

Article

Macroeconomic Shocks, Credit-Risk Persistence, and the Limits of Nonlinear Transmission in Emerging Europe

Ivana Miklošević ^{1,*} , Andreja Todorović ²  and Andrija Popović ² ¹ Department of Economics, University of Slavonski Brod, Ulica 108, Brigade ZNG 36, 35000 Slavonski Brod, Croatia² Innovation Center, University of Niš, Univerzitetski Trg 2, 18000 Niš, Serbia; andrejatod@gmail.com (A.T.); andrija.m.popovic@gmail.com (A.P.)

* Correspondence: imiklosevic@unisb.hr

Abstract

This paper examines how economic downturns and currency movements affect the quality of bank loans in Central, Eastern, and Southeastern Europe, using annual data for 14 national banking systems over 2008–2023. We estimate a bias-corrected dynamic fixed-effects model, verify inference with Driscoll–Kraay, cluster-robust, and wild cluster bootstrap procedures, run formal threshold tests, and conduct scenario simulations. Credit risk is highly persistent. The bias-corrected autoregressive coefficient of 0.944 implies a half-life of 12.0 years, although the bootstrap confidence interval of 0.601 to 1.048 does not rule out near-unit-root behavior. Exchange-rate depreciation predicts higher non-performing loan (NPL) ratios and survives both the strictest few-cluster test ($p = 0.028$) and a correction for euro-adoption breaks, while lower real GDP per capita growth is marginal under the same test ($p = 0.060$). Threshold tests that re-estimate the threshold in every bootstrap replication do not reject linearity in any of 14 configurations (minimum p -value of 0.071). Institutional quality does not measurably moderate the exchange-rate channel. A severe combined adverse scenario raises the projected NPL ratio from 6.54 to 12.32 percent over five years (90 percent interval: 8.2 to 24.6 percent). Together, the surviving channels and the disciplined null results delimit nonlinear transmission in emerging Europe.

Keywords: non-performing loans; banking-sector credit risk; institutional quality; exchange-rate depreciation; dynamic panel; threshold model; CESEE; credit-risk persistence

JEL Classification: G21; C23; E44; F31; O43



Academic Editors: John Malindretos, Giuliana Andreopoulos, Eleftherios Thalassinou and Ana Cristina Siqueira

Received: 5 June 2026

Revised: 22 July 2026

Accepted: 29 July 2026

Published: 1 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Banking-sector credit risk is one of the key ways through which macroeconomic shocks are passed down and create financial instability. When the economy enters a recession, contracting economic activity and an increased real cost of borrowing greatly reduce the ability of companies and households to service debt obligations. Significant depreciation can magnify this effect in countries that have direct or indirect foreign-currency exposure. Non-performing loans (NPLs) under these conditions decrease profitability and reduce the availability of new credit, and support a self-reinforcing dynamic of financial fragility and macroeconomic weakness (Beck et al., 2015; Huljak et al., 2022; Jakubík & Reininger, 2014; Klein, 2013). These dynamics are especially serious in Central, Eastern, and Southeastern Europe (CESEE), where banking systems are operating in an environment with uneven institutional conditions, recurrent external shocks, and a high cross-country variation in

the dynamics of credit and post-crisis adjustment (Ćurak et al., 2013; Škarica, 2014; Tătărici et al., 2020).

The choice of CESEE as the regional focus of this paper is therefore not incidental. Banking sectors in this region have been impacted by the combination of several shocks over the past few years: the global financial crisis, government debt crises, the sudden exchange-rate adjustments, the economic disruption triggered by the COVID-19 pandemic, and a cycle of inflation and money-supply tightening. Yet these shocks did not have the same consequences in observed CESEE countries. In some cases, the quality of loans deteriorated rapidly, and the impact was long-lasting, while in others, similar stress was absorbed through more limited increases in non-performing loans. That cross-country heterogeneity suggests that transmission of adverse shocks to credit risk is not only dependent on the shocks, but also on the structural and institutional conditions in which they occur (Bayar, 2019; Lee et al., 2019; Tanasković & Jandrić, 2015).

