DETERMINANTS OF NONPERFORMING LOANS IN ROMANIA AND CENTRAL, EASTERN AND SOUTHEASTERN EUROPE

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Abstract

This paper investigates the macroeconomic and bank-specific determinants of nonperforming loans in Romania and selected Central and Eastern European countries. Using a combination of econometric approaches, the study employs fixed-effects panel regressions for 18 Romanian banks over the period 2007Q4 – 2023Q4, a Bayesian Vector Autoregression model for Romania, and a Panel VAR framework for six Central, Eastern and South-Eastern European (CESEE) countries over the period 2008Q4 – 2024Q4. The results indicate that bank profitability, capitalisation, and operational efficiency play a significant role in shaping credit risk at the bank level. At the macroeconomic level, economic growth and exchange rate appreciation reduce NPLs, while unemployment, interest rates, and inflation increase default risk. Impulse response functions reveal strong persistence in NPL dynamics and highlight unemployment as the most robust and influential determinant of credit risk across all models. The findings suggest that credit risk is driven by a complex interaction between macroeconomic conditions and bank-specific characteristics, with labour market developments representing the main transmission channel between the real economy and financial stability.

Keywords: credit risk, banks, Bayesian VAR, panel VAR, panel regression

JEL Classification: E44, E51, G21, G32

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1. Introduction

The efficient and stable functioning of the banking system represents an essential prerequisite for economic development, given the crucial role that banks play in financial intermediation and the management of monetary flows. The implementation of a rigorous corporate governance framework, complemented by appropriate risk management and monitoring strategies, becomes indispensable for preventing the emergence of crises and strengthening the resilience of banking institutions.

The Federal Reserve defines credit risk as “the potential that a borrower or counterparty will fail to perform on an obligation”. For most banks, loans are the largest and most obvious source of credit risk.

Nonperforming loans constitute a key indicator analysed within credit risk assessment. Nonperforming loans are defined as loans that are subject to significant payment delays or for which there is a likelihood that they will no longer be repaid by the borrower. The nonperforming loan ratio is calculated as the proportion of nonperforming loans relative to the total loan portfolio.

According to the European Central Bank, a loan becomes nonperforming when there are indications that the borrower is unlikely to repay the debt, or when more than 90 days have elapsed without the borrower fulfilling their payment obligations.

The credit rating agency Moody’s classifies nonperforming loans as follows:

- when the payment of principal and interest is overdue by at least 60 days, in the case of consumer loans;
- when the payment of principal and interest is overdue by at least 90 days, in the case of commercial and leasing loans.

The reasons why a borrower may no longer be able to service their debt are numerous. For instance, an individual may lose their job, or a company that has contracted a loan may experience financial difficulties.

Nonperforming loans affect banks in two main ways. First, they reduce profitability by generating losses, which necessitates the calculation of provisions. Through provisioning, banks create financial reserves to cover nonperforming loans if needed, thereby preventing major losses. Another way in which banks are affected by nonperforming loans is through their reduced capacity to provide adequate credit to companies and firms, limiting job creation and, more broadly, hindering economic well-being.

In order to mitigate credit risk, banks monitor and collect information on borrowers who contract loans. Consequently, managerial efficiency and risk management strategies directly influence loan repayment performance.

2. Literature review

The relationship between nonperforming loans and macroeconomic, as well as bank-specific factors, has been widely examined in the empirical literature, particularly in the context of financial stability and credit risk. Economic theory suggests that both macroeconomic conditions and internal bank characteristics play a crucial role in shaping the dynamics of loan quality.

A large body of empirical evidence highlights the importance of macroeconomic determinants of NPLs. Nkusu (2011), using dynamic panel methods and a structural Panel VAR for developed countries, finds that economic growth, housing prices, stock market performance, and the nominal effective exchange rate reduce NPLs, while unemployment, inflation, and interest rates increase credit risk. Similar results are reported by Louzis et al. (2012) for Greece, who show that GDP growth reduces NPLs, whereas unemployment, interest rates, and public debt exert a positive impact, with consumer loans being particularly sensitive to interest rate changes. For Central and Eastern European countries, Moinescu (2012) and Škarica (2013) confirm that economic growth reduces NPLs, while unemployment, exchange rates, inflation, and interest rates contribute positively to credit risk.

Labor market conditions emerge as one of the most robust determinants of nonperforming loans. Tsagkanos and Bellas (2014), using a difference GMM model for Euro Area countries, find that unemployment and public debt increase NPLs, while economic growth reduces them. Ghosh (2015), analysing U.S. states, reports that higher unemployment and inflation rates significantly increase NPLs, whereas income growth reduces default risk. More recently, Čakajac et al. (2024) provide strong cross-country evidence that higher unemployment rates are systematically associated with higher NPL ratios across European economies.

In addition to macroeconomic factors, several studies emphasize the role of bank-specific characteristics. Klein (2013) shows that higher capital ratios and profitability reduce NPLs in Central and Eastern Europe, while excessive credit growth increases credit risk. Anastasiou et al. (2016) confirm that profitability indicators such as ROA and ROE have a negative effect on NPLs in Euro Area banks. Similar conclusions are drawn by Petkovski et al. (2018) for Czech banks and by Naili and Lahrichi (2022) for banks in the Middle East and North Africa, where capitalisation, efficiency, and profitability are found to significantly improve loan quality, while rapid credit expansion increases default risk.

