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Bank-Specific and Macroeconomic Determinants of Non-Performing Loans in Gulf Cooperation Council Countries: Evidence from Extreme Bounds Analysis

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Abstract

The determinants of bank credit quality have been studied extensively, yet much of the existing evidence rests on a single regression specification, so a variable's apparent significance may be conditioned on which controls a researcher chooses to include. We confront this problem directly for the Gulf Cooperation Council (GCC) countries, providing a robustness analysis of non-performing loans (NPL) determinants for the region's banks. We employ a balanced panel of 45 listed commercial banks drawn from all six GCC countries over the period 2010 to 2024. We examine fifteen bank-specific and four macroeconomic potential determinants of NPLs, utilizing two variants of extreme bounds analysis (EBA), namely, the strict criterion of Leamer and the more lenient criterion of Sala-i-Martin, estimated within a panel fixed-effects framework. The findings show that of the nineteen determinants routinely cited in the literature, seventeen prove fragile once their coefficients are tested across the full range of possible model specifications. None survives Leamer's strict criterion, whereas Sala-i-Martin's less restricted test suggests that only two variables are robust, namely, asset quality (loan intensity), which enters positively, and capital adequacy, which enters negatively, while all four macroeconomic variables are fragile on both tests. For regulators, bank-level balance sheet indicators, especially loan intensity and capital adequacy, offer a more robust starting point for NPL early-warning and stress-testing frameworks and complement macroeconomic forecasts.

Keywords: non-performing loans; credit risk; Gulf Cooperation Council (GCC); banking stability; extreme bounds analysis (EBA); model uncertainty; panel fixed effects

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1. Introduction

Credit quality lies at the heart of banking stability. The share of loans that cease to perform, commonly captured by the non-performing loans (NPL) ratio, signals not only the riskiness of a bank's portfolio but also the resilience of the wider financial system. When NPLs accumulate, banks are required to tie up capital in loss provisions and curtail new lending, and may ultimately face threats to the solvency of the institution itself. Episodes of sharp NPL growth have repeatedly preceded banking crises in both advanced and emerging markets, prompting regulators worldwide to treat asset quality as a frontline indicator of systemic risk (Berger & DeYoung, 1997; Klein, 2013; Louzis et al., 2012). In the Gulf Cooperation Council (GCC), Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates, this concern is sharpened by the region's heavy dependence on hydrocarbon revenues, which transmits oil price volatility into credit cycles and exposes bank portfolios to recurrent shocks (Adedeji et al., 2019; Squalli, 2011).

A substantial empirical literature has examined the drivers of NPLs across advanced and emerging economies. Yet two problems limit what this literature can tell us about the GCC. The first is contextual: the region's structural features, oil dependence, near-universal dollar peg, dual conventional–Islamic banking system, and recurrent geopolitical uncertainty limit the transferability of results obtained elsewhere and motivate a region-specific reassessment. The second is methodological, and it is the problem this paper foregrounds. In the literature in which theory rarely pins down the exact set of regressors that should enter the empirical model, researchers typically report a handful of specifications selected from a much larger universe of plausible alternatives. Leamer (1983) labeled this practice 'con' econometrics, and I. Moosa (2012) described it as 'stir-fry' regressions, in which covariates are added or removed until the estimates align with prior expectations. The result is a body of evidence in which the same variable is reported with opposite signs across studies, and in which apparent statistical significance may reflect specification choice rather than a genuine underlying relationship (I. N. Khatatbeh & Moosa, 2022; Moral-Benito, 2015; Steel, 2020).

This specification uncertainty is precisely what extreme bounds analysis (EBA) was designed to address. Developed by Leamer (1983, 1985) and extended by Sala-i-Martin (1997), EBA estimates a large number of alternative models and asks whether the sign and significance of each coefficient survive variation in the conditioning set; variables that remain stable are classified as robust, those that do not are classified as fragile. Applying EBA to GCC credit quality therefore does more than add another regional study: it screens the determinants that the prior literature reports, many of them with conflicting signs, for stability and so separates findings that are genuine features of the data from those that are artifacts of the particular model in which they were reported.

Against this background, this paper's contribution is single and accurately scoped. We provide the first robustness-screened account of NPL determinants for the GCC, using EBA to distinguish the determinants that survive comprehensive specification variation from those that do not. The originality lies not in a new estimator but in bringing a robustness discipline to the regional literature that has, to date, relied exclusively on single-specification panel and GMM models. This core contribution has three direct implications, which we develop rather than present as separate novelties: it clarifies which determinants merit inclusion in regional early-warning and stress testing frameworks; it speaks to the long-standing debate over the relative weight of bank-specific versus macroeconomic factors in credit-quality formation; and it does so for a set of dollar-pegged, oil-dependent economies in which that debate is especially consequential.

Two theoretical premises discipline the exercise. The first is the trade-off, formalized by Berger and DeYoung (1997), between a moral hazard channel, in which thinly capitalized banks reach for credit risk, and a bad management channel, in which weak cost control foreshadows future loan losses. The second is the contest between a risk-taking view, under which aggressive loan expansion raises subsequent defaults, and a specialization view, under which loan-intensive banks screen borrowers more effectively. EBA is a natural adjudicator between these mechanisms: a determinant that genuinely encodes one of them should retain its sign and significance as the conditioning set varies, whereas one that merely reflects a convenient specification should not. We return to these premises when interpreting the two determinants that survive the robustness screen.

The remainder of this paper is organized as follows. Section 2 reviews the international and GCC-specific literature. Section 3 describes the data and the EBA methodology. Section 4 reports and discusses the empirical results. Section 5 sets out the research implications, recommendations, and limitations, and Section 6 concludes.

2. Literature Review and Hypotheses

Research on the determinants of non-performing loans dates back to the 1970s. Early empirical studies focused on the failures of commercial banks and thrift institutions (e.g., Altman, 1977; Martin, 1977; Sinkey, 1977) and worked on developing early-warning systems. A second generation of studies (e.g., Avery & Hanweck, 1985; Barth et al., 1985; Benston, 1985; Gajewski, 1988) sought to identify the financial factors that raise the likelihood of bank failure (Demirgüç-Kunt, 1989). The literature that followed splits into two strands, one emphasizing bank-specific drivers and the other macroeconomic ones, and, as we show below, the two strands disagree not only with each other but with themselves. Hence, it is this internal divergence that makes a robustness-based econometric methodology the appropriate tool.

2.1. Bank-Specific Determinants

Most empirical research finds that NPLs are shaped primarily by bank-specific factors, size, profitability, capital, cost efficiency, capital structure, liquidity risk, and asset composition (Saliba et al., 2023). However, the signs attached to these factors are strikingly inconsistent. For instance, on capital structure, Berger and DeYoung (1997) and Boudriga et al. (2010) report that better-capitalized banks carry fewer problem loans, consistent with the moral hazard channel; Boudriga et al. (2009) emphasize capital adequacy, bank ownership, and the legal–institutional environment. On size and loan exposure, the evidence is openly contradictory: whereas Cotugno et al. (2010) find that NPLs rise with bank size and gross loans but fall with profitability, Espinoza and Prasad (2010) report a negative capital and efficiency effect alongside a positive size, margin, and lagged credit growth effect. De Bock and Demyanets (2012) add that profitability, capital adequacy, asset quality, and ownership all push NPLs downward. The theoretical line running through these results is the one Berger and DeYoung (1997) drew: whether thin capital and weak cost control cause future losses (moral hazard and bad management channels) or whether loan-intensive expansion reflects prudent specialization rather than reckless risk-taking. Because the same variable proxies opposite mechanisms depending on the controls included, its reported coefficient is the kind of quantity EBA is built to test (Leamer, 1985).

