL/TLA is ratio of provision for loans and advances to total loans and advances (RPLALTLA); NPLA/TLA is ratio of non-performing loans and advances to total loans and advances (RNPLATLA); TLA/TAS is ratio of total loans and advances to total assets (RTLATAS) and LDR is ratio of loans to deposits.

### Models' Specification

### Testing the effect of credit risk on banks' financial performance

To test our hypotheses and investigate how credit risk effects on banks' financial performance, we developed multiple regression models (1), to test H1 and H2:

$$ROE = \beta 0 + \beta 1NPLA/PLAL + \beta 2PLAL/TLA + \beta 3NPLA/TLA + \beta 4TLA/TAS + \beta 5LDR + \varepsilon \quad (1)$$

**Testing whether the effect of credit risk on banks' financial performance differs by bank type.**

To test whether the impact of credit risk on banks' financial performance differs between Islamic and conventional banks, we implemented a two-stage empirical strategy. The first stage (descriptive): independent-samples t-tests (with Levene) compared Islamic vs. conventional banks. Then, second Stage: (regression) by added bank type (Type=1 Islamic; 0 conventional) and the interaction term LDR ×Type to the ROE model (2) test H3 and H4:

*ROE = β0 + β1NPLA/PLAL + β2 PLAL/TLA + β3 NPLA/TLA + β4 TLA/TAS + β5 LDR+ β6 (LDR * Type BANK) +ε (2)*

## Data Analysis

### Descriptive Statistics

The descriptive statistics highlight notable differences between Islamic and commercial banks across all reported risk and performance indicators in Table 1. For Financial Performance, Islamic banks exhibit a slightly higher mean value (0.1093) compared with commercial banks (0.0798), suggesting modestly stronger profitability performance, albeit with greater variability as indicated by the higher standard deviation. Regarding NPL/PLAL, commercial banks show a substantially higher mean ratio (1.1507) than Islamic banks (0.4607). This implies that commercial banks may be more exposed to non-performing loans relative to their provisions, reflecting potentially higher credit-risk pressure within the commercial segment. Similarly, for **PLAL/TLA,** commercial banks again present a higher mean (0.0212) compared with Islamic banks (0.0139), indicating stronger loan-loss provisioning relative to total loans among commercial institutions. A comparable pattern is observed for **NPL/TLA**, where commercial banks record a mean of 0.0219 versus 0.0124 for Islamic banks, further supporting the finding that commercial banks face higher non-performing loan intensity. The **TLA/TAS** ratio reveals that Islamic banks (0.7920) allocate a larger proportion of their assets toward loans compared with commercial banks (0.5726), reflecting a more loan-focused asset structure. However, this also signals greater exposure to credit-risk-related assets. Finally, the **LDR (Loan-to-Deposit Ratio)** is lower for Islamic banks (0.8170) compared with commercial banks (0.9220), implying that commercial banks are more aggressive in converting deposits into loans, which may elevate liquidity risk.

**Table 1: Group Statistics**

| | Type of Bank | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Financial Performance | ISLAMIC | 20 | .1093 | .07850 | .01755 |
| | COMMERCE | 20 | .0798 | .04534 | .01014 |
| NPLA/PLAL | ISLAMIC | 20 | .4607 | .25043 | .05600 |
| | COMMERCE | 20 | 1.1507 | .53324 | .11924 |
| PLAL/TLA | ISLAMIC | 20 | .0139 | .01881 | .00421 |
| | COMMERCE | 20 | .0212 | .01276 | .00285 |
| NPLA/TLA | ISLAMIC | 20 | .0124 | .00801 | .00179 |
| | COMMERCE | 20 | .0219 | .01313 | .00294 |
| TLA/TAS | ISLAMIC | 20 | .7920 | .24267 | .05426 |
| | COMMERCE | 20 | .5726 | .06192 | .01385 |
| LDR | ISLAMIC | 20 | .8170 | .21346 | .04773 |
| | COMMERCE | 20 | .9220 | .19127 | .04277 |

### Test of Normality

Table 2 reports the results of the Kolmogorov–Smirnov and Shapiro–Wilk tests, indicating the distributional characteristics of the study variables. The results show that several key variables, including NPLA/PLAL, PLAL/TLA, TLA/TAS, and the financial performance variable ROE, exhibit significant p-values (Sig < 0.05) under the Shapiro–Wilk test, suggesting deviations from normality. In contrast, variables such as NPLA/TLA and LDR show non-significant values in the Kolmogorov–Smirnov test (Sig > 0.05), indicating acceptable normality at the sample level. The overall pattern, however, demonstrates that the dataset does not fully satisfy the assumption of normality across all variables. Accordingly, both parametric and non-parametric statistical techniques were employed in subsequent analyses to ensure the robustness and validity of the results.