This study is motivated by an important gap in the regional non-performing loans literature. The majority of the existing research identifies average macroeconomic or banking-sector determinants of credit risk, but, at the same time, leaves three issues insufficiently explored. The treatment of institutional quality is one. In most CESEE studies, governance variables either do not appear or are used as additive controls (Erdoğan & Abazi, 2014; Klein, 2013; Škarica, 2014; Szarowská, 2018). Nevertheless, institutional quality should matter, not because it correlates with financial development in cross-section, but because it may alter the rate at which adverse shocks pass through to credit risk. A stricter rule of law and more effective regulation should improve supervisory responsiveness, restructuring capacity, and the credibility of financial intermediation (Beirne & Panthi, 2022; Goyal et al., 2023; Lee et al., 2019). The few CESEE studies that include institutional variables, such as Tanasković and Jandrić (2015), Bayar (2019), Shala et al. (2022), and Tătărici et al. (2020), do not test whether institutions condition the slope of shock transmission. It is this distinction that makes a fundamental part of our research design.

The functional form is another underexplored issue, as the vast majority of evidence at the regional level is based on linear specifications (Bardhan et al., 2019; Bolarinwa et al., 2021; Pop et al., 2018). Under the conditions of already weak profitability in the banking sector, a moderate macroeconomic worsening may trigger a more disproportionate response in an increase in credit risk than it would in a more resilient environment. Detecting this possibility requires formal threshold tests. Despite mounting evidence of state-dependent banking vulnerabilities in other countries, such tests remain rare in CESEE research on non-performing loans.

Beyond these empirical issues, there is an issue of interpretation. Policymakers and institutions operate outside the coefficient space, and are not concerned with it. Any moderate one-time shock to a highly persistent system can cumulate and compound over a few years. Papers that stop at reporting signs and significance leave part of the policy-relevant story untold.

This paper answers these issues within an integrated framework. We construct an annual country-level panel for 14 CESEE and comparator banking systems from 2008 to 2023, and lag construction is based on the entire 2007-to-2024 window of source data. Banking-sector credit risk is implemented as a logit model. A dynamic-panel model with year and country fixed effects is considered the baseline specification, which is estimated using a bias-corrected fixed-effects (BC-FE) estimator with block-bootstrap inference. We also add to that specification Driscoll–Kraay and cluster-robust standard errors, a threshold specification using lagged profitability, and a scenario module that transforms the estimated sensitivities into modeled credit-risk paths. The design also has a clear correction of the

exchange-rate series around years of euro-adoption, which is necessary because raw data may generate artificial values of depreciation that would pollute the estimated FX channel.

The paper makes four contributions. First, it quantifies the persistence of banking-sector credit risk with honest uncertainty, reporting bias-corrected point estimates together with bootstrap intervals, split-panel jackknife sensitivity, and panel unit-root evidence that place the region at the boundary of the unit-root region. Second, it identifies real income growth and exchange-rate depreciation as the transmission channels that survive a demanding verification program, including an explicit correction of euro-adoption breaks in the exchange-rate series, leave-one-out sampling, and restricted wild cluster bootstrap inference designed for a panel of 14 clusters. Third, instead of taking institutional quality as a passive control, it tests whether institutions condition the pass-through of exchange-rate shocks, at the composite level and dimension by dimension, and reports a disciplined null result. Fourth, it subjects the threshold narrative that is gaining ground in this literature to formal testing with a bootstrap that re-estimates the threshold in every replication, and finds that no profitability, liquidity, capital, or institutional cutoff survives corrected inference, a caution with direct implications for earlier regional threshold estimates. A scenario module then translates the surviving coefficients into projected credit-risk paths with explicit uncertainty bands.

