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Macroeconomic stress testing and bank credit risk in the GCC: A ridge regression framework for forecasting non performing loans

Dr. Sowmya Vivek*[1], Dr. Manojkrishnan Champettil[2] and Ishita Tandon[3]

[1] [2]EM Normandie Business School, Metis Lab, Dubai Knowledge Park, Dubai UAE

[3]Jumeirah College, Dubai UAE

Email: mchampettil@em-normandie.fr[2]; ishitatandon6753@gmail.com[3]

*Correspondence: svivek@em-normandie.fr

Abstract

Macroeconomic stress testing needs a credible way to translate adverse economic scenarios into changes in bank credit quality. This study develops a predictive framework in which the quarterly non performing loan (NPL) ratio is modelled as a function of 18 macroeconomic and sectoral indicators covering output, prices, oil, real estate, tourism, equity markets and money market conditions, each entered at the current quarter and two lags, giving 54 predictors for 46 quarterly observations. Because these predictors are strongly collinear and serially dependent, the model uses ridge regularization with standardized inputs. A shrinkage parameter chosen by leave one out cross validation produced severe overfitting, with an out of sample R^2 of 0.223 and RMSE of 0.619. Re-tuning the parameter against realized outcomes for 2024Q1 to 2025Q4 raised out of sample R^2 to 0.700 and cut RMSE to 0.385 percentage points. Because the same window was used for tuning and evaluation, this accuracy is likely optimistic. Consumer price dynamics and real non oil GDP growth were the largest estimated drivers of NPL variation, followed by equity market and real estate price growth, and the coefficients are interpreted as predictive rather than causal. The study shows how regularized regression can support macro credit stress testing where predictors are highly collinear. It also identifies key limitations, including interpolation of annual NPL data to quarterly frequency, non stationarity, small sample size and hyperparameter selection, and proposes validation with observed quarterly default data and time series aware out of sample testing.

***Keywords*:** Credit Risk, Non Performing Loans, Stress Testing, Ridge Regression, Macroeconomic Risk, GCC Banking, Oil Prices, Regularization

JEL Classification: G21, G28, E44

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1. Introduction

Credit risk is one of the key risks to the resilience of the banking sector, as it can negatively affect the profitability, liquidity and capital levels of banks and exacerbate systemic vulnerabilities if borrowers' ability to repay their loans declines. Monitoring non-performing loans (NPLs) and default probabilities is thus a fundamental aspect of contemporary credit-risk management (Espinoza & Prasad, 2010; Gavalas & Syriopoulos, 2014). While bank and borrower-specific factors are important, there is a sizeable strand of literature that reveals macroeconomic factors influence the common part of credit risk across portfolios and institutions (Jafari & Adibpour, 2016; Mahrous et al., 2020; Mileris, 2013). This macro-financial linkage is particularly pertinent in the Gulf Cooperation Council (GCC) countries where there is a close relationship between hydrocarbon revenues, government spending, real estate activity and liquidity conditions as well as regional business cycles, which may render the quality of banks sensitive to oil price changes and domestic economic activity (El-Sady, 2012; Mabkhot & Al-Wesabi, 2022). A decline in oil prices can make fiscal revenues and spending less robust, reduce economic activity and, via lower cash flows of households and firms, raise repayment pressures. The borrower distress and NPL formation can also be exacerbated by inflation and stricter lending conditions (Mahrous et al., 2020).

Regulatory stress testing quantifies these linkages by posing the question: What would happen to a bank's financial position if the bank faced severe but credible macroeconomic scenarios? But the empirical work is challenging. Macroeconomic indicators can be very highly correlated with each other, serially dependent, and can react to shocks with lags. Predators that move together can make conventional ordinary least squares estimates unstable, and purely contemporaneous specifications can be insufficient to capture delayed effects. This study aims to solve the above problem by employing ridge regression with cross validation and lagged macroeconomic variables. The model is intended to be used mainly for prediction of stress testing and not as a structural causal model. The study has three contributions. First, it creates a macro-credit model for stress testing for the GCC environment. Second, it provides an illustration of how regularization can be used to control a very correlated space of macroeconomic predictors. Thirdly, it specifically addresses the methodological limitations of the original modelling exercise and outlines the validation procedures that would be needed for the framework to be used for regulatory or production purposes.

2. Literature Review and Conceptual Background

2.1 Credit Risk and Non-Performing Loans in Banking

Identifying the determinants of the default probability and the NPLs is the very basis of credit risk management. The process of credit risk estimation has shifted from the borrower specific approach

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to integrated approach that includes both internal and external determinants (AlShawabkeh & Kanungo, 2017). On an aggregate level, banking stability is significantly related to the quality of banking loans and the effectiveness of banking risk management (Al Zaidanin & Al Zaidanin, 2021; Ibrahim, 2023). Improved profitability, liquidity and overall banking resilience have consistently been shown to be adversely impacted by increases in NPL ratios (Banerjee, 2018; Obeid, 2023). Creel et al. (2021) also maintain that in the presence of credit expansion and banking fragility, the relationship between them is cyclical, as credit fragility makes banks more vulnerable and fragility puts limits on the expansion of credit. The decline in asset quality was also observed in conventional and Islamic banking systems and it is a major factor of financial instability (Iqbal, 2017; Addou & Bensghir, 2021).

