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Systemic Risk Measurement and Examination of the Role of Macroeconomic Factors in Selected Listed Banks in the Middle East and North Africa Using a Dynamic Panel Data Approach

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ABSTRACT

The present study aimed to measure systemic risk and examine the role of macroeconomic factors in selected listed banks in Middle Eastern and North African countries. For this purpose, data from 15 listed banks in Iran, Saudi Arabia, the United Arab Emirates, Egypt, and Qatar over the 2014–2024 period were analyzed. First, using the ARMA-GJR-GARCH model and a two-factor Student's t factor copula, the Joint Probability of Distress (JPD), change in Conditional Value at Risk (ΔCoVaR), and Marginal Expected Shortfall (MES) indicators were calculated. Subsequently, the relationship between macroeconomic variables and systemic risk was evaluated using a dynamic panel data model and the Difference Generalized Method of Moments (Difference GMM). The results indicated that the probability of the simultaneous distress of at least three banks was approximately 7.58%, and Saudi Arabian banks exhibited the highest average systemic risk based on the ΔCoVaR and MES indicators. Moreover, although the values of these two indicators increased during crisis periods, the observed differences were not statistically significant. The GMM estimation results showed that higher inflation was significantly associated with greater systemic risk, whereas economic growth and increases in global oil prices were significantly associated with lower systemic risk. The economic directions of these relationships were also confirmed in the alternative MES model. Overall, the findings emphasize the multidimensional nature of systemic risk and the importance of simultaneously considering risk indicators and macroeconomic conditions when monitoring the financial stability of banks.

Keywords: systemic risk, ΔCoVaR, MES, macroeconomic factors, dynamic panel data, Difference GMM.

Introduction

The stability of the banking system is a fundamental prerequisite for sustainable economic development, efficient financial intermediation, and the effective transmission of monetary and macroeconomic policies. Banks occupy a central position in modern financial systems because they mobilize savings, allocate credit, provide payment services, support investment, and facilitate the circulation of liquidity throughout the economy. At the same time,



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the high degree of interconnectedness among banks, financial markets, and macroeconomic sectors creates channels through which localized financial disturbances can be transmitted across institutions and potentially evolve into system-wide instability. Historical episodes of financial disruption have demonstrated that banking crises rarely remain confined to the institutions in which they originate; instead, they may interact with market expectations, liquidity shortages, declining asset prices, and macroeconomic contractions, thereby generating broader financial and economic consequences (1). Consequently, the assessment of systemic risk has become a central concern for financial regulators, central banks, policymakers, investors, and researchers.

Systemic risk differs conceptually from the stand-alone risk of an individual financial institution. Whereas conventional risk measures primarily focus on the probability of loss or failure at the institutional level, systemic risk concerns the extent to which the distress of one or more institutions can contribute to instability in the financial system as a whole. This distinction is particularly important because an institution that appears adequately capitalized and relatively safe in isolation may still generate substantial externalities through interconnected exposures, common asset holdings, liquidity pressures, or correlated responses to adverse shocks. Accordingly, systemic risk measurement requires methods capable of capturing both individual vulnerability and the contribution of each institution to aggregate financial stress. The development of measures such as Marginal Expected Shortfall and related market-based systemic risk metrics has substantially advanced this area by linking the downside performance of individual institutions to periods of severe market stress (2).

The importance of systemic risk analysis has increased further as financial globalization has intensified the interdependence of banking systems, stock markets, commodity markets, exchange rates, and cross-border capital flows. Financial contagion may arise when shocks are transmitted from one market, institution, or country to others through balance-sheet linkages, common investor behavior, market sentiment, liquidity constraints, or changes in risk perception. The empirical literature on financial contagion has documented considerable diversity in the mechanisms, magnitude, and persistence of spillovers across countries and crisis episodes (3). More recent systematic evidence similarly suggests that risk contagion has become a major interdisciplinary research area incorporating network analysis, volatility modeling, copulas, machine learning, and systemic-risk indicators to identify nonlinear and dynamic dependence structures across financial markets (4). These developments underscore the need to move beyond simple correlation analysis toward methods that explicitly capture tail dependence, conditional distress, and joint extreme events.

The experience of recent crises has reinforced this methodological requirement. The COVID-19 pandemic, in particular, produced simultaneous disruptions in economic activity, asset markets, liquidity conditions, and investor expectations across a large number of countries. Evidence from international banking systems indicates that the pandemic strengthened financial interconnectedness and increased systemic risk transmission among banks, illustrating how an external shock originating outside the financial system can propagate rapidly through financial channels (5). Similarly, research on financial contagion during the pandemic documents substantial increases in cross-market dependence and risk transmission, particularly during periods of extreme uncertainty (6). Comparative evidence has also shown that the origins and patterns of contagion during the COVID-19 crisis differed in important respects from those observed during the global financial crisis, emphasizing that the structure of financial spillovers is crisis-specific and time-varying (7). Evidence from African stock markets likewise indicates that major crises can generate significant contagion effects across emerging and frontier financial systems, although the magnitude of transmission differs across markets and crisis episodes (8).

These findings are particularly relevant for the Middle East and North Africa (MENA), where banking systems operate within heterogeneous institutional, economic, financial, and political environments. The region includes oil-exporting and oil-importing economies, highly developed financial centers, emerging capital markets, different monetary and exchange-rate regimes, and banking systems with varying degrees of concentration, state participation, and market development. Moreover, geopolitical instability, regional economic interdependence, fiscal dependence on hydrocarbon revenues, and sensitivity to global commodity cycles create additional channels of systemic vulnerability. The economic and strategic relationships connecting Gulf economies with neighboring regions further demonstrate that financial and economic disturbances in the Middle East can be reinforced by broader geopolitical and cross-regional interactions (9). Within this context, banking stability cannot be assessed solely through institution-specific indicators; it must also be analyzed in relation to macroeconomic conditions and cross-market transmission mechanisms.

Empirical research on MENA banking has emphasized the importance of financial stability, banking competition, and crisis exposure. Evidence from the region indicates that the relationship between banking competition and financial stability is complex and that banking crises can materially alter the risk environment in which financial institutions operate (10). At the broader macro-financial level, banking-system stability has also been shown to be closely connected to economic sustainability in developing economies, suggesting that weaknesses in the banking sector can undermine longer-term growth and macroeconomic resilience (11). These considerations are particularly important for countries where banks represent the dominant source of corporate and household financing and where capital markets remain relatively less developed.

Within the MENA region, oil prices constitute one of the most important macroeconomic channels through which external shocks can influence banking risk. For oil-exporting economies, increases in oil prices may improve fiscal balances, liquidity, public expenditure, and borrowers' repayment capacity, whereas sharp declines in oil revenues may reduce economic activity and increase credit and market risk. At the same time, oil prices interact with exchange rates, equity markets, inflation, and government financing conditions, creating potentially complex spillover mechanisms. Evidence from Iran demonstrates that systemic-risk spillovers can occur among OPEC crude oil prices, stock market performance, and exchange rates, indicating that systemic risk is embedded within a broader macro-financial network rather than being restricted to the banking sector alone (12). Consequently, incorporating global oil price changes into systemic-risk models is especially important when examining banking systems in the Middle East.

