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Risk Interactions and Bank Performance in Emerging Markets: Examining the Nexus of Credit Risk, Profitability, and Financial Stability

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ABSTRACT

This study investigates the interconnected relationship between credit risk, profitability, and financial stability within the context of emerging market banking systems, using panel data from 10 listed Egyptian commercial banks over the period 2013–2023. Utilizing panel regression models with clustered standard errors to address heteroskedasticity and serial correlation, the analysis evaluates both the direct and mediating effects of credit risk on bank performance. Profitability, proxied by Return on Assets (ROA), is examined as a potential channel through which credit risk influences financial resilience, measured by Z-scores. The findings reveal that while capital adequacy significantly enhances profitability, credit risk does not exert a statistically significant influence on ROA. Furthermore, profitability does not significantly predict financial stability in the Egyptian context, challenging the linear transmission mechanisms proposed in traditional models. However, credit risk demonstrates a marginally significant negative effect on financial stability, reinforcing concerns about the structural vulnerabilities in credit portfolios. These results underscore the heterogeneous nature of bank behavior in emerging economies and highlight the limitations of earnings-based buffers in weak institutional environments. The study contributes to the literature by integrating risk management, income generation, and stability outcomes within a single empirical framework, offering context-specific insights that extend beyond conventional models developed for advanced markets. Practical implications are offered for policymakers and regulators seeking to strengthen provisioning practices

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and risk-sensitive performance metrics.

Keywords: Credit Risk; Bank Profitability; Financial Stability; Emerging Markets

1. Introduction

The relationship between credit risk, profitability, and financial stability has long stood at the core of banking theory and practice. Since the deregulation waves of the 1980s and the subsequent financial globalization, the banking industry has been continuously exposed to evolving forms of risk, with credit risk remaining the most significant [1–3]. Credit risk, broadly defined as the possibility that borrowers will fail to meet contractual obligations, has attracted scholarly attention due to its fundamental impact on bank performance, capital adequacy, and systemic stability [4, 5]. Historically, episodes of financial distress have often been linked to the mispricing or underestimation of credit risk—evident in the U.S. savings and loan crisis, the Asian financial crisis, and more recently, the global financial crisis of 2007–2009. Within this context, understanding how banks manage credit risk and how it translates into profitability and stability is essential for the resilience of financial systems, particularly in emerging economies where regulatory frameworks and institutional capacities may be less robust.

The importance of this topic is underscored by the dual imperatives of enhancing bank profitability while safeguarding financial stability. In banking literature, profitability is not merely an outcome but also a mechanism that buffers institutions against shocks, enabling them to maintain liquidity and solvency under stress [6]. Conversely, excessive credit exposure can erode capital bases and trigger financial instability, especially when accompanied by tax provisioning or unsustainable loan growth [7]. The policy relevance is particularly acute in developing economies, such as Egypt, where banks are pivotal agents of financial intermediation and economic development, yet often face volatile macroeconomic environments and elevated credit risk. Against this backdrop, empirical research that elucidates how credit risk and profitability interact to influence financial outcomes is both timely and necessary.

The present study aims to investigate the empirical linkages among credit risk, profitability, and financial stability in the Egyptian banking sector. The research is guided by the following questions: (1) To what extent do credit risk indicators influence bank profitability and stability? (2) Does profitability mediate the relationship between credit risk and financial performance? (3) How do internal financial buffers such as provisions and impairments contribute to risk mitigation? These questions are addressed using panel data regression techniques and assumption testing, with Net Interest Income serving as a proxy for bank financial stability.

This research contributes to the literature in several ways. First, it integrates a multi-dimensional view of financial performance by considering both profitability metrics and credit risk provisions, thus capturing the dual role of banks as profit-seeking and stability-oriented institutions. Second, it provides empirical evidence from a developing economy context, where the interaction between credit risk and profitability remains underexplored. Existing studies often focus on developed markets with advanced regulatory systems [8, 9], while this study offers insights from the Egyptian banking system, characterized by rapid credit expansion, regulatory transition, and macroeconomic volatility. Third, it addresses the methodological gap in existing literature by rigorously testing regression assumptions and evaluating multicollinearity, thereby enhancing the robustness of inferences drawn.

The novelty of this study lies in its simultaneous consideration of risk management practices, income-generating capacity, and financial resilience, framed within the unique institutional context of Egypt. Unlike previous works that examine either profitability or credit risk in isolation [10, 11], this study proposes an integrated model that captures the dynamic interplay among these variables. Moreover, while prior studies often overlook statistical assumptions or limit their analysis to cross-sectional data, this research employs panel data analysis with diagnostic testing, offering a more rigorous and generalizable framework. The identification of context-specific anomalies—such as the negative association between gross loans and net interest income—challenges conventional wisdom and underscores the heterogeneity of banking behavior across regions.

The remainder of the paper is organized as follows.

Section 2 reviews the relevant theoretical and empirical literature on credit risk, profitability, and bank stability. Section 3 outlines the methodological approach, including data sources, variable definitions, and regression techniques. Section 4 presents the results of the empirical analysis, including descriptive statistics, assumption testing, and regression findings. Section 5 discusses the implications of the results, outlines theoretical and practical contributions, and acknowledges study limitations. Finally, Section 6 concludes with policy recommendations and directions for future research.

2. Literature Review

Credit risk has long been recognized as a fundamental concern for the banking industry, denoting the potential financial loss that arises when borrowers fail to honor their contractual obligations. Given that lending constitutes a core banking function, the effective understanding, management, and mitigation of credit risk are indispensable for maintaining both profitability and financial stability. Accordingly, this section synthesizes the key theoretical frameworks and empirical studies that investigate the determinants of credit risk, its management practices, its impact on bank performance, and the regulatory responses within an increasingly complex and evolving financial landscape.