Exchange rate dynamics are particularly relevant in economies with a high share of foreign currency lending. Nkusu (2011) shows that exchange rate depreciation increases NPLs by raising the real burden of foreign-denominated debt, while Hada et al. (2020) find similar evidence for Romania, identifying the RON/CHF exchange rate as one of the main drivers of NPL growth during the post-crisis period. Inflation is generally found to increase nonperforming loans, as shown by Ghosh (2015), Us (2020), and Naili and Lahrichi (2022), reflecting the erosion of real incomes and the deterioration of borrowers' repayment capacity.

Recent contributions adopt VAR and Panel VAR frameworks in order to capture dynamic interactions and spillover effects. Huljak et al. (2020), using a Bayesian Panel VAR for Euro Area countries, find that NPL shocks reduce credit growth, economic activity, and house prices. Us (2020), employing a Panel VAR for Turkish banks, confirms that unemployment, inflation, exchange rates, and public debt increase NPLs, while economic growth reduces credit risk. Nerjaku and Sinaj (2024), using a VAR model for Albania, also show that GDP growth lowers NPLs, whereas unemployment and inflation increase default risk.

Overall, the empirical literature consistently supports the view that nonperforming loans are driven by a combination of macroeconomic conditions, particularly economic growth, unemployment, and interest rates, and bank-specific factors such as profitability, capitalisation, and efficiency.

3. Data and Methodology

3.1. Bank-specific and macroeconomic indicators

The panel regression analysis uses data from 18 individual banks from Romania, as well as macroeconomic indicators from the IMF Database and Eurostat from 2008Q4 to 2023Q4. The VAR models use only macroeconomic indicators from 2008Q4 to 2024Q4. The variables were considered as follows:

- **Return on Equity (ROE)** – calculated as the ratio of net profit to shareholders' equity. Poor performance of a credit institution may be associated with certain managerial characteristics that lead to reduced profitability. In situations where profitability is very low, managers may resort to granting loans to riskier borrowers in an attempt to increase returns, which ultimately leads to a higher level of nonperforming loans. Therefore, the expected impact of ROE on the NPL ratio is negative;
- **Return on Assets (ROA)** – calculated as the ratio of net profit to total assets. Inefficient banks with low profitability are more likely to engage in less secure and riskier investments to improve their performance (similarly to ROE, given that both indicators measure profitability). Consequently, the expected impact of ROA on the NPL ratio is negative;
- **Cost-to-Income Ratio (CTI)** – calculated as the ratio of operating expenses to net operating income. According to the *"bad management"* hypothesis proposed by Berger and DeYoung (1997), weak managerial skills lead banks with low cost efficiency to experience higher levels of nonperforming loans due to inadequate collateral evaluation, poor credit scoring, and insufficient monitoring of borrowers. Therefore, the expected impact of CTI on the NPL ratio is positive;
- **Equity Ratio (ER)** – calculated as the ratio of total equity to risk-weighted assets. According to the *"moral hazard"* hypothesis proposed by Keeton and Morris (1987), banks with relatively low capital respond to moral hazard incentives by increasing the riskiness of their loan portfolios, which, on average, leads to higher NPL ratios in the future, as potential losses can be shifted to other parties. Therefore, the expected impact of the equity ratio on the NPL ratio is negative;
- **Economic Growth (GDP)** reflects the overall state of an economy. When GDP increases, economic conditions improve, resulting in higher domestic production and, consequently, higher household incomes. As borrowers' incomes rise, the probability of default decreases. Therefore,

the expected impact of economic growth on the NPL ratio is negative;

- **Unemployment Rate (UNEMP)** represents the number of unemployed individuals relative to the total working-age population. When a borrower loses their job, they typically lose their primary source of income, creating additional pressure on debt repayment. As a result, an increase in the unemployment rate is expected to lead to a rise in nonperforming loans;
- **Inflation Rate (HICP)** is measured using the Harmonised Index of Consumer Prices with a fixed base year of 2015. Inflation affects borrowers' repayment capacity through various channels. Higher inflation may facilitate debt repayment by reducing the real value of outstanding loans when interest rates are fixed, or because it is often associated with lower unemployment, as suggested by the Phillips curve. However, inflation may also reduce real incomes when wages are rigid, negatively affecting borrowers' repayment capacity. Moreover, when interest rates are variable, inflation can further weaken debt-servicing capacity. Consequently, the relationship between inflation and NPLs may be either positive or negative *(*Nkusu*, 2011)*;
- **Interest Rate (INTRATE)** is measured by the yield on 10-year government bonds, in line with the Maastricht convergence criterion. An increase in the interest rate raises the total cost of loan repayments, placing additional financial pressure on borrowers. Therefore, the expected impact of higher interest rates on the NPL ratio is positive;
- **Real Effective Exchange Rate (REER)** is calculated as a weighted average of exchange rates against 42 trading partners for each country. Similar to inflation, an appreciation of the national currency may have mixed effects. On the one hand, it can reduce the competitiveness of export-oriented firms and negatively affect their debt repayment capacity. On the other hand, it can improve the repayment capacity of borrowers who have contracted foreign-currency loans (Nkusu, 2011).

