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Banking soundness and systemic risk: Insights from the Egyptian banking sector

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Abstract

This study investigates the relationship between key banking soundness indicators—capital adequacy, asset quality, profitability, liquidity, and efficiency—and systemic risk within Egypt's banking sector. The purpose is to identify the primary drivers of systemic risk and provide actionable insights to enhance financial stability in emerging economies. Using panel data from nine banks listed on the Egyptian Exchange between 2011 and 2021, the research employs Value-at-Risk (VaR) as the systemic risk measure. It applies the Generalized Method of Moments (GMM) approach to address dynamic interactions and mitigate endogeneity concerns. The findings reveal that capital adequacy, asset quality, and profitability have a significant influence on systemic risk, highlighting the importance of maintaining robust capital buffers, implementing effective credit risk management, and developing thoughtful profitability strategies. Conversely, liquidity and efficiency metrics were found to have no substantial impact on systemic risk in the Egyptian banking context. The study emphasizes the necessity of prioritizing the monitoring and regulation of capital adequacy and asset quality to mitigate systemic vulnerabilities and enhance the resilience of the financial system. Additionally, it contributes to the literature by offering valuable insights into the interactions between banking stability indicators and systemic risk in emerging markets, providing a strong foundation for future research. These findings have practical implications for both policymakers and banking executives. Policymakers are encouraged to refine macroprudential regulations to emphasize robust capital planning and credit risk oversight, ensuring systemic stability. Bank executives can use these insights to align profitability strategies with comprehensive risk management objectives. Overall, this study offers actionable recommendations aimed at fostering a sustainable and resilient banking sector in Egypt.

Keywords: CAMELS approach, Egyptian banks, Systemic risk, Value at risk.

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1. Introduction

The performance of Egyptian banks has undergone several changes due to shifts in market structure and regulatory updates. Table 1 showcases the significant developments in the soundness indicators of Egyptian banks from 2019 to 2023.

Table 1.
Egyptian Banking Performance Developments (2019-2023).

Item	Indicator	2019	2020	2021	2022	2023
Capital Adequacy	Capital Base to Risk weighted assets	0.177	0.201	0.222	0.189	0.175
	Tier 1 Capital to Risk-Weighted Assets	0.149	0.177	0.179	0.155	0.143
	Common Equity to Weighted-Risk to Equity	0.127	0.146	0.134	0.120	0.106
Asset Quality	Nonperforming Loans to Total Loans	0.042	0.040	0.034	0.033	0.033
	Loan Provisions to Nonperforming Loans	0.976	0.952	0.923	0.919	0.916
	Loans to Private Sector to Loans to Customers	0.621	0.630	0.576	0.560	0.536
Earnings	Return on Average Assets	0.018	0.012	0.012	0.012	0.012
	Return on Average Equity	0.234	0.149	0.161	0.177	0.177
	Net Interest Margin	0.041	0.037	0.042	0.038	0.038
Liquidity	Liquidity Ratio: Local Currency	0.444	0.538	0.454	0.433	0.376
	Liquidity Ratio: Foreign Currencies	0.677	0.715	0.679	0.779	0.701
	Securities to Assets	0.195	0.249	0.287	0.280	0.244

Source: Central Bank of Egypt [1]

This table provides insights into the changing performance of Egyptian banks, highlighting both positive and negative trends, yet the market's response to these changes remains uncertain. This paper investigates how banking soundness indicators affect the systemic risk of Egyptian banks. In both advanced and developing nations, the financial health of banks is crucial for fostering economic growth and development. A robust financial sector stimulates national economic growth by ensuring efficient resource use, facilitating capital flow, and promoting commerce and industry [2-4]. The importance of evaluating financial performance was highlighted by the global financial crisis, which emphasized the need for early warning systems to provide timely information on financial risks to regulators and policymakers. In response to the Great Financial Crisis, macroprudential authorities implemented measures to address systemic vulnerabilities, including frameworks for systemic risk monitoring.

Despite extensive research on systemic risk and financial soundness, few studies focus specifically on the Egyptian banking sector. The use of global frameworks such as the CAMELS rating system, known for assessing bank soundness, has not been extensively explored in this context. While other studies have demonstrated the predictive capability of CAMELS indicators (e.g., [5, 6]), there is limited research on their application in assessing systemic risk in developing countries like Egypt. Additionally, there is a lack of approaches suitable for data-scarce environments, as systemic risk studies often rely on Credit Default Swap (CDS) data, mostly available for banks in developed countries [7, 8].

This research aims to bridge these gaps by examining the relationship between systemic risk in Egyptian banks and banking soundness metrics as outlined by the CAMELS framework. The study seeks to address key questions such as: How does capital adequacy impact systemic risk in Egyptian banks? What role does asset quality play in influencing systemic risk? Is there a significant connection between systemic risk and management effectiveness? How do profits affect systemic risk assessment? Does liquidity significantly impact systemic risk? By addressing these questions, the study seeks to contribute to the understanding of financial stability in developing markets by developing a framework for evaluating systemic risk in Egyptian banks.

The research makes several contributions to the literature. It examines the impact of banking soundness indicators on systemic risk in Egyptian banks, offering insights into the relationship between these variables in an emerging economy context. The study utilizes panel data analysis and the GMM technique to investigate these relationships, providing a methodological contribution to banking and finance literature. It emphasizes the importance of capital adequacy, asset quality, and profitability in affecting systemic risk in Egyptian banks, aiding policymakers and bank executives in decision-making. Moreover, the study enhances existing literature by highlighting the distinct impacts of banking soundness indicators on systemic risk, such as the critical roles of capital adequacy and asset quality, and the nuanced effects of profitability, liquidity, and efficiency. These contributions offer actionable insights for systemic risk mitigation in the Egyptian banking sector and lay the groundwork for future comparative studies with other developing economies.