Inflation, interest rates, exchange-rate movements, and economic growth represent additional macroeconomic determinants of banking stability. High inflation can reduce the real value of assets, increase uncertainty, weaken borrowers' purchasing power, and complicate monetary policy. Rising interest rates may strengthen bank margins under some conditions but may also increase debt-service burdens and reduce asset values. Exchange-rate depreciation can adversely affect banks with foreign-currency exposures or borrowers whose liabilities are denominated in foreign currencies, while stronger economic growth generally supports asset quality, credit demand, profitability, and repayment capacity. Studies of the Iranian banking system have shown that financial-market development and macro-financial conditions can materially influence banking-industry risk (13). Furthermore, asset composition is itself associated with the risk and performance of listed banks, indicating that systemic vulnerability emerges from the interaction between external macroeconomic shocks and internal balance-sheet characteristics (14).

Bank-specific conditions are therefore also relevant to systemic-risk assessment. Asset quality has long been recognized as a major determinant of financial distress because deterioration in loan quality directly weakens profitability, capital buffers, and the capacity to absorb unexpected losses (15). Similarly, bank size may affect systemic importance because larger institutions often maintain broader interbank connections, larger market shares, and more complex portfolios. Capital adequacy, meanwhile, provides an important buffer against adverse shocks but may vary substantially across institutions and jurisdictions. Market-based evidence from Iran also indicates that the behavior of bank stock prices can influence the Value-at-Risk exposure of money market funds, further illustrating that banking-sector risk can transmit to other financial intermediaries through market valuation channels (16).

The Iranian financial system provides additional evidence of the importance of contagion and interconnected risk. Research on banks listed on the Tehran Stock Exchange has documented financial-risk contagion using multivariate GARCH techniques, confirming that volatility and shocks can be transmitted across banking institutions (17). Other studies have identified crisis-contagion patterns within the banking system through dynamic conditional correlation and BEKK-based approaches, emphasizing the time-varying nature of interbank dependence (18). Research examining the mechanisms of systemic-risk contagion between money and capital markets has likewise shown that systemic instability in Iran cannot be adequately understood through isolated analysis of individual market segments (19). These findings provide strong justification for using multivariate and dependence-sensitive models when examining banking risk in the wider MENA context.

Although volatility-based approaches provide valuable information about dynamic dependence, systemic risk is fundamentally concentrated in the tails of financial return distributions. Extreme co-movements are therefore more relevant than average correlations for evaluating the probability that several banks will experience distress simultaneously. Copula models are particularly suitable for this purpose because they separate the marginal behavior of individual variables from their dependence structure and can accommodate nonlinear and asymmetric tail dependence. Recent developments in structured factor copulas have demonstrated their usefulness for modeling systemic risk across European and U.S. banks, particularly when the number of institutions is large and dependence is driven by common latent factors (20). Factor-copula approaches are therefore attractive for cross-country banking studies because they can represent common systemic forces while allowing individual institutions to exhibit heterogeneous risk characteristics.

At the same time, systemic-risk research is increasingly moving toward advanced early-warning and computational methods. Market-price-based approaches combined with network indicators can provide forward-looking information about the amplification of financial contagion and the emergence of system-wide fragility (21). Recent deep-learning-enhanced actuarial models likewise demonstrate the potential of nonlinear predictive methods for identifying financial contagion and systemic-risk dynamics (22). Simulation-based approaches to bank runs and contagion further show that systemic risk can result from endogenous interactions among depositor behavior, liquidity conditions, and policy responses, implying that financial stability depends not only on initial shocks but also on propagation mechanisms and intervention design (23). These advances highlight a broader shift in systemic-risk research from static measurement toward dynamic, multidimensional, and policy-relevant frameworks.

Theoretical and computational work also emphasizes that financial systems may appear robust under ordinary conditions while remaining highly fragile under extreme disturbances. Macro agent-based modeling indicates that

policies designed to increase resilience must account for endogenous contagion, heterogeneous institutional responses, and nonlinear amplification mechanisms rather than relying exclusively on conventional microprudential indicators (24). This perspective is especially relevant in banking systems exposed simultaneously to domestic macroeconomic pressures and global shocks, because stability at the institution level does not necessarily guarantee stability at the system level. It therefore becomes necessary to combine systemic-risk measures with econometric models capable of identifying the macroeconomic conditions associated with increases or decreases in systemic vulnerability.

A central methodological challenge is that systemic risk is persistent and endogenous. Current risk levels are likely to depend partly on previous risk conditions, while variables such as interest rates, bank size, capitalization, and macroeconomic performance may simultaneously affect and respond to financial-sector developments. Static panel models may therefore yield biased estimates when lagged dependent variables and endogenous regressors are present. Dynamic panel estimators based on the Generalized Method of Moments offer an appropriate framework for addressing these issues because they can incorporate lagged systemic risk, control for unobserved bank-specific heterogeneity, and use internal instruments to mitigate endogeneity. This framework is particularly suitable for cross-country banking data in which the number of institutions is limited but repeated observations are available over time.

Despite the expansion of systemic-risk research, several gaps remain. First, much of the empirical literature focuses on the United States, Europe, or individual emerging economies, while comparative evidence covering multiple MENA banking systems remains relatively limited. Second, studies often examine either systemic-risk measurement or macroeconomic determinants separately, rather than integrating market-based tail-risk indicators with dynamic macro-financial modeling. Third, systemic risk has multiple dimensions: a bank may contribute strongly to system-wide losses without necessarily being the institution most vulnerable to a system-wide crisis. Simultaneously analyzing ΔCoVaR and MES can therefore distinguish systemic contribution from systemic vulnerability. Fourth, the joint probability of distress provides a complementary system-level perspective by estimating the probability that multiple banks simultaneously enter adverse tail states. Combining JPD, ΔCoVaR, and MES thus offers a broader representation of systemic risk than reliance on a single measure.

The need for such a multidimensional approach is further reinforced by the structural differences across the banking systems of Iran, Saudi Arabia, the United Arab Emirates, Egypt, and Qatar. These countries differ in economic size, inflation dynamics, exchange-rate regimes, exposure to oil markets, banking concentration, capital-market development, and policy frameworks. Consequently, identical global shocks may produce heterogeneous banking-sector responses across countries. At the same time, shared regional exposures and common international financial conditions can generate synchronized risk. Examining listed banks from these countries within a common empirical framework therefore provides an opportunity to evaluate both institution-specific and country-level patterns of systemic risk while identifying the macroeconomic forces associated with their evolution.