2.2. Macroeconomic Determinants

A parallel strand emphasizes macroeconomic drivers, inflation, GDP growth, interest rates, and unemployment. Keeton and Morris (1987) showed that poor economic conditions damage loan portfolios; Salas and Saurina (2002) found real GDP growth central to NPL variation; Quagliariello (2007) reported that growth lowers NPLs while inflation raises them; Khemraj and Pasha (2009) found that growth reduces and interest rates raise NPLs; Adebola and Dahalan (2011) documented a positive interest rate effect; Anastasiou et al. (2016) found that growth lowers and unemployment raises NPLs; and Anita et al. (2022) confirmed that growth and inflation are significant in SAARC banking. Badar et al. (2013) established a long-run link between NPLs, money supply, and interest rates, while Ghosh (2015, 2017) showed regional and sector-specific conditions, public debt and unemployment prominent among them, shaping US NPLs. The pattern here mirrors the bank-specific strand, whereby GDP growth, inflation, and interest rates all switch sign and significance across studies, tracking differences in monetary regime and financial development rather than any stable structural relationship. Crucially, almost none of these studies confront the specification uncertainty this variation implies, as each reports a fixed model and treats its coefficients as settled (I. Moosa, 2012; Moral-Benito, 2015).

2.3. Cross-Country Evidence

In the international context, Gjeçi and Marinč (2018) analyzed banks in 195 countries and found that corruption is positively associated with NPLs; the effect is weaker for larger and thinly capitalized banks and stronger where the legal environment is weak. Gjeçi et al. (2023) extend this by showing that elevated NPLs feed back into more conservative lending, a reminder that credit quality determinants and credit supply are jointly determined. Kuzucu and Kuzucu (2019) compared emerging and advanced economies and concluded that GDP growth is the leading NPL driver, with bank-specific factors being insignificant for emerging markets, suggesting macroeconomic dominance. Karadima and Louri (2021) found that economic policy uncertainty raises NPLs in four European economies, an effect moderated by bank concentration, with GDP growth and ROA lowering NPLs and the net-loans-to-assets ratio raising them. Boussaada et al. (2022) identified threshold effects in the liquidity-risk–NPL relationship for MENA banks. Fitriani et al. (2025) found that growth, lending rates, and credit growth all lower NPLs in the G7, while Ozili and Delgado (2026) documented divergent significant determinants across European and African sub-samples. M. Khan et al. (2020) reach a similar conclusion for developing economies, reporting that the determinants they identify are sensitive to the estimator and control set adopted. Annas et al. (2024) reach a comparable conclusion for an emerging economy, finding that both macroeconomic and bank-specific factors shape non-performing loans, while the significance of individual determinants remains contingent on the specification adopted. Read together, these studies are less a cumulative body of knowledge than a catalogue of context-dependent findings, the very condition under which robustness screening, rather than another point estimate, is the informative next step.

2.4. Evidence from GCC Banking Systems

Studies of GCC banks point to structural features, oil dependence, fixed exchange rate regimes, and the coexistence of Islamic and conventional banks that may shape NPLs differently than elsewhere. Espinoza and Prasad (2010), using a dynamic panel of roughly 80 banks, linked rising NPLs to weaker growth, higher interest rates, and greater risk aversion, with macroeconomic shocks accumulating over a three-year window. Abdelbaki (2019), applying OLS, fixed effects, Arellano–Bond GMM, and VAR, found that non-oil GDP growth, domestic private credit, and inflation lower NPLs and interest rates and financial crises raise them. Farooq et al. (2019), using two-step GMM, reported that ROA lowers NPLs, the cost-to-income ratio raises them, and inflation lowers them. Al-Romaihi and Kumar (2026) found that non-oil real GDP growth and inflation lower NPLs and that a volatility index and inefficiency raise them, alongside adverse crisis effects. Research concerning the region's listed banks consistently concludes that bank-level fundamentals are paramount for stability outcomes (I. N. Khatatbeh et al., 2025). A notable point of controversy arises from four GCC studies utilizing overlapping samples, where inflation is alternately reported to reduce and increase non-performing loans (NPLs). Additionally, the significance of bank size and efficiency fluctuates depending on the estimator and control set employed.

Table 1 provides an overview of the key characteristics of the selected literature. The table highlights the diversity in estimation approaches, model specifications, and explanatory variables employed across prior studies, which motivates the adoption of a robust empirical design in the present study. Given the considerable variation in methodological choices and control variables, the consistency and significance of potential determinants cannot be presumed and should be examined through direct empirical testing.

Table 1. Summary of the surveyed empirical literature.

Authors	Countries	Methodology	Explanatory Variables
Panel A: Cross-country studies			
Gjeçi and Marinč (2018)	195 countries	Static panel	Corruption, size, effectiveness, capital
Kuzucu and Kuzucu (2019)	Emerging/ advanced	Dynamic panel	Exchange rate, inflation, unemployment, growth, loan size, capitalization, FDI
Karadima and Louri (2021)	Europe	Dynamic panel	EPU, concentration, GDP, inflation, profitability
Boussaada et al. (2022)	MENA	Panel smooth transition	Liquidity risk, performance, capital, size, crisis, inflation
Fitriani et al. (2025)	G7	CE/FE/RE	Growth, unemployment, interest rates, assets, NII, Tier-1, credit growth
Ozili and Delgado (2026)	32 EU/African	2SLS	Branches, liquid reserves, inflation, exchange rate, real and lending rates
Panel B: GCC studies			
Espinoza and Prasad (2010)	GCC	Dynamic panel	CAR, efficiency, size, NIM, credit growth
Abdelbaki (2019)	GCC	OLS/FE/GMM/VAR	GDP growth, domestic credit, inflation, interest rate, crisis
Farooq et al. (2019)	GCC	Two-step GMM	ROAA, ROAE, size, cost-to-income, inflation, growth
Al-Romaihi and Kumar (2026)	GCC	OLS/FE/GMM	GDP growth, inflation, volatility index, inefficiency
Elmonshid (2026)	GCC	FE/RE, panel quantile	ROA, CAR, size, liquidity, growth, inflation, GEPU

3. Data and Methodology

3.1. Sample and Data Sources

We construct a balanced panel of 45 listed conventional commercial banks operating in the six GCC countries (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates) over fifteen consecutive years (2010–2024). Bank-level financial data are sourced from Bloomberg, while macroeconomic series are obtained from the IMF's World Economic Outlook database. The sample period begins in 2010 to align with the post-global financial crisis period and ends in 2024, the most recent year for which complete data is available across all banks. The resulting panel comprises 675 bank-year observations. Table 2 presents the distribution of sample banks by country, along with the proportion of each country's listed conventional commercial banking sector that the sample encompasses.

Islamic banks are excluded from the sample because their distinctive risk-sharing structure and Shari'a-compliant asset composition produce profitability and credit quality dynamics that differ systematically from those of conventional commercial banks (Hadriche, 2015; Alharthi, 2017). Accordingly, two considerations bear on the exclusion. First, the direction of the bias is analytically determinate for the pooled alternative. Most importantly, Islamic banks recognize impairment on profit and loss sharing and "Murabaha" exposures under different contractual triggers, so the mapping from a given balance sheet configuration to a reported non-performing ratio is not the same function across the two bank types. Hence, pooling would therefore impose a common slope vector on two distinct data-generating processes, and the resulting coefficients would be a variance-weighted average of the two and informative about neither. Second, the exclusion does limit external validity, as Islamic banks hold a material and rising share of GCC banking assets, so the conventional segment findings cannot be extrapolated to the region's banking system in aggregate. We accordingly narrow the policy implications in Sections 5 and 6 to the listed conventional segment and consider a formal conventional-versus-Islamic comparison.

Table 2. Sample composition by country.