Table 1
Descriptive table of bank-specific and macroeconomic variables

Indicator	Expected Sign
Return on Equity (ROE)	-
Return on Assets (ROA)	-
Equity Ratio (ER)	-
Cost to Income (CTI)	+
Economic Growth (GDP)	-
Unemployment Rate (UNEMP)	+
Inflation Rate (HICP)	+ / -
Interest Rate (INTRATE)	+
Real Effective Exchange Rate (REER)	+ / -

3.2. Panel Regression

Panel data represent a combination of cross-sectional data and time series. In this study, only the fixed-effects panel regression method is employed in order to control for unobserved heterogeneity across individuals. The panel regression model takes the following form:

$$NPL_{it} = \alpha + X'_{it}\beta + u_{it,}\ \text{i = 1, ..., N; t = 1, ..., T} \quad (1)$$

where *i* denotes the number of cross-sectional units (banks), and *t* represents time. Panel models use an error term that can be expressed as $u_{it} = \mu_i + v_{it}$, where μ_i captures the individual-specific effect for each unit, and v_{it} represents the idiosyncratic error term (white noise). It should be noted that μ_i is time-invariant. When the regression model is estimated using fixed effects, μ_i is treated as a fixed parameter, while the error term v_{it} is assumed to be independently and identically distributed, IID(0, σ_v^2). Therefore, the fixed-effects model is correctly specified when the cross-sectional units exhibit heterogeneous behaviour across individuals (Baltagi, 2005).

3.3. Bayesian VAR

To analyse the dynamic interactions between nonperforming loans and macroeconomic conditions in Romania, this study employs a Bayesian Vector Autoregression (BVAR) framework. Compared to classical VAR models, the Bayesian approach is particularly well-suited for systems with relatively short time series and a large number of parameters, as it mitigates over-parameterisation and improves estimation efficiency through the use of prior information. The BVAR model is specified as a standard VAR of order p:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdot\cdot\cdot + A_p y_{t-p} + Cx_t + \varepsilon_{t,\ t = 1, 2, ..., T} \quad (2)$$

where y_t is a vector of endogenous macroeconomic variables, including the nonperforming loan ratio, real GDP growth, unemployment rate, inflation, interest rate, and the real effective exchange rate; A_p is a (n x m) matrix, p being the number of lags; C is a (n x m) matrix; x_t denotes a vector of deterministic components or a constant term and ε_t is a vector of innovations assumed to be normally distributed with zero mean and variance–covariance matrix. In compact matrix notation, the model can be written as:

$$Y = \bar{X}B + \varepsilon \quad (3)$$

In the Bayesian framework, the parameters B and Σ are treated as random variables rather than fixed but unknown quantities. Estimation, therefore, combines information from the data with prior beliefs regarding the parameters' distribution.

Bayesian inference relies on Bayes' rule, according to which the posterior distribution of the parameters is proportional to the product of the likelihood function and the prior distribution. In this study, a Normal–Wishart prior is adopted for the VAR coefficients and the variance–covariance matrix of the residuals. This prior choice allows the variance–covariance matrix to be treated as unknown and jointly estimated with the coefficients, providing greater flexibility compared to alternative priors such as the Minnesota prior, which assumes a fixed covariance structure.

The posterior distribution is obtained analytically under the Normal–Wishart prior, enabling efficient estimation even in small samples. The lag length of the model is selected based on standard information criteria, while stationarity conditions are verified to ensure model stability.

To identify and interpret the dynamic effects of macroeconomic shocks on nonperforming loans, impulse response functions are derived from the estimated BVAR. Structural shocks are identified using a Cholesky decomposition of the variance–covariance matrix, which imposes a recursive ordering consistent with economic theory. The impulse responses trace the effect of a one-standard-deviation innovation in each macroeconomic variable on the evolution of nonperforming loans over time.

3.4. Panel VAR

To capture the dynamic interactions between nonperforming loans and macroeconomic conditions at the regional level, a Panel Vector Autoregression (Panel VAR) framework is employed. This approach allows all variables to be treated as endogenous while exploiting both the time-series and cross-sectional dimensions of the data. The model is specified as:

$$y_{it} = B(L)y_{it} + \varepsilon_{it} \tag{4}$$

where y_{it} is a (k x 1) vector of endogenous macroeconomic variables, including the nonperforming loan ratio; B(L) denotes a matrix polynomial in the lag operator; i = 1, … , N indexes the countries; t = 1, … , T denotes the time dimension; and ε_{it} is a vector of reduced-form innovations with zero mean and a variance–covariance matrix Σ_{ε}.

The Panel VAR framework extends the standard VAR model by allowing for heterogeneity across countries while preserving a common dynamic structure. Under the assumption that the characteristic polynomial associated with B(L) defines a stable process, the model admits a moving-average representation, which forms the basis for impulse response analysis.