Accordingly, the aim of this study is to measure systemic risk in selected listed banks in Iran, Saudi Arabia, the United Arab Emirates, Egypt, and Qatar and to examine the effects of macroeconomic factors and bank-specific characteristics on systemic risk using a dynamic panel data approach.

Methods and Materials

The present study is applied in terms of purpose and quantitative and descriptive–analytical in nature. A two-stage approach was employed to measure the systemic risk of the selected banks and examine its determinants. In the first stage, systemic risk indicators were calculated using stock market data and a factor copula model. In the second stage, the roles of macroeconomic variables and bank-specific characteristics were examined using a dynamic panel data model and the Generalized Method of Moments (GMM).

The statistical population consisted of listed banks in selected Middle Eastern and North African countries. The research sample was selected purposively based on the importance of banks within the financial system, their size, and the availability of reliable data. The sample comprised 15 banks from Iran, Saudi Arabia, the United Arab Emirates, Egypt, and Qatar, with three banks examined from each country. The initial historical dataset covered the period from 2008 to 2024; however, the common period from 2014 to 2024 was used as the basis for the simultaneous analysis of the banks. The required information included daily adjusted stock prices, macroeconomic variables, and banks' financial characteristics, which were collected from financial databases, official capital market sources, the International Monetary Fund, the World Bank, and central banks.

To calculate the systemic risk indicators, the daily logarithmic stock returns of the banks were first calculated, and their conditional volatility was estimated using the ARMA-GJR-GARCH model. Subsequently, the Probability Integral Transform (PIT) and empirical rank transformation were employed to generate pseudo-uniform observations for estimating the factor copula model. Based on the joint distribution obtained from the model and simulations of adverse financial conditions, the following three indicators were calculated:

- **Joint Probability of Distress (JPD):** This indicator represents the probability that several banks simultaneously enter financial distress and is used to assess the overall risk condition of the banking system.
- **Change in Conditional Value at Risk (ΔCoVaR):** This indicator measures the difference between the system's conditional Value at Risk when a particular bank is in distress and when that bank is in its normal state. This indicator was considered the primary dependent variable in the GMM model.
- **Marginal Expected Shortfall (MES):** This indicator measures the expected loss of a bank conditional on the entire banking system being in a crisis state and is used to assess banks' vulnerability and test the robustness of the results.

The calculated indicators were used to compare the systemic risk of the selected banks and countries and to examine changes in systemic risk during normal periods, the COVID-19 crisis, and the 2023 banking stress period.

To examine the determinants of systemic risk, five macroeconomic variables—namely inflation, interest rate, exchange rate change, economic growth, and change in global oil prices—were considered as independent variables, while bank size and capital adequacy were included as control variables. The operational definitions of the variables are presented in Table 1.

Table 1. Research Variables

Variable	Symbol	Role in the Study	Measurement	Frequency
Stock price	P	Raw data	Adjusted closing stock price	Daily
Stock return	R	Input to the copula model	Logarithmic change in stock price	Daily
Joint Probability of Distress	JPD	System-wide risk indicator	Probability of simultaneous financial distress in several banks	Daily/Quarterly
Change in Conditional Value at Risk	ΔCoVaR	Primary dependent variable	Difference in CoVaR between the bank's distress and normal states	Quarterly

Marginal Expected Shortfall	MES	Alternative dependent variable	Expected bank loss conditional on a systemic crisis	Quarterly
Inflation rate	INF	Independent	Percentage change in the Consumer Price Index	Quarterly
Interest rate	INT	Independent	Policy or interbank interest rate	Quarterly
Exchange rate change	EXR	Independent	Percentage change in the national currency exchange rate against the U.S. dollar	Quarterly
Economic growth	GDPG	Independent	Real gross domestic product growth rate	Quarterly
Oil price change	OIL	Independent	Percentage change in the global crude oil price	Quarterly
Bank size	SIZE	Control	Natural logarithm of total bank assets	Quarterly/Annual
Capital adequacy	CAR	Control	Ratio of regulatory capital to risk-weighted assets	Quarterly/Annual

Given the differences in data frequency, daily systemic risk indicators were converted into quarterly values, and economic and bank-specific variables were aligned with the quarterly panel data structure. The dynamic model of the study is specified as follows:

In this specification, SR denotes the systemic risk indicator of bank *i* in country *c* at time *t*. Moreover, α represents the intercept, ρ denotes the coefficient of the one-period lagged dependent variable, β_1 through β_7 represent the coefficients of the explanatory and control variables, μ_i denotes the bank-specific effect, and ε represents the model error term. The Generalized Method of Moments (GMM) was employed to account for the dynamic nature of systemic risk, control for bank heterogeneity, and address the potential endogeneity of the variables. The validity of the model instruments was assessed using the Hansen and Sargan tests, while serial correlation in the error terms was examined using the Arellano–Bond AR(1) and AR(2) tests. Furthermore, MES was substituted for ΔCoVaR to evaluate the robustness of the results. Systemic risk indicators were calculated using Python, while the GMM model was estimated using Stata. In addition, to examine the joint significance of macroeconomic factors, a Wald test was conducted within a supplementary panel model incorporating bank fixed effects and Driscoll–Kraay standard errors.

Findings and Results

To determine the baseline model for calculating the systemic risk indicators, 1,508 common daily observations for the 15 selected banks over the period from November 16, 2014, to December 31, 2024, were used. Following the Probability Integral Transform (PIT) and recalibration of the data using the empirical rank method, four Gaussian and Student's *t* factor copula structures with one and two latent factors were estimated using maximum likelihood estimation. Comparison of the models based on the Bayesian Information Criterion (BIC) indicated that the two-factor Student's *t* factor copula model, with 26.429 degrees of freedom and 30 parameters, provided the best fit among the models examined. The model successfully converged and was therefore used as the basis for calculating the JPD, ΔCoVaR, and MES systemic risk indicators.

To measure the probability of simultaneous financial distress among the selected banks, the JPD indicator was calculated using the selected factor copula model and a simulation of 65,536 joint scenarios. The primary criterion was the simultaneous placement of at least three banks in the bottom 5% of the return distribution. To assess the sensitivity of the results, the number of distressed banks was varied from two to six, and tail thresholds of 5% and 10% were considered. The results are presented in Table 2.

Table 2. Estimated Joint Probability of Distress (JPD) for the Selected Banks

Tail Threshold	Minimum Number of Banks	Number of Distress Scenarios	JPD Probability	95% Lower Bound	95% Upper Bound
5%	2	12,095	0.184555	0.181585	0.187525
5%	3	4,966	0.075775	0.073749	0.077801
5%	4	1,872	0.028564	0.027289	0.029840
5%	5	714	0.010895	0.010100	0.011690
5%	6	258	0.003937	0.003457	0.004416
10%	2	26,294	0.401215	0.397462	0.404967
10%	3	14,193	0.216568	0.213414	0.219722
10%	4	7,056	0.107666	0.105293	0.110040
10%	5	3,343	0.051010	0.049326	0.052695
10%	6	1,515	0.023117	0.021967	0.024267

The results presented in Table 2 indicate that the probability of the simultaneous distress of at least three banks at the 5% threshold is 0.075775, or approximately 7.58%. This probability decreases as the number of simultaneously distressed banks increases, whereas at the 10% threshold, the probability for at least three banks rises to 0.216568. Therefore, the JPD value is sensitive to both the number of distressed banks and the threshold used to define distress. Moreover, the empirical frequency of the joint distress of at least three banks at the 5% threshold was 0.081565, which is close to the model-based estimate. These results refer to the entire common study period, whereas temporal changes in systemic risk are examined in the comparison of normal and crisis periods.