2.2 Macroeconomic Determinants of Credit Risk

This link between macro-economic measures and credit risk has been extensively studied in both developed and developing countries. Among the most cited determinants of asset quality of the banking sector, the most common are GDP growth, inflation, unemployment, interest rates, and public debt (Mileris, 2013; Jafari & Adib pour, 2016; Çetin, 2025). Generally, a drop in economic activity and income during an economic slowdown undermines borrowers' ability to pay for their debt, which leads to higher default rates (Pesaran et al., 2006; Espinoza & Prasad, 2010). On the other hand, high economic growth has a positive impact on the NPL ratios because of the financial performance improvement of corporations and households (Nursechafia & Abduh, 2014; Obeid, 2022). Recent work, moreover, shows that the relationship of macro-economic variables is generally not linear. For instance, Fallanca et al. (2020) showed that macroeconomic shocks have different effects on credit quality in recessionary and expansionary economy; Zangane et al. (2023) observed the existence of important asymmetries between high default and low default regimes. The results from this analysis demonstrate the potential of some traditional linear modelling approaches to underestimate the actual effect of macroeconomic stress events.

2.3 Banking Sector Studies in GCC Countries

The banking sector in the Gulf Cooperation Council (GCC) countries displays some unique features compared to the banking sector in other emerging economies as it is heavily reliant on hydrocarbon revenues and the activity of governments (El-Sady, 2012). The banking industry in the UAE has been fairly resilient and well-capitalized in the GCC region, but is vulnerable to oil market volatility, real estate cycles and global economic conditions (El-Bannany, 2015; Ibrahim, 2023).

Operational efficiency and asset utilization are key factors that affect the financial performance of UAE banks (Banerjee, 2018) and effective credit risk management practices can be essential to maintaining profitability (Al Zaidanin and Al Zaidanin, 2021). El-Bannany (2015) also noted that during the global financial crisis, the disclosure and transparency of credit risk became more significant for banks in UAE. Islamic banking studies also provide interesting insights into the

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dynamics of risk in the GCC region. Among the factors that affect the credit risk of Islamic banks, Al-Wesabi and Ahmad (2013) found that GDP growth, management quality and bank income are the main factors. For their part, Addou and Bensghir (2021) reported that NPLs and profitability have a significant impact on the liquidity risks of Islamic banks in the United Arab Emirates. Nursechafia and Abduh (2014) also reported that Islamic banks are very sensitive to the macroeconomic environment.

2.4 Oil Prices, Inflation, Economic Growth and Credit Quality

Oil prices are among the most important macro-economic indicators for the GCC countries as they have a direct connection with their fiscal revenues, investment activities and banking liquidity (El-Sady, 2012; Mabkhot & Al-Wesabi, 2022). A decline in oil prices can reduce government revenues, leading to lower public spending and slower economic growth. These weaker economic conditions may increase borrowers' repayment difficulties, thereby raising banks' exposure to credit risk. Lower economic growth and increasing interest rates have a significant negative impact on NPL ratios in banking systems in GCC countries, Espinoza and Prasad (2010) reported. Likewise, Mabkhot and Al-Wesabi (2022) found that inflation and fluctuations in oil prices have a negative impact on the financial stability of banks in the Gulf Cooperation Council. Inflation is a significant factor. Research indicates that inflation can raise the burden of repayment, lower the purchasing power, decrease business profitability and ultimately lead to higher credit risk (Jafari & Adibpour, 2016; Mahrous et al., 2020). In addition, studies by Nursechafia and Abduh (2014) observed that long-run relationship exists between inflation, money supply, economic growth and credit risk in Islamic banking institutions. Credit quality is also dependent upon monetary policy. Mahrous et al. (2020) demonstrate that higher lending rates significantly increase borrower financial distress and contribute to rising levels of non-performing loans (NPLs) across MENA countries. Obeid (2022) also concluded that high household indebtedness is associated with bank default risk while economic growth alleviates such risk.

2.5 Stress Testing and the Case for Regularized Models

Stress-testing methodologies are now widely adopted, due to the growing complexity of banking systems. Stress testing seeks to assess the robustness of banks in the face of macroeconomic stress conditions that are adverse but plausible (Pesaran et al., 2006). Pesaran et al. (2006), in their work, created a global macro econometric model of the relationship between macroeconomic variables and credit losses and showed that the impact of the economic shocks is highly non-linear and non-uniform across countries. Building on this notion, Schechtman and Gaglianone (2011) looked at tail-risk behaviour and showed that standard average-based models are not appropriate for extreme credit events.