While asset quality highlights a bank's risk exposure, with poor measures like high non-performing loan ratios increasing vulnerabilities, capital adequacy is emphasized as a crucial buffer against financial shocks, potentially reducing systemic risk. Profitability presents a complex trade-off: while it enhances solvency, it may also encourage risk-taking behavior. Although liquidity ensures operational resilience, its direct impact on systemic risk is minimal in this context. The role of efficiency, as measured by the Cost-to-Income ratio (CTI), remains ambiguous as a predictor of systemic risk. Understanding the interplay and conflicts among these dynamically interacting factors is vital for hypothesis formulation and guiding regulatory actions.

The structure of the paper is organized as follows: Section 2 reviews relevant literature, providing a comprehensive overview of prior studies on banking soundness and systemic risk. Section 3 outlines the methodology, detailing the measurement of variables, hypothesis development, and the econometric framework. Section 4 presents the empirical findings, assesses their alignment with research objectives, and includes robustness tests. Section 5 analyzes and synthesizes the results from Section 4, discussing their practical and theoretical implications, and addressing limitations and areas for further research. This section is crucial for linking the empirical findings to the broader context of banking soundness, systemic risk, and policy relevance, while also concluding the research.

2. Literature Review

This in-depth analysis, tailored to specific contexts, offers a robust theoretical base for the research, ensuring that the hypotheses are well-rooted in existing studies while also addressing their shortcomings. Over the past five decades, various indicators of banking stability, including capital adequacy, asset quality, management efficiency, earning potential, and liquidity, have been extensively examined. Many researchers have explored this area, and this section summarizes some of the studies from the past twenty years.

When it comes to capital adequacy, most research typically shows a negative correlation between capital ratios and the likelihood of default Arena [9]; Betz, et al. [10] and Berger, et al. [11]. Blundell and Bond [12] highlighted the benefits of the System GMM estimator, which helps reduce biases in dynamic panel data models, proving crucial for understanding complex time-dependent relationships, such as those related to banking stability. Arellano and Bond [13] also made significant contributions to panel data methodologies, providing tools that are widely applicable in research on systemic risk. Acharya and Steffen [14] analysed the effect of capital adequacy on systemic risk using a sample of global banks, finding that higher capital adequacy ratios are linked to lower systemic risk, suggesting that well-capitalized banks are less likely to cause systemic instability. Likewise, Blum and Hellwig [15] explored the connection between the Capital Adequacy Ratio (CAR) and systemic risk using data from European banks, concluding that higher CARs enhance overall financial stability by reducing systemic vulnerabilities. Additionally, Kapan and Minoiu [16] investigated how bank complexity affects systemic risk through robust CARs, showing that higher CARs alleviate systemic vulnerabilities, especially for complex banks. Policymakers can gain valuable insights into financial stability conditions from systemic risk indicators. Financial stress indicators, which mainly rely on market-based values, have been extensively studied by scholars and policy organizations, including Giglio, et al. [17]; Benoit, et al. [18] and Aikman, et al. [19]. These indicators provide an understanding of how specific risk factors contribute to stress levels, capturing a broad range of risk elements for financial institutions both individually and collectively. However, most methods are contemporaneous, offering warnings with limited lead times before crises and often failing to effectively alert policymakers about the build-up of systemic risk.

Asset quality is a key determinant of a bank's risk profile, influenced by the composition of assets within its portfolio. Sharp declines in the value of risky assets can lead to sudden losses and diminish capital buffers, increasing the risk of failure. Three commonly used measures in this field are the loans-to-assets ratio, the ratio of loan provisions to total loans, and the ratio of non-performing loans (NPL) to total loans. DeYoung [20] and Altunbas, et al. [21] associate high loans-to-assets ratios with increased default risk, particularly in high-risk loans such as real estate development. The ratio of loan provisions to total loans reflects anticipated potential losses as an indicator of asset quality, with Betz, et al. [10] and Jin, et al. [22] confirming its strong association with default risk. Lastly, the NPL ratio is recognized as a reliable indicator of loan defaults, consistently showing positive correlations with systemic risk in studies by Cole and White [23]; Berger, et al. [11] and Chiaramonte, et al. [24]. Anginer, et al. [25] further examined the relationship between systemic risk and bank-specific variables, including CAMELS components, finding that banks with lower capital adequacy, poorer asset quality, and weak management quality are more prone to systemic risk. This underscores the potential of monitoring CAMELS indicators to identify banks with higher systemic risk. Bhattacharya, et al. [26] also discuss the regulatory implications of the CAMELS framework in evaluating bank performance and systemic risk, offering important insights for supervisory practices.

In terms of management efficiency, the cost-to-income ratio (CTI) is widely used as a measure of management effectiveness, yet findings are inconsistent. Mayes and Stremmel [27] and Shrivastava, et al. [28] find a positive correlation between CTI and bank default risk, while Betz, et al. [10] observe no significant relationships, highlighting the methodological challenges of capturing this aspect with a single metric. Given these inconsistencies, management efficiency will not be included in the study's model, but its relevance to systemic risk suggests it should be explored in future research with refined methodologies.

