

***Development of Financial Relations***

Marianna KICHURCHAK,
Iryna PASLAVSKA

**NON-PERFORMING LOANS DURING WAR-INDUCED
SHOCKS AND THEIR REGULATION IN UKRAINE IN
THE CONTEXT OF EU INTEGRATION****Abstract**

Key macroeconomic determinants of non-performing loan (NPL) dynamics under war-induced shocks and Ukraine's ongoing adaptation of its banking sector to European Union (EU) regulatory standards have been identified. The analysis employs a Bayesian autoregressive distributed lag (ARDL) model estimated using 79 quarterly observations over the period 2006–2025, allowing the integration of probabilistic parameter estimation with a dynamic lag structure under conditions of multiple structural breaks. The results reveal statistically and economically significant lagged effects of real GDP growth, the consumer price index, the National Bank of Ukraine's policy rate, and average wages on NPL dynamics. The military shocks of 2014 and 2022 exert pronounced but temporally differentiated impacts on the NPL accumulation, reflecting distinct phases of banking sector stress and institutional adaptation. The findings provide policy-relevant approaches to enhancing banking sector resilience through harmonisation with EU standards and to mitigating systemic credit risks in the course of Ukraine's post-war recovery.

Key Words:

Bayesian ARDL, European integration, lagged effects, macroeconomic instability, non-performing loans, Ukraine's economy, wartime shocks.

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Kichurchak Marianna, DSc (Economics), Professor, Acting Head of the Department of Economy of Ukraine, Ivan Franko National University of Lviv, Lviv, Ukraine. ORCID: 0000-0002-1927-5704 Email: Marianna.Kichurchak@lnu.edu.ua

Paslavska Iryna, PhD (Economics), Associate Professor, Department of Economic Cybernetics, Ivan Franko National University of Lviv, Lviv, Ukraine. ORCID: 0000-0003-3955-5751 Email: Iryna.Paslavska@lnu.edu.ua

JEL: C11, E44, E52, G21, H56, P24.

1 table, 4 figures, 5 formulas, 48 references.

Problem Statement and Literature Review

Over the period 2006–2025, Ukraine’s banking sector operated through a succession of macroeconomic, political, and institutional shocks that fundamentally reshaped the dynamics of non-performing loans (NPLs). The global financial crisis of 2007–2009 constituted the first major systemic shock, triggering a pronounced economic downturn, real-sector contraction, and significant currency depreciation. These developments undermined borrowers’ solvency (National Bank of Ukraine, 2010) and led to a substantial increase in NPLs on banks’ balance sheets (National Bank of Ukraine, n.d.-a).

A substantially deeper structural shock occurred in 2014–2015, driven by political instability, the annexation of Crimea, the outbreak of hostilities in eastern Ukraine, and a sharp deterioration in macroeconomic fundamentals. This period saw a pronounced GDP decline, a steep weakening of the national currency, rising inflation, and a marked deterioration in banks’ loan portfolio quality, resulting in a surge in NPLs (Baiaşvili & Frewer, 2016; National Bank of Ukraine, n.d.-a). In response, the NBU overhauled its supervisory framework, adopting zero tolerance for financially weak and non-transparent banks and initiating a shift towards macroprudential regulation. As part of this sector-wide clean-up, many banks were declared insolvent or withdrawn from the market, while regulatory requirements for credit risk assessment, capital adequacy, and ownership transparency were significantly strengthened, reflecting the transformation of the regulatory model towards a risk-oriented supervisory approach (Bazhenova, 2023). The next stage of destabilisation, associated with the COVID-19 pandemic in 2020–2021, triggered a temporary contraction of economic activity and elevated credit risks for both households and businesses, prompting regulatory easing measures such as loans payment holidays and temporary relaxation of selected supervisory requirements.

Nevertheless, in scale and long-term economic consequences, this shock was markedly less severe than the new stage of the War for Independence of Ukraine that commenced on February 24, 2022 (Kravchuk, 2024). Key macroeconomic fundamentals, including GDP growth, inflation, exchange rates dynamics, unemployment, and fiscal deficits, emerged as primary determinants of credit risk and major drivers of fluctuations in NPLs. Owing to the NBU’s timely stabilization measures, encompassing liquidity support, foreign exchange restrictions, and adaptive regulatory adjustments, the banking sector maintained operationally resilient under martial law (National Bank of Ukraine, 2023b).

A major institutional development affecting the measurement and interpretation of credit risk was the introduction of IFRS 9 “Financial Instruments”, which has been mandatory for banks since 2018. The shift to the expected credit loss (ECL) framework promoted a more conservative approach to risk assessment, reinforced the procyclical behaviour of credit risk indicators, and heightened the

sensitivity of bank balance sheets to macroeconomic fluctuations, all of which are crucial for the empirical analysis of credit risk determinants (National Bank of Ukraine, 2018). In parallel, Ukraine advanced the practical steps to align its banking regulation with the *acquis* of the European Union (EU). The adoption of Law of Ukraine No. 590-IX (Verkhovna Rada of Ukraine, 2020) established the legal basis for strengthening regulatory independence, enhancing bank resolution mechanisms, and implementing European supervisory practices, thereby contributing to the development of a resilient banking system aligned with European standards.

Furthermore, the introduction of the Liquidity Coverage Ratio and Net Stable Funding Ratio standards in 2018–2019, aligned with Basel III requirements and EU practices, enhanced the structural resilience of bank balance sheets and shaped the transmission of macroeconomic shocks to credit risk dynamics. This underscores the importance of incorporating these factors into empirical credit risk models (National Bank of Ukraine, 2020). The interplay of recurring macroeconomic crises, military shocks, and regulatory reforms under Ukraine's European integration agenda provides a complex but highly relevant context for examining the macroeconomic determinants of credit risk, particularly in the pursuit of banking stability amid the War for Independence of Ukraine and gradual integration into the European financial system.

Recent empirical research consistently shows that macroeconomic conditions are key determinants of NPLs in banking systems. Zawadzki (2023), analysing 106 countries over the period 2009–2019, finds that real GDP growth, the unemployment rate, inflation, and the public debt-to-GDP ratio systematically affect NPL levels: higher economic growth and a well-developed credit market are associated with lower NPL ratios, whereas elevated unemployment and public debt are linked to higher NPL ratios. Similar patterns are also observed regionally: a review of the banking sector in SAARC countries indicates that GDP decline and high inflation exacerbate credit risk, whereas macroeconomic stability mitigates it (Anita et al., 2022). Comparable evidence was provided by Salas et al. (2024) in a global analysis of 1,631 banks across 111 countries over the period 2007–2021 using panel data techniques. The authors show that NPL ratios are driven by a set of bank-specific factors irrespective of banks' geographical location and operating period, highlighting the robustness of these relationships, including in EU countries. In African countries, cyclical economic indicators correlate with NPL shares, with the governance quality moderating these relationships (Ahiase et al., 2024).