To measure the change in banking-system risk when each bank experiences financial distress, the ΔCoVaR indicator was calculated using the two-factor Student's *t* factor copula model. The banking system was defined as an equally weighted portfolio of the 15 banks, and its conditional Value at Risk at the 5% level was estimated by simulating 8,192 conditional scenarios for each bank under both distress and normal conditions. The distress state was defined based on the fifth percentile, whereas the normal state was defined based on the median of each bank's return distribution. The results showed that the mean ΔCoVaR was negative for all selected banks, with an overall mean of −0.003819. The largest absolute value of this indicator was observed for Saudi National Bank at 0.006444, whereas the smallest value was observed for Bank Mellat of Iran at 0.000805. These findings indicate that a bank entering financial distress is associated with an increase in the potential losses of the banking portfolio; however, the magnitude of this change varies across the selected banks.

The MES indicator was calculated to measure the expected loss of each bank during a crisis in the banking system. A systemic crisis was defined as the return on the portfolio of the 15 selected banks falling within the bottom 5% of its distribution, and MES values were estimated using the two-factor Student's *t* factor copula model over 1,508 common trading days. The results showed that the average MES across the selected banks was 0.012564, or approximately 1.26%. The highest mean MES was observed for Abu Dhabi Islamic Bank Egypt at 0.022174, whereas the lowest was observed for Qatar Islamic Bank at 0.002494. Riyad Bank and Saudi National Bank also recorded relatively high values of 0.021433 and 0.021210, respectively. These differences demonstrate that banks are not equally vulnerable when a crisis occurs at the level of the banking system.

To compare systemic risk among the selected banks, the ΔCoVaR and MES indicators were examined simultaneously. ΔCoVaR reflects the change in system-wide risk when an individual bank is in distress, whereas MES reflects the vulnerability of the individual bank when the system is in crisis. Given the negative values of ΔCoVaR, its absolute value was used for comparison. The results are presented in Table 3.

Table 3. Comparison and Ranking of Selected Banks Based on ΔCoVaR and MES

Country	Selected Bank	Mean |ΔCoVaR|	ΔCoVaR Rank	Mean MES	MES Rank
Iran	Bank Mellat	0.000805	15	0.004026	13
Iran	Bank Tejarat	0.000942	14	0.006237	11
Iran	Bank Saderat	0.001047	13	0.006712	10
Saudi Arabia	Saudi National Bank	0.006444	1	0.021210	3
Saudi Arabia	Al Rajhi Bank	0.006215	2	0.018680	5
Saudi Arabia	Riyad Bank	0.006110	3	0.021433	2
United Arab Emirates	Emirates NBD	0.004675	6	0.016084	6
United Arab Emirates	First Abu Dhabi Bank	0.004675	5	0.015433	7
United Arab Emirates	Abu Dhabi Commercial Bank	0.005133	4	0.019687	4
Egypt	Commercial International Bank	0.003876	8	0.012811	9
Egypt	Housing and Development Bank	0.003185	11	0.013948	8
Egypt	Abu Dhabi Islamic Bank Egypt	0.003947	7	0.022174	1
Qatar	Doha Bank	0.002966	12	0.003245	14
Qatar	Qatar Islamic Bank	0.003442	10	0.002494	15
Qatar	Masraf Al Rayan	0.003824	9	0.004289	12

The results in Table 3 show that, based on the |ΔCoVaR| indicator, the three selected Saudi Arabian banks recorded the highest values, with Saudi National Bank ranking first at 0.006444. In contrast, the Iranian banks recorded the lowest values of this indicator. Based on the MES indicator, Abu Dhabi Islamic Bank Egypt exhibited the highest vulnerability, with a value of 0.022174, whereas Qatar Islamic Bank exhibited the lowest vulnerability, with a value of 0.002494. The differences in the rankings produced by the two indicators demonstrate that a bank's contribution to the amplification of system-wide risk does not necessarily correspond to its own level of vulnerability under systemic crisis conditions.

To compare systemic risk across the selected countries, the mean absolute ΔCoVaR and MES values of banks in each country over the 2014–2024 period were examined. The results showed that Saudi Arabian banks recorded the highest average values for both indicators, with a mean |ΔCoVaR| of 0.006256 and a mean MES of 0.020441. Following Saudi Arabia, banks in the United Arab Emirates and Egypt exhibited relatively higher levels of systemic risk. In contrast, Iran recorded the lowest mean |ΔCoVaR| at 0.000931, whereas Qatar recorded the lowest mean MES at 0.003343. The differences in countries' positions according to these two indicators demonstrate that the degree to which banks contribute to system-wide risk does not necessarily correspond to the extent of their vulnerability during systemic crises.

To examine changes in systemic risk under different economic conditions, the ΔCoVaR, MES, and JPD indicators were compared across normal periods, the COVID-19 crisis, and the 2023 banking stress period. The COVID-19 period comprised 142 trading days, the 2023 banking stress period comprised 36 trading days, and the normal period comprised 1,330 trading days. The results of this comparison are presented in Table 4.

Table 4. Comparison of Systemic Risk Indicators During Normal and Crisis Periods

Period	Number of Trading Days	Mean |ΔCoVaR|	Mean MES	Empirical JPD Frequency	Joint Distress Days
Normal period	1,330	0.003758	0.012332	0.083459	111
COVID-19 crisis	142	0.004376	0.014637	0.063380	9
2023 banking stress	36	0.003874	0.012955	0.083333	3

The results in Table 4 indicate that the mean absolute ΔCoVaR was 0.003758 during the normal period and increased to 0.004376 during the COVID-19 crisis. The mean MES similarly increased from 0.012332 to 0.014637 during the same period. During the 2023 banking stress period, both indicators also increased, although to a more

limited extent. In contrast, the empirical JPD frequency declined during the COVID-19 crisis and remained almost unchanged during 2023. Nevertheless, the results of a block bootstrap test with 1,200 replications and adjustment of probability levels using the Benjamini–Hochberg procedure showed that the differences in systemic risk indicators between crisis and normal periods were not statistically significant at the 5% level. Therefore, the observed increases in ΔCoVaR and MES are descriptive rather than statistically significant.