Earning ability, assessed through Return on Equity (ROE) and Return on Assets (ROA), plays a crucial role in enhancing financial performance and bolstering banks' solvency. Most studies indicate a negative relationship between earning ability and default risk [9, 11, 29] although some [10, 30] point to positive links due to risk-return trade-offs. Furthermore, metrics like non-interest income ratios to operating income highlight income diversification as a stabilizing factor Stiroh [31]; Cipollini and Fiordelisi [32]; Altunbas, et al. [21]. Demirgüç-Kunt, et al. [4] note that CAMELS-based regulatory standards significantly reduce bank risk-taking behavior, thereby lowering systemic risk, and emphasizing the practical importance of these indicators. Abid, et al. [33] further analysed systemic risk within Islamic and conventional banks in the Gulf Cooperation Council (GCC) countries, emphasizing how capital adequacy, asset quality, and management quality significantly influence systemic risk and highlighting the importance of monitoring CAMELS components to mitigate these risks.

Liquidity analysis examines the risk of bank failure due to difficulties in meeting liquidity demands. Measures such as the ratio of liquid assets to total assets and deposits-to-loans ratio have shown negative correlations with default risk [9, 24, 32]. Additionally, the Basel III liquidity coverage ratio (LCR) provides more precise standards for assessing liquidity adequacy, linking highly liquid assets to short-term liabilities to reduce systemic risk. However, the varied definitions of liquidity metrics underscore the need for tailored analytical frameworks for different banking contexts.

Regarding systemic risk, researchers have adopted various methodologies to quantify banks' contributions to financial instability. Lehar [34] suggests estimating the systemic risk of North American, European, and Japanese banks using stock market dynamics, while Huang, et al. [35] assess systemic risk through distress insurance premiums using CDS data. Similarly, Schinasi [36] defines financial stability as the system's ability to effectively address systemic risks, emphasizing its capacity to allocate resources, assess risks, and absorb economic shocks. Models such as Segoviano and Goodhart [37] multivariate copula settings and De Jonghe [38] expand the tools for evaluating interbank dependencies and systemic vulnerabilities. Going further, Markose, et al. [39] introduce Marginal Expected Shortfall (MES) for systemic risk contributions, complemented by simulation-based approaches and network stress-test models Martinez-Jaramillo, et al. [40]. Adrian and Brunnermeier [41] define ΔCoVaR as a predictive tool for systemic contributions through leverage and size, with Borri and Di Giorgio [42] highlighting leverage's critical role during post-Lehman periods. Building on these, recent studies by Laeven and Levine [43] and Schaeck, et al. [44] emphasize the disproportionate systemic risk posed by large, organizationally complex banks.

This vast body of literature illustrates the interconnectedness of banking soundness metrics and systemic risk, highlighting both theoretical advancements and ongoing gaps. By employing context-specific analytical approaches, this study aims to bridge those gaps and provide new insights into systemic risk management in emerging economies.

3. Methodology

3.1. Research Gap and Hypothesis Development

The examination of current scholarly works unveils significant gaps in understanding how banking stability indicators influence systemic risk, with a particular focus on emerging economies. Previous research predominantly addresses the determinants of stability indicators, whereas this study explores their effects. The research identifies essential areas needing further investigation, such as the interactions between capital adequacy, asset quality, earning potential, and systemic risk.

This study examines the following hypotheses:

1. H1: Capital adequacy does not significantly affect the systemic risk of banks listed on the Egyptian Exchange.
2. H2: Asset quality does not significantly affect the systemic risk of banks listed on the Egyptian Exchange.
3. H3: Management efficiency does not significantly affect the systemic risk of banks listed on the Egyptian Exchange.
4. H4: Earning ability does not significantly affect the systemic risk of banks listed on the Egyptian Exchange.
5. H5: Liquidity does not significantly affect the systemic risk of banks listed on the Egyptian Exchange.

To test these hypotheses, the significance of the following function is examined:

VaR_0.90 = f (CAR, NPL, CTI, ROE, LIQ)

This suggests that the alternative hypothesis Ha: $\beta \neq 0$, is tested against the null hypothesis Hb: $\beta = 0$, where β is the regression coefficient.

3.2. Sample and Data Collection

The research draws from a sample of nine banks out of fourteen listed on the Egyptian Exchange from 2011 to 2021. The sample frame encompasses all listed banks, with the selection based on data availability and relevance to the research objectives. Criteria ensured only banks with consistent and complete financial data over the study period were included, minimizing bias while providing a comprehensive view of the Egyptian banking sector. Biases, mainly from omitting banks with inadequate data, were mitigated by comparing excluded institutions to ensure the sample reflected broader industry characteristics. Data was sourced from reputable and verified secondary sources, including financial reports from the Egyptian Exchange and audited statements from the banks. These were cross-validated for consistency and reliability.

3.3. Measures

The study utilizes the following constructs and metrics to assess banking soundness indicators and systemic risk:

1. Capital Adequacy (CAR): Ratio of capital to risk-weighted assets.
2. Asset Quality (NPL): Ratio of non-performing loans to total loans.
3. Profitability (ROE): Bank's ability to generate profit from shareholder equity.
4. Liquidity (LIQ): Ratio of liquid assets to total deposits.
5. Efficiency (CTI): Evaluated through the cost-to-income ratio.

Statistical approaches, including the Jarque-Bera test, were used to evaluate normality. Correlation analysis addressed multicollinearity among independent variables. These metrics were selected due to their prominence in existing literature and alignment with the CAMELS framework. Their reliability was confirmed through descriptive statistics and normality tests, ensuring they were appropriate for the analysis.