An important clarification of the sectoral dimension of credit risk is provided by an analysis of Central and South-eastern European countries (CESEE). In the report published by the Vienna Institute for International Economic Studies, Bykova & Pindyuk (2019) show that the dynamics of NPLs strongly depend on the loan portfolio composition: corporate loans exhibit considerably greater sensitivity to fluctuations in GDP and industrial output, whereas household loans are more resilient. For Ukraine, these findings are particularly relevant for developing a sustainable banking sector aligned with EU standards, considering currency composition of loans and the active involvement of European banking groups in asset restructuring.

The cases of Greece and Cyprus, both of which experienced systemic banking crises accompanied by a sharp increase in NPLs comparable to Ukrainian levels, are of particular analytical relevance for Ukraine. Louzis et al. (2012), based on an analysis of the nine largest Greek banks, demonstrate that NPLs across all loan categories (consumer, business, and mortgage lending) were driven primarily by macroeconomic factors,

including GDP, unemployment, interest rates, and public debt, as well as governance quality, whereas mortgage loans appeared to be the least sensitive to macroeconomic fluctuations. Anastasiou et al. (2019), using a Bayesian panel cointegration VAR model for the euro area over the period 2003–2016, identified a pronounced asymmetry between core economies (Germany, France, and the Netherlands) and peripheral economies (Greece, Cyprus, Spain, Portugal, and Ireland): NPLs increased substantially more in peripheral countries after 2008 and were predominantly associated with deteriorating macroeconomic conditions, a finding that is particularly relevant for the analysis of Ukraine's gradual integration into the EU's financial system. Karadima & Louri (2021), applying the ARDL approach to quarterly aggregate data for Greece over 2003–2020, confirmed the dominant role of macroeconomic rather than banking-specific factors and identified a significant long-run positive effect of public debt on NPL dynamics. Evidence from Cyprus, examined by Christodoulou-Volos (2025), further underscores the critical importance of institutional reforms in the regulation of insolvent borrowers and credit servicers as an effective mechanism for reducing NPLs in the post-crisis period, which is directly pertinent to Ukraine's post-war recovery trajectory.

Plikas et al. (2024), drawing on panel data covering 2015–2021, show that the scale of pandemic-related shocks and the severity of lockdown measures led to an increase in NPLs in Europe, while economic support initiatives helped mitigate this effect. They further find that profitable and well-capitalised banks exhibited greater resilience, and that securitisation contributed significantly to NPL reduction. Apergis (2022) notes a convergence in NPL levels among euro area banks during crisis periods and demonstrates that coordinated EU-level regulatory responses substantially mitigate the effects of systemic stresses. These findings provide a comparative benchmark for assessing the effectiveness of the NBU's crisis measures. A similar logic of regulatory easing – through credit holidays and liquidity support – partially offset the short-term impact of the 2022 war shock in Ukraine, underscoring the importance of coordinated regulatory responses in the context of systemic crises and Ukraine's European integration process.

Recent studies increasingly employ machine learning techniques to uncover complex nonlinear relationships between macroeconomic variables and NPLs under the specific conditions of emerging economies (Bakır et al., 2025). In addition to general economic determinants, specific structural factors critically influence the quality of credit portfolios in Ukraine. Vyshnevskiy & Sohn (2023) demonstrate that related-party lending was one of the major drivers of NPL accumulation. The authors found that such loans have a substantially higher probability of default than market-based loans, underlining the importance of maintaining banking system stability.

A comprehensive assessment of Ukraine's banking sector resilience during the War for Independence of Ukraine requires accounting for the regulatory framework shaped by the European integration agenda. A key aspect of this process was the alignment of national legislation with international capital and liquidity standards. In examining Ukraine's integration into the European banking system through banking sector clean-up, restructuring, and the adoption of Basel III standards, Ramskyi et al. (2017) show that these transformations laid the foundation for enhancing system resilience and aligning national credit risk management practices with European standards. This resilience framework enabled Ukraine's banking sector to remain operational despite unprecedented military shocks.

An examination of Ukraine's adoption of European practices in the management of NPLs reveals a gradual process of institutional transfer at several levels. First, the risk-based reform of banking supervision in 2014–2016 reflected the logic of the European Central Bank's (ECB) Single Supervisory Mechanism (SSM), previously tested in countries such as Greece and Cyprus. Specifically, the NBU removed 97 insolvent banks from the market and nationalised the country's largest bank, JSC CB "PrivatBank" (National Bank of Ukraine, 2025), while introducing mandatory stress tests and provisioning requirements for impaired assets, following an approach similar to the Supervisory Review and Evaluation Process (SREP) applied to Greek banks (National Bank of Ukraine, 2017). Second, the implementation of IFRS 9 in 2018 and the harmonisation of the definition of NPLs with EU standards as of 1 January 2025 represent an ongoing process of regulatory convergence, the effects of which are reflected in the lagged determinants identified by the estimated model (National Bank of Ukraine, n.d.-a). Third, the development of infrastructure for Asset Resolution Companies represents a direct transfer of schemes implemented in Greece (the Hellenic Asset Protection Scheme) and Cyprus (the sale of NPL portfolios to the credit servicer Apollo). In October 2024, the NBU and the International Finance Corporation (IFC) signed relevant agreements to support the development of the legal framework for such companies (National Bank of Ukraine, 2024). Fourth, the NBU's work on legislation governing credit servicers and insolvency resolution procedures aligns with the logic of EU Directive 2019/1023 on preventive restructuring (European Parliament & Council of the European Union, 2019), implemented by Cyprus in 2022, and forms part of a broader process of harmonising Ukraine's banking legislation with the EU *acquis* (National Bank of Ukraine, 2023a). Collectively, these four layers of policy transfer suggest that regulatory harmonisation with the EU performs not only an institutional but also a macro-financial stabilisation function, acting as a "regulatory anchor" that constrains the emergence of systemic credit risks even under extreme war-related shocks.

These regulatory transformations form part of broader EU-oriented banking reforms in Ukraine. The NBU is implementing the provisions of the Association Agreement (European Union, 2025), which encompass the alignment of national banking legislation with the *acquis communautaire* (National Bank of Ukraine, 2023a), the introduction of European regulatory and supervision standards, and the enhancement of credit risk assessment and internal control requirements, thereby strengthening the resilience of banks. Complementing these integration efforts, the EU provides technical assistance and supervisory support programmes (Directorate-General for Neighbourhood and Enlargement Negotiations, 2023), enhancing financial sector oversight in accordance with best European practices and fostering a resilient banking environment amid military shocks. According to the International Monetary Fund (2023), banks' successful completion of stress tests and adherence to capitalisation plans remain critical for maintaining financial resilience under martial law.

Taken together, the previous studies show a strong consensus on the inverse relationship between economic growth, income dynamics, and the share of NPLs. However, empirical evidence regarding the effects of inflation and interest rates on the dynamics of NPLs remains mixed and depends substantially on the prevailing monetary regime, institutional quality, and the degree of macroeconomic stability (Laeven & Valencia, 2020; Ari et al., 2021; Anita et al., 2022; Zawadzki, 2023; Bakır et al., 2025). These divergences highlight the importance of conducting country-specific analyses, particularly in the case of Ukraine, amid war-related structural disruptions and ongoing regulatory convergence with the European Union.