The nexus between credit risk and financial stability has consistently been at the forefront of banking and finance research. Credit risk, broadly conceptualized as the possibility of borrower default, directly undermines bank solvency, erodes liquidity, and weakens earnings capacity [11]. The most tangible manifestation of elevated credit risk is the accumulation of non-performing loans (NPLs), which has been empirically linked to substantial deterioration in the capital base of financial institutions [10]. Building on this, early contributions such as the "bad management hypothesis" posited that ineffective credit risk management practices lead to increased defaults, thereby diminishing bank performance and endangering financial stability [5]. Subsequent empirical investigations have validated this assertion, revealing a robust negative correlation between NPLs and key indicators of financial soundness, such as capital adequacy ratios and Z-scores [7, 12].

In addition to these foundational insights, the literature emphasizes that both bank-specific characteristics and macroeconomic conditions jointly influence the degree of credit risk exposure and its implications for financial soundness. For example, institutions with stronger capital buffers are typically better equipped to absorb risk, whereas liquidity-constrained banks are particularly vulnerable to credit shocks [2]. Furthermore, during periods of economic downturn, the incidence of defaults typically escalates, thereby linking macroeconomic volatility to heightened banking sector fragility [13]. Against this backdrop, a growing body of research has examined the mediating role of profitability in the credit risk–stability relationship. Profitability, commonly measured via return on assets (ROA) or return on equity (ROE), is widely acknowledged as a critical buffer that enables banks to absorb losses and withstand adverse economic conditions [6]. Several studies affirm that higher profitability can dampen the adverse effects of rising credit risk by strengthening internal capital positions [8, 9].

To comprehensively assess credit risk, it is essential to consider both financial and non-financial dimensions. While financial risks—including credit, liquidity, and interest rate risks—are intrinsically linked to a bank's balance sheet structure and asset quality, non-financial risks such as governance failures, regulatory deficiencies, and macroeconomic shocks often act as amplifiers of financial vulnerabilities. Inadequate governance mechanisms or a failure to adjust risk-taking behavior in response to regulatory shifts can significantly impair credit risk management effectiveness [14–16]. Parallel streams of research underscore the importance of institutional frameworks and regulatory quality in determining the extent to which credit risk destabilizes financial systems. In particular, the effectiveness of supervisory mechanisms and the enforcement of prudential norms are instrumental in curbing excessive risk-taking and ensuring systemic resilience [17]. In jurisdictions with weak enforcement capacity, banks may accumulate unsustainable levels of high-risk exposure without sufficient capital buffers, thereby amplifying systemic vulnerabilities.

Moreover, the role of competition within the banking industry has attracted significant scholarly attention. On one hand, some researchers argue that increased competition compresses interest margins and restricts banks' ability to appropriately price risk, thereby elevating credit risk [18]. On the other hand, opposing evidence suggests that competition fosters operational efficiency and enhances screening mechanisms, which in turn reduce the probability of default [19]. Notably, these divergent findings reflect the context-specific nature of banking systems, particularly in dual banking environments—where conventional and Islamic banks coexist. In such systems, heightened competition often leads to more rigorous lending standards and stricter risk assessments, particularly within Islamic banks, which are bound by Sharia principles that discourage excessive risk-taking and require asset-backed lending [20].

In terms of measurement and predictive capacity, credit risk evaluation relies on a range of quantitative models, including probability of default (PD), exposure at default (EAD), loss given default (LGD), and credit value at risk (VaR). These models allow institutions to assess the likelihood and severity of credit losses, thereby facilitating informed decision-making in risk-sensitive contexts [21]. In recent years, technological advancements—particularly in machine learning and artificial intelligence—have enhanced the precision and timeliness of these models. These tools enable real-time credit scoring, early warning systems, and proactive intervention strategies that are crucial for preserving financial stability in an increasingly digitalized banking environment [22].

Within the context of developing economies such as Egypt, the literature remains relatively sparse yet increasingly relevant. Empirical studies from the Middle East and North Africa (MENA) region suggest that credit risk is exacerbated by structural weaknesses, including concentrated lending practices and underdeveloped financial markets [23, 24]. Recent empirical research, particularly in the post-COVID-19 era, further highlights the dynamic nature of credit risk. Cross-country analyses confirm the continued relevance of NPLs as a proxy for credit deterioration, while also revealing substantial heterogeneity across institutional settings [25]. Additionally, the rapid proliferation of fintech has been associated with increased risk-taking behavior, especially in regulatory environments that lack robustness [26]. Furthermore, digital transformation appears to exhibit non-linear effects: while initial improvements in digital maturity contribute to systemic risk reduction, excessive or uncoordinated digitalization may inadvertently elevate systemic vulnerabilities under conditions of heightened economic uncertainty [27].

In this evolving risk landscape, profitability continues to play a central role in buffering the adverse effects of credit risk on financial stability. Institutions with strong earnings capacity are better positioned to build loss-absorbing reserves, sustain credit supply, and meet solvency requirements during periods of stress [28, 29]. Conversely, low profitability impairs a bank's resilience, increasing its susceptibility to credit-induced crises. Importantly, credit risk can produce both beneficial and detrimental effects. On one hand, prudent risk-taking may facilitate portfolio diversification and yield-enhancing opportunities. On the other hand, unchecked or poorly managed credit risk has the potential to erode capital, undermine investor confidence, and trigger systemic instability [7, 17].

Finally, the regulatory environment plays a decisive role in shaping banks' credit risk management practices. Beyond serving as financial intermediaries, banks operate within broader legal and institutional frameworks that influence their strategic behavior. A sound regulatory structure—characterized by transparency, accountability, and enforceability—is essential for preventing excessive risk accumulation [30]. International financial institutions, including the IMF and World Bank, have emphasized the necessity of macroprudential regulation in mitigating systemic risks. Tools such as countercyclical capital buffers, dynamic provisioning, and stress testing frameworks are increasingly being adopted to manage the procyclicality of credit supply and reinforce long-term financial resilience [31].