The dynamic effects of macroeconomic shocks on nonperforming loans are examined using impulse response functions (IRFs). These responses trace the effect of a one-standard-deviation innovation in each macroeconomic variable on the evolution of the NPL ratio over time, while accounting for feedback effects among all variables in the system.

To identify the shocks, generalised impulse response functions are employed. This approach accounts for the contemporaneous correlation among the reduced-form residuals and has the advantage of being invariant to the ordering of variables, unlike recursive identification schemes based on Cholesky decomposition. As a result, the estimated responses reflect average dynamic effects across the panel of countries without imposing potentially restrictive identifying assumptions.

4. Results

4.1. Panel regression results

In order to examine the determinants of the nonperforming loan ratio at the bank level, a sample consisting of 18 banks from the Romanian banking system is used over the period 2007Q4–2023Q4.

Five-panel regression models were estimated, combining bank-specific and macroeconomic indicators in order to minimise the effects of multicollinearity. The regression models are estimated using fixed effects to account for unobserved heterogeneity across banks.

Table 2

Variance – Covariance matrix of bank-specific and macroeconomic indicators

%	NPL	ROA	ROE	CTI	ER	GDP	UNEMP	INTRATE
NPL	100							
ROA	-44.70	100						
ROE	-41.96	88.98	100					
CTI	16.05	-24.82	-36.46	100				
ER	-12.20	24.04	11.97	-9.68	100			
GDP	-6.75	13.66	14.31	2.37	2.55	100		
UNEMP	69.18	-28.39	-27.00	3.53	-10.31	-11.89	100	
INTRATE	17.14	-13.22	-13.64	-1.95	-4.61	-15.55	35.96	100

Source: Own EViews calculations

The variance–covariance matrix indicates a positive correlation between the nonperforming loan ratio, the cost inefficiency indicator, the unemployment rate, and the interest rate, as well as a negative correlation with financial profitability, return on assets, the equity ratio, and economic growth, in line with the empirical literature and economic theory. The strongest correlation is observed between the profitability indicators, namely ROA and ROE, with a positive correlation coefficient of 88.98%, which implies that these two variables cannot be used simultaneously in the regression model.

Table 3

Panel regression results

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
ROE	-0.13***		-0.13***		
	[-16.13]		[-16.58]		
ROA		-0,97***			
		[-15.49]			
ER			-0,06***	-0.08***	-0.08***
			[-4.38]	[-5.84]	[-5.96]
CTI				0.01***	0.01***
				[6.19]	[6.32]
GDP	-0,10**				-0.13**
	[-2.12]				[-2.23]
UNEMP		5,45***			
		[29.29]			
INTRATE			0.65***	0.95***	0.94***
			[5.35]	[10.21]	[9.42]
R-Squared	0.4765	0.6194	0.4932	0.5223	0.5223
Adjusted R-Squared	0.4679	0.6131	0.4844	0.5139	0.5146
F-Statistic (Prob)	0.00000	0.00000	0.00000	0.00000	0.00000
***p < 0.01; **p < 0.05; *p < 0.1			t – statistic in [ ]		

Source: Own EViews calculations

The estimated models include different combinations of bank-specific and macroeconomic variables in order to reduce multicollinearity and assess the robustness of the results. The findings indicate that bank profitability plays a crucial role in explaining credit risk, as both return on equity and return on assets exhibit negative and highly statistically significant coefficients. In particular, ROE has a coefficient of -0.13 in Models 1 and 3, while ROA displays a much stronger effect in Model 2, with a coefficient of -0.97, suggesting that asset profitability is a more relevant indicator for capturing lending performance and credit quality. These results support the “bad management” hypothesis, according to which inefficient and poorly performing banks tend to engage in riskier lending practices, leading to higher levels of nonperforming loans.

Furthermore, bank capitalisation, measured by the equity ratio, has a negative and statistically significant impact on NPLs in Models 3, 4, and 5, indicating that better-capitalised banks are more resilient and less exposed to credit risk. Similarly, the cost-to-income ratio enters positively and significantly in Models 4 and 5, implying that higher operational inefficiency is associated with higher levels of nonperforming loans.

From a macroeconomic perspective, economic growth has a negative and statistically significant effect on NPLs in Models 1 and 5, confirming that economic expansions improve borrowers' income and repayment capacity, thereby reducing default risk. In contrast, the unemployment rate exerts by far the strongest impact on credit risk, as shown in Model 2, where a one percentage point increase in unemployment leads to an increase of approximately 5.45 percentage points in the NPL ratio. This result highlights the central role of labour market conditions in shaping credit risk dynamics, as job losses directly undermine borrowers' ability to service debt. Additionally, the interest rate has a positive and highly significant effect in Models 3, 4, and 5, indicating that higher borrowing costs increase debt-servicing burdens and contribute to higher default rates, in line with the classical interest rate transmission mechanism.

In terms of model performance, the R-squared values range between 0.47 and 0.62, suggesting a moderate to good explanatory power for panel data, with the highest fit observed in Model 2. All F-statistics are highly significant, confirming the overall statistical validity of the estimated specifications. Overall, the results indicate that nonperforming loans in the Romanian banking sector are driven by a combination of bank-level factors related to management quality and efficiency, as well as macroeconomic conditions, particularly labour market developments and financing costs, thus confirming both economic theory and the empirical literature on credit risk determinants.