Despite substantial progress in NPL research, existing empirical approaches predominantly rely on frequentist or static panel models, which only partially capture the dynamic nature of credit risk amid prolonged structural breaks and elevated macroeconomic uncertainty in Ukraine. This underscores the need for an analytical framework that combines a dynamic time series approach with probabilistic assessment and flexible interpretation of structural changes in the banking sector.

This study aims to investigate the macroeconomic drivers of NPLs in Ukraine in response to the Ukraine's War of Independence and its key stages, specifically the first quarters of 2014 and 2022, with particular emphasis on the adaptive capacity of the banking sector in the process of EU regulatory alignment. The following hypotheses are formulated:

– **H1:** The dynamics of NPLs in Ukraine over Q1 2006–Q3 2025 are expected to exhibit persistence, with the banking sector demonstrating resilience to wartime shocks and ongoing EU integration efforts;

– **H2:** The changes in NPLs are anticipated to be determined by key macroeconomic factors, including inflation, the policy rate, real GDP fluctuations, and quarterly average wages, as well as war-related shocks of 2014 and 2022, with the corresponding effects potentially manifesting with one or more quarterly lags;

– **H3:** Military shocks may have a statistically significant and delayed impact on NPL trajectory, reflecting the gradual transmission of economic and military disruptions to borrowers' solvency, as well as the impact of European integration initiatives.

Methodology

For the empirical analysis of macroeconomic drivers affecting NPL dynamics, a Bayesian autoregressive distributed lag (ARDL) model is employed. This framework accounts simultaneously for the dynamic nature of credit risk, lagged effects of macroeconomic variables, and parametric uncertainty in time series subject to structural breaks. War shocks are incorporated into the model using dummy variables, enabling the evaluation of their delayed impact on NPL dynamics without imposing rigid deterministic assumptions on parameter behaviour.

The empirical implementation of ARDL models integrates time series analysis with factor-based independent variables, allowing for the modelling of lagged effects on the current values of the dependent variable and the delayed impact of various shocks. To examine interactions between lagged effects and parameter variations, Wilson et al. (2017) employ Bayesian distributed lag interaction models, which decompose the ARDL framework into a functional predictor and a scalar parameter, enabling simultaneous estimation of time lags, effect sizes, or both. Within a broader class of dynamic models, Chan (2019) explores large Bayesian vector autoregressions and addresses challenges arising from parameter proliferation and computational complexity. These studies underscore the potential of Bayesian methods for robust identification and modelling of macroeconomic shocks.

Leveraging recent advances in programming, Kripfganz & Schneider (2023) applied the `ardl` command, which facilitates the selection of the optimal lag lengths and assessment of both short- and long-term effects. Similarly, Natsiopoulou &

Tzeremes (2024) demonstrated the capabilities of the ARDL package in R for post-regression diagnostics, providing an intuitive API and an extensive suite of functions for comprehensive econometric analysis. To further enhance lag model assessment and account for parameter uncertainty, Dempsey & Wyse (2026) implemented Bayesian variable selection in Distributed Lag Models, enabling the examination of binary and count dependent variables and estimating probability of predictors through automated MCMC procedures. These software developments enhance the practical applicability of ARDL models and, when combined with the Bayesian framework, offer a flexible and robust toolkit for assessing complex lagged relationships.

In general, the Bayesian ARDL model with dummy variables can be expressed as follows:

$$Y_t = \alpha + \sum_{i=1}^p \beta_i Y_{t-i} + \sum_{j=1}^q \sum_{k=0}^{l_j} \gamma_{jk} X_{j,t-k} + \sum_{s=1}^m \sum_{h=0}^{d_s} \delta_{sh} D_{s,t-h} + \varepsilon_t, \\ \varepsilon_t \sim N(0, \sigma^2) \quad (1)$$

where: Y_t – dependent variable; Y_{t-i} – lagged values of the dependent variable capturing autoregressive dynamics; $X_{j,t-k}$ – lagged exogenous predictors; $D_{s,t-h}$ – lagged dummy variables; α – intercept term; β_i , γ_{jk} , δ_{sh} – coefficients of the lagged dependent variable, independent variables, and lagged dummy variables, respectively; p – number of lags of the dependent variable; q – number of independent variables, l_j – number of lags for the j -th independent variable; m – number of dummy variables; d_s – number of lags for the s -th dummy variable; ε_t – stochastic error term.

In the Bayesian ARDL model, prior distributions are assigned to all parameters as follows:

$$\alpha \sim \text{Normal}(\mu_\alpha, \sigma_\alpha^2), \beta_i \sim \text{Normal}(\mu_{\beta_i}, \sigma_{\beta_i}^2), \gamma_{jk} \sim \text{Normal}(\mu_{\gamma_{jk}}, \sigma_{\gamma_{jk}}^2), \\ \delta_{sh} \sim \text{Normal}(\mu_{\delta_{sh}}, \sigma_{\delta_{sh}}^2), \sigma^2 \sim \text{Normal}(0, s_0^2) \quad (2)$$

The observation equation is specified as follows:

$$Y_t \sim \text{Normal} \left(\alpha + \sum_{i=1}^p \beta_i Y_{t-i} + \sum_{j=1}^q \sum_{k=0}^{l_j} \gamma_{jk} X_{j,t-k} + \sum_{s=1}^m \sum_{h=0}^{d_s} \delta_{sh} D_{s,t-h}, \sigma^2 \right) \quad (3)$$

The model parameters are estimated within a Bayesian framework using Bayes' theorem:

$$P(\theta|X_t) \propto P(X_t|\theta) \cdot P(\theta) \quad (4)$$

where: $P(\theta|X_t)$ – posterior distribution of model parameters given the observed data; $P(X_t|\theta)$ – likelihood function representing the probability of the observed data given the parameters; $P(\theta)$ – prior distribution reflecting prior beliefs about the parameters; X_t – observed data; the normalizing constant $P(X_t)$ is typically omitted in computation.

The full posterior distributions of parameters (α , β_i , γ_{jk} , δ_{sh} , σ) are estimated using Markov chain Monte Carlo (MCMC) methods. To comprehensively assess the adequacy of the Bayesian model, trace plots and density plots are employed to examine parameter convergence and distribution, while R-hat and effective sample size (ESS) are used to evaluate the quality of the MCMC sample. Posterior predictive check (PPC) is applied to verify the model's ability to reproduce empirical data, Bayesian R^2 is used to estimate the proportion of variance explained, and leave-one-out cross-validation (LOO-CV) with Pareto-smoothed importance sampling diagnostics assesses predictive accuracy and stability of importance weights. Additionally, predictive error metrics, including mean absolute error (MAE) and root mean square error (RMSE), are employed to evaluate the model's capacity for accurate prediction.

Research Results

Let the dependent variable (Y) represent the share of NPLs (%). The exogenous variables are defined as follows: X_1 – the real GDP growth rate, % compared to the same quarter of the previous year; X_2 – the consumer price index, %; X_3 – the NBU's policy rate, %; X_4 – average quarterly wage (UAH), derived from the monthly records of the Pension Fund of Ukraine (PFU); *War2014* – dummy variable for the first quarter of 2014 (equal to 1 in Q1 2014, 0 otherwise); *War2022* – dummy variable for the first quarter of 2022 (equal to 1 in Q1 2022, 0 otherwise). The dataset covers the period from Q1 2006 to Q3 2025, comprising 79 observations.