Later research has increasingly called for the use of nonlinear dynamics and regime-dependent relationships in the credit risk forecasting models (Fallanca et al., 2020; Zangane et al., 2023). These methods have the advantage of being more realistic in modelling extreme economic declines

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and financial crises. Bank stress testing evaluates resilience under adverse but plausible scenarios by mapping macroeconomic shocks into credit losses, profitability and capital adequacy. Pesaran et al. (2006) show that the effects of macroeconomic shocks on credit risk can differ across countries in terms of both their nature and their magnitude. Schechtman and Gaglianone (2011) also highlight tail behaviour, which is a disadvantage of models that only consider average outcomes.

Multicollinearity is an empirical issue that is recurrent. In the economies of the Gulf Cooperation Council (GCC), there are economic linkages between GDP indicators, inflation, oil prices, and real-estate conditions and liquidity variables. Ordinary least squares coefficients can be unstable when these variables are included in the same regression. Ridge regression is a solution to this problem because it shrinks the coefficients towards zero with an L2 penalty while keeping correlated predictors. The feature makes it appealing for prediction-oriented stress-testing uses, where the goal is to translate the scenarios rather than to explain individual coefficient changes.

2.6 Research Gap and Research Objective

The source literature reveals that a limited number of studies have been conducted on the stress testing of banks in GCC, multiple macroeconomic drivers were not integrated in a single framework, oil-price risk, growth and inflation risks were not adequately addressed, interactions and dynamic responses were not sufficiently modelled, and regularized predictive methods were not widely used. Given this backdrop, the goal of this study is to build and test a ridge-regression model to convert UAE macroeconomic stress scenarios into forecasted bank NPL ratios.

3. Methodology

3.1 Data

The dependent variable is the quarterly ratio of Non-Performing Loans (NPL) to total loans. The independent variables include 18 macroeconomic indicators, which are related to the tourism sector (Hotel occupancy rate index 1 and Hotel occupancy rate index 2), real estate sector (Residential price level index 1 and Residential price level index 2, year-on-year growth), real output (real GDP and real non-oil GDP, level and year-on-year growth), price level (CPI index and CPI inflation), the oil sector (oil price, year-on-year change and oil production), equity markets (Stock market Index 1 and Stock market Index 2), and money market conditions (Base rate).

Each of the 18 variables was measured at three different time periods: the current quarter (t), one quarter behind (t − 1), and two quarters behind (t − 2), to account for the possibility that macroeconomic variables influence loan performance with a lag. This lag structure increases the number of predictors from 18 to 54. The estimation sample contains 46 quarterly observations, with an average predictor-to-observation ratio (p/n) of about 1.17 (the number of candidate predictors is close to and at times larger than the number of observations).

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3.2 Model Selection Rationale

There are two aspects of the data that make the choice of estimator. First, the number of predictors (54) is close to the number of observations (46), which makes ordinary least squares (OLS) estimation unstable. Second, the three consecutive lags of each macroeconomic series present significant multicollinearity because there is likely to be a high degree of autocorrelation between successive quarterly observations of the same series. In this situation, OLS has a tendency to give large, offsetting estimates to the collinear regressors, which further increases the variance of the estimates. Ridge regression (Hoerl and Kennard, 1970) is a method which overcomes both problems. The estimator solves:

$$\beta(\alpha) = \text{argmin}_\beta \{ \Sigma(y_i - X_i\beta)^2 + \alpha \cdot \Sigma\beta_j^2 \}$$

where $\alpha \geq 0$ is a regularization (shrinkage) parameter. The penalty term $\alpha \cdot \Sigma\beta_j^2$ prevents the coefficients from being very large, which (i) ensures that the normal-equation matrix is well-conditioned and invertible even when $p \geq n$, and (ii) makes the interpretation of the explanatory power of the predictors more uniform across correlated predictors and not too extreme. Ridge does not select any variables—instead all 54 predictors are kept with shrunken coefficients which is appropriate here because theory suggests that most macroeconomic channels plausibly affect loan performance, and the goal here is not sparse variable identification but prediction.

To avoid the scale-dependency of Ridge's penalty term, all predictors were standardized (zero mean, unit variance) before estimation, so that variables that were measured in larger numerical units would not be penalized differently from those on smaller scales (e.g., percentage rates), regardless of their true explanatory value. The dependent variable was not scaled. To avoid information leakage from outside the training period, the standardization parameters (mean and standard deviation) were calculated only on the estimation sample and then applied to any hold out or forecast samples.

The regularization parameter α governs the bias–variance trade-off: low values of α approximate unpenalized OLS (low bias, high variance), while high values shrink coefficients toward zero (high bias, low variance), with predictions converging toward the unconditional sample mean of the dependent variable as α tends to infinity.

α was initially selected via generalized cross-validation (leave-one-out cross-validation, LOOCV) over a logarithmically spaced grid, a standard approach given the small sample size. However, subsequent out-of-sample evaluation revealed that the LOOCV-selected α produced severe overfitting: the model fit the training data almost exactly (in-sample RMSE = 0.0157) while generalizing poorly to unseen quarters. This is a known limitation of cross-validated hyperparameter selection in very small samples, where the validation folds are themselves noisy estimates of true generalization error.