4.2. Bayesian VAR results

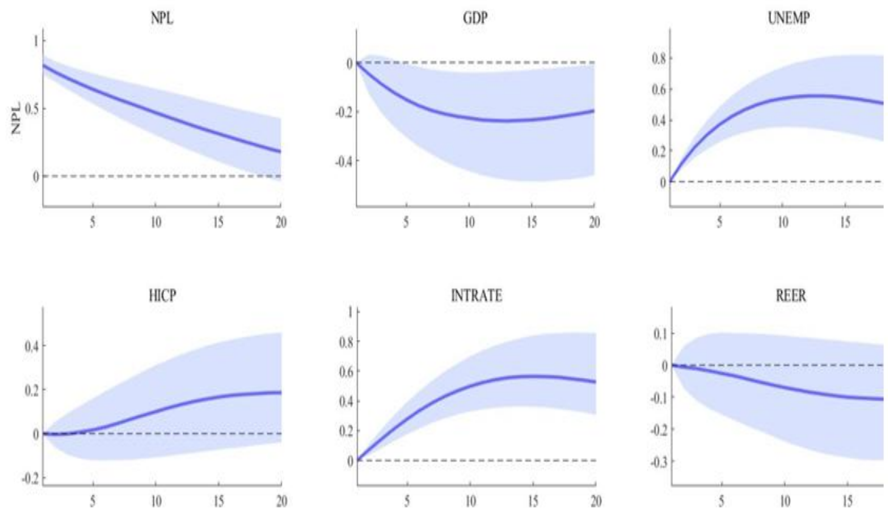
The VAR model was estimated in MATLAB using the BEAR toolbox developed by Dieppe, Legrand, and van Roye (2016). In the empirical analysis, the model was estimated for Romania over the period 2008Q4 – 2024Q4. The number of lags was chosen based on the information criteria test (Appendix, Table 4), and the confidence interval has a 68% probability level.

The variables are introduced into the model in the following order: the nonperforming loan ratio, economic growth, the unemployment rate, the inflation rate, the interest rate, and the real effective exchange rate. This ordering is chosen because the nonperforming loan ratio contemporaneously affects the macroeconomic environment through the credit channel, whereas the remaining macroeconomic variables affect nonperforming loans with a lag (Klein, 2013).

VAR models are characterised by a specific stability condition. If the modulus of the roots of the characteristic polynomial is less than one, then the roots lie within the unit circle, and the model is considered stable (Appendix, Table 5).

Figure 1

Romania, BVAR impulse response functions



Source: Own estimation in MATLAB

A positive shock to the NPL ratio generates an immediate and persistent increase in NPLs, with an initial impact of approximately 0.8 percentage points. The persistence of the response indicates a strong inertia effect in the dynamics of nonperforming loans, suggesting that once credit quality deteriorates, banking sector vulnerabilities tend to propagate over time. This result reflects the existence of structural rigidities in the banking system and confirms that financial distress has long-lasting effects.

A positive GDP shock leads to a decline in the NPL ratio, with a maximum impact of around -0.21 percentage points. However, the effect becomes statistically significant only after a few quarters, indicating a delayed transmission mechanism. This result is consistent with economic theory, according to which economic expansion improves borrowers' income levels and financial conditions, thereby strengthening their repayment capacity and reducing the probability of default.

A shock to the unemployment rate generates a strong and persistent increase in the NPL ratio, reaching up to 0.55 percentage points. This is one of the most pronounced effects observed across all variables. The result confirms that labour market conditions play a crucial role in determining credit risk. When borrowers lose their jobs, they typically lose their main source of income, which significantly weakens their ability to service debt and leads to a higher incidence of loan defaults.

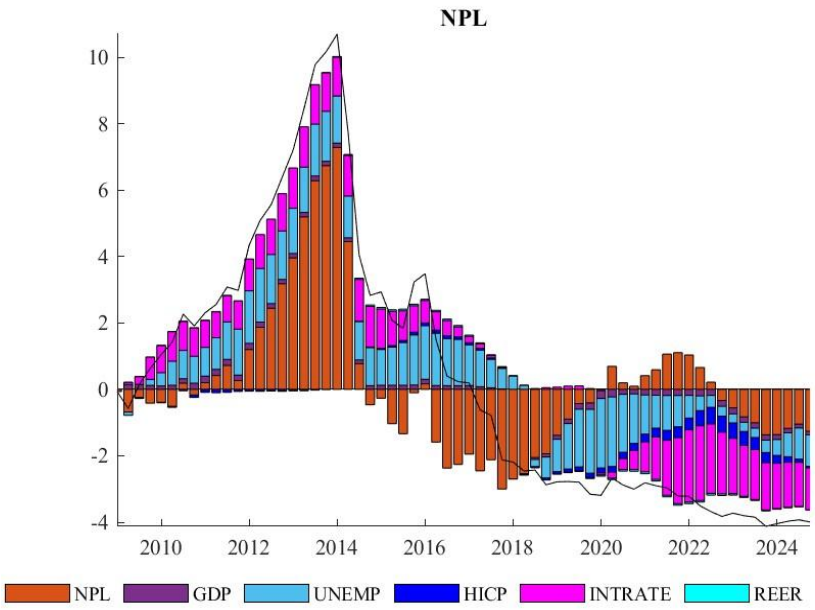
A positive shock to inflation begins to produce a negative effect on the NPL ratio after a few quarters, indicating a gradual decline in NPLs. Although the initial impact is weak and statistically insignificant, the effect becomes relevant in the medium term, suggesting the existence of a lagged transmission mechanism. The economic interpretation is that inflation reduces the real value of outstanding debt, particularly for loans with fixed interest rates, thereby easing debt servicing and lowering default risk. The delayed response reflects the time required for real income and balance sheet adjustments to materialise.