Country	Banks in Sample	Bank-Year Observations	Coverage (%)
Bahrain	6	90	13%
Kuwait	5	75	11%
Oman	5	75	11%
Qatar	6	90	13%
Saudi Arabia	9	135	20%
United Arab Emirates	14	210	31%
Total	45	675	100%

3.2. Variables and Measurement

The dependent variable is the non-performing loans (NPL) ratio, measured as non-performing loans divided by total loans. The potential set comprises 19 regressors drawn from the empirical NPL literature: 15 bank-specific variables, capturing liquidity, size, profitability, efficiency, loan intensity, asset and operating management, deposit funding, loan growth, capitalization, intermediation spreads, and revenue diversification, and 4 macroeconomic variables, capturing the exchange rate, the lending rate, inflation, and GDP growth. Variable definitions are reported in Table 3.

Table 3. Variables, definitions, and measurements.

Variable	Code	Measure	Equation/Definition
NPL Ratio	Y	Non-Performing Loans Ratio	Non-Performing Loans/Total Loans
Bank-specific determinants			
	X1	Liquidity (LTA)	Liquid assets/total assets
	X2	Age	Years since establishment
	X3	Total assets	Log of total assets
	X4	Cash liquid assets	Log of cash and tradable securities
	X5	Profitability (ROA)	Net profit/total assets
	X6	Efficiency	Operating expenses/operating income
	X7	Loan intensity (LTA_L)	Loans/total assets
	X8	Asset management	Operating income/total assets
	X9	Operating efficiency	Operating expenses/total assets
	X10	Deposits ratio	Deposits/total assets
	X11	Loan growth	Year-over-year growth of loans

Table 3. *Cont.*

Variable	Code	Measure	Equation/Definition
	X12	Capital adequacy	Total equity/total assets
	X13	Interest rate margin	Net interest income/average earning assets
	X14	Bank diversification	Noninterest income/total revenues
	X15	Diversification (NII/TA)	Noninterest income/total assets
Macroeconomic determinants			
	X16	Exchange rate	Annual average nominal exchange rate, units of domestic currency per US dollar
	X17	Lending rate	Lending interest rate (%)
	X18	Consumer price index	Annual % change in end-of-period consumer prices
	X19	GDP growth	Real GDP percentage change

Source: Authors' compilation based on the empirical NPL literature, including Berger and DeYoung (1997), Klein (2013), Boussaada et al. (2023), and S. Khan (2022).

3.3. Outliers and Data Screening

The descriptive statistics display extreme values for several variables, notably efficiency (X6), loan growth (X11), the NPL ratio, and loan intensity (X7). These arise from a small number of bank-years in which operating income approaches zero or a bank undertakes a step change in its loan book. The presence of these tails matters in an EBA setting, and we do not minimize it: because the procedure classifies a variable by the behavior of its coefficient across hundreds of specifications, a handful of leverage points can in principle move the extreme bounds and shift a classification without reflecting anything systematic in the data. The design and results disposition incorporate two features that address this concern without eliminating it. Firstly, the Sala-i-Martin criterion, which underpins both robust classifications, evaluates the entire distribution of coefficients rather than focusing solely on the extreme bounds. This approach reduces its susceptibility to a single leverage-driven specification compared to the Leamer criterion. The Leamer criterion, being more sensitive to outliers, classifies every variable as fragile, ensuring that no positive claim in the paper relies on it. Secondly, variables with the most pronounced tails (X6, X11) are deemed fragile, ensuring that no robust classification is influenced by an outlier-heavy series. Moreover, this limitation is explicitly noted in Section 5, where re-estimation on a winsorized panel is identified as a priority for future research.

3.4. Model Specification and the Extreme Bounds Procedure

The issue EBA addresses is that a researcher testing whether, say, capital adequacy affects NPL must also decide which other variables to control for, where theory offers little guidance (I. Moosa, 2012). In this sense, different defensible choices yield different coefficients, and EBA declines to make that choice. Instead, it estimates the model repeatedly under every admissible combination of controls and inspects the resulting distribution of the coefficient on the variable of interest. Accordingly, a variable is deemed robust if its estimated effect keeps the same sign and remains statistically significant no matter which controls accompany it; thus, the conclusion does not depend on the model specification (selection of the control variables set). By the same logic, a variable is fragile if its coefficient changes sign, or loses significance, as the control set varies, indicating that a study reporting it as significant may simply have chosen a control set in which it was.

In this study, we utilize two variants of EBA. First, the strict variant of EBA is Leamer's (1985), which looks only at the two extreme estimates (the lowest and highest coefficient obtained across all specifications) and requires both to be significant with the same sign. It is an all-or-nothing test, where a single specification in which the coefficient crosses zero condemns the variable, regardless of how well it performs in the other several hundred estimates. Second, Sala-i-Martin (1997) argued this is an unreasonably hard-to-pass test since it lets one outlying model overturn an otherwise consistent body of evidence. His alternative examines the whole distribution of coefficients and asks what fraction of it falls on one side of zero; a variable is robust if at least 95% does.

The baseline specification is a fixed-effects (within) regression of the NPL ratio on the focus variable Z and a rotating subset of the remaining doubtful variables, with bank-level fixed effects:

$$Y_{it} = \alpha + \beta_f Z_{f,it} + \Sigma_{j\in M} \beta_j X_{j,it} + \mu_i + \varepsilon_{it} \quad (1)$$

where Y_{it} is the NPL ratio of bank i in year t; $Z_{f,it}$ is the focus variable whose robustness is being tested; M is a subset of three regressors drawn from the remaining eighteen potentials; $X_{j,it}$ denotes those doubtful regressors; α is the intercept; μ_i is a bank fixed effect; and ε_{it} is an idiosyncratic error term, for which heteroskedasticity-consistent (HC1) standard errors clustered at the bank level are computed following MacKinnon and White (1985).

For a given focus variable, the procedure draws every possible subset of three doubtful variables from the eighteen remaining potentials. This yields C(18,3) = 816 candidate specifications per focus variable. Because each of the 19 potential determinants takes its turn as the focus variable, the procedure estimates 19 × 816 = 15,504 regressions in total. Accordingly, the number of distinct four-variable models spanned C(19,4) = 3876.

Furthermore, the choice of three doubtful variables per subset follows the convention established in the applied EBA literature (e.g., Levine & Renelt, 1992; Sala-i-Martin, 1997; I. A. Moosa & Cardak, 2006) and reflects a trade-off rather than a natural constant. A larger conditioning set tests robustness against richer models; however, it rapidly exhausts the degrees of freedom available in a panel of 675 observations across 45 bank fixed effects and raises the incidence of near-singular design matrices that the collinearity filter must then discard, so the surviving specifications become a selected, rather than a representative, subset of the model space. On the other hand, a smaller set makes the test weaker and less informative. Following Sala-i-Martin's (1997) seminal work, three is the standard compromise, and it is the size used in the canonical applications against which our results are comparable.

We implement the procedure using the ExtremeBounds package in R (version 4.5.2) (Hlavac, 2016). The fixed-effects estimator is used as the baseline because the within transformation absorbs time-invariant bank heterogeneity, differences in business model, ownership, and supervisory regime across the 45 banks that would otherwise contaminate the cross-sectional comparison of determinants (Sala-i-Martin, 1997; Hlavac, 2016). Multicollinearity is addressed at the specification level, where any combination of regressors yielding a variance inflation factor above 10 is automatically excluded, ensuring that surviving estimates are not artifacts of near-singular design matrices (I. Khatatbeh, 2019).