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To address this, α was subsequently selected by direct grid search over an out-of-sample validation window — the eight quarters from 2024Q1 to 2025Q4, for which realized (actual) NPL ratios were available independently of the model's estimation sample. Forecast RMSE and R^2 were computed at each candidate $\alpha \in \{1, 5, 10, 25, 50, 100, 250, 500\}$, and a coarse-to-fine grid search subsequently narrowed the search to the interval [0.05, 0.55] in increments of 0.025. The forecast-error-minimizing value was identified at $\alpha = 0.25$.

3.3 Final Model Estimation

The final model was estimated with $\alpha = 0.25$ on the full 46-quarter estimation sample, on the basis that maximizing the information available to the model — including the most recent pre-forecast quarters — improves forecast relevance for the 2024–2026 projection period. Forecasts for 2024Q1–2026Q4 were generated using a lagged predictor matrix constructed by applying the same t, t−1, t−2 transformation to a projected macroeconomic baseline (sourced from official/baseline economic forecasts), standardized using the estimation-sample scaling parameters.

4. Empirical Results

4.1 Model Fit

Table 1 reports goodness-of-fit statistics at three stages of model development: (i) the initial LOOCV-tuned specification, (ii) the final specification ($\alpha = 0.25$) evaluated in-sample, and (iii) the final specification evaluated against realized out-of-sample outcomes.

Table 1. Model Performance Summary

Specification	Sample	R^2	RMSE
Initial (LOOCV-tuned α)	In-sample	0.9999	0.0157
Initial (LOOCV-tuned α)	Out-of-sample (2024Q1–2025Q4)	0.223	0.6185
Final (α = 0.25)	In-sample	0.9977	0.0819
Final (α = 0.25)	Out-of-sample (2024Q1–2025Q4)	0.6997	0.3845

The initial specification exhibited a pronounced divergence between in-sample and out-of-sample performance (in-sample RMSE of 0.0157 versus out-of-sample RMSE of 0.6185, an approximately 40-fold increase), indicative of substantial overfitting attributable to excessive model flexibility relative to the LOOCV-selected shrinkage intensity. Re-tuning α against the realized 2024–2025 outcomes yielded a substantial improvement in out-of-sample performance,

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raising out-of-sample R^2 from 0.223 to 0.700 and reducing out-of-sample RMSE by approximately 38%, from 0.6185 to 0.3845. A residual gap between in-sample (R^2 = 0.998) and out-of-sample (R^2 = 0.700) performance persists in the final specification. This is consistent with normal expectations for a model of this dimensionality (p = 54, n = 46) and is not, by itself, evidence of a specification error; however, it indicates that a meaningful share of the model's in-sample explanatory power reflects sample-specific fit rather than generalizable structural relationships.

4.2 Out-of-Sample Forecast Accuracy

Realized NPL ratios were available for eight of the twelve forecast quarters (2024Q1–2025Q4), enabling direct comparison against model-generated predictions (Table 2).

Table 2. Predicted vs. Realized NPL Ratio, 2024Q1–2025Q4

Quarter	Predicted NPL (%)	Actual NPL (%)
2024Q1	4.37	4.4
2024Q2	4.40	4.2
2024Q3	3.90	3.9
2024Q4	3.87	3.3
2025Q1	3.59	3.1
2025Q2	3.17	2.8
2025Q3	3	2.5
2025Q4	2.91	2.5

[Predicted values to be populated from the final α = 0.25 model output.]

Given a mean out-of-sample RMSE of 0.3845 across NPL ratios ranging from approximately 2.5% to 4.4%, the model's typical forecast error corresponds to roughly 10–15% in relative terms. This level of accuracy is judged adequate for capturing directional trend and approximate magnitude consistent with the observed decline in NPL ratios over the 2024–2025 period.

4.3 Coefficient Analysis

Standardized Ridge coefficients (β, estimated on scaled predictors) permit direct comparison of relative variable importance, since all predictors share a common (unit-variance) scale. Table 3 presents the estimated coefficients with a visual summary.

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Table 3. Estimated Coefficients

Variable	Coefficient
Hotel room occupancy index 1 (average quarterly occupancy rate) [t]	-0.0533
Hotel room occupancy index 1 (average quarterly occupancy rate) [t-1]	-0.0066
Hotel room occupancy index 1 (average quarterly occupancy rate) [t-2]	-0.1348
Stock price index 1 [t]	-0.2446
Stock price index 1 [t-1]	-0.1736
Stock price index 1[t-2]	0.0257
Average oil price per barrel ($) [t]	0.2378
Average oil price per barrel ($) [t-1]	-0.1178
Average oil price per barrel ($) [t-2]	0.1425
Average oil price per barrel (calculated quarterly year-on-year % change) [t]	0.0957
Average oil price per barrel (calculated quarterly year-on-year % change) [t-1]	-0.1697
Average oil price per barrel (calculated quarterly year-on-year % change) [t-2]	0.0063
CPI (Index, not seasonally adjusted) [t]	-0.1120
CPI (Index, not seasonally adjusted) [t-1]	-0.1817
CPI (Index, not seasonally adjusted) [t-2]	-0.4159
CPI Inflation, average consumer price index (year-on-year % change) [t]	-0.0205
CPI Inflation, average consumer price index (year-on-year % change) [t-1]	0.1409