A positive shock to the interest rate leads to a clear and statistically significant increase in the NPL ratio, reaching up to 0.5 percentage points. The effect is persistent and reflects the classical interest rate channel of monetary transmission. An increase in interest rates raises the cost of borrowing and debt servicing, placing additional financial pressure on households and firms, which ultimately increases the probability of default and the level of nonperforming loans.

A positive shock to the real effective exchange rate starts to generate a negative and statistically significant effect on the NPL ratio after approximately five quarters, indicating a decline in NPLs. This result suggests that an appreciation of the domestic currency improves the repayment capacity of borrowers with foreign currency–denominated loans, as the real burden of servicing external debt decreases. The effect appears with a delay, reflecting the indirect nature of the exchange rate transmission channel.

Figure 2

Romania, Historical decomposition of NPL



Source: Own MATLAB estimations

Romania recorded the highest value of the nonperforming loan ratio in 2014, reaching 22.36%, which represents the largest value in the analysed sample. This peak was mainly driven by the large volume of loans denominated in Swiss francs contracted prior to the 2008 financial crisis. As the Romanian leu depreciated, a significant number of borrowers faced difficulties in servicing their debt, which led to a sharp increase in nonperforming loans. The historical decomposition indicates that, in addition to the interest rate and the unemployment rate, the NPL ratio was influenced by an additional determinant during the period 2011–2014. In 2010, due to the increase in the budget deficit and the decline in gross domestic product, the government decided to reduce public sector wages and increase the value-added tax (IMF, 2010; IMF, 2012). These measures exerted additional pressure on borrowers and weakened their capacity to meet financial obligations. The NPL shock declines sharply in 2014 because, in order to mitigate the alarming rise in nonperforming loans, the National Bank of

Romania issued a series of recommendations aimed at encouraging banks to sell their NPL portfolios to other financial institutions. During the period 2016–2020, the NPL shock became negative as many banks adopted the new IFRS accounting standards, which increased prudential behaviour and strengthened balance sheet discipline. After 2020, regulations concerning loan moratoria during the Covid-19 pandemic, labour market policies designed to control unemployment, and the reduction in interest rates contributed to stabilising the NPL ratio.

4.3. Panel VAR results

The sample includes data from the following countries: the Czech Republic, Croatia, Poland, Romania, Slovenia, and Hungary over the period 2008Q4 – 2024Q4, while the set of endogenous variables consists only of the macroeconomic variables used in the previous Bayesian model.

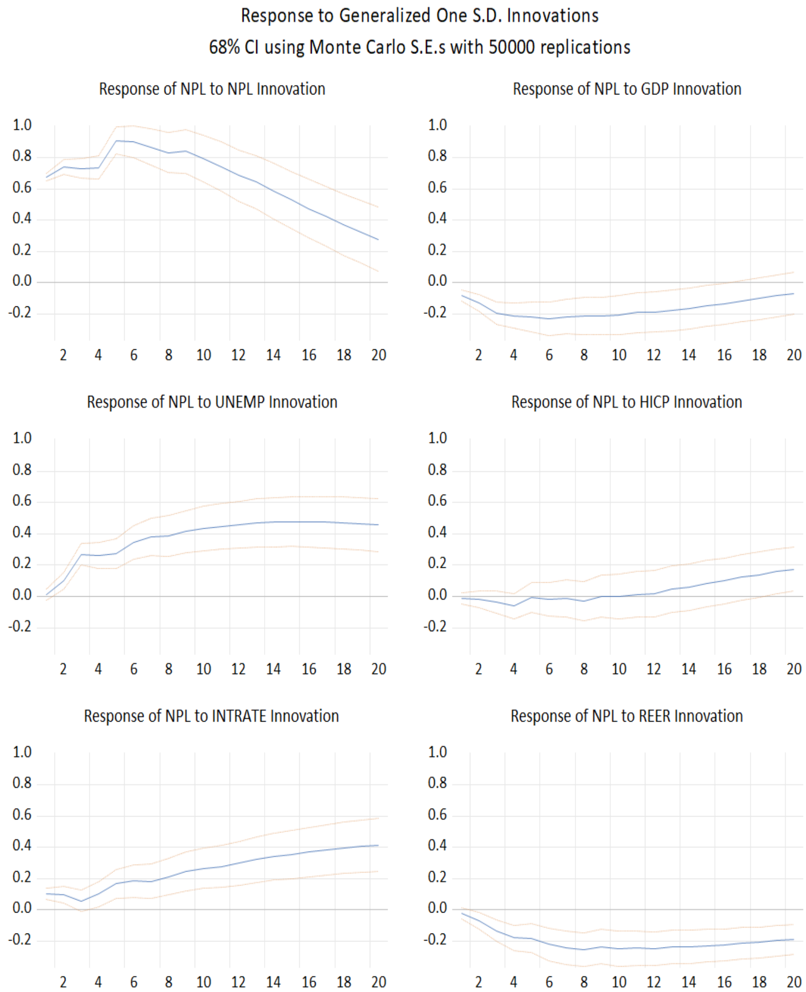
The stationarity tests (Appendix, Table 6) indicate that the inflation rate, economic growth, and the real effective exchange rate are stationary at the 1% significance level. The nonperforming loan ratio is stationary at the 5% level, while the interest rate is also stationary at the 5% level; however, the Phillips–Perron test suggests the presence of a unit root. The unemployment rate is stationary at the 10% level, although the Augmented Dickey–Fuller test indicates non-stationarity. In the model, the variables are included in levels, as economic reasoning suggests that rate variables are generally stationary.