4. Empirical Results

4.1. Descriptive Statistics and Pairwise Correlations

Appendix A Table A1 reports descriptive statistics for the dependent variable and the 19 potential regressors. The mean NPL ratio across the panel is 4.15% with a standard deviation of 5.59%, indicating considerable cross-sectional and time-series variation in credit quality. Bank size (X3, log of total assets) has a mean of 24.05 and a standard deviation of 1.83, reflecting the well-known concentration of GCC banking around a small number of large institutions. Profitability (X5, ROA) averages 1.31%. The efficiency ratio (X6) and loan growth (X11) exhibit the most pronounced tails, driven by bank-years with near-zero operating income and by step changes in loan books, respectively. Moreover,

Appendix A Table A2 reports the pairwise Pearson correlation matrix. Two pairs warrant attention. Total assets (X3) and cash liquid assets (X4) correlate at 0.932, reflecting their shared scale dependence on bank size. Profitability (X5) and asset management (X8) correlate at 0.970, since asset management is a near-mechanical reformulation of operating income relative to total assets. These patterns are addressed at the specification level by the VIF > 10 exclusion rule described in Section 3.4.

4.2. Leamer's EBA

Table 4 reports the strict variant of EBA introduced by Leamer (1985). For each potential determinant, we report the minimum and maximum coefficient estimates obtained across all admissible specifications, their associated t-statistics, the percentage of regressions in which the coefficient is statistically significant at the 5% level with the same sign as the median, and the resulting classification. Of the 19 potential determinants, none survives Leamer's strict test: for every variable, the extreme bounds straddle zero or at least one bound is statistically insignificant. The variable that comes closest is efficiency (X6), which is statistically significant in 57.2% of the admissible regressions but reverses sign across specifications, with a minimum coefficient of −0.0032 (t = −2.03) and a maximum of 0.0030 (t = 1.36). All 19 potential variables are accordingly fragile under the Leamer criterion.

Table 4. Fragile and robust determinants of NPLs (Leamer's EBA—fixed effects).

Variable	β_{min}	t-Stat	β_{max}	t-Stat	% Sign.	Classification
Liquidity—LTA (X1)	2.0417	0.716	15.7750	1.231	0.65%	Fragile
Age (X2)	−0.0185	−0.306	0.5321	1.148	0.00%	Fragile
Total assets (X3)	−6.1386	−1.145	1.8366	2.441	2.93%	Fragile
Cash liquid assets (X4)	−2.7480	−1.675	1.5338	0.894	4.67%	Fragile
Profitability—ROA (X5)	−1.6003	−2.434	−0.5608	−1.300	0.94%	Fragile
Efficiency (X6)	−0.0032	−2.028	0.0030	1.362	57.25%	Fragile
Loan intensity (X7)	0.0245	3.064	0.0879	1.206	21.48%	Fragile
Asset management (X8)	−126.7836	−1.972	264.5455	1.816	4.94%	Fragile
Operating efficiency (X9)	−90.8012	−0.998	158.4660	0.794	0.00%	Fragile
Deposits ratio (X10)	−7.8729	−2.512	13.2457	1.164	4.29%	Fragile
Loan growth (X11)	−0.0329	−2.059	0.0045	0.272	17.20%	Fragile
Capital adequacy (X12)	−44.9626	−1.975	−10.0761	−1.396	20.02%	Fragile
Interest rate margin (X13)	−1.7963	−1.412	−0.4749	−1.601	0.00%	Fragile
Bank diversification (X14)	−0.1961	−1.550	0.0144	0.740	0.00%	Fragile
Diversification—NII/TA (X15)	−73.6088	−0.739	188.6122	4.017	14.51%	Fragile
Exchange rate (X16)	−89.8938	−1.649	13.2491	0.229	1.14%	Fragile
Lending rate (X17)	0.3653	0.890	0.7517	1.093	0.00%	Fragile
CPI (X18)	0.0513	0.599	0.2559	1.193	0.00%	Fragile
GDP growth (X19)	−0.0846	−1.763	0.1418	1.100	0.52%	Fragile

Note: β_{min} and β_{max} are the minimum and maximum coefficient estimates across all admissible specifications. % Sign. is the percentage of regressions with statistically significant coefficients (5% level) of the same sign as the median.

Nevertheless, Leamer's criterion is exceptionally demanding and is failed by the great majority of variables in most published applications (Levine & Renelt, 1992; I. N. Khatatbeh & Abu-Alfoul, 2024); therefore, its informational value is comparative as it tells us that no NPL determinant in this literature is unconditionally stable and it establishes the baseline for the Sala-i-Martin results in the following subsection.

4.3. Sala-i-Martin's EBA

Table 5 reports Sala-i-Martin's (1997) less restrictive EBA. We report the weighted mean coefficient across all admissible specifications and the value of the cumulative distribution function on the dominant side of zero, CDF(0), under the generic model variant, which makes no distributional assumption about the coefficient distribution across specifications. A variable is classified as robust if its CDF(0) is at least 95% on either side of zero. Only two variables emerge as robust: loan intensity (X7), with CDF(0) = 95.35% and a positive sign, and capital adequacy (X12), with CDF(0) = 95.21% and a negative sign. Efficiency (X6), significant in the majority of Leamer specifications, falls short here (CDF(0) = 91.95%) and is classified as borderline robust.

Table 5. CDF(0) of fragile and robust determinants of NPLs (Sala-i-Martin's EBA—fixed effects).

Variable	β (Weighted Mean)	CDF(0)	Sign
Liquidity—LTA (X1)	4.8053	85.70%	+
Age (X2)	0.1706	83.01%	+
Total assets (X3)	−1.0812	55.54%	−
Cash liquid assets (X4)	0.0715	55.67%	+
Profitability—ROA (X5)	−0.8712	91.75%	−
Efficiency (X6)	−0.0010	91.95%	−
Loan intensity (X7)	**0.0472**	**95.35%**	**+**
Asset management (X8)	−27.2988	78.88%	−
Operating efficiency (X9)	53.2531	68.79%	+
Deposits ratio (X10)	1.6735	54.90%	−
Loan growth (X11)	−0.0207	92.38%	−
Capital adequacy (X12)	**−24.9913**	**95.21%**	**−**
Interest rate margin (X13)	−1.0392	92.02%	−
Bank diversification (X14)	−0.0681	76.97%	−
Diversification—NII/TA (X15)	−4.0913	52.31%	−
Exchange rate (X16)	−48.2624	88.45%	−
Lending rate (X17)	0.5843	84.90%	+
CPI (X18)	0.1597	85.22%	+
GDP growth (X19)	0.0244	57.49%	+

Note: Robust variables (CDF(0) ≥ 95% on the dominant side of zero) are shown in bold. β is the weighted mean coefficient across all admissible specifications. CDF(0) values are reported under Sala-i-Martin's (1997) generic model variant. The symbols (+) and (−) indicate the direction of the effect, whereby (+) denotes a positive effect, whereas (−) denotes a negative effect.

Furthermore, Figure 1 plots each determinant's CDF(0) against the 95% cut-off, marking the proximity of the two robust variables to the threshold. Moreover, four variables, clustered between 91% and 93%, could also be considered robust under the 90% cut-off threshold (loan growth, interest rate margin, efficiency, ROA).