3.4. Data Analysis

Panel data analysis was employed to consider both cross-sectional and time-series variations. The Generalised Method of Moments (GMM) was chosen for its capacity to handle endogeneity and unobserved heterogeneity, ensuring robust parameter estimates. Advanced econometric methods, including the Generalised Method of Moments (GMM), were used to manage dynamic relationships and endogeneity. Foundational work by Arellano and Bond [13] provided a basis for using the Difference GMM estimator in panel data analysis. Blundell and Bond [12] introduced the System GMM estimator to improve efficiency and reduce bias, especially when the dependent variable is persistent or samples are small. Roodman

[45] offered guidelines for implementing GMM in Stata, ensuring instrument validity and avoiding overfitting. Wooldridge [46] emphasized diagnostic techniques and bias correction for panel data, reinforcing the study's methodological rigor.

3.4.1. Model Specifications

Regression analysis focused on the impact of banking soundness indicators—CAR, NPL, CTI, ROE, and LIQ—on systemic risk, measured as 1-day Value-at-Risk (VaR) at 90%, 95%, and 99% confidence levels.

- Dependent Variable: Systemic risk (1-day VaR).
- Independent Variables: Banking soundness indicators (CAR, NPL, ROE, LIQ, CTI).
- Control Variables: Bank size (LnA) and bank type (ISL).
- Systemic Risk (SR) is assessed using VaR, indicating the maximum stock price loss within a 0.90 confidence interval:

VaR_0.90 = maximum stock price loss within a 0.90 confidence interval

Capital Adequacy Ratio (CAR) is defined as:CAR = Capital Base / Risk-weighted assets
Non-Performing Loans (NPL) is defined as:NPL = Non-Performing Loans / Gross Loans
Cost-to-Income Ratio (CTI) is defined as:CTI = Administrative Cost / Operating Income
Return on Equity (ROE) is defined as:ROE = Net Profits / Average Equity
Liquidity Ratio (LIQ) is defined as:LIQ = Liquid Assets / Deposits and Short-Term Funds
Bank size is measured by the natural logarithm of its assets (LnA): LnA = natural logarithm of its assets
Bank type (ISL) is defined as: ISL = 1 (if the bank is Islamic) and 0 (otherwise)

4. Data Description and Hypothesis Testing

4.1. Descriptive Statistics

Descriptive statistics for independent and dependent variables were calculated to summarize dataset features. Variables such as mean, median, standard deviation, skewness, kurtosis, and the Jarque-Bera test were used to assess normality. It was determined that the Capital Adequacy Ratio (CAR), Non-Performing Loans Ratio (NPL), Return on Average Equity (ROE), and Cost-to-Income Ratio (CTI) followed normal distributions, while the Liquid Assets to Deposits Ratio (LIQ) did not.

The following two tables present the descriptive statistics of the research variables for a sample of 9 banks (out of 14 banks listed on the Egyptian Exchange) from 2011 to 2021.

Table 2.
Descriptive statistics of independent variables.

Item	CAR	NPL	CTI	ROE	LIQ
Mean	17.37127	10.37155	37.77025	18.71238	37.51803
Median	17.02000	4.960967	35.07662	19.92636	37.70165
Maximum	32.20000	56.26080	152.9748	45.53385	69.28667
Minimum	8.910000	0.752073	14.56111	-128.2174	12.01382
Std. Dev.	5.102751	13.97112	20.07208	20.78890	15.02818
Skewness	0.754092	2.386951	3.320785	-4.918561	0.098993
Kurtosis	3.347942	7.463718	17.29815	32.96033	2.024609
Jarque-Bera	9.283275	165.5203	963.1215	3853.262	3.838522
Probability	0.009642	0.000000	0.000000	0.000000	0.146715
Sum	1615.528	964.5543	3512.633	1740.252	3489.177
Sum Sq. Dev.	2395.502	17957.68	37065.73	39760.42	20777.86
Observations	99	99	99	99	99

Table 2 indicates the descriptive statistics of the independent variables using 99 observations for each of the 8 independent variables. Jarque-Bera test has shown that each of CAR, NPL, ROE and CTI are normally distributed at p-value of 0.01, while LIQ is not normally distributed.

Table 3.
Descriptive statistics of control and dependent variables.

Item	LnA	ISL	VAR_90	VAR_95	VAR_99
Mean	15.35942	0.336842	3.281659	4.205040	5.937335
Median	15.12420	0.000000	2.553757	3.265663	4.607834
Maximum	17.27222	1.000000	23.10166	28.84819	39.62888
Minimum	13.91571	0.000000	1.027340	1.317392	1.861540
Std. Dev.	0.771919	0.475138	2.953707	3.707132	5.122137
Skewness	0.903395	0.690425	4.318863	4.245298	4.164289
Kurtosis	2.936295	1.476687	25.50410	24.76825	23.97025
Jarque-Bera	12.93799	16.73279	2299.969	2161.039	2015.253
Probability	0.001551	0.000233	0.000000	0.000000	0.000000
Sum	1459.145	32.00000	311.7576	399.4788	564.0468
Sum Sq. Dev.	56.01073	21.22105	820.0924	1291.826	2466.211
Observations	99	99	99	99	99

Table 3 shows that VaR within 0.90 confidence interval range from 1.027% to 23.102%, while VaR within 0.95 confidence interval range from 1.317% to 28.848% and VaR within 0.99 confidence interval range from 1.862% to 39.629%. Besides, Jarque-Bera test has shown that each of LnA, ISL, VaR_90, VaR_95 and VaR_99 are normally distributed at p-value of 0.01.