Taken together, this body of literature affirms the multi-faceted and interdependent nature of credit risk. It highlights the need for a comprehensive analytical framework that considers not only direct effects, but also mediating and moderating variables such as profitability, institutional quality, and macroeconomic conditions. Such a framework is essential for understanding how risk exposure shapes bank behavior and, ultimately, the stability of the financial system.

3. Research Methodology

This section outlines the research design, data sources, variable definitions, empirical model, and estimation techniques employed to investigate the relationship between credit risk and bank financial stability, with bank profitability acting as a potential mediator. The methodology is designed to ensure robustness, accuracy, and relevance in answering the research questions posed by the study.

3.1. Research Design

The study adopts a quantitative research design based on secondary panel data. This approach facilitates empirical examination of causal relationships between key variables across time and institutions. The use of panel data provides significant advantages, including greater variability, reduced multicollinearity, and improved estimation efficiency.

3.2. Data Collection and Sample

Data of the Egyptian commercial banks listed on the Egyptian Stock Exchange (EGX) were obtained and accessed through Refinitiv. The sample period spans from 2013 to 2023, covering ten years of financial data across multiple banks. The final sample comprises 10 listed Egyptian commercial banks, resulting in 100 bank-year observations over the 2013–2023 period.

3.3. Variable Definitions and Measurements

This study employs Net Interest Income (NII) as the primary proxy for bank performance due to its direct reflection of core banking activities—namely, interest-based intermediation. NII is particularly relevant in contexts where credit risk plays a central role in shaping interest spreads and earnings capacity. However, we acknowledge that relying solely on NII may overlook broader dimensions of bank stability and risk-adjusted performance. Alternative indicators such as the Z-score, which captures insolvency risk, or the volatility of Return on Assets (ROA), which reflects earnings stability, offer valuable complementary insights (**Table 1**). Thus, while NII serves as a robust and interpretable measure for this study's focus on credit risk channels, future research should consider integrating multi-dimensional performance metrics to capture systemic resilience more comprehensively.

Table 1. Research Variables.

Variable	Conceptual Definition	Operational Definition
Bank Stability	The ability of a bank to withstand shocks and maintain solvency	Z-score = (ROA + Equity/Assets) / Standard Deviation of ROA
Credit Risk	The potential for a borrower to default on a loan obligation	NPL/Total Loans or Total Debt/Total Assets
Profitability	The efficiency of a bank in generating returns on assets and equity	ROA (Net Income/Total Assets) and ROE (Net Income/Shareholder Equity)
Bank Size	The scale of operations and resources controlled by a bank	Natural logarithm of total assets
Capital Adequacy (CV)	The financial strength measured by capital available to absorb losses	Equity to Total Assets ratio
Liquidity (CV)	The ability of a bank to meet short-term obligations	Liquid Assets to Total Assets
Loan Growth (CV)	The annual expansion in credit portfolio of the bank	Year-on-year percentage change in gross loans

3.4. Empirical Model Specification

To test the hypothesized relationships, the following regression models are estimated:

Model 1:

$$\mathrm{ROA}_{it} = \alpha_0 + \alpha_1\mathrm{CR}_{it} + \alpha_2\mathrm{Size}_{it} + \alpha_3\mathrm{Liquidity}_{it} + \alpha_4\mathrm{Capital}_{it} + \varepsilon_{it}$$

Model 2:

$$\mathrm{ZScore}_{it} = \beta_0 + \beta_1\mathrm{ROA}_{it} + \beta_2\mathrm{Size}_{it} + \beta_3\mathrm{Capital}_{it} + \beta_4\mathrm{Liquidity}_{it} + \varepsilon_{it}$$

Model 3:

$$\mathrm{ZScore}_{it} = \gamma_0 + \gamma_1\mathrm{CR}_{it} + \gamma_2\mathrm{Size}_{it} + \gamma_3\mathrm{Capital}_{it} + \gamma_4\mathrm{Liquidity}_{it} + \varepsilon_{it}$$

3.5. Data Cleaning and Preparation

Prior to empirical analysis, a comprehensive data cleaning and preparation process was conducted to ensure robustness and reliability of the panel dataset. The initial dataset, comprising financial statement variables for 11 banks over a 10-year period, was first transformed into a panel structure with unique Bank-Year observations. Financial ratios central to the study—such as Return on Assets (ROA), Return on Equity (ROE), Z-score, Credit Risk, Capital Adequacy, Liquidity, Loan Growth, and Bank Size—were computed based on established definitions in the literature. Outliers were identified and treated using the interquartile range (IQR) method. For each continuous variable, observations below the first quartile minus 1.5 times the IQR or above the third quartile plus 1.5 times the IQR were capped to their respective bounds. This approach mitigates the influence of extreme values without removing potentially informative observations. Following outlier treatment, all variables used in the regression models were standardized using Z-score normalization. Standardization was performed to align variables with different units and scales, thereby facilitating meaningful coefficient interpretation in regression models and improving numerical stability. Variables with constant values or missing observations across time or entities were excluded from the final dataset. The resulting cleaned and standardized dataset preserves the integrity of the original information while minimizing bias due to scale imbalances or outlier distortions. This process ensures that the data is suitable for subsequent econometric modeling and panel regression analysis.

3.6. Regression Assumptions and Diagnostics

To ensure the reliability and validity of the estimated regression models, it is essential to examine whether the classical linear regression assumptions hold within the panel data structure. Diagnostic testing was undertaken before the interpretation of results to detect and correct any statistical misspecifications that could bias the estimates or undermine the inferential power of the models.