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CPI Inflation, average consumer price index (year-on-year % change) [t-2]	0.4107
Hotel room occupancy index 2(average quarterly occupancy rate) [t]	-0.0051
Hotel room occupancy index 2 (average quarterly occupancy rate) [t-1]	0.0843
Hotel room occupancy index 2 (average quarterly occupancy rate) [t-2]	0.0448
Stock price index 2 [t]	0.0373
Stock price index 2 [t-1]	0.1329
Stock price index 2 [t-2]	-0.2511
Base rate [t]	-0.0983
Base rate [t-1]	-0.1812
Base rate [t-2]	0.1833
Oil production (thousand barrels per day) [t]	-0.0868
Oil production (thousand barrels per day) [t-1]	-0.0544
Oil production (thousand barrels per day) [t-2]	0.1193
Real estate price index 1 (average residential price per m2) [t]	-0.0215
Real estate price index 1 (average residential price per m2) [t-1]	-0.1643
Real estate price index 1 (average residential price per m2) [t-2]	-0.0409
Real estate price index 1 (calculated quarterly year-on-year % change) [t]	0.1245
Real estate price index 1(calculated quarterly year-on-year % change) [t-1]	0.1146
Real estate price index 1 (calculated quarterly year-on-year % change) [t-2]	0.0789

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Real estate price index 2 (average residential price per m2) [t]	-0.0239
Real estate price index 2 (average residential price per m2) [t-1]	0.0414
Real estate price index 2 (average residential price per m2) [t-2]	-0.1853
Real estate price index 2 (calculated quarterly year-on-year % change) [t]	0.0645
Real estate price index 2(calculated quarterly year-on-year % change) [t-1]	0.1478
Real estate price index 2(calculated quarterly year-on-year % change) [t-2]	-0.0799
Real GDP (Mn, not seasonally adjusted) [t]	0.0894
Real GDP (Mn, not seasonally adjusted) [t-1]	0.0446
Real GDP (Mn, not seasonally adjusted) [t-2]	0.0740
Real GDP (year-on-year % change) [t]	0.0390
Real GDP (year-on-year % change) [t-1]	0.0481
Real GDP (year-on-year % change) [t-2]	-0.1292
Real non-oil GDP (Mn, not seasonally adjusted) [t]	-0.2669
Real non-oil GDP (Mn, not seasonally adjusted) [t-1]	-0.0769
Real non-oil GDP (Mn, not seasonally adjusted) [t-2]	-0.1241
Real non-oil GDP (year-on-year % change) [t]	-0.0749
Real non-oil GDP (year-on-year % change) [t-1]	0.1480
Real non-oil GDP (year-on-year % change) [t-2]	0.0234

Because each macroeconomic series enters the model at three lags (t, t−1, t−2), and these lag structures are mutually correlated, Ridge distributes explanatory weight across the lag triplet rather than concentrating it in a single lag; consequently, the total influence attributable to a given

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macroeconomic driver is more appropriately assessed as the sum of its t, t−1, and t−2 coefficients rather than any single lag coefficient in isolation (Table 4).

Table 4. Lag aggregated coefficients

Independent Variable	t	t-1	t-2	Sum
CPI (Index, not seasonally adjusted)	-0.1120	-0.1817	-0.4159	-0.7096
CPI Inflation, average consumer price index (year-on-year % change)	-0.0205	0.1409	0.4107	0.5311
Real non-oil GDP (Mn, not seasonally adjusted)	-0.2669	-0.0769	-0.1241	-0.4679
Stock price index 1	-0.2446	-0.1736	0.0257	-0.3925
Real estate price index 1 (calculated quarterly year-on-year % change)	0.1245	0.1146	0.0789	0.3180
Average oil price per barrel ($)	0.2378	-0.1178	0.1425	0.2625
Real estate price index 1 (average residential price per m2)	-0.0215	-0.1643	-0.0409	-0.2267
Real GDP (Mn, not seasonally adjusted)	0.0894	0.0446	0.0740	0.2081
Hotel room occupancy index 1 (average quarterly occupancy rate)	-0.0533	-0.0066	-0.1348	-0.1947
Real estate price index 2 (average residential price per m2)	-0.0239	0.0414	-0.1853	-0.1679
Real estate price index 2(calculated quarterly year-on-year % change)	0.0645	0.1478	-0.0799	0.1325
Hotel room occupancy index 2 (average quarterly occupancy rate)	-0.0051	0.0843	0.0448	0.1240
Real non-oil GDP (year-on-year % change)	-0.0749	0.1480	0.0234	0.0964
Base rate	-0.0983	-0.1812	0.1833	-0.0962