4.2. Multicollinearity Analysis

To tackle the issue of multicollinearity, a correlation analysis was performed. The results showed a significant level of multicollinearity between CTI and ROE, necessitating careful adjustments to the model to reduce possible biases in the regression analysis. Before proceeding with hypothesis testing, it's crucial to examine the problem of multicollinearity. Table 4 displays the correlation coefficients among the independent variables, indicating that the issue arises when both CTI and ROE are included in the same model. Initial analysis involved checking for normality using the Jarque-Bera test, which confirmed that most variables followed a normal distribution, except for LIQ. The multicollinearity analysis identified strong correlations between CTI and ROE, leading to the decision to exclude them from the same model. Four different models were created to investigate the relationships, with results emphasizing the importance of CAR and NPL in systemic risk, while CTI and LIQ were found to have minimal effects.

Table 4.
Correlation coefficient between independent variables.

Variable	CAR	NPL	CTI	ROE	LIQ
CAR	1.000000				
NPL	-0.155208	1.000000			
CTI	-0.271857	0.535259	1.000000		
ROE	0.074363	-0.585054	-0.795236	1.000000	
LIQ	0.309055	0.130263	-0.158854	0.120408	1.000000

4.3. Diagnostic Tests

To verify the strength and accuracy of the models described in the methodology, a series of diagnostic tests were performed. The Breusch-Pagan LM Test was utilized to assess heteroskedasticity, and the results showed no signs of it, indicating consistent variance in residuals and dependable regression coefficients. To tackle multicollinearity among the independent variables, correlation coefficients were assessed, revealing a notable multicollinearity between the Cost-to-Income Ratio (CTI) and Return on Equity (ROE). This required the removal of these variables from the same models to preserve the validity of the regression findings. The Durbin-Watson Statistic was applied to detect autocorrelation, uncovering time-related patterns in residuals. This calls for careful consideration of regression results and points to potential areas for improvement in future studies. Finally, the normality of independent variables was tested using the Jarque-Bera Test. While most variables such as Capital Adequacy Ratio (CAR), Non-Performing Loans Ratio (NPL), ROE, and CTI conformed to normal distributions, Liquidity (LIQ) did not. These observations were thoughtfully incorporated into the development of regression models to reduce bias and strengthen reliability.

4.4. Hypothesis Testing Results

To evaluate the research hypotheses, the study examined the impact of Banking Soundness on Systemic Risk using three metrics: (1-day, 0.90 VaR), (1-day, 0.95 VaR), and (1-day, 0.99 VaR). The data analysis, employing the Generalized Method of Moments (GMM), involved panel data from 9 out of 14 Egyptian banks listed on the Egyptian Exchange, covering the years 2002 to 2021. This analysis offered comprehensive insights into how banking soundness indicators relate to systemic risk across various models and confidence levels.

In Model (1), the importance of the Capital Adequacy Ratio (CAR), Non-Performing Loans Ratio (NPL), and Return on Average Equity (ROE) on systemic risk, assessed by 1-day, 0.90 VaR, was highlighted, explaining 33.32% of the variance. Model (2), which accounts for bank size, confirmed the significance of CAR and NPL, explaining 34.86% of the variance. Model (3), considering bank type, also demonstrated the importance of CAR, NPL, and ROE, providing an explanatory power of 33.85%. Model (4), which controls for both bank size and type, verified the significance of CAR and NPL, achieving an explanatory power of 35.36%. In all models, CAR, NPL, and ROE were positively correlated with 1-day, 0.90 VaR. The Durbin-Watson (DW) statistic indicated autocorrelation, while the Breusch-Pagan LM test showed no signs of heteroskedasticity.

For robustness checks using 1-day, 0.95 VaR, Model (5) highlighted the significance of CAR, NPL, and ROE, with an explanatory power of 33.40%. Model (6), controlling for bank size, confirmed CAR and NPL as significant, explaining 34.96% of the variance. Model (7), adjusting for bank type, reinforced the importance of CAR and NPL, with an explanatory power of 33.96%. Finally, Model (8), considering both bank size and type, validated the significance of CAR and NPL, achieving an explanatory power of 35.49%. Similar to the 1-day, 0.90 VaR results, positive correlations were observed between CAR and NPL and systemic risk. The DW statistic suggested autocorrelation, while the Breusch-Pagan LM test confirmed no heteroskedasticity.

The analysis led to the rejection of the null hypotheses for the first three hypotheses, supporting the alternative hypotheses and affirming the significant impact of CAR, NPL, and ROE. However, the fourth and fifth hypotheses showed no significant effects, resulting in acceptance of the null hypotheses for these cases.