The analysis yields the following empirical patterns. The credit risk in the banking sector is highly persistent, as it is evident from the bias-corrected autoregressive coefficient, exceeding 0.94, which implies a half-life of 12.02 years. Reduced real income growth and depreciation of the exchange rate are associated with significantly greater future credit risk, with the growth coefficient between -0.014 and -0.018 and the FX coefficient between 0.008 and 0.012 across estimators. Under a severely adverse combined scenario over the 5-year period, the ratio of non-performing loans grows to 12.32 percent, as compared to approximately 6.5 percent. Exchange-rate depreciation and institutional quality interaction fail to achieve standard levels of significance in the small panel, and the simple linear moderation of the FX channel is not conclusively found in this sample. This is a limitation that must be considered in the balance of the theoretical relevance of the institutional channel, and not simply viewed as an indication of its irrelevance. The threshold analysis does not reject the null of a fully linear specification once the bootstrap re-estimates the threshold in every replication, as the Hansen procedure requires (corrected bootstrap $p = 0.218$). Regime-specific coefficients are therefore reported as descriptive patterns, rather than established nonlinearities.

These results accentuate the international dimension of financial vulnerability. Exchange-rate shocks are a primary channel of international monetary and financial transmission (Beck et al., 2013, 2015). Their impact on the credit risk in the banking sector depends on the institutional environment of the receiving economy and the prevailing level of banking-sector resilience (Beck et al., 2013, 2015).

The rest of the paper is designed to present reviews of the related literature and develop the hypotheses, followed by the description of the data, variables, and empirical strategy. Further, the paper reports the baseline results and presents the nonlinear, robustness, and scenario evidence. Finally, in conclusion, we summarize the findings, discuss their implications for macro-prudential policy in the CESEE region, and note the limitations of the analysis.

2. Literature Review and Hypothesis Development

The literature that is relevant to this paper can be structured around the following four questions: what macroeconomic shocks are most closely linked to banking-sector credit risk? What does the CESEE evidence imply for this relationship? Do institutional quality

effects modify the transmission of shocks to credit quality? And are these effects stable across states of the world? The section ends with four hypotheses that relate directly to the empirical design.

2.1. Macroeconomic Determinants of Banking-Sector Credit Risk

The growth channel is one of the most consistent determinants of non-performing loans dynamics (Beck et al., 2013, 2015). Weaker real GDP growth leads to reduced household and corporate cash flows, a decline in the value of the collateral, and a higher probability of deterioration in performing exposures (Beck et al., 2015). This finding holds consistently across CESEE-specific panels (Jakubík & Reininger, 2014; Klein, 2013; Škarica, 2014), larger European samples (Lee et al., 2019; Makri et al., 2014; Sfakianakis et al., 2022), transition-economy research articles (Bilan & Roman, 2016; Ćurak et al., 2013; Mazreku et al., 2018), and global designs (Ayhan & Kartal, 2021; Beck et al., 2015). Some Western Balkan GMM studies show unusual positive signs for GDP-NPLs (Beka & Abazi-Alili, 2023; Gashi et al., 2022), which seem to reflect sample-specific endogeneity, rather than a real reversal of the repayment-capacity mechanism. Pandemic-era evidence reinforces the shock-transmission logic. Plikas et al. (2024) find that COVID-19 mortality and the stringency of lockdown measures raised NPL ratios across European subregions over 2015Q1 to 2021Q4, while economic support policies contained them, and profitable, well-capitalized banking systems fared better, a pattern directly relevant to a sample that spans the pandemic years.

The interest-rate channel is also well documented, but the estimates are more heterogeneous (Tătărici et al., 2020). An increase in real rates increases the cost of debt service and can accelerate the transition process from payment difficulty to outright impairment (Ćurak et al., 2013; Moinescu, 2012; Sfakianakis et al., 2022; Tătărici et al., 2020). The magnitude is generally less than the growth effect, and is dependent on the maturity structure of credit and the prevalence of floating-rate contracts (Jakubík & Reininger, 2014; Szarowská, 2018).

The exchange-rate channel is particularly outstanding in emerging and transition economies (Beck et al., 2015). Currency depreciation can negatively impact the quality of credit due to foreign currency mismatches, imported inflation, and tighter external financing (Beck et al., 2013, 2015). Beck et al. (2015) demonstrate that this effect is highly conditional upon the share of foreign-currency lending. Jakubík and Reininger (2014) affirm that FX-weighted depreciation is one of the notable predictors of non-performing loan developments in CESEE. Similar associations are reported by Tătărici et al. (2020) and Tanasković and Jandrić (2015). This channel is the focus of the current analysis, as it connects the vulnerability of domestic banking to the transmission of the problem to other countries.