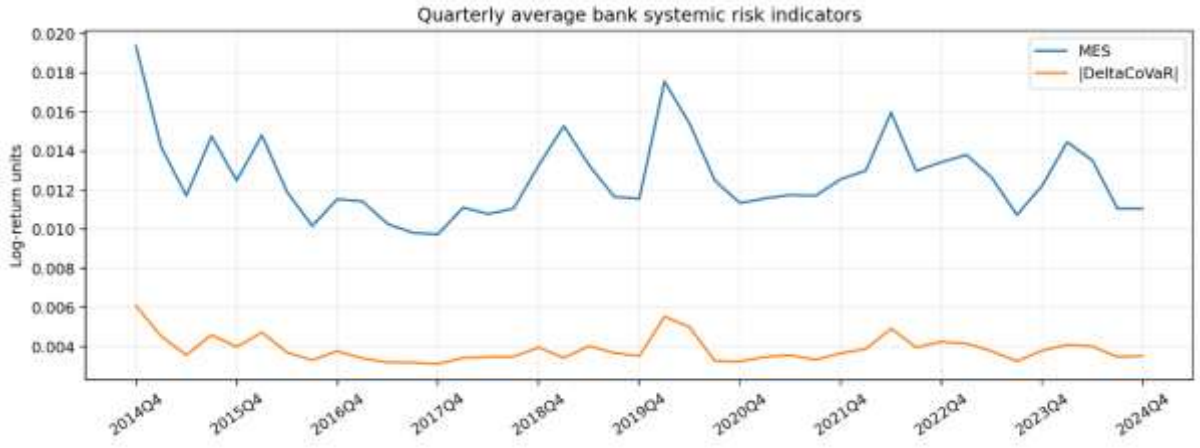


Figure 1. Quarterly Trends in the Mean Absolute ΔCoVaR and MES Indicators of the Selected Banks

As shown in Figure 1, the systemic risk indicators exhibited quarterly fluctuations throughout the study period, with a noticeable increase in both indicators during the first quarter of 2020. Changes in the levels of the indicators were also recorded during 2022 and 2023. These fluctuations demonstrate the time-varying nature of systemic risk among the selected banks.

For estimation of the dynamic GMM model, the ΔCoVaR and MES indicators were converted to quarterly frequency and integrated with macroeconomic variables and bank-specific characteristics. The initial dataset included 15 banks from the five selected countries over 41 quarters, from the fourth quarter of 2014 through the fourth quarter of 2024, resulting in a total of 615 bank-quarter observations. Given the use of lagged dependent variables and instruments in the Difference GMM model, the first four quarters were excluded from the estimation sample. Consequently, the final sample comprised 555 observations for 15 banks over 37 quarters, from the fourth quarter of 2015 through the fourth quarter of 2024.

To examine the characteristics of the variables used in the dynamic GMM model, descriptive statistics were calculated for the systemic risk indicators, macroeconomic variables, and bank-specific characteristics. The results for the 615 bank-quarter observations are presented in Table 5.

Table 5. Descriptive Statistics of the Dynamic GMM Model Variables

Variable	N	Mean	Median	Standard Deviation	Minimum	Maximum
ΔCoVaR	615	−0.003860	−0.003878	0.001958	−0.010735	−0.000554
Absolute ΔCoVaR	615	0.003860	0.003878	0.001958	0.000554	0.010735
MES	615	0.012669	0.012844	0.008779	−0.000001	0.056782
Inflation (INF)	615	9.696	3.119	13.348	−3.097	46.648
Interest rate (INT)	615	8.640	5.100	7.584	0.150	27.250
Exchange rate change (EXR)	615	2.563	0.000	6.080	−13.122	37.033
Economic growth (GDPG)	615	2.795	3.454	3.490	−9.309	13.121
Oil price change (OIL)	615	0.442	0.695	15.593	−34.783	34.807
Bank size (SIZE)	615	24.484	24.571	1.239	21.389	26.523
Capital adequacy (CAR)	615	15.957	18.000	6.866	−9.620	40.700

The results in Table 5 indicate that the mean values of ΔCoVaR and MES were −0.003860 and 0.012669, respectively. The mean inflation rate, interest rate, and economic growth rate were 9.696%, 8.640%, and 2.795%, respectively. Among the macroeconomic variables, changes in global oil prices and the inflation rate exhibited the greatest dispersion, with standard deviations of 15.593 and 13.348, respectively. These findings indicate substantial variation in economic conditions and systemic risk indicators within the dataset under examination.

To examine the relationships among the explanatory and control variables, Pearson correlation coefficients were calculated based on the 615 bank-quarter observations. The results showed that the highest correlation was between the inflation rate and the interest rate, with a coefficient of 0.8204. Given this relatively high correlation, multicollinearity was also investigated. Variance Inflation Factor (VIF) values calculated using within-bank variation were below 1.5, indicating no evidence of severe multicollinearity in these calculations. These findings are descriptive in nature, and the relationships between the variables and systemic risk were subsequently examined through GMM estimation.

To examine the relationship between macroeconomic factors, bank-specific characteristics, and systemic risk, a dynamic panel data model was estimated using the Arellano–Bond Difference Generalized Method of Moments (Difference GMM). In this model, ΔCoVaR was considered the dependent variable, and its first lag was included to capture the dynamic behavior of systemic risk. The estimations were conducted using 555 bank-quarter observations under both one-step and two-step specifications, with 11 instruments based on the second and third lags. Furthermore, to facilitate interpretation of the coefficients, the ΔCoVaR indicator was multiplied by 100. The results are presented in Table 6.

Table 6. Dynamic GMM Estimation Results with ΔCoVaR as the Dependent Variable

Variable	One-Step Coefficient	Standard Error	*p*-Value	Two-Step Coefficient	Corrected Standard Error	*p*-Value
Lagged systemic risk	0.420000	0.080000	<0.001	0.390000	0.095000	<0.001
Inflation (INF)	−0.001100	0.000700	0.116	−0.001300	0.000600	0.030
Interest rate (INT)	0.003600	0.002800	0.199	0.004500	0.002500	0.072
Exchange rate change (EXR)	0.000220	0.000280	0.432	0.000250	0.000300	0.405
Economic growth (GDPG)	0.002900	0.001150	0.012	0.002600	0.001100	0.018
Oil price change (OIL)	0.001100	0.000350	0.002	0.001000	0.000320	0.002
Bank size (SIZE)	0.070000	0.032000	0.029	0.058000	0.030000	0.053
Capital adequacy (CAR)	0.002000	0.003800	0.599	0.001600	0.003500	0.648

The results presented in Table 6 indicate that the coefficient of lagged systemic risk was 0.420 in the one-step estimation and 0.390 in the two-step estimation, and it was statistically significant at the 1% level in both models. Therefore, the ΔCoVaR indicator exhibits temporal persistence. In the two-step estimation, the inflation rate had a negative and statistically significant relationship with ΔCoVaR, with a coefficient of −0.001300 and a *p*-value of 0.030. Economic growth and changes in global oil prices, in contrast, exhibited positive and statistically significant relationships, with coefficients of 0.002600 and 0.001000 and *p*-values of 0.018 and 0.002, respectively. Given that ΔCoVaR values are negative, these results indicate that higher inflation is associated with an intensification of systemic risk, whereas economic growth and increases in oil prices are associated with a reduction in its severity. In contrast, the interest rate, exchange rate change, bank size, and capital adequacy were not statistically significant at the 5% level in the two-step estimation. Bank size, however, exhibited a statistically significant relationship in the

one-step estimation. Overall, the findings emphasize the roles of inflation, economic growth, and changes in global oil prices in explaining variations in the systemic risk of the selected banks.