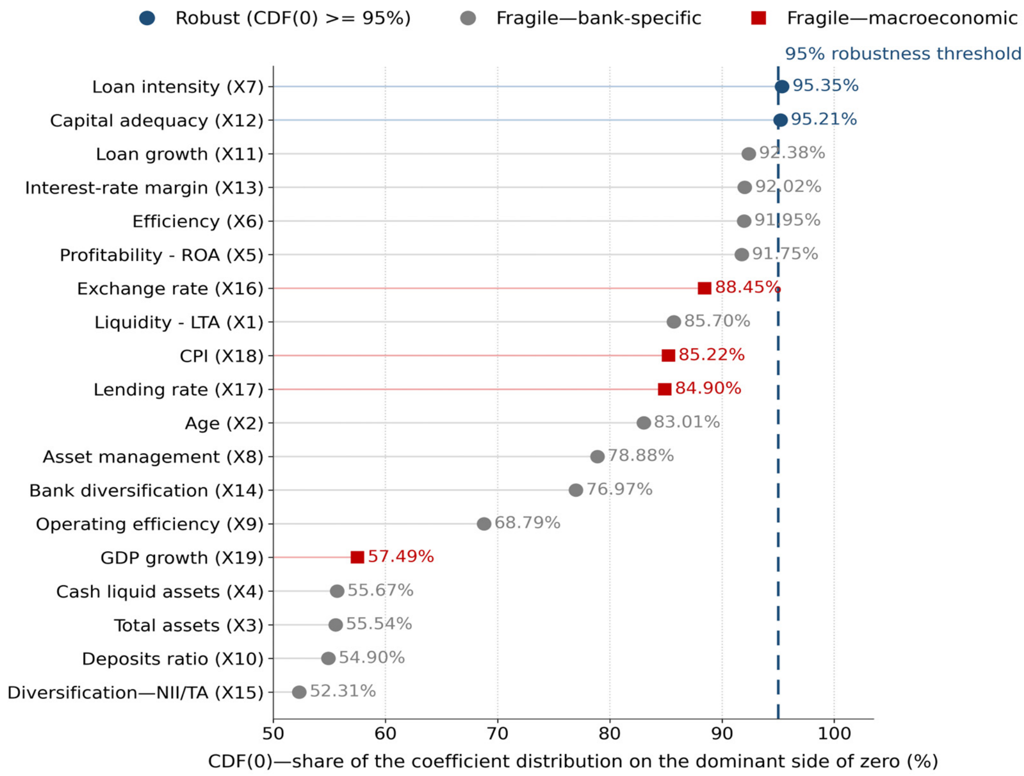

Figure 1. Distribution of CDF(0) across the nineteen potential determinants.

4.4. Discussion of Results

Under the fixed-effects EBA, no determinant satisfies Leamer's strict robustness criterion. Efficiency (X6) comes closest, significant in 57.2% of the specifications, but its sign is not stable across conditioning sets, and its Sala-i-Martin CDF(0) of 91.95% is marginal to the threshold. Its fragility is directly instructive for the theoretical debate of EBA application. The bad management hypothesis of Berger and DeYoung (1997) predicts that cost inefficiency precedes loan losses, and single-specification GCC studies have duly reported efficiency (measured by the cost-to-income ratio) as a significant NPL driver (Espinoza & Prasad, 2010; Al-Romaihi & Kumar, 2026; Farooq et al., 2019). Our results do not refute that hypothesis, but they do show that the empirical support for it in this region is conditional on the control set; once bank fixed effects absorb persistent differences in the operating model, the efficiency–NPL relationship cannot be signed reliably.

Under the 95% threshold cut-off suggested by Sala-i-Martin (1997), two variables are deemed robust. First, loan intensity (X7), which is measured by the ratio of loans to total assets, has a weighted mean coefficient of +0.0472 with CDF(0) = 95.35%. The positive sign indicates that banks committing a larger share of their balance sheet to lending exhibit higher NPL ratios, an association consistent with the risk-taking channel, in which expansion of loan exposure relative to total assets raises subsequent default rates (Naili & Lahrichi, 2022; Misman & Bhatti, 2020), and inconsistent with the specialization view under which loan-intensive banks develop superior screening capabilities. The result also corresponds to the prior literature, in which Karadima and Louri (2021) report a positive net-loans-to-assets effect for European banks, whereas the specialization reading has been advanced for banks operating in more concentrated lending markets. Boussaada et al. (2023) document comparable loan-growth–credit-risk dynamics for European banks under system GMM. Accordingly, we stress that a bank whose loan book is deteriorating will mechanically show both a rising NPL ratio and, if impairment shrinks other asset classes more slowly, a shifting loans-to-assets share.

Second, capital adequacy (X12), which is measured by the ratio of total equity to total assets, has a weighted mean coefficient of −24.9913 with CDF(0) = 95.21%. The negative sign indicates that better-capitalized banks have lower NPL ratios, consistent with the moral hazard hypothesis (Berger & DeYoung, 1997). From this perspective, banks with thinner equity buffers face stronger incentives to take credit risk in pursuit of higher returns (Saliba et al., 2023; Bayar, 2019; Makri et al., 2014). Moreover, a complementary mechanism, distinct from moral hazard and observationally similar, is regulatory arbitrage, under which banks holding equity buffers close to the regulatory minimum may have incentives to delay recognition of impaired exposures, since each additional NPL recognized erodes the capital ratio further (Beck et al., 2013).

Furthermore, the results show that there are four determinants classified as borderline robust that exhibit cumulative distribution function (CDF(0)) values ranging from 90% to less than 95%. Specifically, these four determinants fall just below the robust threshold, with CDF(0) values between 91.75% and 92.38%, and could be considered as robust using the less restrictive requirements of Sala-i-Martin EBA. Namely, profitability (X5, CDF(0) = 91.75%), efficiency (X6, 91.95%), interest rate margin (X13, 92.02%), and loan growth (X11, 92.38%). Each of these determinants is associated with a negative weighted mean coefficient. To begin with, profitability (X5) has a negative weighted mean (−0.8712), indicating that more profitable banks tend to report lower NPL ratios. Economically, this is the most intuitive, as banks generating stronger operating returns can absorb loan losses, can price risk more conservatively, and are less pressed to reach for yield in marginal borrowers. The sign accords with the bad management hypothesis of Berger and DeYoung (1997), with weak profitability being a symptom of the same managerial deficiencies that later surface as impaired loans. The results correspond to previous studies by De Bock and Demyanets (2012), Ghosh (2015), Karadima and Louri (2021), and, within the GCC, Farooq et al. (2019) and Al-Romaihi and Kumar (2026).

Likewise, the interest rate margin (X13) has a negative weighted mean (−1.0392). Thus, a wider net interest margin is associated with lower NPLs. Accordingly, margin proxies franchise value and pricing power, whereby banks able to sustain wide spreads enjoy charter value rents they are reluctant to jeopardize through lax underwriting, dampening risk-taking (Keeley, 1990). Moreover, a wide margin reflects efficient intermediation and strong core earnings, the same underlying quality that profitability captures. Loan growth (X11) exhibits a negative weighted mean coefficient (−0.0207), suggesting that higher lending growth is associated with lower contemporaneous NPL ratios. This result may reflect a denominator effect, whereby rapid loan expansion increases total loans faster than new loans become non-performing, temporarily reducing the NPL ratio. Its borderline robustness (CDF(0) = 92.38%) indicates a relatively stable but timing-sensitive relationship, highlighting the need for future dynamic analyses using lagged credit growth measures.

Lastly, efficiency (X6) has a CDF(0) value of 91.95% and is based on a predominantly negative weighted mean (−0.0010), indicating that lower operating expenses relative to income are associated with lower non-performing loans (NPLs), as predicted by the bad management hypothesis (Berger & DeYoung, 1997) and supported by the findings of Farooq et al. (2019). The GCC literature has regarded cost efficiency as a definitive NPL driver (Espinoza & Prasad, 2010; Al-Romaihi & Kumar, 2026).

The fragility of the macroeconomic determinants is equally notable. None of GDP growth (X19), inflation (X18), the lending rate (X17), or the exchange rate (X16) survives either test. The fragility indicates specification sensitivity, not economic irrelevance. That a variable's coefficient changes sign or loses significance as the conditioning set varies establishes that studies reporting it as significant may owe that significance to their control set; it does not establish that the variable carries no information about future credit quality.

In other words, a macroeconomic indicator can be fragile in the EBA sense and still have genuine early-warning value. The finding is that GDP growth, inflation, and interest rates are not unconditionally stable determinants of NPLs in the GCC. This is a corrective to the macro-dominant conclusions of Kuzucu and Kuzucu (2019), Abdelbaki (2019), and Al-Romaihi and Kumar (2026), whose specifications omit the bank-level aggregates against which the macroeconomic effect does not survive, but it is not a verdict against macroeconomic monitoring.