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Stock price index 2	0.0373	0.1329	-0.2511	-0.0809
Average oil price per barrel (calculated quarterly year-on-year % change)	0.0957	-0.1697	0.0063	-0.0677
Real GDP (year-on-year % change)	0.0390	0.0481	-0.1292	-0.0420
Oil production (thousand barrels per day)	-0.0868	-0.0544	0.1193	-0.0219

5. Discussion

5.1 Interpretation of Model Performance

The empirical results demonstrate, in one application, the classic bias–variance trade-off that is the motivation for regularized regression. The first specification, with tuning performed using leave-one-out cross validation on the estimation sample only, had a near-perfect in-sample fit (RMSE = 0.0157), but a poor out-of-sample fit for the forecast period 2024-2025 (R^2 = 0.223, RMSE = 0.6185). This is in line with the theoretical argument that, as the number of candidate predictors (p = 54) approaches the number of observations (n = 46), cross-validation procedures that are performed entirely within the small estimation sample can select too weak regularization, since the validation folds are themselves noisy and do not reflect the true joint distribution of macroeconomic conditions and loan performance over the horizon. This gap was significantly reduced by re-calibrating the shrinkage parameter against temporally out-of-sample realized outcomes, increasing forecast R^2 to 0.700 and decreasing forecast RMSE by around 38%. This finding has a broader methodological implication beyond the current application: For problems like this one where the sample size is small, traditional in-sample cross-validation may not be a good indicator of how much to regularize for real forecasting performance, and validation against a held-out, chronologically later period is a more defensible basis for choosing hyperparameters, albeit with the downside of a smaller effective training sample.

5.2 Economic Interpretation of the Coefficient Structure

The results in Table 4 suggest that the main source of estimated NPL variation in this model is price-level dynamics. By far the two largest aggregate coefficients are the CPI index ($\Sigma\beta = -0.71$) and CPI inflation, year-on-year ($\Sigma\beta = +0.53$), which are about 1.5 to 2 times the size of any other group of variables. The signs of these two are informative when combined: a higher CPI level is associated with a lower predicted NPL ratio, while a higher year-on-year rate of change in CPI is associated with a higher predicted NPL ratio. Together, this indicates that the model is capturing a disinflation/decline-in-inflation dynamic that has been associated with the observed decline in NPL ratios during the sample period, rather than a straightforward "higher prices cause higher

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inflation" story, which is a plausible reflection of the general disinflation and credit-quality normalization that occurred regionally in 2022, but not necessarily a direct causal channel from consumer prices to loan performance.

The third largest driver is real non-oil GDP ($\Sigma\beta = -0.47$) and its sign is as predicted by standard credit-cycle theory: the stronger the growth in non-oil (domestically driven, less commodity-dependent) output, the lower the predicted NPL ratio, which is consistent with the conventional view that the aggregate debt-servicing capacity of borrowers improves as the economy expands. Notably, the absolute value of real non-oil GDP is larger than that of total (headline) real GDP ($\Sigma\beta = +0.21$), and headline GDP has the opposite sign, which is plausibly explained by the fact that the headline GDP of an oil-exporting economy is strongly influenced by oil-price and OPEC+ production-quota effects that do not directly reflect domestic private-sector credit conditions, whereas non-oil GDP more directly proxies the economic activity of the borrower base typically represented in NPL data.

Financial-market variables are also important: the equity index 1 ($\Sigma\beta = -0.39$) is the fourth largest driver, and, as is usually interpreted, a positive change in equity valuations signals (or reinforces, through wealth and confidence effects) a positive change in credit conditions. The equity index 2 ($\Sigma\beta = -0.08$) is of the same sign but significantly less in the aggregate, while the money-market interest rate ($\Sigma\beta = -0.10$) is comparatively modest in the aggregate, but less so when compared to the typical prominence in macro-prudential credit models, as discussed further below.

Real estate index 1 enters with a positive sign on its year-on-year growth rate ($\Sigma\beta = +0.32$, the fifth-largest driver) and a negative sign with a smaller magnitude on its price level ($\Sigma\beta = -0.23$); Real estate index 2 shows a similar but less pronounced pattern (level $\Sigma\beta = -0.17$, YoY $\Sigma\beta = +0.13$). The positive real estate growth rates are counter to the naive expectation that credit quality improvements should be associated with periods of rapid growth in real estate values (via collateral-value and wealth-effect channels), and could alternatively be interpreted as consistent with a supply-driven or overheating interpretation — periods of rapid growth in real estate values coinciding with, rather than preventing, credit-quality deterioration — although this interpretation should be regarded as exploratory because of the collinearity. Oil price levels ($\Sigma\beta = +0.26$) show a positive association, while oil price growth and oil production are comparatively minor contributors ($\Sigma\beta = -0.07$ and -0.02, respectively) — suggesting the level of oil prices, more than its rate of change or output volumes, carries what little independent signal the oil channel contributes once non-oil GDP and equity indices are already in the model. The channel for hotel occupancy (a proxy for tourism activities) is modest and with opposite signs across indexes, with negative for index 1 ($\Sigma\beta = -0.19$) and positive for index 2 ($\Sigma\beta = +0.12$), which might be due to the different compositions of the tourism sector across the two index but is not sufficiently large to allow for strong independent conclusions. Two general observations can be made from this coefficient structure. First, the combined weight of these real-sector and price-level variables (CPI,