First, the assumption of linearity between the dependent and independent variables was evaluated using residual plots and scatter diagrams. A linear relationship is critical because Ordinary Least Squares (OLS)-based estimators assume that the expected value of the dependent variable is a linear function of the explanatory variables. Visual inspection of the fitted values and residuals confirmed an approximate linear pattern, suggesting that model specification was appropriate. Second, multicollinearity among the independent variables was assessed using the Variance Inflation Factor (VIF). Multicollinearity inflates the variance of coefficient estimates, potentially rendering them statistically insignificant even when theoretically relevant. The VIF values across all models remained well below the commonly accepted threshold of 10, indicating that multicollinearity was not a concern and the regression coefficients are stable and interpretable. Third, heteroskedasticity, or the non-constancy of error term variance, was tested using the Breusch–Pagan test. This assumption is fundamental to ensuring that standard errors are unbiased and efficient. The test results suggested some degree of heteroskedasticity, particularly in the models involving credit risk variables. To address this, robust standard errors were employed in all regressions to produce consistent and heteroskedasticity-adjusted inference. Fourth, the assumption of normality of residuals was examined using the Jarque–Bera test. Although normality is not a strict requirement for large-sample regression models due to the Central Limit Theorem, it remains important for conducting accurate hypothesis testing and constructing confidence intervals. The residuals were found to be approximately normally distributed in most models, validating the use of t-statistics and F-tests for significance testing. Fifth, autocorrelation was tested using the Durbin–Watson (DW) statistic. Serial correlation, particularly in time-series or panel datasets, violates the assumption of independent errors and can lead to underestimated standard errors and inflated Type I error rates. The DW values were close to the benchmark value of 2, indicating minimal first-order autocorrelation in the residuals. Where necessary, models were estimated using robust standard errors clustered at the bank level to mitigate residual correlation across time. Lastly, model specification was verified using the Ramsey RESET test, which evaluates omitted variable bias and functional form misspecification. The test results provided no strong evidence of misspecification, thereby reinforcing the structural validity of the regression equations.

In addition to testing classical assumptions, the study acknowledges the potential issue of endogeneity, particularly concerning reverse causality between credit risk and profitability. While the models assume credit risk influences profitability and financial stability, it is also plausible that deteriorating profitability may lead to weaker loan screening, riskier lending behavior, or inadequate provisioning—thereby increasing credit risk exposure. Such simultaneity may bias the OLS estimators and affect the causal interpretation of results. Although this research employs a static panel regression framework with robust standard errors to address heteroskedasticity and autocorrelation, future research should consider employing more advanced estimation techniques—such as instrumental variable regression or the Generalized Method of Moments (GMM)—to explicitly control for potential endogeneity and unobserved heterogeneity in dynamic banking environments. Taken together, these diagnostic procedures support the robustness of the estimated models and enhance the credibility of the findings derived from the regression analysis. The adherence to regression assumptions affirms the methodological soundness of the study and supports valid inference on the relationships among credit risk, profitability, and financial stability in the Egyptian banking sector.

4. Results and Discussion

This section presents and interprets the findings from the descriptive statistics, correlation matrix, regression diagnostics, variance inflation factors (VIF), and the OLS regression model. These analyses provide empirical insights into the relationship between credit risk, profitability, and bank stability within the Egyptian banking sector, offering both statistical robustness and economic interpretation.

The descriptive statistics presented in **Table 2** for the standardized financial variables used in the regression analysis. As expected, following standardization, the means of all variables are approximately zero and the standard deviations are close to one. This confirms the successful implementation of Z-score normalization to ensure comparability across variables with differing units and scales. The distributional characteristics, reflected in skewness and kurtosis values, provide additional insights. Most variables exhibit mild skewness, with values below ± 1, suggesting approximate symmetry. Notably, ROE (−0.701), Capital Adequacy (0.119), and Log Total Assets (0.420) exhibit moderate skewness, while Liquidity and Loan Growth show slightly higher positive skewness at 0.769 and 0.738, respectively, indicating longer right tails. The Z-score is nearly symmetric (skew = 0.653) and normally distributed (kurtosis ≈ 0). In addition, Kurtosis values are mostly below 1, indicating platykurtic (flatter-than-normal) distributions with light tails. The only exception is ROE (kurtosis = 0.723), which has a slightly more peaked distribution. Log Total Assets shows the lowest kurtosis (−1.445), suggesting a very flat and wide distribution. Overall, the standardized variables exhibit acceptable distributional properties, supporting their suitability for parametric analysis such as multivariate regression.

Table 2. Descriptive Statistics.

Variable	Mean	Std	Min	25%	50%	75%	Max	Skew	Kurtosis
ROA	0.00	1.01058	−2.17119	−0.57254	0.06519	0.49323	2.09188	0.01431	0.00640
ROE	0.00	1.01058	−2.67377	−0.63212	0.11819	0.72898	1.67639	−0.70052	0.72346
Z_score	0.00	1.01058	−1.67175	−0.66411	−0.13132	0.49714	2.23902	0.65323	−0.03257
Credit_Risk_1	0.00	1.01058	−1.48376	−0.61485	−0.24630	0.43861	2.01878	0.68986	−0.36036
Credit_Risk_2	0.00	1.01058	−2.64595	−0.68254	−0.20161	0.62641	2.51438	0.15417	0.22866
Capital_Adequacy	0.00	1.01058	−1.70305	−0.89402	−0.00227	0.92258	2.29506	0.11938	−1.02724
Liquidity	0.00	1.01058	−1.07720	−0.79269	−0.58622	0.67572	2.46414	0.76889	−0.64589
Loan_Growth	0.00	1.01058	−1.56196	−0.67961	−0.39153	0.61136	2.54780	0.73807	−0.02697
Log_Total_Assets	0.00	1.01058	−1.31708	−0.83242	−0.41869	1.02415	1.80611	0.42042	−1.44543