5. Research Implications, Limitations, and Future Research

The findings carry far-reaching implications for prudential supervision in the GCC banking sector, but their scope is bounded in two respects that we state first. Particularly, the estimates describe listed conventional commercial banks and not the GCC banking system as a whole, and they identify stable associations rather than causal effects.

The results reveal two robust bank-level balance sheet indicators: loan intensity and capital adequacy. These indicators set a starting point for NPL early-warning frameworks. This argues for weighting balance sheet indicators at least as heavily as macroeconomic forecasts in supervisory dashboards. Moreover, the negative association between capital adequacy and NPLs provides conditional empirical support for the emphasis on equity-based capital buffers in the GCC's implementation of Basel III.

Furthermore, four limitations bound the findings and serve as venues for future research. First, the sample covers listed conventional commercial banks only; Islamic banks, which hold a material share of GCC banking assets, are excluded, so the results do not describe the regional banking system in aggregate. Second, the macroeconomic potential set is narrow, omitting the oil price, non-oil GDP growth, the fiscal stance, real estate dynamics, and macro-governance factors. Third, the EBA framework addresses specification uncertainty, not endogeneity; the estimates are robust associations, and a causal account of the capital–NPL and loan-intensity–NPL relationships would require an identification strategy the current design does not supply. Fourth, the static framework leaves aside other sources of model uncertainty, functional form, dynamic specification, and structural breaks, as well as emerging risks, including climate exposure, digital disruption, and geopolitical instability.

These boundaries define a constructive agenda that would extend and generalize the present evidence. A natural first step is to broaden the sample beyond listed conventional commercial banks to include Islamic institutions, whose risk-sharing contracts reshape the moral hazard calculus and whose inclusion would permit a system-wide characterization of GCC credit risk and a test of whether the robust determinants identified here carry over to that segment. A second avenue is to enlarge the macroeconomic conditioning set by incorporating oil prices, non-oil output growth, the fiscal stance, and real estate dynamics so that regional credit risk is assessed against a specification more fully matched to the area's structural features. A third research direction is to complement the extreme-bounds screen with dynamic panel estimators, notably system GMM, that accommodate the feedback between credit quality and balance sheet composition and advance the analysis from robust association to causal identification. The static design further invites attention to additional sources of model uncertainty, including functional form and structural breaks. Finally, as longer panels become available, the framework can be extended to emerging banking risks, climate exposure, digital disruption, and geopolitical instability, whose relevance to the region is set to intensify.

6. Conclusions

This study examines the robustness of NPL determinants in GCC banking systems. Using a balanced panel of 45 listed conventional commercial banks across the six GCC countries over the period 2010–2024, we evaluate the stability of commonly employed NPL determinants under model uncertainty arising from specification choice. We apply two complementary variants of EBA, namely, Leamer's (1985) stringent criterion and Sala-i-Martin's (1997) modified variant of EBA, to assess whether the estimated effects of candidate determinants remain stable across a comprehensive set of alternative model specifications.

The findings indicate that most determinants traditionally associated with NPLs in the GCC and the broader banking literature are not robust to specification changes. In particular, under Leamer's strict criterion, none of the examined variables satisfy the robustness requirement. However, under the less restrictive Sala-i-Martin criterion, only two bank-specific variables remain robust: loan intensity, which is positively associated with NPLs, and capital adequacy, which exhibits a negative association. In contrast, all four macroeconomic variables considered, namely, GDP growth, inflation, lending rates, and exchange rates, fail to demonstrate robustness under either criterion, suggesting that their estimated effects are highly sensitive to model specification.

These findings carry important implications for prudential supervision and risk monitoring frameworks in the GCC. The evidence suggests that bank-level balance sheet indicators, particularly loan intensity and capital adequacy, provide a more reliable basis for monitoring credit risk than the macroeconomic variables examined in this study. Consequently, variables that fail the robustness screen may still possess predictive value in particular institutional or macroeconomic environments. Supervisory frameworks should therefore view robust bank-specific indicators as a stronger foundation for early-warning systems while continuing to incorporate broader macroeconomic surveillance. This consideration is particularly relevant in the GCC context, where banking sector performance remains closely linked to oil market dynamics and fiscal conditions, factors not explicitly incorporated into the present analysis.

The interpretation of these results is subject to several limitations. First, the analysis is restricted to listed conventional commercial banks and therefore does not capture the credit risk dynamics of Islamic banks, which constitute a significant component of GCC financial systems. Second, the study focuses on a predefined set of conventional determinants and does not consider other potentially important drivers of credit risk, including oil prices, non-oil economic activity, fiscal sector indicators, climate-related financial risks, and geopolitical uncertainty. Future research may extend the analysis by incorporating these factors and by employing dynamic estimation techniques capable of addressing potential endogeneity.

The principal contribution of this study is methodological. It offers a more rigorous evaluation of the credit risk literature in the region by distinguishing between determinants whose relationships with NPLs remain stable across a wide range of plausible model specifications and those whose significance depends on particular modeling choices. The results demonstrate that bank-specific fundamentals exhibit greater stability than the macroeconomic variables considered, while several determinants commonly regarded as established predictors of NPLs fail to withstand robustness testing. More broadly, the findings underscore the importance of explicitly addressing model uncertainty when identifying the drivers of credit risk. Determinants that appear significant in a single specification may not retain their explanatory power once alternative model structures are considered. By separating robust relationships from fragile ones, this study provides a more cautious and methodologically grounded understanding of the factors shaping credit risk in GCC banking systems.

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Appendix A

Appendix A Table A2 presents the Pearson correlation matrix. The results indicate two high correlations exceeding the conventional multicollinearity threshold of $|r| = 0.80$. Specifically, total assets (X3) and cash liquid assets (X4) show a strong correlation ($r = 0.932$), reflecting their common scale effect related to bank size. Similarly, profitability (X5) and asset management (X8) are highly correlated ($r = 0.970$) due to the close conceptual relationship between these measures.

Table A1. Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
NPL ratio (Y)	675	4.148	5.592	0.000	71.827
Liquidity—LTA (X1)	675	0.177	0.115	0.010	0.875
Age (X2)	675	37.778	18.544	2.000	98.000
Total assets (X3)	675	24.045	1.834	19.854	27.892
Cash liquid assets (X4)	675	22.104	1.879	17.148	26.441
Profitability—ROA (X5)	675	1.305	1.632	−26.265	7.294
Efficiency (X6)	675	4.318	42.495	−23.965	836.667
Loan intensity (X7)	675	99.984	21.360	41.682	296.334
Asset management (X8)	675	0.013	0.019	−0.354	0.069
Operating efficiency (X9)	675	0.015	0.009	−0.002	0.089
Deposits ratio (X10)	675	0.651	0.122	0.024	0.901
Loan growth (X11)	675	12.042	53.673	−34.390	1284.621
Capital adequacy (X12)	675	0.151	0.048	0.023	0.586
Interest rate margin (X13)	673	2.909	1.369	−8.129	10.235
Bank diversification (X14)	675	22.807	14.144	−16.423	211.237
Diversification (X15)	675	0.012	0.010	−0.008	0.170
Exchange rate (X16)	675	2.506	1.600	0.276	3.755
Lending rate (X17)	675	3.847	1.948	0.600	7.360
CPI (X18)	675	1.681	1.849	−3.374	6.473
GDP growth (X19)	675	3.099	3.604	−5.911	17.746

Note: The sample comprises 45 listed conventional commercial banks across the six GCC countries over 2010–2024 (675 bank-year observations). Variable definitions are reported in Table 3.