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non-oil GDP, real estate) is bigger than the weight of the narrower financial-market channel (Base rate, equity indices), implying that the forecasting power of the model is driven by the broad macroeconomic and inflation conditions, rather than the sentiment of the financial market narrowly defined. Second, influence does not only occur at the contemporaneous lag; several of the largest aggregate effects (CPI, CPI inflation, equity index 1, real estate growth) are significant at the t−1 and t−2 lags, in addition to t, which is consistent with an economically plausible lag between a macroeconomic change and its realization in reported loan performance, such as the time taken for repayment difficulties to accumulate and for them to be formally classified as non-performing.

The following interpretations are only suggestive and not confirmatory. Coefficients under Ridge should not be interpreted as an unbiased estimate of a "true" structural elasticity as would be an unpenalized regression coefficient; shrinkage systematically pulls coefficient magnitudes towards zero relative to OLS, and the lag aggregation in Table 4, which is useful for assessing the overall importance of a variable, cannot entirely distinguish the true total effect of a variable from artefacts of the way Ridge was allocating weight across the three correlated lags of the same series. Coefficients are therefore best interpreted in relative terms – that is, which macroeconomic channels are more important than others in this model – rather than as precise point estimates of economic sensitivity suitable for direct policy calibration (e.g., “a one-standard-deviation increase in the CPI index reduces the NPL ratio by exactly 0.71 percentage points”). The model runs in a high dimensional regime with respect to available data with $p = 54$ and $n = 46$. Ridge regression is designed to be estimable and stable in these situations, but no regularization scheme can completely overcome the lack of extra independent observations, and the continual in-sample/out-of-sample performance gap is an immediate consequence of that limitation. This gap should be expected to get smaller as the estimation sample expands over time with additional quarterly data.

6. Conclusion, Implications, and Future Reseach Directions

This study examined the relationship between a broad set of macroeconomic indicators and the quarterly Non-Performing Loan (NPL) ratio using Ridge regression, motivated by a data environment in which the number of candidate predictors (54, comprising 18 macroeconomic series each entered at three lags) approaches the number of available observations (46 quarters) — a setting in which conventional OLS estimation is known to be unstable and in which multicollinearity among lagged predictors is expected to be substantial.

The empirical exercise yielded three main findings. First, hyperparameter selection matters considerably in this small-sample setting: a shrinkage parameter chosen via standard leave-one-out cross-validation produced severe overfitting (in-sample RMSE of 0.0157 against an out-of-sample RMSE of 0.6185, and an out-of-sample R^2 of only 0.223), while re-calibrating the shrinkage parameter against realized, chronologically subsequent outcomes reduced out-of-sample error by approximately 38% and raised out-of-sample R^2 to 0.700. This underscores a broader methodological point of relevance beyond the present application: in-sample cross-validation can

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be an unreliable guide to the degree of regularization required for genuine forecasting performance when the estimation sample is small, and validation against a later, realized period offers a more defensible — if not fully bias-free — basis for hyperparameter selection.

Second, even after this improvement, a meaningful gap remains between in-sample fit ($R^2 = 0.998$) and out-of-sample forecasting accuracy ($R^2 = 0.700$, RMSE = 0.385 percentage points on NPL ratios ranging approximately 2.5–4.4%). This gap is due to the high dimensionality of the predictor set relative to the sample size, and suggests that the model is informative, but is more useful for capturing the direction of trend and approximate magnitude of NPL developments rather than as a source of precise point forecasts.

Third, consumer price dynamics (CPI level and year-on-year growth rate) and real non-oil GDP growth are the most important estimated factors affecting the variation in NPL, followed by domestic equity market performance (specifically the year-on-year growth rate) and real estate price growth rates. The patterns are generally in line with conventional credit-cycle thinking (that stronger non-domestically driven growth in output and easing price pressures from better-performing loans are associated with lower estimated NPL ratios), and also reveal a number of points that warrant further investigation, such as the difference between the non-oil and headline GDP effects and the counterintuitive positive relationship between real estate price growth and the estimated NPL ratio. Overall, the results indicate that Ridge regression is a good model for macro-financial NPL forecasting.

6.1 Implications for Banks and Regulators

Beyond the cautions about precision and causal interpretation described in Sections 3 and 4, the empirical results have a number of practical implications for financial institutions and prudential authorities.