For these variables, the Bayesian ARDL model can be expressed as follows:

$$Y_t = \alpha + \beta_1 \cdot Y_{t-1} + \gamma_1 \cdot X_{1,t-1} + \gamma_2 \cdot X_2 + \gamma_3 \cdot X_{2,t-4} + \gamma_4 \cdot X_{3,t-4} + \gamma_5 \cdot X_{4,t-4} + \delta_1 \cdot \text{War2014}_{t-2} + \delta_2 \cdot \text{War2022}_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma^2) \quad (5)$$

where: Y_{t-1} – lagged dependent variable, reflecting the sector's dynamic inertia; $X_{1,t-1}$ – the real GDP growth rate compared to the same quarter of the previous year with a 1-quarter lag; $X_{2,t-4}$ – consumer price index with a 4-quarter lag; $X_{3,t-4}$ – the NBU policy rate with a 4-quarter lag; $X_{4,t-4}$ – the quarterly average wage (UAH) with a 4-quarter lag; War2014_{t-2} – the dummy variable for the first quarter of 2014 with a 2-quarter lag; War2022_{t-1} – the dummy variable for the first quarter of 2022 with a 1-quarter lag; α – constant term; γ_i – coefficients of influence; δ_s – coefficients of dummy variables capturing war shocks; ε_t – random error term.

The Bayesian ARDL model confirms the presence of inertia in the dynamics of NPLs within Ukraine's banking sector, as well as the significant influence of key macroeconomic factors in the short- and medium term. Variations in economic growth rates, inflationary pressures, monetary conditions, and average quarterly wages are associated with corresponding changes in the NPL ratio. The military shocks in 2014 and 2022, along with their respective lagged effects, reflect profound structural shifts in the functioning of the banking sector. The model further highlights the high sensitivity of credit portfolio quality to macroeconomic instability and wartime shocks. Collectively, the evidence demonstrates not only the adaptive capacity and resilience of the banking sector amid the War for Independence of Ukraine, but also its ability to progressively align regulatory approaches with European practices.

To ensure the adequacy of the posterior distributions, all independent variables were assessed for multicollinearity, stationarity, residual autocorrelation of first and higher order, and heteroscedasticity, while dummy variables were evaluated solely for statistical significance in the model. Potential multicollinearity among the explanatory variables Y_{t-1} , $X_{1,t-1}$, X_2 , $X_{2,t-4}$, $X_{3,t-4}$, and $X_{4,t-4}$ was assessed using the variance inflation factor (VIF). The corresponding VIF values were 1.859, 1.249, 1.483, 1.568, 1.968, and 1.858, respectively. These values indicate a sufficient degree of independence among the explanatory variables and support stability of the coefficient estimates, ensuring the reliability of the Bayesian ARDL model results.

Stationarity of Y_{t-1} , $X_{1,t-1}$, X_2 , $X_{2,t-4}$, $X_{3,t-4}$, and $X_{4,t-4}$ was tested using the Augmented Dickey-Fuller (ADF) and KPSS tests. The ADF results indicate that Y_{t-1} (ADF = -1.3851, $p = 0.826$), $X_{1,t-1}$ (ADF = -3.241, $p = 0.088$), X_2 (ADF = -2.514, $p = 0.366$), $X_{2,t-4}$ (ADF = -2.3771, $p = 0.422$), and $X_{4,t-4}$ (ADF = -0.246, $p = 0.99$) are non-stationary, whereas $X_{3,t-4}$ (ADF = -4.391, $p = 0.01$) is stationary. KPSS test results corroborate these findings, with Y_{t-1} and $X_{4,t-4}$ exceeding critical values at all conventional significance levels, confirming their non-stationarity, while the remaining variables are stationary. The model's dynamic structure, combined with the Bayesian estimation approach, mitigates potential risks from non-stationarity series, ensuring stable and reliable coefficient estimates.

First-order residual autocorrelation was assessed using the Durbin-Watson test (DW = 2.034, $p = 0.345$), indicating no systematic dependence between consecutive residuals. To examine potential higher-order autocorrelation, the Breusch-Godfrey test (LM = 4.824, $df = 4$, $p = 0.306$) was applied, revealing no statistically significant evidence of autocorrelation. The Wald test ($F = 941.71$, $p < 2.2E-16$) confirmed the set of explanatory variables Y_{t-1} , $X_{1,t-1}$, X_2 , $X_{2,t-4}$, $X_{3,t-4}$, and $X_{4,t-4}$ has a statistically significant effect on the dependent variable Y , supporting the inclusion of lagged terms in the model.

The Breusch-Pagan test indicated the presence of heteroscedasticity in the residuals (BP = 20.382, $df = 8$, p -value = 0.009). This supports the use of the Bayesian framework and modelling, which accommodates the stochastic nature of variance. Overall, the diagnostic results support the inclusion of lagged predictors. The identified non-stationarity of most variables, the absence of first-order autocorrelation, and the presence of heteroscedasticity align with the characteristics of dynamic financial time series and are appropriately addressed in the Bayesian model specification.

Weakly informative prior distributions were employed to specify the model parameters, mitigating excessive complexity and ensuring stable estimates. Regression coefficients (β_j , γ_{jk} , δ_{sh}) and intercept term α were assigned normal priors with the following specifications: $\alpha \sim \text{Normal}(-15, 10)$, $\beta_1 \sim \text{Normal}(0.97, 0.05)$, $\gamma_1 \sim \text{Normal}(-0.08, 0.05)$, $\gamma_2 \sim \text{Normal}(-0.19, 0.1)$, $\gamma_3 \sim \text{Normal}(0.36, 0.1)$, $\gamma_4 \sim \text{Normal}(0.1, 0.05)$, $\gamma_5 \sim \text{Normal}(-0.0005, 0.0002)$, $\delta_1 \sim \text{Normal}(2.39, 1.0)$, $\delta_2 \sim \text{Normal}(3.11, 1.2)$. Residual heteroscedasticity was accounted for specifying a robust Student-t prior for the standard deviation ($\sigma \sim \text{Student}_t(3, 0, 5)$). This specification allowed for data uncertainty, supported the stability and reliability of posterior estimates, and facilitated the appropriate interpretation of econometric effects within the Bayesian framework.

The Bayesian estimation was conducted using four independent Markov Chain Monte Carlo (MCMC) chains, each with 50,000 iterations, of which the first

5,000 serves as the warm-up phase. Following the warm-up, 45,000 post-warm-up samples per chain were retained without thinning (thin = 1), yielding a total of 180,000 samples for constructing the posterior distribution.