Table A2. Pairwise Pearson correlations (reformatted).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) Y	1.000																			
(2) X1	−0.007	1.000																		
(3) X2	−0.015	0.115 *	1.000																	
(4) X3	−0.114 *	−0.096 *	0.362 *	1.000																
(5) X4	−0.099 *	0.236 *	0.403 *	0.932 *	1.000															
(6) X5	−0.317 *	−0.004	0.069 *	0.201 *	0.196 *	1.000														
(7) X6	−0.029	0.025	0.052	−0.075 *	−0.060	−0.016	1.000													
(8) X7	0.122 *	−0.235 *	−0.208 *	−0.178 *	−0.267 *	−0.084 *	0.012	1.000												
(9) X8	−0.260 *	−0.025	0.100 *	0.195 *	0.181 *	0.970 *	−0.052	−0.060	1.000											
(10) X9	−0.008	−0.005	−0.314 *	−0.306 *	−0.308 *	−0.072 *	−0.017	−0.023	−0.106 *	1.000										
(11) X10	0.038	−0.147 *	0.179 *	0.252 *	0.208 *	0.123 *	−0.063	−0.413 *	0.134 *	−0.119 *	1.000									
(12) X11	−0.065 *	0.019	−0.138 *	0.002	0.009	0.031	0.020	0.134 *	0.010	0.063	−0.105 *	1.000								
(13) X12	−0.094 *	−0.079 *	−0.229 *	−0.154 *	−0.176 *	0.091 *	0.006	0.156 *	0.054	0.316 *	−0.244 *	0.338 *	1.000							
(14) X13	−0.107 *	−0.159 *	0.044	0.150 *	0.103 *	0.486 *	−0.011	−0.008	0.457 *	0.265 *	0.375 *	0.072 *	0.132 *	1.000						
(15) X14	−0.072 *	0.295 *	−0.047	−0.087 *	0.024	−0.277 *	0.006	−0.256 *	−0.338 *	0.352 *	−0.364 *	−0.104 *	0.136 *	−0.417 *	1.000					
(16) X15	−0.047	0.138 *	−0.114 *	−0.123 *	−0.067 *	0.198 *	−0.006	−0.159 *	0.180 *	0.632 *	−0.288 *	−0.051	0.177 *	−0.079 *	0.631 *	1.000				
(17) X16	0.037	−0.167 *	0.030	0.671 *	0.590 *	0.119 *	−0.085 *	−0.088 *	0.095 *	0.037	0.349 *	0.055	0.122 *	0.297 *	−0.074 *	−0.013	1.000			
(18) X17	−0.014	−0.008	−0.063	−0.344 *	−0.361 *	−0.046	0.014	0.063 *	−0.028	−0.163 *	−0.281 *	−0.001	−0.215 *	−0.305 *	−0.108 *	−0.087 *	−0.590 *	1.000		
(19) X18	0.001	0.160 *	0.046	−0.059	0.014	0.039	0.027	−0.001	0.036	−0.019	0.017	0.041	−0.023	0.009	0.026	−0.019	−0.085 *	0.060	1.000	
(20) X19	0.014	0.155 *	−0.142 *	0.007	0.070 *	0.144 *	−0.037	−0.109 *	0.095 *	0.081 *	0.058	0.112 *	0.093 *	0.102 *	0.070 *	0.064 *	0.153 *	0.032	0.282 *	1.000

Note: Asterisks (*) denote statistical significance at the 10% level. Cells highlighted in red indicate pairs with $|r| \geq 0.80$, which are flagged for collinearity-driven exclusion under the VIF > 10 rule applied in the EBA estimation.

References

Abdelbaki, H. H. (2019). Macroeconomic determinants of non-performing loans in GCC economies: Does the global financial crisis matter? *International Journal of Economics and Business Research*, *17*(4), 433–447. [CrossRef]

Adebola, S., & Dahalan, J. (2011). An ARDL approach to the determinants of nonperforming loans in Islamic banking system in Malaysia. *Arabian Journal of Business and Management Review (Kuwait Chapter)*, *1*(2), 20–30.

Adedeji, M. O. S., Alatrash, Y., & Kirti, M. D. (2019). *How do changing US interest rates affect banks in the Gulf Cooperation Council (GCC) countries?* (IMF working paper No. 19/268). International Monetary Fund.

Alharthi, M. (2017). Financial performance and stability in Islamic banks: Evidence from GCC countries. *Corporate Ownership and Control*, *14*(4), 103–113. [CrossRef]

Al-Romaihi, M. A., & Kumar, M. (2026). Analysis of credit risk in the GCC banking sector: A dynamic panel data analysis. *Journal of Financial Regulation and Compliance*, *34*(2), 237–258.

Altman, E. I. (1977). Predicting performance in the savings and loan association industry. *Journal of Monetary Economics*, *3*(4), 443–466. [CrossRef]

Anastasiou, D., Louri, H., & Tsionas, M. (2016). Determinants of non-performing loans: Evidence from Euro-area countries. *Finance Research Letters*, *18*, 116–119. [CrossRef]

Anita, S. S., Tasnova, N., & Nawar, N. (2022). Are non-performing loans sensitive to macroeconomic determinants? An empirical evidence from banking sector of SAARC countries. *Future Business Journal*, *8*(1), 7. [CrossRef]

Annas, M., Humairoh, H., & Endri, E. (2024). Macroeconomic and bank-specific factors on non-performing loans: Evidence from an emerging economy. *Calitatea*, *25*(199), 155–161. [CrossRef]

Avery, R., & Hanweck, G. (1985). A dynamic analysis of bank failures. In *Bank structure and competition* (Conference proceedings). Federal Reserve Bank of Chicago.

Badar, M., Javid, A. Y., & Zulfiquar, S. (2013). Impact of macroeconomic forces on nonperforming loans: An empirical study of commercial banks in Pakistan. *WSEAS Transactions on Business and Economics*, *10*(1), 40–48.

Barth, J., Brumbaugh, R., Sauerhaft, D., & Wang, G. (1985). Thrift institutions failures: Causes and policy issues. In *Bank structure and competition* (Conference proceedings). Federal Reserve Bank of Chicago.

Bayar, Y. (2019). Macroeconomic, institutional and bank-specific determinants of non-performing loans in emerging market economies: A dynamic panel regression analysis. *Journal of Central Banking Theory and Practice*, *8*(3), 95–110. [CrossRef]

Beck, R., Jakubik, P., & Piloiu, A. (2013). *Non-performing loans: What matters in addition to the economic cycle?* (ECB working paper No. 1515). European Central Bank.

Benston, G. (1985). *An analysis of the causes of savings and loan associations failures* (Monograph series in finance and economics). New York University.

Berger, A. N., & DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks. *Journal of Banking and Finance*, *21*(6), 849–870. [CrossRef]

Boudriga, A., Boulila, N., & Jellouli, S. (2009). *Does bank supervision impact nonperforming loans: Cross-country determinants using aggregate data* (MPRA paper No. 18068). Munich Personal RePEc Archive.

Boudriga, A., Taktak, N. B., & Jellouli, S. (2010). Bank specific, business and institutional environment determinants of banks nonperforming loans: Evidence from MENA countries. In *Economic research forum working paper* (Vol. 547, pp. 1–28). The Economic Research Forum (ERF).

Boussaada, R., Hakimi, A., & Karmani, M. (2022). Is there a threshold effect in the liquidity risk–non-performing loans relationship? A PSTR approach for MENA banks. *International Journal of Finance and Economics*, *27*(2), 1886–1898.

Boussaada, R., Hakimi, A., & Karmani, M. (2023). Non-performing loans and bank performance: What role does corporate social responsibility play? A system GMM analysis for European banks. *Journal of Applied Accounting Research*, *24*(5), 859–888. [CrossRef]

Cotugno, M., Stefanelli, V., & Torluccio, G. (2010, December 15–17). *Bank intermediation models and portfolio default rates: What's the relation?* 23rd Australasian Finance and Banking Conference, Sydney, Australia.