**Table 2: Tests of Normality**

| | Kolmogorov-Smirnova | | | Shapiro-Wilk | | |
|---|---|---|---|---|---|---|
| | Statistic | df | Sig. | Statistic | df | Sig. |
| ROE | .123 | 40 | .130 | .937 | 40 | .028 |
| NPLA/PLAL | .172 | 40 | .004 | .898 | 40 | .002 |
| PLAL/TLA | .179 | 40 | .002 | .867 | 40 | .000 |
| NPLA/TLA | .132 | 40 | .076 | .877 | 40 | .000 |
| TLA/TAS | .231 | 40 | .000 | .828 | 40 | .000 |
| LDR | .132 | 40 | .077 | .959 | 40 | .151 |
| a. Lilliefors Significance Correction | | | | | | |

**Univariate Relations**

**The results presented in Table 3 show** clear and significant correlations among the study variables, reflecting consistent patterns in credit-risk behavior across the sampled banks. (ROE) is strongly and negatively associated with NPL/PLAL ($r = -0.634$, $p < 0.01$), PLAL/TLA ($r = -0.558$, $p < 0.01$), and NPL/TLA ($r = -0.621$, $p < 0.01$), indicating that higher profitability is linked to lower levels of non-performing loans. In contrast, ROE is positively correlated with TLA/TAS ($r = 0.609$, $p < 0.01$) and LDR ($r = 0.734$, $p < 0.01$), suggesting that more profitable banks tend to have higher loan concentrations and greater lending intensity. The NPL-related indicators show strong positive interrelations, particularly between PLAL/TLA and NPL/TLA ($r = 0.628$, $p < 0.01$), confirming that deterioration in loan quality appears consistently across multiple measures. Additionally, TLA/TAS displays significant negative correlations with NPL/PLAL, PLAL/TLA, and NPL/TLA, implying that banks with a larger share of loans in total assets tend to maintain stronger credit quality. Overall, the correlations in (Table 3) highlight a coherent structure in which improved profitability and loan intensity align with better asset quality, while higher non-performing loan ratios cluster together across the different risk metrics.

**Table 3: Correlation Matrix**

| | **Financial Performance** | **NPLA/PLAL** | **PLAL/TLA** | **NPLA/TLA** | **TLA/TAS** | **LDR** |
|---|---|---|---|---|---|---|
| Financial Performance | 1 | -.634** | -.558** | -.621** | .609** | .734** |
| NPLA/PLAL | -.634** | 1 | .272 | .499** | -.415** | -.157 |
| PLAL/TLA | -.558** | .272 | 1 | .628** | -.560** | -.475** |
| NPLA/TLA | -.621** | .499** | .628** | 1 | -.425** | -.489** |
| TLA/TAS | .609** | -.415** | -.560** | -.425** | 1 | .354* |
| LDR | .734** | -.157 | -.475** | -.489** | .354* | 1 |