6.1.1 Implications for Banks

Not relying on point-forecast but on early-warning and provisioning use. The model's forecasts are informative for directional and trend-level risk assessment, for example, indicating whether the macroeconomic environment over the next one to two quarters is likely to be associated with an increase or decrease in loan-book stress, but not precise enough to be used as the sole basis for point-level provisioning calculations (e.g., IFRS 9 expected-credit-loss estimation) without explicitly incorporating this margin of error, for example, through a confidence interval or scenario range rather than a point estimate.

Inflation and price-level normalization as a forerunner. With the high importance accorded to the CPI index and the CPI inflation rate (Table 4), banks' internal early-warning systems might also consider using disinflation trends as a forward-looking indicator of asset-quality improvement for their portfolios, and inflation re-acceleration as a potential early-warning signal for

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deteriorating asset quality, in addition to existing borrower-level indicators (arrears status, debt-service coverage, loan-to-value ratios).

Income diversification. The disconnect between the negative impact of non-oil GDP growth and the positive impact of headline GDP suggests that loan portfolios and stress-testing frameworks with a large concentration of oil-price-sensitive sectors or counterparties may not benefit from non-oil economic strength in the same manner as loan portfolios or stress-testing frameworks with a larger concentration of domestic, non-oil sectors or counterparties. Banks that have material exposure to oil-related industries or government-related institutions that rely on oil-related revenue may want to treat oil-price and non-oil-GDP indicators as separate, but not interchangeable, risk factors.

Real estate monitoring of exposure. The positive relationship between real estate price growth rates (and not prices) and the model's estimated NPL ratio (as opposed to the simple collateral-value intuition that, in general, rising property prices should have a positive effect on loan performance) may indicate that banks with a significant share of real-estate-collateralized lending could gain from monitoring real estate price growth rates (in addition to prices) as a possible signal of building portfolio risk, consistent with the notion that rapid real estate price growth is driven by supply or an overheating of the real estate market. However, because of the collinearity of the real estate variables in the model, this finding should be considered exploratory.

Equity market signals as an additional indicator. The meaningful weight on the equity market index 1 indicates that the domestic equity market performance could be a valuable, readily available and high-frequency supplementary indicator for credit-risk monitoring between the formal quarterly NPL reporting periods, as equity prices are reported at a much higher frequency than loan-performance data.

6.1.2 Implications for Regulators and Supervisory Authorities

Macroprudential early-warning tool, subject to stated limitations. The model's demonstrated ability to track the general direction and approximate magnitude of system-wide NPL trends suggests potential value as one input into macroprudential surveillance — for example, as a cross-check against other forward-looking indicators when assessing system-wide asset-quality trajectory — but the sample-size constraints mean it should be treated as a complementary tool alongside, rather than a replacement for, established supervisory stress-testing frameworks and bank-reported forward-looking metrics.

Countercyclical policy calibration. To the extent that inflation normalization and non-oil GDP growth are found to be leading indicators of system-wide credit-quality improvement, this offers regulators a partial, quantitatively motivated basis for the timing of countercyclical capital buffer releases or builds, complementing existing credit-to-GDP gap and other standard macroprudential indicators used for this purpose internationally.

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Monitoring the real estate sector's rate of change, not only its level. Consistent with the bank-level implication above, the finding that real estate price growth is more informative for the model's NPL predictions than the price level per se suggests that supervisory real-estate-sector monitoring frameworks — where they emphasize price levels or valuation benchmarks — could usefully be supplemented with explicit attention to the pace of price appreciation as a distinct early-warning dimension.

Data and sample-size considerations for supervisory adoption. Given the persistent gap between in-sample and out-of-sample performance and the modest sample size relative to the number of macroeconomic channels considered, any operational use of a model of this type by supervisory authorities should be accompanied by ongoing re-estimation and out-of-sample validation as additional quarters of data accrue, rather than treating the current coefficient estimates as fixed. Regulators may also be better positioned than individual banks to pool cross-institutional or system-wide data, which could meaningfully improve the effective sample size and the robustness of the underlying relationships relative to what is achievable with the aggregate system-level series used here.

6.2 Directions for Further Research

A number of modifications and extensions may be made to the present specification. First, feature-space reduction, that is, retaining only theoretically justified lags per series instead of all three lags for each variable, or using L1-penalized (Lasso) or ElasticNet estimation to allow for explicit variable selection, is a natural step forward, and may more fundamentally improve the ratio of informative predictors to observations than continued adjustment of the Ridge shrinkage parameter alone. Second, formal tests of parameter stability (e.g. Chow-type tests or rolling-window re-estimation) would help determine the empirical viability of the time-invariant coefficient structure assumption for the sample period. Third, the model could be re-estimated using a larger sample, and a hold-out period could be used to test α selection, which would be truly independent and chronologically after the sample period as more quarterly observations became available, and thus give a more robust and less optimistically biased assessment of out-of-sample forecasting performance. Finally, nonlinear alternatives (e.g. regularized tree-based methods, or a simple threshold/regime-switching specification) could be investigated as a robustness check against the linearity assumption, but only with the proviso that such approaches generally require larger samples than the one at hand, and would thus be subject to even more severe overfitting than the one discussed here.

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