The Bayesian ARDL model produces high-quality posterior estimates and demonstrates robust reliability (Table 1). The Rhat convergence diagnostic equals 1 for all model parameters, and the effective sample size (n_{eff}) is substantial (103,000–194,000), confirming convergence of the chains and stability of the resulting estimates. The posterior estimates of the coefficients β_j , γ_{jk} , and δ_{sh} lie entirely within the credible intervals without crossing zero. The estimated value of σ indicates a moderate level of unexplained variability in the dynamics of the NPL ratio in Ukraine's banking sector. The model adequately captures the primary determinants, accounts for the lagged effects of two shocks associated with the War for Independence of Ukraine, and leaves room for other shocks, including regulatory changes, commercial bank insolvencies, and other extraordinary events.

Table 1

Bayesian posterior estimates and convergence diagnostics of the model

Parameter	Posterior Mean	SE Mean	Posterior SD	Quantile			Effective Sample Size (n_{eff})	Rhat
				2.5 th	Median	97.5 th		
α	-20.903	0.0144	4.994	-30.639	-20.935	-11.052	121054	1.00
$\square_{t-1} Y_{t-1}$	0.978	0.0000	0.017	0.944	0.978	1.013	174034	1.00
$\gamma_{t-1} X_{1,t-1}$	-0.110	0.0001	0.022	-0.153	-0.110	-0.067	175152	1.00
$\gamma_{2-1} X_{2,t-1}$	-0.158	0.0001	0.0480	-0.252	-0.158	-0.064	120212	1.00
$\gamma_{3-1} X_{3,t-1}$	0.366	0.0001	0.0484	0.271	0.366	0.460	119584	1.00
$\gamma_{4-1} X_{4,t-1}$	0.106	0.0001	0.0352	0.037	0.106	0.175	161265	1.00
$\gamma_{5-1} X_{5,t-1}$	-0.0002	0.0000	0.0001	-0.0003	-0.0002	-0.0001	186372	1.00
$\delta_{t-1} \text{War}2014_{t-2}$	2.186	0.0020	0.8898	0.438	2.186	3.934	193978	1.00
$\delta_{2-1} \text{War}2022_{t-1}$	2.658	0.0024	1.0351	0.637	2.656	4.691	190222	1.00
sigma	1.902	0.0004	0.164	1.613	1.890	2.256	165415	1.00
Bayesian R²	0.9852	0.0000	0.0008	0.9832	0.9853	0.9862	103259	1.00

Source: authors' calculations based on data from the State Statistics Service of Ukraine (n.d.-a,b,c), Pension Fund of Ukraine (n.d.), the National Bank of Ukraine (n.d.-a,b,c), and the Ministry of Economic Development, Trade and Agriculture of Ukraine (2019).

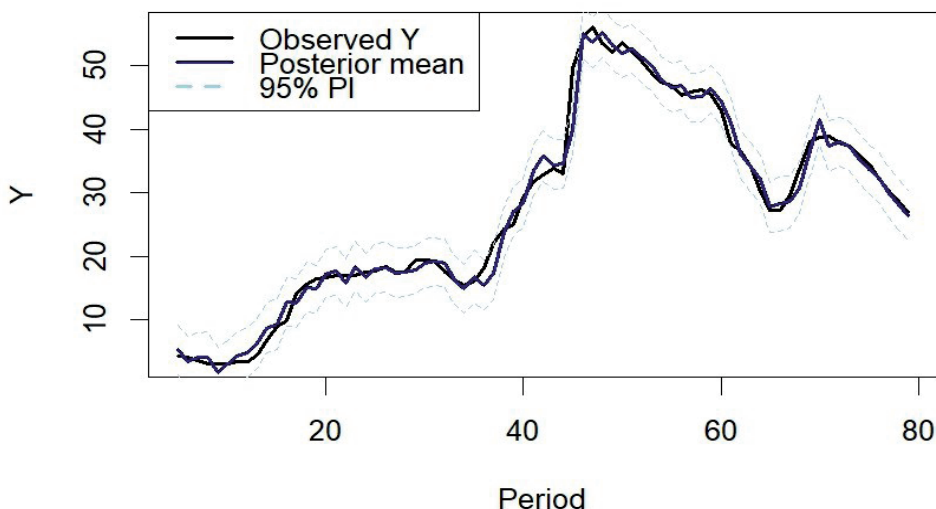
Additional diagnostics of posterior estimates further confirm the high adequacy of the Bayesian ARDL model. Low standard error of the mean posterior distribution (Se Mean) were observed for all parameters (Table 1). This indicates high precision in estimating the mean values of the coefficients of all explanatory variables, the intercept α , and the residual standard deviation δ , as well as good MCMC convergence. Model adequacy was additionally evaluated using the Bayesian

p-value, which was 0.4963, very close to the theoretically expected value of 0.5. This suggests that the model can accurately reproduce the variance of the observed data without systematic deviations between the actual and predicted values.

A comparison of observed and model-reproduced values (Figure 1) shows that the Bayesian ARDL model effectively captures the dynamics of NPLs in Ukraine's banking sector over Q1 2006–Q3 2025. Between the 40th and 45th observations, corresponding to Q4 2015–Q1 2017, pronounced structural shifts in NPL dynamics are observed. This period coincides with the implementation of large-scale banking reforms designed to strengthen financial stability, restore confidence in commercial banks, and harmonise regulatory and operational standards with EU practices. These insights underscore the suitability of the Bayesian ARDL model for assessing the adaptive capacity and resilience of Ukraine's banking sector under the impact of two major military shocks.

Figure 1

Observed and posterior-predicted NPL ratios in Ukraine's banking sector with 95% predictive uncertainty bounds



Note: The first observation corresponds to Q1 2006, while the 79th observation corresponds to Q3 2025.

Source: Authors' calculations based on data from the State Statistics Service of Ukraine (n.d.-a,b,c), Pension Fund of Ukraine (n.d.), the National Bank of Ukraine (n.d.-a,b,c), and the Ministry of Economic Development, Trade and Agriculture of Ukraine (2019).

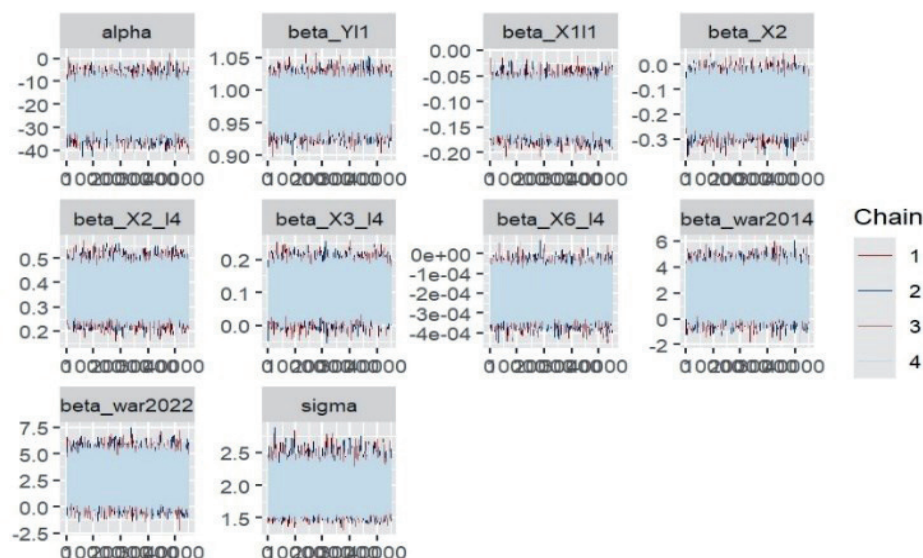
The LOO-CV analysis, based on a 180000×75 log-likelihood matrix, yielded the expected log-predictive density (elpd_loo) of −164.0 (SE = 19.9). The effective number of model parameters (p_loo) was 15.5 (SE = 10.1), and the LOO

information criterion (LOOIC) was 327.9 (SE = 39.8). These results demonstrate the high reliability and adequacy of the Bayesian ARDL model. The model exhibit strong predictive performance for out-of-sample observations without evidence of overfitting, confirming its suitability for analysing NPL dynamics in the banking sector of Ukraine amid the War for Independence of Ukraine and gradual alignment with EU regulatory standards.