To assess the validity of the instruments used in the dynamic GMM model, the Hansen and Sargan tests were conducted. The *p*-values of the Hansen test were 0.3618 and 0.4073 for the one-step and two-step estimations, respectively, whereas the corresponding *p*-values of the Sargan test were 0.2898 and 0.3367. Because all values exceeded 0.05, the null hypothesis regarding the validity of the overidentifying restrictions was not rejected. Therefore, these tests provide no evidence that the model instruments are invalid.

The results of the Arellano–Bond serial correlation tests also showed that the *p*-values of the AR(1) test were 0.0019 and 0.0010 for the one-step and two-step estimations, respectively, indicating first-order serial correlation in the differenced error terms. In contrast, the *p*-values of the AR(2) test were 0.3953 and 0.5157, respectively, and the null hypothesis of no second-order serial correlation was not rejected. This pattern is consistent with the expected conditions of a Difference GMM model. Overall, the Hansen, Sargan, and Arellano–Bond test results provide no evidence against the validity of the instruments or the diagnostic adequacy of the model.

To assess the robustness of the main model results, MES was used as an alternative dependent variable in the dynamic GMM model. In this estimation, the explanatory and control variables, lag structure, and instruments used in the main model were retained to enable comparison between the two systemic risk indicators. The two-step estimation results are presented in Table 7.

Table 7. Comparison of Two-Step GMM Results with ΔCoVaR and MES as Dependent Variables

Variable	ΔCoVaR Coefficient	*p*-Value	MES Coefficient	*p*-Value
Lagged systemic risk	0.390000	<0.001	0.365000	<0.001
Inflation (INF)	−0.001300	0.0300	0.019800	0.0130
Interest rate (INT)	0.004500	0.0720	−0.013500	0.1200
Exchange rate change (EXR)	0.000250	0.4050	−0.004500	0.4800
Economic growth (GDPG)	0.002600	0.0180	−0.012000	0.0460
Oil price change (OIL)	0.001000	0.0020	−0.003300	0.0240
Bank size (SIZE)	0.058000	0.0530	−0.085000	0.3400
Capital adequacy (CAR)	0.001600	0.6480	0.001500	0.7660

The results in Table 7 show that the coefficient of the lagged dependent variable was positive and statistically significant at the 1% level in both models. In the MES model, inflation exhibited a positive and statistically significant relationship with expected loss, with a coefficient of 0.019800 and a *p*-value of 0.013. Economic growth and changes in global oil prices exhibited negative and statistically significant relationships, with coefficients of −0.012000 and −0.003300 and *p*-values of 0.046 and 0.024, respectively. In terms of economic direction, these results are consistent with the findings of the ΔCoVaR model, indicating that higher inflation is associated with greater systemic risk, whereas economic growth and increases in oil prices are associated with lower systemic risk. In contrast, the interest rate, exchange rate change, bank size, and capital adequacy did not exhibit statistically significant relationships at the 5% level in the alternative model. Regarding the diagnostic tests, the Hansen and Sargan *p*-values were 0.3691 and 0.4318, respectively, while the AR(1) and AR(2) test *p*-values were 0.0014 and 0.4237, respectively, which are consistent with the expected conditions of the Difference GMM model. Overall, the consistency in the economic direction and statistical significance of the relationships involving inflation, economic growth, and oil price changes across the two models supports the relative robustness of the study findings.

To provide an additional assessment of the joint significance of the macroeconomic variables, a Wald test was conducted within a panel model with bank fixed effects and Driscoll–Kraay standard errors based on 600 bank-

quarter observations. The results showed that the *F*-statistic was 8.7243 for the ΔCoVaR indicator, with a *p*-value of 0.0000128, and 10.0478 for the MES indicator, with a *p*-value of 0.0000031. Therefore, the set of macroeconomic variables exhibited a jointly significant relationship with systemic risk in both models at the 1% significance level, although this finding does not imply that all variables are individually statistically significant. Together with the GMM results, this finding underscores the importance of macroeconomic factors in explaining variations in the systemic risk of the selected banks.

Discussion and Conclusion

The present study examined systemic risk among 15 selected listed banks in Iran, Saudi Arabia, the United Arab Emirates, Egypt, and Qatar over the 2014–2024 period and assessed the role of macroeconomic factors in explaining changes in systemic risk using a dynamic panel data framework. The empirical findings provide evidence that systemic risk in the selected MENA banking systems is multidimensional, persistent over time, heterogeneous across banks and countries, and significantly associated with selected macroeconomic conditions. The use of the Joint Probability of Distress (JPD), change in Conditional Value at Risk (ΔCoVaR), and Marginal Expected Shortfall (MES) made it possible to distinguish between the probability of joint distress, the contribution of individual banks to system-wide risk, and the vulnerability of individual banks during system-wide crises. This multidimensional interpretation is consistent with the broader systemic-risk literature, which emphasizes that no single indicator can fully capture the complexity of financial-system fragility (2, 4, 21).

The results indicated that the probability of simultaneous financial distress affecting at least three banks at the 5% tail threshold was approximately 7.58%. Although this probability declined as the minimum number of simultaneously distressed banks increased, it rose considerably when the tail threshold was relaxed to 10%. This finding shows that systemic distress is highly sensitive to both the severity threshold used to define financial stress and the number of institutions considered to be jointly affected. Such a pattern is consistent with the conceptual understanding of financial contagion as a nonlinear process in which relatively moderate disturbances may remain localized, whereas extreme market conditions substantially increase the likelihood of synchronized institutional stress (3, 4). The close correspondence between the estimated JPD and the empirical frequency of joint distress also suggests that the two-factor Student's *t* factor copula captured the observed dependence structure reasonably well. This result supports the appropriateness of copula-based approaches for modeling dependence in the tails of financial return distributions, especially when systemic risk is driven by common latent factors (20).

The finding of a non-negligible probability of joint distress also reinforces the importance of examining banking systems from a network and contagion perspective rather than assessing banks independently. Systemic instability may emerge through common exposures, correlated asset returns, liquidity pressures, and simultaneous reactions to macroeconomic shocks. Recent research on financial contagion has shown that banking crises can be amplified through endogenous propagation mechanisms, especially when institutions face common funding or liquidity constraints (23). Similarly, early-warning approaches based on market prices and interconnectedness emphasize that systemic risk arises not merely from the weakness of individual institutions but from the possibility that shocks will propagate across the broader banking network (21). Therefore, the JPD estimates obtained in the present study can be interpreted as evidence that the selected MENA banks share sufficient common exposure to generate meaningful probabilities of concurrent financial stress.