Table 5.
Effects of Banking Soundness on Systemic Risk measured by 1-day, 0.90 VaR. Each cell contains the estimated parameters, with the standard error between brackets,

	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**
C(1)	-3.928991 (3.105280)	5.308937 (7.597841)	-1.610943 (4.323789)	7.476283 (8.142955)
Capital Adequacy Ratio (CAR)	0.156582 (0.079788)*	0.200932 (0.086097)**	0.129476 (0.087355)*	0.174166 (0.093345)*
Non-Performing Loans Ratio (NPL)	0.150940 (0.031222)***	0.152301 (0.031082)***	0.137969 (0.035522)***	0.139678 (0.035375)***
Cost to Income Ratio (CTI)	0.017824 (0.026728)	0.009585 (0.027305)	0.019536 (0.026891)	0.011327 (0.027480)
Return on Average Equity (ROE)	0.075010 (0.036818)**	0.032193 (0.757167)	-0.683942 (0.037798)**	0.054671 (0.042718)
Liquid Assets to Deposits Ratio (LIQ)	-0.013558 (0.022783)	-0.016883 (0.022805)	-0.025007 (0.027229)	-0.027984 (0.027192)
Ln of Total Assets (LnA)		-0.677175 (0.508821)		-0.670851 (0.510356)
Bank Type (ISL)			-0.747297 (0.967198)	-0.726522 (0.962669)
R^2	0.333212	0.348596	0.338478	0.353571
Adjusted R^2	0.263024	0.270427	0.259095	0.266216
DW statistic	1.530615	1.560728	1.535683	1.561765
Breusch-Pagan LM Prob.	0.0000	0.0000	0.0000	0.0000
Periods included	11	11	11	11
Cross-sections	9	9	9	9
Obs.	99	99	99	99

Note: where * denotes a p-value of 10%, ** denotes 5%, and *** denotes 1%.

Table 6.
Effects of Banking Soundness on Systemic Risk measured by 1-day, 0.95 VaR.Each cell contains the estimated parameters, with standard error between brackets.

	Model (5)	**Model (6)**	**Model (7)**	**Model (8)**
C(1)	-4.788100 (3.895130)	6.901079 (9.528425)	-1.797908 (5.422333)	9.698411 (10.20972)
Capital Adequacy Ratio (CAR)	0.192443 (0.100083)*	0.248561 (0.107974)**	0.157478 (0.109549)*	0.214015 (0.117037)*
Non-Performing Loans Ratio (NPL)	0.190278 (0.039163)***	0.192001 (0.038979)***	0.173547 (0.044547)***	0.175709 (0.044353)***
Cost to Income Ratio (CTI)	0.021550 (0.033527)	0.011124 (0.034243)	0.023758 (0.033723)	0.013372 (0.034455)
Return on Average Equity (ROE)	0.093522 (0.046183)**	0.049588 (0.949561)	-0.861634 (0.890008)	0.067947 (0.053560)
Loans to Assets Ratio (LTA)	-0.077430 (0.474117)	0.237767 (0.526816)	-0.238649 (0.516751)	0.077942 (0.566862)
Ln of Total Assets (LnA)		-0.856860 (0.638111)		-0.848699 (0.639890)
Bank Type (ISL)			-0.963983 (1.212934)	-0.937702 (1.207004)
R^2	0.334005	0.349640	0.339567	0.354902
Adjusted R^2	0.263900	0.271597	0.260315	0.267726
DW statistic	1.542246	1.573004	1.547503	1.574090
Breusch-Pagan LM Prob.	0.0000	0.0000	0.0000	0.0000
Periods included	11	11	11	11
Cross-sections	9	9	9	9
Obs.	99	99	99	99

Note: where * denotes p-value of 10%, ** denotes 5% and *** denotes 1%.

A separate evaluation was performed to verify the robustness of the findings using systemic risk measured by 1-day, 0.99 Value at Risk (VaR). The outcomes, as detailed in Table 7, offer additional insights into the importance of various banking soundness indicators. Model (9) underscores the relevance of the Capital Adequacy Ratio (CAR), Non-Performing Loans Ratio (NPL), and Return on Average Equity (ROE) in relation to systemic risk, with an explanatory power of 33.47%. After considering bank size, Model (10) confirms the influence of CAR and NPL on systemic risk, accounting for 35.06% of the variance. Model (11) evaluates the impact based on bank type, reinforcing the significance of CAR and NPL with an explanatory power of 34.06%. Finally, Model (12), which factors in both bank size and type, further affirms the importance of CAR and NPL, explaining 35.62% of the variance. In all models, the regression coefficients for CAR, NPL, and ROE remain positive, indicating that 1-day, 0.99 VaR is positively influenced by these indicators. The Durbin-Watson statistic points to potential autocorrelation, while the Breusch-Pagan LM test confirms the absence of heteroskedasticity.

The findings suggest that the null hypotheses for the first, second, and third propositions can be rejected, supporting the alternative hypotheses that CAR, NPL, and ROE have a notable impact on systemic risk. In contrast, the fourth and fifth hypotheses reveal no significant effects for liquidity (LIQ) and the cost-to-income ratio (CTI), resulting in the acceptance of their respective null hypotheses.

The analysis highlights important connections between certain indicators and systemic risk. CAR shows a significant negative correlation with systemic risk, highlighting the importance of strong capital buffers in maintaining financial stability. Similarly, NPL has a significant positive association with systemic risk, indicating that poor asset quality can heighten systemic vulnerabilities. ROE also shows a positive correlation with systemic risk, underscoring the potential trade-off between profitability and risk-taking. However, liquidity metrics (LIQ) and management efficiency (CTI) did not significantly affect systemic risk, indicating their limited predictive value in the context of Egyptian banks.

To ensure the stability of these conclusions, a robustness check was performed by assessing systemic risk at a 99% confidence interval (VaR_99). The results, presented in Table 7 align with previous analyses conducted at lower confidence intervals. For example, in Model (9), CAR, NPL, and ROE were significant predictors, with an adjusted R^2 of 33.47%. Similarly, Model (10), which accounts for bank size, reaffirmed the significance of CAR and NPL with an adjusted R^2 of 35.06%. Model (11), which controls for bank type, also confirmed CAR and NPL as significant predictors, with an adjusted R^2 of 34.06%. Finally, Model (12), which includes controls for both bank size and type, demonstrated the strongest effects for CAR and NPL, with an adjusted R^2 of 35.62%.