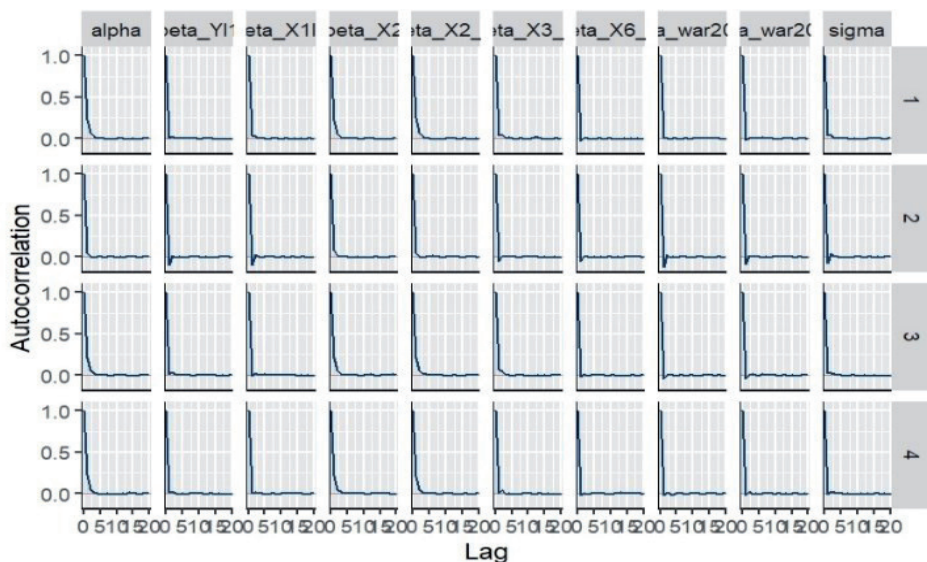
Pareto k-diagnostics show that 74 of 75 observations (98.7%) fall within the “good” range ($k \leq 0.7$), while a single observation has a high value ($k = 1.317$). Given that this represents only one observation out of 75, it is likely to reflect a structural shock. This observation corresponds to Q1 2016, a period of intensive banking sector reforms in Ukraine and gradual macroeconomic adjustment following the onset of the War for Independence of Ukraine, the annexation of Crimea, and the temporary occupation of parts of the Donetsk and Luhansk regions. Owing to the large sample size and the context of the event, this does not pose a critical concern but should be considered when interpreting the results. Consequently, the Bayesian ARDL model successfully captures the main structure of the data-generating process, provides accurate predictions, offers a realistic representation of residual uncertainty while appropriately flagging influential observations.

Figure 2

Trace and autocorrelation plots of posterior samples for Bayesian ARDL parameters



(a)



(b)

Note: $\beta_{Y1} = \square_{1,t-1}$; $\beta_{X1} = \gamma_{1,t-1}$; $\beta_{X2} = \gamma_{2,t-1}$; $\beta_{X3} = \gamma_{3,t-1}$; $\beta_{X6} = \gamma_{6,t-1}$; $\beta_{war2014} = \delta_{1,t-1}$; $\beta_{war2022} = \delta_{1,t-1}$.

Source: Authors' calculations based on data from the State Statistics Service of Ukraine (n.d.-a,b,c), Pension Fund of Ukraine (n.d.), the National Bank of Ukraine (n.d.-a,b,c), and the Ministry of Economic Development, Trade and Agriculture of Ukraine (2019).

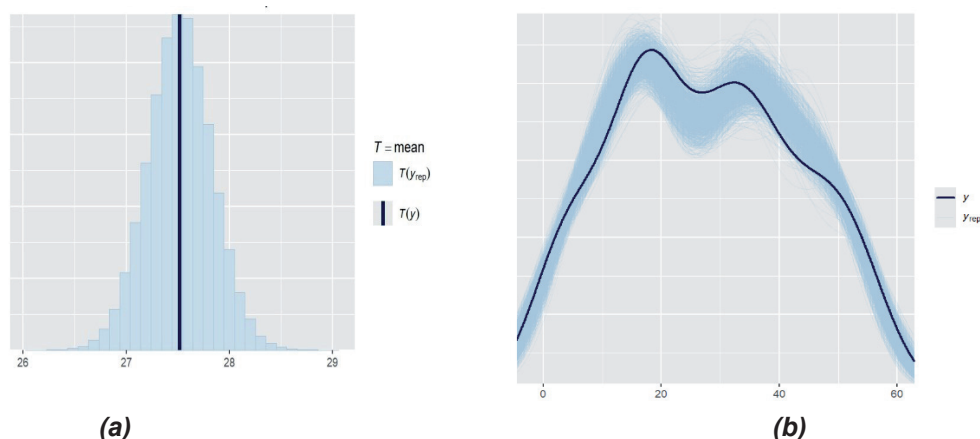
For each parameter of the Bayesian ARDL model, the MCMC trace plots (Figure 2a) exhibit good mixing, with no signs of stagnation or slow exploration of the parameter space. Figure 2a shows the convergence of four independent chains for each parameter which are closely superimposed and display no discernible trends. Parameter values fluctuate around stable means without directional drift, indicating stable posterior estimates. Autocorrelation diagnostics (Figure 2b) reveal a rapid decay at the first few lags for all parameters. These results confirm the reliability of MCMC samples and support valid inference regarding the posterior distributions. The favourable behaviour of the chains enables a robust assessment of both short- and long-run effects of the explanatory variables on NPL dynamics in Ukraine's banking sector, while explicitly accounting for the lagged impacts of the 2014 and 2022 military shocks.

The Posterior Predictive Check (PPC), based on a comparison of the test statistic $T(y) = \text{mean}$ with the distribution of replicated means $T(Y_{rep})$, indicates that the Bayesian ARDL model adequately reproduces the mean of the observed data (Figure 3a). The PPC results show that the estimated density of the observed data lies well within the cloud of densities generated from 1,000 posterior predictive simulations of Y_{rep} , confirming the model's ability to capture the overall distribution, its central tendency, and residual variability (Figure 3b). The combined analysis of both plots indicates that the model has high predictive accuracy and is well suited for describing the underlying data-generating process.