De Bock, R., & Demyanets, A. (2012). *Bank asset quality in emerging markets: Determinants and spillovers* (IMF working paper No. 12/71). International Monetary Fund.

Demirgüç-Kunt, A. (1989). Deposit-institution failures: A review of empirical literature. *Economic Review (Federal Reserve Bank of Cleveland)*, *25*(4), 2–18.

Elmonshid, L. B. E. (2026). Determinants of non-performing financing in GCC Islamic banks: Evidence from fixed-effects and panel quantile regression. Working paper. *Preprint*. [CrossRef]

Espinoza, R. A., & Prasad, A. (2010). *Nonperforming loans in the GCC banking system and their macroeconomic effects* (IMF working paper No. 10/224). International Monetary Fund.

Farooq, M. O., Abou Elseoud, M. S., Turen, S., & Abdulla, M. (2019). Causes of non-performing loans: The experience of Gulf Cooperation Council countries. *Entrepreneurship and Sustainability Issues*, *6*(4), 1955–1974. [CrossRef]

Fitriani, F., Yusuf, M., & Maksar, M. S. (2025). Evolution and determinants of non-performing loan burden in the Group of Seven (G7) banking sector. *Golden Ratio of Finance Management*, *5*(2), 372–385. [CrossRef]
Gajewski, G. (1988). *Bank risk, regulator behavior, and bank closure in the mid-1980s: A two-step logit model* [Doctoral dissertation, The George Washington University].
Ghosh, A. (2015). Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability*, *20*, 93–104. [CrossRef]
Ghosh, A. (2017). Sector-specific analysis of non-performing loans in the US banking system and their macroeconomic impact. *Journal of Economics and Business*, *93*, 29–45. [CrossRef]
Gjeçi, A., & Marinč, M. (2018). *Corruption and non-performing loans* (SSRN working paper No. 3263966).
Gjeçi, A., Marinč, M., & Rant, V. (2023). Non-performing loans and bank lending behaviour. *Risk Management*, *25*(1), 7. [CrossRef]
Hadriche, M. (2015). Banks performance determinants: Comparative analysis between conventional and Islamic banks from GCC countries. *International Journal of Economics and Finance*, *7*(9), 169–177. [CrossRef]
Hlavac, M. (2016). ExtremeBounds: Extreme bounds analysis in R. *Journal of Statistical Software*, *72*(9), 1–22. [CrossRef]
Karadima, M., & Louri, H. (2021). Economic policy uncertainty and non-performing loans: The moderating role of bank concentration. *Finance Research Letters*, *38*, 101458. [CrossRef]
Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *American Economic Review*, *80*(5), 1183–1200.
Keeton, W. R., & Morris, C. S. (1987). Why do banks' loan losses differ? *Economic Review*, *72*(5), 3–21.
Khan, M., Siddique, A., & Sarwar, Z. (2020). Determinants of non-performing loans in the banking sector in developing state. *Asian Journal of Accounting Research*, *5*(1), 135–145. [CrossRef]
Khan, S. (2022). Determinants of banks' profitability: An evidence from GCC countries. *Journal of Central Banking Theory and Practice*, *11*(3), 99–116. [CrossRef]
Khatatbeh, I. (2019). *The macroeconomic consequences of financialisation* [Doctoral dissertation, RMIT University].
Khatatbeh, I. N., & Abu-Alfoul, M. N. (2024). The determinants of the hidden economy in developed and developing countries. *Applied Economics Letters*, *31*(18), 1851–1855.
Khatatbeh, I. N., & Moosa, I. A. (2022). Financialization and income inequality: An extreme bounds analysis. *The Journal of International Trade and Economic Development*, *31*(5), 692–707.
Khatatbeh, I. N., Tayeh, M., Freihat, A. F., & Aldeki, R. G. (2025). ESG and bank stability in Gulf Cooperation Council countries: Empirical evidence from listed commercial banks. *South African Journal of Economic and Management Sciences*, *28*(1), 9. [CrossRef]
Khemraj, T., & Pasha, S. (2009). *The determinants of non-performing loans: An econometric case study of Guyana* (MPRA paper No. 53128). Munich Personal RePEc Archive.
Klein, N. (2013). *Non-performing loans in CESEE: Determinants and impact on macroeconomic performance* (IMF working paper No. 13/72). International Monetary Fund.
Kuzucu, N., & Kuzucu, S. (2019). What drives non-performing loans? Evidence from emerging and advanced economies during pre- and post-global financial crisis. *Emerging Markets Finance and Trade*, *55*(8), 1694–1708. [CrossRef]
Leamer, E. E. (1983). Let's take the con out of econometrics. *The American Economic Review*, *73*(1), 31–43.
Leamer, E. E. (1985). Sensitivity analyses would help. *The American Economic Review*, *75*(3), 308–313.
Levine, R., & Renelt, D. (1992). A sensitivity analysis of cross-country growth regressions. *The American Economic Review*, *82*(4), 942–963.
Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking and Finance*, *36*(4), 1012–1027. [CrossRef]
MacKinnon, J. G., & White, H. (1985). Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties. *Journal of Econometrics*, *29*(3), 305–325. [CrossRef]
Makri, V., Tsagkanos, A., & Bellas, A. (2014). Determinants of non-performing loans: The case of Eurozone. *Panoeconomicus*, *61*(2), 193–206. [CrossRef]
Martin, D. (1977). Early warning of bank failure: A logit regression approach. *Journal of Banking and Finance*, *1*(3), 249–276. [CrossRef]
Misman, F. N., & Bhatti, M. I. (2020). The determinants of credit risk: An evidence from ASEAN and GCC Islamic banks. *Journal of Risk and Financial Management*, *13*(5), 89. [CrossRef]
Moosa, I. (2012). The failure of financial econometrics: Stir-fry regressions as an illustration. *Journal of Financial Transformation*, *34*, 43–50.
Moosa, I. A., & Cardak, B. A. (2006). The determinants of foreign direct investment: An extreme bounds analysis. *Journal of Multinational Financial Management*, *16*(2), 199–211. [CrossRef]
Moral-Benito, E. (2015). Model averaging in economics: An overview. *Journal of Economic Surveys*, *29*, 46–75.
Naili, M., & Lahrichi, Y. (2022). The determinants of banks' credit risk: Review of the literature and future research agenda. *International Journal of Finance and Economics*, *27*(1), 334–360.

Ozili, P., & Delgado, E. (2026). Bank non-performing loan determinants: A comparison of European and African countries. *Journal of Central Banking Theory and Practice*, *15*(1), 119–143. [CrossRef]

Quagliariello, M. (2007). Banks' riskiness over the business cycle: A panel analysis on Italian intermediaries. *Applied Financial Economics*, *17*(2), 119–138. [CrossRef]

Sala-i-Martin, X. (1997). I just ran two million regressions. *The American Economic Review*, *87*(2), 178–183.

Salas, V., & Saurina, J. (2002). Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research*, *22*, 203–224. [CrossRef]

Saliba, C., Farmanesh, P., & Athari, S. A. (2023). Does country risk impact the banking sectors' non-performing loans? Evidence from BRICS emerging economies. *Financial Innovation*, *9*(1), 86. [CrossRef] [PubMed]

Sinkey, J. F., Jr. (1977). Identifying large problem/failed banks: The case of Franklin National Bank of New York. *Journal of Financial and Quantitative Analysis*, *12*(5), 779–800. [CrossRef]

Squalli, J. (2011). Is the dollar peg suitable for the largest economies of the Gulf Cooperation Council? *Journal of International Financial Markets, Institutions and Money*, *21*(4), 496–512. [CrossRef]

Steel, M. F. (2020). Model averaging and its use in economics. *Journal of Economic Literature*, *58*(3), 644–719. [CrossRef]

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