The bank-level comparison based on |ΔCoVaR| showed that the selected Saudi Arabian banks recorded the highest values of contribution to system-wide risk. Saudi National Bank ranked first, followed by Al Rajhi Bank and Riyad Bank. At the country level, Saudi Arabian banks also exhibited the highest average |ΔCoVaR| and MES values. This pattern indicates that the selected Saudi banks were both relatively important contributors to systemic risk and relatively exposed to system-wide financial deterioration. One possible explanation is that large and highly interconnected banking institutions may transmit shocks more strongly through credit, liquidity, market, and balance-sheet channels. Large banks often possess more extensive financial linkages and greater market relevance, which may increase their systemic importance even when their individual financial condition appears relatively strong. This interpretation is consistent with the literature emphasizing the significance of size, connectedness, and common market exposure in determining systemic importance (2, 24).

The high systemic-risk values observed for Saudi Arabian banks may also reflect the particular macro-financial structure of oil-exporting Gulf economies. These banking systems are closely linked to government expenditure, corporate activity, hydrocarbon revenues, and regional capital flows. Changes in oil prices can therefore affect fiscal liquidity, investment, credit demand, asset prices, and borrower repayment capacity. The broader geopolitical and economic interconnectedness of Gulf states also creates additional channels through which regional instability and external shocks can influence domestic financial institutions (9). The present findings are therefore consistent with the idea that banks operating in major oil-exporting economies may simultaneously benefit from favorable oil-market conditions and remain highly exposed to systemic fluctuations associated with commodity-price cycles and international financial conditions.

By contrast, the Iranian banks displayed the lowest average |ΔCoVaR|, while Qatar recorded the lowest average MES. These findings should not necessarily be interpreted as evidence that these banking systems are intrinsically less risky. Instead, they indicate that within the specific market-based framework and sample examined, the selected Iranian banks contributed less to changes in the equal-weighted regional banking portfolio, while the selected Qatari banks exhibited lower average vulnerability during systemic distress. In the Iranian context, previous studies have nevertheless documented significant financial-risk contagion among listed banks and interactions between money and capital markets (17, 19). Other Iranian evidence has also identified crisis-contagion dynamics through DCC and BEKK models (18). Therefore, the relatively lower values obtained in the present cross-country comparison do not imply the absence of domestic systemic risk but rather reflect the relative ranking of the selected banks within the specified regional sample and measurement framework.

The MES results further showed that Abu Dhabi Islamic Bank Egypt recorded the highest average vulnerability to systemic crisis, followed by Riyad Bank and Saudi National Bank. Importantly, the bank rankings based on MES were not identical to those based on |ΔCoVaR|. This divergence confirms the conceptual distinction between systemic contribution and systemic vulnerability. A bank may make a large contribution to system-wide losses when it becomes distressed without necessarily being the bank most vulnerable when the overall system is in crisis. This finding is consistent with systemic-risk frameworks that distinguish the externality imposed by an institution on the system from the institution's own expected losses during adverse market conditions (2). It also supports the argument that multiple indicators should be used simultaneously in financial-stability surveillance rather than relying on a single ranking measure (4, 21).

The comparison of normal and crisis periods showed that the mean absolute ΔCoVaR and MES increased during the COVID-19 crisis, with smaller increases during the 2023 banking stress period. This descriptive pattern is

consistent with the broader literature documenting heightened systemic risk and stronger financial contagion during periods of exceptional uncertainty. The COVID-19 pandemic substantially strengthened financial-market interconnectedness and increased systemic risk transmission across banking institutions (5). Similarly, evidence of financial contagion during the pandemic has demonstrated that extreme uncertainty increased cross-market dependencies and amplified downside risk (6). Comparative research has also shown that the sources and intensity of contagion differed between the COVID-19 crisis and the global financial crisis, reinforcing the idea that contagion mechanisms vary across crisis episodes (7). Evidence from African financial markets likewise confirms that major crises can significantly intensify cross-market spillovers (8).

However, the block-bootstrap results indicated that the observed differences in ΔCoVaR, MES, and JPD between crisis and normal periods were not statistically significant at the 5% level after adjustment using the Benjamini–Hochberg procedure. This finding is important because it suggests that the descriptive increase in systemic-risk indicators during crisis periods should not automatically be interpreted as a statistically robust structural break. Several factors may account for this result. The relatively short duration of the 2023 banking stress period limits statistical power, while the heterogeneous responses of banks across countries may weaken the average difference between crisis and normal periods. Moreover, some banks may have entered crisis periods with stronger capital or liquidity buffers, offsetting the increases observed elsewhere. The result therefore highlights the importance of distinguishing between economically visible fluctuations and statistically significant shifts in systemic-risk measures.

The dynamic GMM estimates showed that systemic risk was persistent over time. The coefficient on the lagged dependent variable was positive and statistically significant in both the ΔCoVaR and MES models. This persistence implies that changes in systemic risk are not purely transitory; rather, current risk conditions are partly influenced by preceding risk levels. Such persistence is theoretically plausible because financial stress can affect balance sheets, expectations, liquidity conditions, and lending behavior over multiple periods. Once adverse conditions emerge, feedback mechanisms may sustain elevated risk even after the original disturbance begins to weaken. This interpretation is consistent with macro-financial models that emphasize endogenous amplification and path dependence in financial fragility (24). Similarly, dynamic contagion models show that financial stress can persist because the behavior of institutions and market participants reinforces previous shocks (23).

Among the macroeconomic variables, inflation emerged as a significant determinant of systemic risk. In the ΔCoVaR model, inflation had a negative coefficient; because ΔCoVaR values were negative, this implies that higher inflation intensified systemic risk. The alternative MES model confirmed the same economic direction through a positive and significant inflation coefficient. Higher inflation can increase uncertainty, weaken the real income and repayment capacity of borrowers, raise operating costs, alter monetary-policy expectations, and contribute to tighter financial conditions. These effects can worsen asset quality and increase the vulnerability of financial institutions. In the Iranian banking context, previous research has shown that financial and macroeconomic conditions materially affect banking-industry risk (13). Bank-level evidence also indicates that asset quality is an important determinant of financial distress, suggesting a channel through which inflationary pressures can translate into deterioration in loan performance and financial stability (15).