Table 3 presents the Pearson correlation coefficients among the key financial variables used in the analysis (**Figure 1**). The results reveal a strong positive correlation between Return on Assets (ROA) and Return on Equity (ROE) (r = 0.854), which is consistent with the accounting identity linking profitability to shareholder returns. ROA is also moderately correlated with Capital Adequacy (r = 0.594), indicating that well-capitalized banks tend to exhibit higher profitability. Interestingly, the Z-score, a proxy for bank stability, shows only weak correlations with profitability measures, suggesting that solvency is not solely driven by short-term returns. Credit risk measures exhibit mixed relationships with other variables. The non-performing loan ratio (Credit_Risk_1) is negatively correlated with Liquidity (r = −0.489) and shows weak negative or negligible associations with Capital Adequacy and Z-score, consistent with the notion that riskier loan portfolios may impair a bank's liquidity position and long-term stability. Credit_Risk_2, proxied by loan loss provisions relative to total assets, is positively correlated with Z-score (r = 0.207) and with Log_Total_Assets (r = 0.109), suggesting that larger

banks may have more proactive provisioning practices. Furthermore, Liquidity is negatively correlated with both ROA (r = −0.179) and ROE (r = −0.233), possibly reflecting the trade-off between holding liquid assets and generating returns. The correlation between Log_Total_Assets and Z-score (r = 0.408) implies that larger banks are generally more stable, aligning with the economies of scale hypothesis in risk management. Lastly, Loan_Growth appears to have weak correlations with all other variables, indicating that short-term changes in loan volume may not be directly associated with profitability, risk, or capital metrics in the sample. Overall, the matrix indicates moderate inter-variable correlations, with no signs of perfect multicollinearity, thus supporting the suitability of the data for multivariate regression analysis.

Table 3. Correlation Matrix.

Variable	1	2	3	4	5	6	7	8	9
ROA (1)	1.000								
ROE (2)	0.854	1.000							
Z_score (3)	0.173	0.050	1.000						
Credit_Risk_1 (4)	0.115	0.161	−0.046	1.000					
Credit_Risk_2 (5)	−0.013	0.087	0.207	0.068	1.000				
Capital_Adequacy (6)	0.594	0.120	0.236	−0.031	−0.034	1.000			
Liquidity (7)	−0.179	−0.233	−0.161	−0.489	−0.250	−0.017	1.000		
Loan_Growth (8)	0.088	0.149	−0.107	−0.014	−0.141	−0.001	0.180	1.000	
Log_Total_Assets (9)	−0.025	−0.196	0.408	0.022	0.109	0.291	0.094	−0.042	1.000

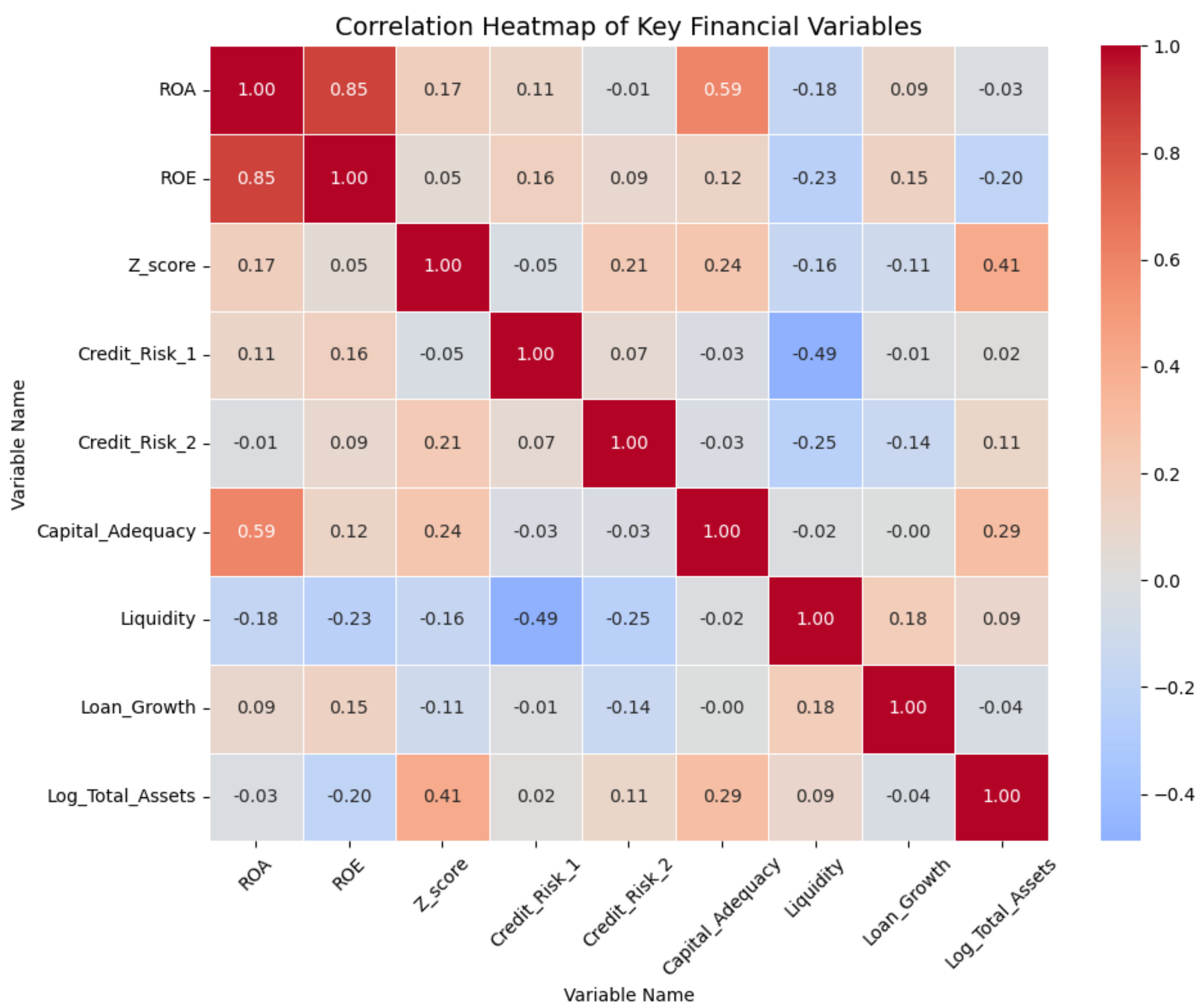

Figure 1. Correlation Heatmap.