All models displayed autocorrelation, as indicated by the Durbin-Watson statistic, while the Breusch-Pagan LM test verified the lack of heteroskedasticity. These diagnostic results reinforce confidence in the robustness of the findings, despite the presence of autocorrelation, which merits further exploration.

A summary of results across different confidence intervals (90%, 95%, and 99%) is provided in Table 8 for easier interpretation. CAR and NPL consistently showed significant relationships with systemic risk, while CTI and LIQ did not exhibit any significant effects. ROE's significant yet positive relationship across models highlights the potential risks associated with profitability within the banking sector. The analysis identifies meaningful connections between certain indicators and systemic risk. Capital Adequacy (CAR) displayed a significant positive relationship with systemic risk, highlighting the role of strong capital buffers in reducing vulnerabilities. Likewise, Non-Performing Loans (NPL) demonstrated a significant positive relationship with systemic risk, indicating that higher credit risk and poor asset quality are key contributors to systemic vulnerabilities. Moreover, Earning Ability (ROE) showed a significant positive relationship, suggesting that greater profitability may correlate with increased risk-taking, emphasizing a risk-return trade-off in the banking sector. Conversely, liquidity metrics (LIQ) showed no significant effect on systemic risk, implying that while liquidity may bolster operational resilience, its direct connection to systemic risk in the Egyptian banking landscape is limited. Similarly, management efficiency (CTI) did not show a significant relationship with systemic risk, highlighting the difficulties in using operational efficiency as a consistent predictor of systemic vulnerabilities.

Table 7.
Effects of Banking Soundness on Systemic Risk measured by 1-day, 0.99 VaR .Each cell contains the estimated parameters, with standard error between brackets,

	Model (9)	**Model (10)**	**Model (11)**	**Model (12)**
C(1)	-6.399815 (5.379050)	9.887990 (13.15559)	-2.148661 (7.486180)	13.86720 (14.09270)
Capital Adequacy Ratio (CAR)	0.259719 (0.138212)*	0.337915 (0.149077)**	0.210010 (0.151245)*	0.288773 (0.161549)*
Non-Performing Loans Ratio (NPL)	0.264079 (0.054083)***	0.266479 (0.053817)***	0.240291 (0.061503)***	0.243304 (0.061222)***
Cost-to-Income Ratio (CTI)	0.028539 (0.046299)	0.014012 (0.047278)	0.031678 (0.046559)	0.017209 (0.047559)
Return on Average Equity (ROE)	0.128251 (0.063778)**	0.082221 (1.311028)	-1.194990 (1.228763)	0.092852 (0.073930)
Liquid Assets to Deposits Ratio (LIQ)	-0.021567 (0.039465)	-0.027430 (0.039487)	-0.042565 (0.047144)	-0.047811 (0.047060)
Ln of Total Assets (LnA)		-1.193957 (0.881019)		-1.182347 (0.883254)
Bank Type (ISL)			-1.370495 (1.674601)	-1.333881 (1.666054)
R^2	0.334734	0.350635	0.340622	0.356211
Adjusted R^2	0.264705	0.272711	0.261497	0.269213
DW statistic	1.555202	1.586656	1.560672	1.587803
Breusch-Pagan LM Prob.	0.0000	0.0000	0.0000	0.0000
Periods included	11	11	11	11
Cross-sections	9	9	9	9
Obs.	99	99	99	99

Note: where * denotes p-value of 10%, ** denotes 5%, and *** denotes 1%.

Table 8.
Summary of Variable Significance Across Confidence Levels (90%, 95%, and 99%).This table summarizes the regression coefficients and adjusted R2R^2 values for the impact of banking soundness indicators (CAR, NPL, CTI, ROE, LIQ) on systemic risk at 90%, 95%, and 99% confidence intervals.

Variable	**Model 1 (90%)**	**Model 2 (95%)**	**Model 3 (99%)**
Capital Adequacy Ratio (CAR)	0.174*	0.192*	0.259*
Non-Performing Loans Ratio (NPL)	0.140***	0.190***	0.264***
Cost-to-Income Ratio (CTI)	NS	NS	NS
Return on Average Equity (ROE)	0.075**	0.093**	0.128**
Liquid Assets to Deposits Ratio (LIQ)	NS	NS	NS
Adjusted R^2	0.263	0.263	0.265
Observations	99	99	99

Note: NS = Not Significant; ***p < 0.01, **p < 0.05, p < 0.10.

Table 9.
Hypotheses, Results, and Remarks Summary.

Hypothesis	**Description**	**Results**	**Remarks**
H1: Capital adequacy negatively impacts systemic risk	Investigates the relationship between capital adequacy and systemic risk.	Significant negative impact. Higher capital adequacy ratios reduce systemic risk.	Strong capital buffers are crucial for absorbing losses and enhancing financial stability.
H2: Asset quality plays a substantial role in systemic risk	Examines how asset quality influences systemic risk.	Significant positive impact. Poor asset quality, reflected by high NPL ratios, increases systemic risk.	Emphasizes the importance of credit risk management to maintain asset quality.
H3: Earning ability significantly affects systemic risk	Assesses the influence of profitability on systemic risk.	Significant positive impact. High profitability correlates with systemic risk due to risk-taking behavior.	Highlights the risk-return trade-off in profitability metrics for emerging markets.
H4: Liquidity strongly impacts systemic risk	Evaluates the effect of liquidity on systemic risk.	Non-significant impact. Liquidity measures show limited direct influence on systemic risk.	Indicates liquidity may not be a major standalone determinant in Egypt's banking sector.
Management Efficiency	Examines operational effectiveness using CTI metrics.	Non-significant impact. Efficiency does not consistently predict systemic risk.	Efficiency is excluded from the model due to inconsistent results in systemic risk literature.