The mean absolute error (MAE = 1.222) indicates a small deviation of the Bayesian ARDL model forecasts from observed values. The root mean square error (RMSE = 1.7974) reflects the typical magnitude of forecast errors, with larger deviations having a disproportionately greater influence on the estimated indicator. The mean absolute percentage error (MAPE = 7.55%) demonstrates the relatively high accuracy of the model's predictions. Taken together, these metrics indicate an acceptable level of accuracy in reproducing variation in the dependent variable and confirm the model's effectiveness for analysing the dynamics of NPL ratio in Ukraine's banking sector.

Figure 3

Posterior predictive density check and test statistic comparison



Source: Authors' calculations based on data from the State Statistics Service of Ukraine (n.d.-a,b,c), Pension Fund of Ukraine (n.d.), the National Bank of Ukraine (n.d.-a,b,c), and the Ministry of Economic Development, Trade and Agriculture of Ukraine (2019).

The economic interpretation of the Bayesian ARDL model is as follows. With a probability of 98.52%, it can be stated that the dynamics of the NPL ratio in Ukraine's banking sector are driven by the macroeconomic indicators included in the model and by two military shocks with their respective lags (Table 1). The median R^2 value (0.9853), which is close to the mean value, confirms the stability of the estimates, the appropriateness of the selected lag structure of the Bayesian ARDL specification, and the relevance of all included variables.

The dominant role of inertia in the formation of NPLs in Ukraine's banking sector is confirmed by the posterior coefficient of the lagged variable Y_{t-1} , which approaches unity (Table 1). Specifically, a 1% increase in the NPL ratio in the previous quarter is associated, on average, with a 0.9784% increase in the current quarter. The loan portfolios of commercial banks adjust slowly to changes in the macroeconomic environment and war-related shocks. The quarterly speed of convergence towards equilibrium ($1 - \beta \approx 0.0216$) is relatively low, which may be explained by prolonged

enforcement procedures, low collateral liquidity, high litigation risks, and delayed restoration of banking sector integrity following territorial losses. The presence of a single quarterly lag further implies that the dynamics of NPLs are largely predictable for Ukraine's banking sector, a feature of particular relevance for Ukraine's integration into the EU financial framework. As Ari et al. (2021) note, the NPL accumulation occurs gradually, whereas their reduction is characterised by inertia and takes a prolonged period.

Simultaneously, real GDP growth creates conditions conducive to a short-term reduction in the NPL ratio (Table 1). Specifically, a 1% increase in real GDP is associated, on average, with a 0.1103% decrease in the NPL ratio in the subsequent quarter. The recovery of economic growth in Ukraine has a positive effect on borrowers' solvency and reduces the likelihood of an increase in the NPL ratio in the banking sector. This underscores the importance of macroeconomic policy initiatives that foster economic growth, ensure the resilience of the country's banking sector, and enhance its capacity to adapt to the effects of military and other macroeconomic shocks.

On the one hand, a 1% increase in the current CPI is associated, on average, with a 0.1578% reduction in the NPL ratio in the same quarter. This effect can be explained by the fact that, over a short time horizon, inflation contributes to the stabilisation of banks' loan portfolios through the behaviour of commercial banks, which adjust lending rates in response to changes in price dynamics and the conditions created by monetary policy measures, which indirectly support bank liquidity and borrowers' solvency. On the other hand, a 1% increase in the CPI four quarters earlier corresponds, on average, to a 0.3655% rise in the NPL ratio. Thus, a decline in the real purchasing power of households and businesses leads to difficulties in servicing loans approximately one year after the occurrence of an inflationary shock.

Furthermore, an 1% increase in the NBU policy rate leads, on average, to a 0.1058% rise in the share of NPLs after approximately one year. This result reflects that the standard monetary policy transmission mechanism associated with an increase in the policy rate raises borrowing costs and, consequently, creates additional pressure on borrowers' debt burden. The effect manifests itself with a time lag, which is characteristic of credit markets, where borrower behaviour exhibits significant inertia. Consequently, anti-inflationary monetary policy measures indirectly affect borrowers' debt burden and gradually increase in NPL ratio in Ukraine's banking sector.

In parallel, the results the Bayesian ARDL model indicate that a one-hryvnia increase in the average quarterly wage four quarters earlier is associated with an average reduction of 0.0002% in the NPL ratio in the current quarter. Although the magnitude of this effect is small, it reflects a delayed positive influence of household income on borrowers' ability to service loans. Rising wages gradually improve households' financial position and, over time, contribute to a reduction in the NPL ratio in the banks' loans portfolios.

Meanwhile, the coefficient for War2014_{t-2} indicates that the effects of the first military aggression by the Russian Federation materialised with a two-quarter lag, raising the average share of NPLs in Ukraine's banking sector by 2.1861%. In contrast, the coefficient for War2022_{t-1} shows that the full-scale invasion led to an average increase of 2.6575% in the share of NPLs with a one-quarter lag. The

stronger impact of the 2022 shock reflects the widespread destruction of enterprises, suspension of business operations, loss of household income due to internal and external migration, and the rapid occupation of parts of Ukrainian territory. Both coefficients are the largest among all model parameters, underscoring the critical role of war-related shocks in shaping the dynamics of NPLs. The 2014 shock exhibited a prolonged effect, consistent with the gradual adaptation of the regulatory environment, whereas the 2022 shock manifested rapidly, reflecting the immediate realisation of systemic risks and highlighting both the high inertia of the banking sector and the cumulative impact of exogenous shocks.

The intercept term (α) is negative (Table 1), indicating a systematically lower baseline level of NPLs when the lagged dependent variable and all predictors are held constant. This may reflect the structural characteristics of the development of Ukraine's banking sector under the influence of institutional transformations, military shocks, monetary policy interventions, and borrower solvency. The results of the Bayesian ARDL model indicate a high level of latent financial stress embedded in the system, even under neutral macroeconomic conditions.

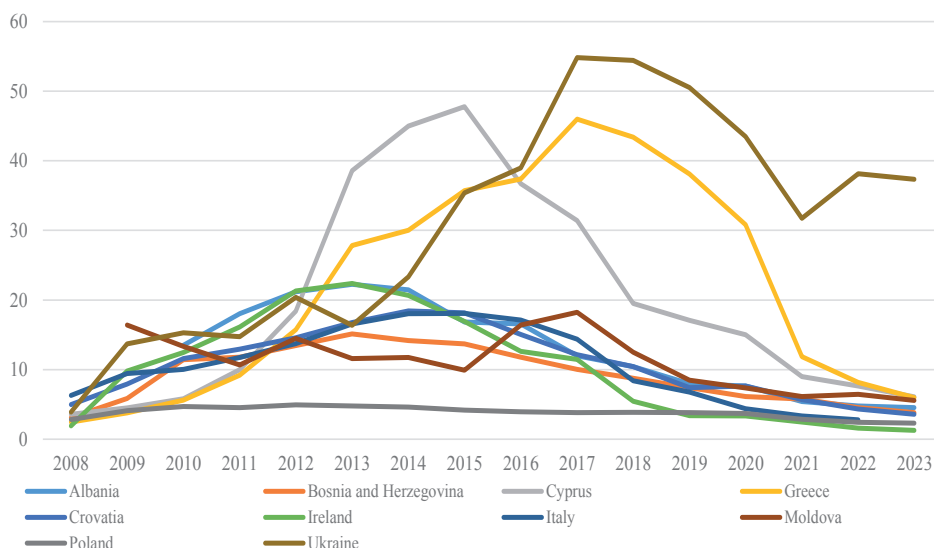
A comparative analysis of the dynamics of the NPL ratio in Ukraine and selected European countries with the highest values of this indicator, based on the World Bank methodology (Fig. 4), shows that Ukraine not only recorded a higher NPL ratio than the countries considered but also exhibited substantially greater volatility. During the period 2008–2013, the trajectory of the NPL ratio in Ukraine broadly followed the pattern of post-crisis accumulation of NPLs observed after the 2008–2009 global financial and economic crisis, also evident in Central and South-Eastern European countries. In contrast, from 2014 onwards, Ukraine experienced a marked acceleration in the growth of the NPL ratio, which remained persistently higher than in other European countries considered. By comparison, these countries generally recorded a relatively steady downward trend in NPL ratios after 2014, supported by banking sector stabilisation measures and an overall more favourable macroeconomic environment.