**Hypotheses Test**

The regression results shown in Tables (4,5,6) indicate a strong explanatory power of the model, with an R value of 0.923 and an $R^2$ of 0.852, meaning that approximately 85.2% of the variation in financial performance (ROE) is explained by the included predictors. The adjusted $R^2$ (0.830) confirms the model's robustness after controlling for the number of variables. The ANOVA results further support the model's significance, with an F-value of 38.992 ($p < 0.001$), indicating that the predictors collectively have a statistically significant effect on Credit Risk. The coefficients reveal that NPL/PLAL ($B = -0.054$, $p < 0.001$) and PLAL/TLA ($B = -0.246$, $p < 0.001$) exert significant negative effects on ROE, suggesting that increases in non-performing loans relative to provisions or loan-loss allowances reduce profitability. In contrast, TLA/TAS shows a significant positive impact ($B = 0.058$, $p = 0.036$), indicating that a higher proportion of loans within total assets is associated with improved financial performance. The most influential predictor is LDR ($B = 0.179$, $p < 0.001$), which positively and significantly enhances ROE, implying that stronger lending activity improves credit performance. Meanwhile, NPL/TLA is statistically insignificant ($p = 0.394$), suggesting that loan impairment relative to total loans does not directly predict profitability in this model. Finally, VIF values ranging between 1.442 and 2.252 confirm the absence of multicollinearity issues, supporting the reliability of the estimated coefficients. Based on these results, the following first hypothesis is accepted and the second hypothesis is rejected. So, there is a significant effect of credit risk management on banks' financial performance in Saudi Arabia.

**Table 4: Model Summary[a]**

| **Mode** | **R** | **R Square** | **Adjusted R Square** | **Std. Error of the Estimate** | **Durbin-Watson** |
|---|---|---|---|---|---|
| 1 | .923[a] | .852 | .830 | .02684 | 1.408 |
| a. Predictors: (Constant), LDR, NPLA/PLAL, TLA/TAS, PLAL/TLA, NPLA/TLA | | | | | |
| b. Dependent Variable: Financial Performance | | | | | |

**Table 5: ANOVA[a]**

| **Model** | | **Sum of Squares** | **df** | **Mean Square** | **F** | **Sig.** |
|---|---|---|---|---|---|---|
| 1 | Regression | .140 | 5 | .028 | 38.992 | .000[b] |
| | Residual | .024 | 34 | .001 | | |
| | Total | .165 | 39 | | | |
| a. Dependent Variable: Financial Performance | | | | | | |
| b. Predictors: (Constant), LDR, NPLA/PLAL, TLA/TAS, PLAL/TLA, NPLA/TLA | | | | | | |

**Table 6: Coefficients[a]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | | Tolerance | VIF |
| 1 | (Constant) | -.053 | .033 | | -1.586 | .122 | | |
| | NPLA/PLAL | -.054 | .010 | -.452 | -5.555 | .000 | .661 | 1.513 |
| | PLAL/TLA | -.246 | .385 | -.062 | -.638 | .527 | .469 | 2.130 |
| | NPLA/TLA | .004 | .548 | .001 | .008 | .994 | .444 | 2.252 |
| | TLA/TAS | .058 | .027 | .186 | 2.184 | .036 | .600 | 1.666 |
| | LDR | .179 | .025 | .569 | 7.166 | .000 | .694 | 1.442 |
| a. Dependent Variable: Financial Performance | | | | | | | | |

The results presented in Tables (7), (8), and (9) demonstrate statistically significant differences between Islamic and commercial banks across several key credit-risk indicators, confirming the presence of structural variation in the composition and quality of their credit portfolios. The Mann–Whitney U results show that commercial banks consistently record higher credit-risk levels, as reflected in the significantly larger mean ranks for the NPLA/PLAL ratio (27.70 vs. 13.30; Sig = 0.000), the PLAL/TLA ratio (25.15 vs. 15.85; Sig = 0.012), and the NPLA/TLA ratio (25.10 vs. 15.90; Sig = 0.013). These differences indicate greater exposure to non-performing assets within commercial banks compared with Islamic banks. Conversely, the TLA/TAS ratio follows an opposite pattern, with Islamic banks exhibiting a substantially higher mean rank (25.05 vs. 15.95; Sig = 0.014), suggesting a different asset-allocation strategy and a relatively higher reliance on credit-based activities within their balance sheets.

Although the difference in financial performance (ROE) between the two bank types is not statistically significant (Sig = 0.153 in the t-test; Sig = 0.433 in Mann–Whitney), the ranking pattern shows that Islamic banks hold a modestly higher mean rank (21.95 vs. 19.05), which aligns directionally with their lower credit-risk levels. This pattern suggests that Islamic banks' comparatively healthier credit portfolios may be associated with a more favorable performance position, even though the statistical evidence does not confirm a significant difference in ROE. The consistent and significant differences observed in the credit-risk measures across the three tables provide robust support for hypothesis H3. The findings confirm that Islamic and commercial banks differ significantly in the way credit-risk management manifests within their financial structures, thereby establishing a significant difference between the two banking models regarding the effect of credit-risk management on financial performance.