The model is estimated with five lags, as indicated by the information criteria for the optimal lag length (Appendix, Table 7).

The stability testing procedure aims to identify the roots of the characteristic polynomial associated with the coefficient matrices. According to the results obtained, the estimated VAR model is stable (Appendix, Figure 4). To assess the robustness of the results, the presence of autocorrelation is tested using the Lagrange Multiplier (LM) test. The results indicate that the null hypothesis of the test, namely, that there is no autocorrelation at lag *h,* cannot be rejected. Therefore, the model can be considered efficient (Appendix, Table 8).

Figure 3

Impulse Response Functions of Panel VAR



Source: Own EViews estimations

A positive innovation in the NPL ratio leads to a large and persistent increase in NPLs, which gradually decays over time but remains positive throughout the entire horizon. This suggests a strong persistence of financial stress at the regional level: once loan quality deteriorates in one period, its effects tend to propagate over several years across the banking systems of the region. This pattern indicates that credit risk displays high temporal dependence, meaning that past financial conditions strongly influence future outcomes.

A positive GDP shock generates a systematic decline in NPLs, with the strongest effect appearing in the medium term. This result suggests that economic expansion has a generalised stabilising effect on banking systems in the region. Rather than acting instantaneously, growth improves credit quality gradually, reflecting the cumulative effect of higher income, stronger corporate performance, and improved labour market conditions across countries.

An unemployment shock leads to a pronounced and sustained increase in NPLs, making it one of the most influential variables in the Panel VAR. The effect intensifies over time and remains persistently positive. This indicates that labour market deterioration represents a systemic source of financial vulnerability in the region. Rising unemployment translates into widespread repayment difficulties, which aggregate into higher levels of credit risk across countries.

An inflation shock produces a relatively modest and gradual increase in NPLs. The effect is weaker compared to other variables and becomes visible only in the medium to long run. This suggests that inflation plays a secondary role in explaining regional credit risk dynamics. Its influence appears to operate indirectly, through changes in real incomes, real interest rates, and general macroeconomic uncertainty, rather than as a primary driver of loan defaults.

A positive interest rate shock leads to a steady and monotonic increase in NPLs, which becomes stronger over time. This reflects a broad regional pattern: higher financing costs systematically worsen borrowers' debt servicing capacity, leading to a gradual accumulation of nonperforming loans across banking systems. Unlike GDP or unemployment, the interest rate effect is progressive and cumulative, indicating that prolonged periods of high interest rates have long-lasting consequences for financial stability.

A positive REER shock (currency appreciation) results in a negative response of NPLs, particularly in the medium term. This suggests that exchange rate appreciation improves overall credit quality in the region, most likely due to the prevalence of foreign currency lending in Central and Eastern Europe. As domestic currencies strengthen, the real burden of foreign-denominated debt declines, which reduces default risk at the aggregate level.

5. Conclusions

Based on the analyses conducted, the economic determinants of the nonperforming loan (NPL) ratio in Romania and, subsequently, in six Central and Eastern European countries were identified. Three types of models were estimated within the study: fixed-effects panel regressions for Romania using a sample of 18 banks, including four bank-specific indicators and three macroeconomic indicators; a Bayesian VAR model with Cholesky decomposition for Romania, employing six macroeconomic variables, namely the nonperforming loan ratio, economic growth, the unemployment rate, the inflation rate, the interest rate, and the real effective exchange rate; and finally, a Panel VAR analysis with generalized impulse responses, applied to the Czech Republic, Croatia, Poland, Romania, Slovenia, and Hungary, using the same set of macroeconomic variables.

At the level of the Romanian banking sector, the six fixed-effects panel regression models capture the dynamics between the nonperforming loan ratio and indicators of profitability, capitalisation, and efficiency, alongside macroeconomic variables. Poor management significantly contributes to an increase in nonperforming loans, with profitability exerting the strongest impact, in line with economic theory. In order to mitigate the problem of nonperforming loans, banks should improve their overall performance, particularly the profits generated by their assets, equity and increase the profitability (Ferreira, 2022). Efficient and highly profitable banks tend to engage in safer and less risky investments, whereas poorly performing banks resort to riskier placements in an attempt to enhance profitability. This behaviour ultimately increases their exposure to credit risk and leads to higher levels of nonperforming loans.