Meanwhile, the dynamics of NPLs in Greece and Cyprus exhibit distinct trajectories shaped by the legacy of the sovereign debt crisis, structural imbalances in the banking sector, and a pronounced deterioration in the financial system's liquidity. In contrast to Ukraine, both countries recorded a sustained downward trend in NPL ratios after 2017–2018, driven by the implementation of financial stabilisation programmes, the clean-up of bank balance sheets, securitisation of non-performing assets, and support from EU institutions. A comparison of the results with the experience of Greece and Cyprus confirms that high NPL persistence and the dominance of macroeconomic determinants are characteristic features of banking systems undergoing crises within the process of integration into the EU financial area (Louzis et al., 2012; Anastasiou et al., 2019; Laeven & Valencia, 2020; Ari et al., 2021; Karadima & Louri, 2021). At the same time, Greece's positive experience in reducing the NPL ratio from approximately 49% in 2016–2017 to around 6.6% by the end of 2023 through institutional reforms (the implementation of HAPS securitisation schemes, bankruptcy reform, and the strengthening creditor rights) (Bank of Greece, 2024), together with Cyprus's successful restructuring of loan portfolios through specialised credit servicers (Christodoulou-Volos, 2024), provides a practical benchmark for Ukraine's post-war recovery, where a comparable institutional framework is currently being developed. The comparative analysis suggests that NPL dynamics in Ukraine

have been shaped not only by macroeconomic shocks but also by elevated military risks, resulting in slower banking sector recovery and a more gradual adaptation to EU regulatory standards under conditions of macroeconomic and security instability.

Figure 4

Dynamics of NPLs in Ukraine and selected European countries, as a percentage of total gross loans



Source: World Bank. (n.d.)

Despite the absence of a formally established threshold for the NPL ratio in the banking sector of the EU countries, supervisory practice developed by the European Banking Authority suggests that an NPL ratio above 5% may signal emerging sectoral vulnerabilities and the need for enhanced monitoring and early intervention (European Banking Authority, 2018). In the academic literature, higher NPL levels, particularly those reaching double-digit values, are commonly associated with systemic banking instability and episodes of financial crisis (Laeven & Valencia, 2020; Ari et al., 2021). Accordingly, as of 2023, the NPL ratio in all the European countries analysed, unlike in Ukraine, had declined to below the 10% level, ranging from 1.2% in Ireland to 6.1% in Cyprus (Fig. 4). This pattern reflects the continued recovery and stabilisation of the banking sectors across the analysed European economies. In the context of Ukraine's banking sector integration into the EU, the downward trend in the NPL ratio after 2022 signals increased banking sector resilience and reflects the effectiveness of NBU's measures aimed at mitigating the adverse effects of the full-scale invasion. At the same time, the Bayesian ARDL model indicates that policy initiatives to enhance borrowers' solvency, foster economic growth, and maintain a low-inflation environment would be conducive to post-war economic recovery.

Conclusions

To sum up, the impact of the macroeconomic environment on the quality credit portfolios in Ukraine's banking sector was comprehensively assessed under conditions of severe war-related shocks and ongoing European integration reforms. The results of the Bayesian ARDL model confirmed the hypothesis of pronounced persistence in the NPL ratio, reflecting both the complexity of the institutional environment and the specific features of bank balance sheet adjustment during periods of heightened uncertainty. The use of the Bayesian methodology enabled more accurate probabilistic estimation of parameters during the critical episodes of 2014 and 2022, when extreme volatility reduced the effectiveness of conventional econometric techniques. The analysis quantitatively differentiates the effects of two waves of war-related shocks, demonstrating a gradual manifestation of the first shock and the rapid realisation of systemic risks during the second. These findings indicate a transformation in the adaptive mechanisms of Ukraine's banking sector. Furthermore, the study established the nature of the lagged responses of credit risk to changes in real GDP and inflation.

The theoretical significance of the findings lies in advancing the conceptual understanding of banking sector resilience under conditions of martial law. The research extends the financial stability literature by showing that harmonisation with EU regulatory standards serves not only as an institutional requirement but also as a strategic regulatory anchor, enabling system parameters to remain within predictable bounds even amid extreme exogenous shocks. The proposed model further illustrates how the integration of European supervisory practices shapes banks' response to crises, thereby enhancing overall sectoral resilience.

The practical implications of the findings highlight the need to align macroeconomic stabilisation policies with proactive banking supervision as elements of an integrated macro-financial strategy. Supporting sustainable economic growth and ensuring price stability provide the fundamental conditions for containing the accumulation of NPLs in the medium term. At the same time, the identified persistence in NPL dynamics underscores the need to establish a system of preventive prudential buffers and to consistently improve the regulatory architecture in line with EU standards.

In the short term, the findings point to the important role of crisis-oriented measures aimed at preventing abrupt deterioration in asset quality during macro-financial shocks. Such measures include ensuring banking sector liquidity, the flexible application of temporary regulatory relief, and targeted supervisory tools. The observed lagged effects of inflation and the policy rate suggest that monetary tightening may temporarily elevate credit risk, necessitating compensatory supervisory actions.

In the long term, the results are pertinent to Ukraine's post-war recovery and institutional integration into the EU financial environment. The pronounced inertia of NPLs underscores the need for structural reforms, including the development of a distressed asset market, the strengthening of insolvency frameworks, and the establishment of a sustainable system of regulatory convergence to mitigate systemic credit risk in the post-war period.

The limitations of the study include the reliance on aggregated banking sector data, which precludes capturing the heterogeneity of individual banks and credit segments. Additionally, the use of binary variables to identify war-induced shocks does not fully reflect the spatial and temporal escalation of hostilities. Further research could extend the model by incorporating currency risks, the sectoral composition of lending, and nonlinear or regime-switching modelling approaches.

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Received: January 5, 2026.

Reviewed: July 15, 2026.

Accepted: August 28, 2026.