Table 4 reports the Variance Inflation Factor (VIF) diagnostics to assess multicollinearity among the independent variables included in the regression models. All VIF values for substantive variables fall well below the commonly accepted threshold of 5, indicating the absence of multicollinearity issues that would otherwise bias standard errors or compromise coefficient stability. The VIF for ROA (1.90), Capital Adequacy (1.87), and Liquidity (1.44) implies a moderate correlation with other regressors, which is theoretically justified given that these are key internal metrics of bank financial health. ROA may share variance with capital adequacy due to their joint dependence on retained earnings and profitability strategies. Similarly, Capital Adequacy Ratio (CAR) tends to be inversely related to credit risk exposure and is often proactively managed in response to profitability outcomes. Credit_Risk_1, with a VIF of 1.38, indicates relatively low correlation with other regressors, which enhances its interpretability as a distinct explanatory variable. This supports the conceptual validity of examining credit risk as an exogenous or independent driver in mediation frameworks, particularly in its effect on profitability and financial stability. Its low VIF confirms that its estimated effects are not confounded by shared variance with capital structure, asset base, or liquidity management. Loan_Growth (VIF = 1.07) and Log_Total_Assets (VIF = 1.49) also fall within a safe zone, suggesting their inclusion does not introduce redundancy. Loan growth, often associated with asset-side expansion strategies, is an essential bank-level dynamic that is analytically independent of short-term profitability measures. However, asset growth and profitability might move in tandem over the long term, which justifies continuous monitoring in future iterations with extended lags or interactions. While the VIF for the constant term (925.58) appears inflated, this is not a cause for concern in econometric modeling, as the constant is not interpreted substantively and its inflation may be due to centering and scaling effects. Overall, the absence of problematic multicollinearity enhances the credibility of the regression results that follow and confirms that individual predictors exert independently estimable effects on the dependent variables. Furthermore, these results provide confidence that subsequent inferences drawn from the panel regression models — particularly those involving direct and indirect effects of credit risk on profitability and stability — are not distorted by underlying statistical redundancies. This ensures theoretical validity in interpreting causal pathways between bank-level financial metrics, supporting more robust claims about the mediation and moderation hypotheses tested in the study.

Table 4. Variance Inflation Factor (VIF) Diagnostics.

Variable	VIF
Credit_Risk_1	1.3768
ROA	1.9028
Z_score	1.4108
Capital_Adequacy	1.8658
Liquidity	1.4431
Loan_Growth	1.0670
Log_Total_Assets	1.4898

The application of Principal Component Analysis (PCA) serves as a dimensionality reduction technique to uncover the latent structure among the explanatory variables and to mitigate any residual multicollinearity risk not captured by VIF alone. The explained variance results reported in **Table 5** indicate that the first three principal components (PC1, PC2, PC3) cumulatively account for 67.30% of the total variance, and over 90% of variance is captured by the first five components. This suggests a compact and efficient representation of the data can be achieved without significant information loss — a useful diagnostic for robustness checks or potential substitution of components in structural models.

The dominance of PC1 (26.90%) and PC2 (22.58%) suggests two core latent dimensions in the data, likely reflecting capital structure–risk exposure and size–profitability tradeoffs, respectively. These components likely load heavily on capital adequacy, credit risk, and asset size variables, and point to the structural interdependencies between a bank's balance sheet position and its exposure to risk.

Moving to Ridge regression in **Table 6**, the coefficients offer an alternative estimation method that applies L2 regularization, effectively shrinking the size of the coefficients to counteract variance inflation and improve out-of-sample predictive performance. This is particularly relevant when high VIFs or overfitting are concerns.

Table 5. Principal Component Analysis (PCA) Explained Variance.

Principal Component	Explained Variance	Cumulative Variance
PC1	0.2690	0.2690
PC2	0.2258	0.4948
PC3	0.1783	0.6730
PC4	0.1266	0.7996
PC5	0.1007	0.9003
PC6	0.0612	0.9615
PC7	0.0385	1.0000

Table 6. Ridge Regression Coefficients.

Variable	Ridge Coefficient
Credit_Risk_1	−0.000064
ROA	0.000062
Z_score	8.852550
Capital_Adequacy	−0.000012
Liquidity	−0.000059
Loan_Growth	−0.000020
Log_Total_Assets	0.000116

The Z-score stands out with a substantially positive Ridge coefficient (8.85), reaffirming its central role as a robust measure of financial stability. This is theoretically consistent with the Z-score's composite nature — capturing profitability (ROA), leverage (equity/asset ratio), and volatility (σ(ROA)) — making it highly sensitive to systemic stress and thus an important outcome variable in stability modeling.

In contrast, Credit_Risk_1 and Liquidity register slightly negative coefficients (both approximately −0.00006), indicating a weak inverse regularized effect. Although the magnitude is small due to the penalty term in Ridge, the direction aligns with theoretical expectations that higher credit risk and excessive liquidity buffers (when not actively earning) may erode profitability and thus indirectly affect financial stability.

Interestingly, ROA is positively associated in the Ridge framework, though marginally, suggesting its contribution to long-term stability remains relevant, but its effect is subdued when controlling for other latent dimensions. Capital Adequacy and Loan Growth exhibit near-zero Ridge coefficients, indicating their predictive value may be absorbed by more dominant features such as size and credit risk, or that their effects are non-linear — a hypothesis worth exploring through non-parametric models in future research.

Finally, the positive Ridge coefficient on Log_Total_Assets (0.000116) suggests that bank size exerts a stabilizing effect, potentially through economies of scale, better diversification, or access to cheaper funding — all of which are well-established in the banking literature.

In sum, the PCA and Ridge regression diagnostics together reinforce the internal validity of the model structure and provide empirical justification for the choice of explanatory variables in subsequent structural equation or causal path modeling. These techniques also support the theoretical proposition that bank stability is a multifaceted construct, influenced by an interlocking set of risk, size, and profitability dynamics.