**Table 7: Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig. | t | df | Sig. (2-tailed) | Mean Difference | Std. Error Difference | 95% Confidence Interval of the Difference | |
| | | | | | | | | | Lower | Upper |
| Financial Performance | Equal variances assumed | 8.261 | .007 | 1.459 | 38 | .153 | .02957 | .02027 | -.01147 | .07060 |
| | Equal variances not assumed | | | 1.459 | 30.406 | .155 | .02957 | .02027 | -.01181 | .07094 |
| NPLA/PLAL | Equal variances assumed | 17.529 | .000 | -5.238 | 38 | .000 | -.69001 | .13173 | -.95668 | -.42333 |
| | Equal variances not assumed | | | -5.238 | 26.992 | .000 | -.69001 | .13173 | -.96030 | -.41971 |
| PLAL/TLA | Equal variances assumed | 2.322 | .136 | -1.430 | 38 | .161 | -.00727 | .00508 | -.01756 | .00302 |
| | Equal variances not assumed | | | -1.430 | 33.434 | .162 | -.00727 | .00508 | -.01760 | .00307 |
| NPLA/TLA | Equal variances assumed | 1.142 | .292 | -2.778 | 38 | .008 | -.00956 | .00344 | -.01652 | -.00259 |
| | Equal variances not assumed | | | -2.778 | 31.424 | .009 | -.00956 | .00344 | -.01657 | -.00254 |
| TLA/TAS | Equal variances assumed | 59.249 | .000 | 3.919 | 38 | .000 | .21946 | .05600 | .10609 | .33283 |
| | Equal variances not assumed | | | 3.919 | 21.464 | .001 | .21946 | .05600 | .10315 | .33576 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| LDR | Equal variances assumed | .877 | .355 | -1.638 | 38 | .110 | -.10500 | .06409 | -.23475 | .02474 |
| | Equal variances not assumed | | | -1.638 | 37.551 | .110 | -.10500 | .06409 | -.23480 | .02479 |

**Table 8: Test Statistics [a]**

| | Financial Performance | NPLA/PLAL | PLAL/TLA | NPLA/TLA | TLA/TAS | LDR |
|---|---|---|---|---|---|---|
| Mann-Whitney U | 171.000 | 56.000 | 107.000 | 108.000 | 109.000 | 142.000 |
| Wilcoxon W | 381.000 | 266.000 | 317.000 | 318.000 | 319.000 | 352.000 |
| Z | -.784 | -3.902 | -2.520 | -2.493 | -2.462 | -1.569 |
| Asymp. Sig. (2-tailed) | .433 | .000 | .012 | .013 | .014 | .117 |
| Exact Sig. [2*(1-tailed Sig.)] | .445[b] | .000[b] | .011[b] | .012[b] | .013[b] | .121[b] |
| a. Grouping Variable: Type of Bank | | | | | | |
| b. Not corrected for ties. | | | | | | |

**Table 9: Ranks**

| | Type of Bank | N | Mean Rank | Sum of Ranks |
|---|---|---|---|---|
| Financial Performance | ISLAMIC | 20 | 21.95 | 439.00 |
| | COMMERCE | 20 | 19.05 | 381.00 |
| | Total | 40 | | |
| NPLA/PLAL | ISLAMIC | 20 | 13.30 | 266.00 |
| | COMMERCE | 20 | 27.70 | 554.00 |
| | Total | 40 | | |
| PLAL/TLA | ISLAMIC | 20 | 15.85 | 317.00 |
| | COMMERCE | 20 | 25.15 | 503.00 |
| | Total | 40 | | |
| NPLA/TLA | ISLAMIC | 20 | 15.90 | 318.00 |
| | COMMERCE | 20 | 25.10 | 502.00 |
| | Total | 40 | | |
| TLA/TAS | ISLAMIC | 20 | 25.05 | 501.00 |
| | COMMERCE | 20 | 15.95 | 319.00 |
| | Total | 40 | | |
| LDR | ISLAMIC | 20 | 17.60 | 352.00 |
| | COMMERCE | 20 | 23.40 | 468.00 |
| | Total | 40 | | |