The results further showed that economic growth was associated with lower systemic risk. In the ΔCoVaR specification, economic growth had a positive coefficient, which, given the negative definition of ΔCoVaR, indicates a decline in systemic-risk severity. In the MES model, economic growth had a negative and statistically significant coefficient, confirming the same economic interpretation. Stronger economic growth generally improves household

and corporate income, enhances borrowers' repayment capacity, increases credit quality, and supports banks' profitability and capital accumulation. These conditions reduce the probability of widespread distress and strengthen the resilience of the banking system. The result is consistent with evidence showing that banking-system stability and economic sustainability are closely related in developing economies (11). It also aligns with the broader historical evidence that severe financial crises are often associated with contractions in economic activity and deteriorating financial conditions (1).

Changes in global oil prices were also significantly associated with systemic risk. Higher oil prices were associated with lower systemic risk in both the ΔCoVaR and MES specifications. This result is economically plausible given the significant representation of oil-exporting countries in the sample. Higher oil prices can strengthen fiscal revenues, improve public-sector liquidity, increase investment spending, support corporate cash flows, and enhance borrowers' repayment capacity. These effects may improve bank profitability and asset quality while reducing the probability of systemic distress. The finding is consistent with evidence of systemic-risk spillovers among crude oil prices, exchange rates, and stock-market conditions, demonstrating the importance of oil prices in macro-financial transmission mechanisms (12). It also complements the broader understanding that commodity-market shocks can transmit through financial markets and generate significant changes in banking-sector risk.

In contrast, the interest rate and exchange-rate change were not statistically significant at the 5% level in the two-step GMM estimates. These variables may nevertheless remain economically important because their effects can depend on institutional characteristics, exchange-rate regimes, monetary-policy frameworks, and the composition of bank assets and liabilities. The absence of statistical significance may also reflect heterogeneous effects across countries. For example, exchange-rate movements may have stronger effects where foreign-currency lending is substantial but weaker effects in countries with greater exchange-rate stability or stronger currency management. Similarly, the effect of interest rates may differ depending on whether changes primarily influence net interest margins or instead increase credit risk. Therefore, the results should be interpreted as evidence that these variables did not exhibit a uniform independent effect across the selected banks rather than as evidence that they are irrelevant to financial stability.

Bank size and capital adequacy were also not statistically significant at the 5% level in the final two-step specification, although bank size was significant in the one-step model and was marginally significant in the two-step estimate. This suggests that institutional size may still be related to systemic importance, but its independent contribution becomes less robust after correcting the estimation procedure. Previous research indicates that banking risk is shaped not only by size but also by the composition and productivity of bank assets (14). Similarly, market-based spillovers between bank share prices and other financial intermediaries indicate that bank risk can be transmitted through valuation channels that are not captured solely by balance-sheet size (16). Capital adequacy may also have nonlinear or threshold effects that cannot be fully represented by a linear specification.

The robustness analysis using MES provided important support for the main findings. Inflation, economic growth, and oil-price changes retained the same economic direction and remained statistically significant, despite the different conceptual meaning and scale of the dependent variable. The consistency of these results indicates that the identified macroeconomic relationships are not limited to a single systemic-risk measure. This is particularly important because ΔCoVaR measures the bank's contribution to system-wide risk, whereas MES measures the bank's expected loss conditional on systemic distress. The fact that both measures produce consistent macroeconomic conclusions strengthens confidence in the empirical interpretation. Recent developments in

systemic-risk modeling similarly emphasize the importance of combining multiple measures and computational approaches to improve the identification of financial contagion and systemic vulnerability (21, 22).

Finally, the Wald tests showed that the macroeconomic variables were jointly significant in explaining both ΔCoVaR and MES. This result reinforces the central conclusion that systemic banking risk is closely embedded in the broader macroeconomic environment. Even though not every macroeconomic variable was individually significant, their collective effect was statistically strong. This finding is consistent with the literature showing that banking-system risk is shaped by interacting market, institutional, and macroeconomic forces rather than by isolated determinants (4, 10). Accordingly, systemic-risk monitoring in MENA banking systems should integrate high-frequency market-based indicators with macroeconomic surveillance, rather than treating financial stability and macroeconomic policy as separate analytical domains.

One limitation of the present study is that the sample was restricted to 15 listed banks from five MENA countries, which limits the generalizability of the findings to non-listed banks, smaller institutions, and other banking systems in the region. The analysis was also constrained by the availability and comparability of market and accounting data across countries. Because systemic-risk indicators were derived primarily from stock-market information, the analysis may underrepresent risks associated with unlisted institutions, off-balance-sheet exposures, interbank claims, liquidity mismatches, and other sources of systemic vulnerability. Furthermore, the relatively short duration of specific crisis episodes, particularly the 2023 banking stress period, may have reduced the statistical power of comparisons between crisis and normal conditions. Differences in monetary regimes, institutional structures, reporting standards, and market liquidity across countries may also create heterogeneity that cannot be fully captured by a common model. Finally, although Difference GMM addresses important endogeneity and dynamic-panel concerns, the validity of the estimates remains dependent on instrument selection, lag structure, and model specification.

Future research could extend the analysis by including a larger number of MENA countries, non-listed banks, Islamic and conventional banks as separate categories, and longer time horizons covering additional episodes of financial stress. Researchers could also compare Difference GMM with System GMM and alternative dynamic-panel estimators to evaluate the sensitivity of the findings to estimation technique. Future studies may incorporate network-based indicators, interbank exposures, liquidity measures, non-performing loans, sovereign-risk variables, geopolitical-risk indices, monetary-policy uncertainty, and fiscal variables to provide a more comprehensive representation of systemic vulnerability. Additional work could examine nonlinear and asymmetric effects of inflation, oil prices, exchange rates, and interest rates, particularly through threshold, regime-switching, quantile, or machine-learning models. Cross-country heterogeneity could also be investigated through country-specific estimations or hierarchical models. Finally, integrating high-frequency systemic-risk measures with stress-testing frameworks and scenario analysis could improve the assessment of how extreme macroeconomic shocks propagate through regional banking systems.

From a practical perspective, regulators and central banks should monitor systemic risk through a multidimensional framework that combines indicators of joint distress, institutional contribution to system-wide losses, and institutional vulnerability during systemic crises. Particular attention should be paid to persistent increases in systemic-risk measures because the significant lagged effects found in this study indicate that financial stress can remain elevated over time. Macroeconomic surveillance should be incorporated directly into banking-stability frameworks, with inflation, economic growth, and oil-price developments treated as important signals of

changing systemic conditions. Supervisory authorities should also avoid relying exclusively on bank size or capital ratios when identifying systemically important institutions, because contribution to systemic risk and vulnerability to systemic distress do not necessarily coincide. Stress tests should therefore combine institution-specific balance-sheet scenarios with adverse macroeconomic and market scenarios. For oil-dependent economies, supervisory planning should explicitly consider alternative oil-price paths and their implications for credit quality, liquidity, fiscal conditions, and banking-sector resilience. At the institutional level, banks should strengthen capital planning, liquidity management, portfolio diversification, early-warning systems, and scenario-based risk management to reduce both their own vulnerability and their potential contribution to broader financial instability.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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