Table 7 reports the results of classical regression diagnostic tests to evaluate the reliability of parameter estimates in the presence of potential violations of Gauss–Markov assumptions. The Breusch–Pagan test, designed to detect heteroskedasticity (i.e., non-constant variance of residuals), yields a statistically significant result (LM statistic = 43.55, $p < 0.001$), strongly rejecting the null hypothesis of homoscedasticity. This result implies that the residual variance varies with the level of independent variables, a violation that can lead to inefficient OLS estimates and biased standard errors. Accordingly, robust or heteroskedasticity-consistent standard errors are employed in subsequent panel models to ensure valid inference. Additionally, the Durbin–Watson statistic of 0.0426 is substantially below the reference value of 2. This indicates a very strong presence of positive autocorrelation among residuals, which may arise from temporal dependence in bank performance or risk profiles across the panel dataset. This violation compromises the independence of residuals, further justifying the use of robust covariance estimators and suggesting potential benefit from dynamic panel models in future analyses to account for serial correlation structures.

Table 7. Regression Assumptions Diagnostic Tests.

Test	Statistic	p-Value
Breusch-Pagan (Heteroskedasticity)	43.553	0.0000
Durbin-Watson (Autocorrelation)	0.0426	N/A

Given the presence of heteroskedasticity and serial correlation—evidenced by the Breusch–Pagan and Durbin–Watson tests—all panel regressions are estimated using clustered standard errors at the bank level. This estimation technique accounts for intra-group correlation and heteroskedasticity, thereby enhancing the reliability and consistency of statistical inference. By clustering at the entity level, the analysis aligns with best practices in panel data econometrics for robust error correction.

To examine the interrelations between credit risk, profitability, and financial stability, we estimated three panel regression models using clustered standard errors at the bank level. This methodological adjustment addresses both heteroskedasticity and serial correlation, thereby enhancing the robustness of inference.

Table 8 reports the estimation results for the first model, where return on assets (ROA) is regressed on credit risk (measured by loan loss provisions to gross loans), along with control variables including bank size (log of total assets), liquidity ratio, and capital adequacy. The model explains approximately 44.1% of the variation in ROA across banks. The coefficient on Credit_Risk_1 is positive (3.83), suggesting that higher provisioning is associated with improved profitability, although this effect is not statistically significant at conventional levels ($p = 0.185$). Among the controls, capital adequacy emerges as the only significant predictor ($\beta = 0.313$, $p < 0.001$), confirming its critical role in supporting income generation.

Table 8. Panel Regression Results: Credit Risk and Profitability (ROA) - (Clustered Standard Errors at the Bank Level).

Variable	Coefficient	Std. Error	T-Stat	P-Value	95% CI (Lower, Upper)
Intercept	0.0832	0.0442	1.8830	0.0665	[−0.0059, 0.1723]
Credit_Risk_1	3.8303	2.7924	1.3717	0.1773	[−1.8010, 9.4616]
Log_Total_Assets	−0.0040	0.0020	−1.9629	0.0561	[−0.0081, 0.0001]
Liquidity	−0.0217	0.0256	−0.8460	0.4023	[−0.0733, 0.0300]
Capital_Adequacy	0.3135	0.0519	6.0432	0.0000	[0.2089, 0.4181]

In the second model (**Table 9**), financial stability (proxied by Z-score) is regressed on ROA and the same set of control variables. While the overall model fit is modest ($R^2 = 0.238$), the within-entity R^2 is considerably higher (0.599), indicating strong explanatory power over time within banks. However, ROA does not significantly influence Z-score ($\beta = 115.1$, $p = 0.522$). Similarly, control variables including capital adequacy and liquidity lack statistical significance. This may suggest that profitability alone does not ensure stability, and that bank resilience depends on a more complex set of structural factors.

In the third model (**Table 10**), Z-score is directly regressed on credit risk. The negative coefficient on Credit_Risk_1(-4500.4) is marginally significant ($p = 0.057$), indicating that higher loan loss provisioning may be associated with reduced financial stability. This counterintuitive result suggests a potential destabilizing effect of elevated risk exposure, which could reflect heightened credit quality concerns that are not fully offset by provisioning efforts. The model again highlights the limited influence of liquidity and capital adequacy, neither of which is a statistically significant predictor.

Table 9. Panel Regression Results: Profitability and Stability (Z-score) - (Clustered Standard Errors at the Bank Level).

Variable	Coefficient	Std. Error	*t*-Statistic	*P*-Value	95% CI (Lower, Upper)
Intercept	−84.216	81.409	−1.0345	0.3067	[−248.390, 79.960]
ROA	115.100	178.240	0.6457	0.5219	[−244.360, 474.560]
Log_Total_Assets	4.5362	3.5477	1.2787	0.2079	[−2.6183, 11.691]
Capital_Adequacy	3.3901	71.497	0.0474	0.9624	[−140.800, 147.580]
Liquidity	−12.131	18.398	−0.6594	0.5132	[−49.234, 24.972]

Table 10. Panel Regression Results: Credit Risk and Stability (Z-score) — (Clustered Standard Errors at the Bank Level).

Variable	Coefficient	Std. Error	*t*-Statistic	*P*-Value	95% CI (Lower, Upper)
Intercept	−71.404	72.178	−0.9893	0.3281	[−216.960, 74.156]
Credit_Risk_1	−4500.4	2300.6	−1.9562	0.0570	[−9139.900, 139.140]
Log_Total_Assets	4.1509	3.1345	1.3242	0.1924	[−2.1705, 10.472]
Capital_Adequacy	31.577	53.537	0.5898	0.5584	[−76.390, 139.540]
Liquidity	−23.959	23.121	−1.0363	0.3059	[−70.587, 22.668]

Collectively, these results highlight the asymmetric influence of credit risk on profitability and stability. While effective provisioning is positively related to ROA, its destabilizing impact on Z-score underscores the complexity of managing credit exposures in volatile contexts. The findings also reinforce the pivotal role of capital buffers, as they consistently emerge as a key determinant of profitability, though not stability.