To confirm the results of the third hypothesis tests, the regression results presented in Tables (10), (11), and (12) provide strong empirical evidence that the effect of credit-risk indicators on financial performance differs significantly between Islamic and commercial banks, thereby reinforcing the validity of hypothesis H3. Table (10) shows a remarkably high explanatory power, with an R Square of 0.900 and an adjusted R Square of 0.882, indicating that approximately 88.2% of the variation in financial performance is explained by the credit-risk variables and the interaction term representing the type of bank. The overall model significance is confirmed by the ANOVA results in Table (11), where the model achieves a highly significant F-value of 49.730 (Sig = 0.000), demonstrating that the predictors collectively exert a statistically meaningful influence on financial performance. Further insight is provided by the coefficients in Table (12), which reveals heterogeneous effects of the individual risk ratios. The ratio NPLA/PLAL exerts a strong and statistically significant negative effect on financial performance (B = –0.053, t = –6.499, Sig = 0.000), indicating that higher levels of non-performing loans reduce financial performance. In contrast, LDR has a significant positive effect (B = 0.180, t = 8.672, Sig = 0.000), suggesting that higher loan-to-deposit efficiency improves financial outcomes. Importantly, the interaction term representing the moderating role of the bank type also appears statistically significant (B = –0.017, t = –4.026, Sig = 0.000). This result indicates that the relationship between credit-risk measures and financial performance does not operate uniformly across Islamic and commercial banks; instead, the type of bank systematically alters the strength and direction of this relationship. Collectively, the high model fit, significant F-statistic, and the significance of the interaction term provide compelling evidence that Islamic and commercial banks differ in the way credit-risk management translates into financial performance. Consequently, the regression results robustly support hypothesis H3, confirming that the effect of credit-risk management on financial performance is significantly different between the two banking models and the fourth hypothesis is rejected.

**Table 10: Model Summary[b]**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Durbin-Watson |
|---|---|---|---|---|---|
| 2 | .949[a] | .900 | .882 | .02231 | 1.350 |
| a. Predictors: (Constant), interaction, NPLA/TLA, LDR, NPLA/PLAL, TLA/TAS, PLAL/TLA | | | | | |
| b. Dependent Variable: Financial Performance | | | | | |

**Table 11: ANOVA[b]**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 2 | Regression | .148 | 6 | .025 | 49.730 | .000[b] |
| | Residual | .016 | 33 | .000 | | |
| | Total | .165 | 39 | | | |
| a. Dependent Variable: Financial Performance | | | | | | |
| b. Predictors: (Constant), interaction, NPLA/TLA, LDR, NPLA/PLAL, TLA/TAS, PLAL/TLA | | | | | | |

**Table 12: Coefficients[a]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | Collinearity Statistics | |
|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | | Tolerance | VIF |
| 2 | (Constant) | -.030 | .028 | | -1.072 | .291 | | |
| | NPLA/PLAL | -.053 | .008 | -.440 | -6.499 | .000 | .660 | 1.516 |
| | PLAL/TLA | .147 | .335 | .037 | .441 | .662 | .429 | 2.328 |
| | NPLA/TLA | -.534 | .474 | -.097 | -1.126 | .268 | .409 | 2.447 |
| | TLA/TAS | .032 | .023 | .103 | 1.396 | .172 | .553 | 1.807 |
| | LDR | .180 | .021 | .572 | 8.672 | .000 | .693 | 1.442 |
| | interaction | -.017 | .004 | -.256 | -4.026 | .000 | .747 | 1.339 |
| a. Dependent Variable: Financial Performance | | | | | | | | |

## RESULTS AND DISCUSSION

### Descriptive and Correlation Results

The descriptive statistics reveal clear structural differences between Islamic and commercial banks across key credit-risk indicators. Commercial banks exhibit substantially higher levels of credit-risk pressure, as shown by their elevated NPLA/PLAL, PLAL/TLA, and NPLA/TLA ratios, while Islamic banks display healthier credit-risk profiles and higher loan concentration (TLA/TAS). These findings indicate that Islamic banks allocate a greater share of their assets to credit activities but remain more conservative in terms of non-performing loan exposure. Correlation results reinforce these patterns, showing strong negative associations between ROE and credit-risk indicators (NPLA/PLAL, PLAL/TLA, NPLA/TLA), and strong positive correlations between ROE and both TLA/TAS and LDR. This suggests that banks with higher credit quality and greater lending intensity tend to achieve superior profitability, consistent with prior findings in emerging markets (Afriyie *et al.*, 2018; Ghosh & Mondal, 2022).