5. Discussion and Conclusion

This research enhances the understanding of how banking stability metrics relate to systemic risk within the Egyptian banking industry. The results highlight the critical role of capital adequacy, asset quality, and profitability in shaping the systemic risk of banks in Egypt, whereas liquidity and efficiency appear to have minimal impact. The study emphasizes the necessity for policymakers and bank executives to vigilantly manage these crucial banking stability indicators to alleviate systemic risk and maintain the robustness of the Egyptian banking system. The outcomes of this study can guide the development of effective risk management strategies and regulatory frameworks tailored to the unique aspects and challenges of Egypt's banking sector. Future investigations might extend this research by exploring additional potential factors that influence systemic risk, examining the influence of macroeconomic elements, and performing comparative studies with other emerging markets. Although there are limitations, this study offers significant insights into the link between banking stability metrics and systemic risk, providing practical guidance for boosting the resilience of the Egyptian banking industry. The conclusions align with previous studies that stress the necessity of sufficient capital buffers and robust credit risk management to reduce systemic vulnerabilities. The strong findings regarding capital adequacy and asset quality suggest that regulators should focus on these measures, as they significantly contribute to systemic risk management through risk absorption and credit quality oversight. Moreover, the use of the System GMM methodology, as detailed by Blundell and Bond [12] minimizes bias and enhances estimator accuracy, especially considering the persistence of key variables like systemic risk. This methodological precision aligns with best practices in dynamic panel data analysis as discussed by Roodman [45] and Wooldridge [46].

The study demonstrates that capital adequacy plays a significant role in reducing systemic risk, corroborating findings by Acharya and Steffen [14] and Berger, et al. [11] which highlight the importance of solid capital buffers for financial stability. Asset quality, particularly poor metrics such as high non-performing loan ratios, was found to positively correlate with systemic risk, consistent with evidence from Cole and White [23] and Chiaramonte, et al. [24] that underscores the crucial role of credit risk management. Profitability has a notable impact, indicating that it can influence systemic risk through risk-taking behaviors, as supported by Mannaso and Mayes [30]. In contrast, liquidity and management efficiency metrics showed no substantial effect on systemic risk, which reflects mixed findings in the literature, including Arena [9] and Betz, et al. [10]. These findings reaffirm the importance of focusing on capital buffers and credit quality rather than liquidity and efficiency in systemic risk management frameworks.

While the findings are insightful, it is important to acknowledge the study's limitations. The sample size of nine banks, although representing a significant portion of the sector, limits the generalizability of the results. Additionally, the study focuses solely on banking soundness measures, excluding macroeconomic variables such as inflation, exchange rates, and political stability, which could influence systemic risk. Furthermore, while the Generalized Method of Moments (GMM) technique addresses endogeneity issues, the presence of weak instruments may still affect the robustness of the results. Moreover, the use of GMM techniques, as recommended by Blundell and Bond [12] and Arellano and Bond [13] address dynamic interactions, yet future studies could investigate alternative models and larger datasets to build on Wooldridge [46] principles for panel data analysis. Future research could expand on this work by increasing the sample size, incorporating broader macroeconomic factors, and conducting comparative analyses with other emerging economies to gain a deeper understanding of systemic risk drivers.

The findings have numerous practical implications. Policymakers should prioritize continuous monitoring of capital adequacy and asset quality within macroprudential regulatory frameworks to ensure systemic stability. Improving regulations that promote prudent capital management and effective credit evaluation processes will be crucial in addressing systemic vulnerabilities. For bank managers, the findings emphasize the importance of prioritizing capital planning and credit risk management over liquidity and operational efficiency, which seem to play lesser roles in systemic risk. Overall, this report offers valuable recommendations for enhancing the resilience of Egypt's banking sector. Future research can provide even more detailed insights into the dynamics of banking stability and systemic risk in emerging markets if its limitations are addressed and expanded.

The conclusions of this study have several practical implications for Egyptian bank managers, investors, and policymakers. For bank leaders, the findings underscore the importance of strong capital planning and stringent credit risk management policies. Strengthening these areas can help mitigate systemic risks and enhance individual bank resilience. Profitability metrics, such as Return on Equity, should be closely monitored to ensure that the pursuit of higher returns does not inadvertently increase systemic risks. Investors can use the study's findings to assess the financial health of banks and make more informed investment choices by prioritizing institutions with solid capital adequacy and asset quality metrics. For regulators, the emphasis on capital sufficiency and asset quality highlights the need to enhance macroprudential regulations, ensuring that banks maintain adequate capital buffers and implement effective credit risk assessment processes. Although liquidity and operational efficiency had limited direct impact on systemic risk in this study, policymakers should not overlook their potential interaction with other systemic issues that may be addressed through comprehensive regulatory measures. These practical insights can help shape targeted policies and strategies for Egypt's financial sector, fostering stability and sustainability.

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