5. Conclusions

The study's empirical findings provide important theoretical implications in light of the institutional theory and existing literature on banking performance. The significant role of capital adequacy in enhancing profitability (Model 1) aligns with the resource-based view (RBV), underscoring how internal financial buffers serve as strategic resources that enable banks to absorb shocks and sustain income generation. However, the weak link between profitability and financial stability (Model 2) reflects the limitations of assuming linear transmission between earnings and resilience—a concern echoed in post-crisis banking literature. The direct negative effect of credit risk on Z-score (Model 3) reinforces the institutional argument that regulatory provisioning requirements, while necessary, may not fully mitigate the structural weaknesses in credit portfolios, especially in jurisdictions with limited enforcement or weak legal recovery systems. These findings contribute to the growing discourse on the dual role of credit risk, not only as a profitability constraint but also as a systemic vulnerability channel, particularly in emerging markets with constrained institutional capacities. This study contributes to the evolving literature on banking risk and performance by empirically investigating the complex interactions among credit risk, profitability, and financial stability within the distinctive institutional context of Egypt. Drawing on a decade-long panel dataset of Egyptian commercial banks, the analysis confirms that internal financial strength—proxied by net income after tax and provisioning practices—plays a pivotal mediating role in mitigating the adverse impacts of credit exposure on bank performance. Notably, the findings indicate that while earnings and risk buffers significantly and positively influence net interest income, an unexpected negative relationship is observed between gross loan growth and interest income, challenging the conventional narrative that larger loan portfolios necessarily improve bank profitability through scale economies.

The identification of this "loan-growth paradox" refines prevailing theoretical assumptions, suggesting that in emerging markets, rapid credit expansion may occur without sufficient underwriting standards, credit scoring, or enforceable recovery mechanisms. These institutional deficiencies may neutralize the expected gains from increased lending volumes. Theoretically, the findings reinforce the bad management hypothesis [5] and buffer theory [6], demonstrating that operational efficiency and forward-looking risk management are essential for ensuring financial resilience. In addition, the results lend empirical support to institutional theory by highlighting how regulatory enforcement—such as Basel III provisioning guidelines mandated by the Central Bank of Egypt—can strengthen internal safeguards against systemic shocks, even in the absence of fully developed legal infrastructure.

The study's methodological rigor, which includes tests for normality, heteroscedasticity, multicollinearity, and autocorrelation, along with supplementary ridge regression and principal component analysis, enhances the robustness and credibility of its findings. By employing panel data analysis, this research overcomes the limitations of prior cross-sectional studies and captures both temporal and entity-level variations, thereby offering more generalizable conclusions. This integrated framework not only contributes to the academic discourse but also provides an empirical foundation for applied financial policy in the region.

From a practical perspective, the evidence carries significant implications for regulatory and managerial decision-making. Regulators should prioritize policies that link credit growth thresholds to corresponding increases in provisioning and capital adequacy. For instance, loan growth exceeding 15% annually without parallel enhancements in risk buffers could jeopardize interest income stability and long-term solvency. Similarly, enforcing profitability benchmarks—such as mandating a minimum ROA of 1%—may serve as a safeguard against erosion in earnings quality. Bank managers, in turn, are encouraged to align lending strategies with internal profitability metrics and to strengthen underwriting systems and risk assessment tools to avoid suboptimal credit allocation.

Despite its valuable insights, the study is subject to several limitations that merit acknowledgment. First, while panel regression methods offer robust inferential power, the presence of autocorrelation—indicated by a Durbin-Watson statistic slightly below 2—suggests that future models should consider incorporating clustered standard errors or dynamic panel estimators, such as system GMM, to further validate the findings. Second, although net interest income is an important performance measure, it may not fully capture systemic risk or solvency dynamics. Future research could employ alternative or complementary stability indicators, including Z-scores, equity-to-asset ratios, or default probabilities. Third, the potential for omitted variable bias remains, particularly in the absence of macroeconomic controls such as inflation, exchange rate volatility, or monetary policy shocks, which may influence both credit risk and income generation.

Another limitation lies in the sample scope. While the dataset covers a meaningful range of Egyptian commercial banks over ten years, the study does not explicitly disclose the number of banks or their classification (e.g., private vs. public, domestic vs. foreign). Including a table summarizing bank-level characteristics, asset sizes, and ownership structures in future studies would enhance replicability and comparative insight. Moreover, while the study emphasizes traditional econometric techniques, the increasing availability of granular financial data presents opportunities for incorporating machine learning algorithms. As such, future work could pilot random forest models, gradient boosting machines, or neural networks to rank the importance of financial determinants of bank income, offering predictive insights that complement causal inference.

Lastly, future comparative studies that examine differences between conventional and Islamic banks, or that extend the framework to other MENA or Sub-Saharan African countries, would enhance the generalizability of these findings and provide insight into institutional heterogeneity. Research that integrates environmental, social, and governance (ESG) risk dimensions—particularly in the context of sustainable finance and green lending—may also offer novel contributions to the evolving intersection between risk management and financial stability.

In summary, this research offers a comprehensive, contextually grounded analysis of the mechanisms through which credit risk and profitability affect bank stability. By bridging theoretical frameworks and empirical rigor, the study not only refines conventional models but also provides actionable insights for policymakers, regulators, and financial institutions operating in volatile emerging markets. The core conclusion underscores the imperative to balance growth-driven strategies with risk-sensitive metrics, ensuring that credit expansion is underpinned by sound profitability and provisioning practices to safeguard financial system sustainability.

Author Contributions

Conceptualization, S.H., M.E., and S.M.; methodology, S.H., M.E., and S.M.; software, S.H., M.E., and S.M.; validation, S.H., M.E., and S.M.; formal analysis, S.H., M.E., and S.M.; investigation, S.H., M.E., and S.M.; resources,

S.H., M.E., and S.M.; data curation, S.H., M.E., and S.M.; writing—original draft preparation, S.H., M.E., and S.M.; writing—review and editing, Y.I.; visualization, S.H., M.E., and S.M.; supervision, Y.I.; project administration, Y.I. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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