At the macroeconomic level, deteriorating economic conditions systematically translate into higher levels of nonperforming loans. Economic growth and the real effective exchange rate have a negative impact on nonperforming loans, whereas the unemployment rate, the interest rate, and the inflation rate exert a positive impact on NPLs. These results are also consistent with economic theory. Moreover, the historical decomposition of the NPL ratio indicates that, in addition to the macroeconomic variables included in the model, there were other unobserved determinants that contributed to the deterioration of the banking system, such as wage cuts or tax increases.

At the panel level, the results of the generalised impulse response functions are similar to those obtained from the Bayesian model. Economic growth and the real effective exchange rate have a negative impact on nonperforming loans, whereas the unemployment rate and the interest rate have a positive impact on nonperforming loans. These results are, once again, consistent with economic theory. The inflation rate is found to be statistically significant in this type of estimation only in the medium to long run. The unemployment rate is the variable that exerts the strongest impact on nonperforming loans across all three types of models. This result can be explained by the fact that when a borrower loses their job, they usually lose their main source of income, which significantly weakens their ability to service debt and increases the likelihood of default.

As future research directions, regression models could incorporate a dynamic estimation approach based on the Generalised Method of Moments (GMM) in order to capture potential endogeneity among variables, while VAR models could employ alternative shock identification strategies, such as sign restrictions. With regard to the choice of variables, other relevant indicators in credit risk analysis could also be considered, such as the probability of default or the loan loss provisioning coverage ratio.

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APPENDIX

Table 4

Information criteria for BVAR model, Romania

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-779.8915	NA	1279.252	24.18128	24.38199	24.26047
1	-493.7874	510.5859	0.584811*	16.48577	17.89075*	17.04012*
2	-457.8748	57.46018	0.602892	16.48845	19.09772	17.51798
3	-427.7069	42.69911	0.775694	16.66790	20.48145	18.17259
4	-383.4557	54.46298*	0.695557	16.41402*	21.43184	18.39387

Source: Own EViews estimations

Table 5

Roots of the characteristic polynomial for BVAR model, Romania

Roots of the characteristic polynomial (modulus):
0.951 0.951 0.746 0.746 0.500 0.500
No root lies outside the unit circle.
The estimated VAR model satisfies the stability condition

Source: Own EViews estimations

Table 6

Stationary tests for Panel VAR

Variabie	ADF Test	PP Test
NPL	0.0251	0.0041
GDP	0.0000	0.0000
UNEMP	0.1765	0.0527
HICP	0.0000	0.0000
INTRATE	0.0222	0.2030
REER	0.0000	0.0000

Source: Own EViews estimations

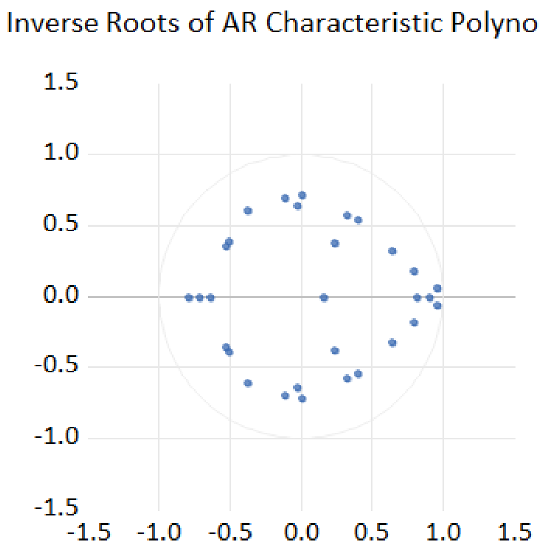
Table 7

Informational criteria for Panel VAR

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-4616.35...	NA	8846.251	26.11501	26.18059	26.14110
1	-2662.40...	3830.619	0.174108	15.27915	15.73822*	15.46180
2	-2596.25...	127.4529	0.146859	15.10878	15.96134	15.44799*
3	-2549.00...	89.42212	0.137875	15.04524	16.29128	15.54100
4	-2499.86...	91.34234	0.128111	14.97099	16.61052	15.62331
5	-2453.70...	84.23114*	0.121122*	14.91360*	16.94662	15.72248
6	-2426.25...	49.17515	0.127352	14.96187	17.38838	15.92730

Source: Own EViews estimations

Figure 4
Roots of the characteristic polynomial for Panel VAR



Source: Own EViews estimations

Table 8
Lagrange Multiplier test for autocorrelation for Panel VAR

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	58.23891	36	0.0109	1.631648	(36, 1399.2)	0.0109
2	53.07151	36	0.0331	1.484147	(36, 1399.2)	0.0332
3	66.54639	36	0.0015	1.869910	(36, 1399.2)	0.0015
4	64.08921	36	0.0027	1.799291	(36, 1399.2)	0.0027
5	34.35564	36	0.5469	0.954397	(36, 1399.2)	0.5470

Source: Own EViews estimations