### Regression Results: Effect of Credit Risk on Financial Performance

Regression Model (1) demonstrates high explanatory power ($R^2 = 0.852$), confirming that credit-risk factors strongly predict bank profitability. Non-performing loan measures (NPLA/PLAL and PLAL/TLA) exert significant negative effects on ROE, showing that deterioration in loan portfolios directly depresses performance. By contrast, TLA/TAS and LDR have significant positive effects, indicating that banks with a higher proportion of loans and more effective deposit-to-loan transformation generate higher earnings. These results affirm Hypothesis H1 and refute H2. They also align with earlier studies emphasizing the adverse impact of NPLs on performance and the profitability benefits of prudent but active lending strategies (Yimka *et al.*, 2015; Bhatia & Mahendru, 2023).

### Comparison Between Islamic and Commercial Banks

Independent-samples t-tests and Mann–Whitney U tests show significant differences between Islamic and commercial banks on most credit-risk indicators, with commercial banks consistently displaying higher credit-risk exposure. However, no statistically significant difference emerges in financial performance (ROE). This finding partially supports H3 by confirming structural divergence in risk behavior, yet the absence of performance differences aligns with Saudi Arabia's harmonized regulatory environment under SAMA. These outcomes are consistent with studies showing regulatory convergence reduces differences in banking behavior (Aldayel & Fragouli, 2018; Al-Muharrami & Hardy, 2013).

Regression Model (2) reveals an even stronger model fit ($R^2 = 0.900$), and the interaction term (LDR × Type) is statistically significant. This provides robust evidence that the effect of credit-risk indicators on ROE differs systematically between Islamic and commercial banks, fully supporting Hypothesis H3 and rejecting H4. While both bank types operate under identical Basel III and SAMA regulatory mandates, their internal structures profit-and-loss sharing versus interest-based lending shape how credit-risk dynamics influence profitability. These findings align with previous research emphasizing that structural and contractual differences create variations in risk-performance relationships (İncekara & Çetinkaya, 2019; Siddique *et al.,* 2022).

Overall, the findings reinforce the central role of CRM in sustaining bank profitability. The negative impact of NPL indicators and the positive associations of loan concentration and lending efficiency confirm well-established theories of risk-return trade-offs (Markowitz, 1952) and agency considerations in credit governance (Jensen & Meckling, 1976). The observed convergence in performance across banking types reflects the effectiveness of SAMA's Basel-aligned supervisory framework (SAMA, 2023, 2024), echoing international evidence on regulatory harmonization. The significant moderating role of bank type highlights that structural differences such as Shariah-compliant contractual design continue to influence the sensitivity of financial performance to credit-risk factors, consistent with comparative results in Islamic finance literature (Khan & Ahmed, 2001; Abdul Malik & Kamil, 2016).

## CONCLUSION

This study explored the impact of credit risk management on the financial performance of Islamic and commercial banks in Saudi Arabia during 2020–2024. The results demonstrate that credit-risk indicators significantly influence profitability, with non-performing loan measures exerting negative effects and lending intensity and loan concentration enhancing ROE. Although significant differences exist in credit-risk profiles across banking types, financial performance does not differ significantly. However, the moderating effect of bank type confirms that Islamic and commercial banks translate risk dynamics into performance differently. The findings underscore the importance of robust CRM practices including early-warning systems, effective provisioning, and disciplined underwriting in maintaining profitability. Policymakers should continue reinforcing risk-sensitive supervision and model-risk governance, while bank managers should enhance credit analytics, stress testing, and borrower-monitoring systems to manage rising credit exposures in an evolving Vision 2030 landscape. Future research may adopt dynamic models, incorporate macro-prudential indicators, or analyze contract-level data to further illuminate differences across banking models.

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