A consistent pattern across the literature is the persistent nature of credit risk. Once the quality of assets declines, resolution tends to become a long process (Beck et al., 2015; Klein, 2013; Milenković et al., 2024; Moinescu, 2012). Huljak et al. (2022) go even further by demonstrating that high levels of non-performing loans hinder bank lending and real economic activity in the euro area, thereby reinforcing the macro-financial feedback loop. As a result, macroeconomic shocks not only increase current credit risk, but also interact with pre-existing weaknesses in the banking sector, and the deterioration that comes may take many years, and even decades. The strength of the feedback from impaired assets to credit supply is not uniform across the region, however. For the Polish banking sector, Tuncay and Grzegorzczak-Akin (2025) find in a VAR framework that credit rationing is not significantly driven by NPL-related risk, which they attribute to a low share of loans in total assets and the predominance of collateralized mortgage lending. Cross-country heterogeneity in this feedback is one more reason to model transmission with country fixed effects.

Banking-sector controls appear in this literature systematically. Better-capitalized and more profitable systems tend to be associated with less future credit risk, while aggressive credit expansion is often correlated with future credit deterioration (Ahmed et al., 2021; Bayar, 2019; Ciukaj & Kil, 2020; Kil et al., 2020). The relationship between profitability and credit risk also runs in both directions: in emerging banking systems, credit risk is itself a critical determinant of bank profitability, as Cangombe et al. (2025) document for Angola, using the dynamic-panel GMM, which is one reason the present design enters profitability only as a lagged, predetermined regressor. A parallel strand applies machine-learning early-warning models to credit risk: unemployment and inflation emerge as leading predictors for the United Kingdom in Sharma et al. (2024), and bank-level financial ratios outperform macroeconomic factors in short-horizon NPL forecasting in Gafsi (2025). These predictive designs complement, rather than substitute, the transmission-oriented econometric framework adopted here.

2.2. Emerging Europe and CESEE Evidence

Table 1 brings together the most important characteristics of 27 existing studies that are directly relevant to the empirical context, and is organized to point to the locations where the coverage is dense and where there is a lack of material.

Table 1. Selected empirical studies on NPL determinants in emerging Europe and comparator panels.

Study	Region	Period	Estimation	DV Form	GDP	IR	FX	Inst.	Threshold
Klein (2013)	CESEE	1998–2011	FE, Diff-GMM, Sys-GMM, PVAR	Ratio	(−)	.	(−)	.	No
Moinescu (2012)	10 CEE	2003–2011	Dynamic FE	Logit	(−)	(+)	(+)	.	No
Jakubík and Reininger (2014)	9 CESEE	2004–2012	Sys-GMM, FE	Ratio	(−)	(+)	(+)	.	No
Škarica (2014)	7 CEE	2007–2012	OLS-FE	Change	(−)	.	n.s.	.	No
Makri et al. (2014)	14 Eurozone	2000–2008	Diff-GMM	Ratio	(−)	.	.	.	No
Erdoğan and Abazi (2014)	20 emerging European	2000–2011	Sys-GMM, Diff-GMM	Log	(−)	(+)	n.s.	n.s.	No
Tanasković and Jandrić (2015)	CEEC/SEE	2006–2013	Static FE	Log	(−)	(−)	(+)	(−)	No
Beck et al. (2015)	75 countries	2000–2010	Diff-GMM, FE	Ratio	(−)	(+)	(+)	.	No
Çifter (2014)	10 CEE	2000–2009	Sys-GMM, IV, FMOLS	Ratio	(−)	.	(−)	n.s.	No
Bilan and Roman (2016)	11 CEE	2000–2013	FE (time + country)	Ratio	(−)	.	n.s.	.	No
Čurak et al. (2013)	8 SEE	2003–2010	GMM	Ratio	(−)	(+)	n.s.	.	No
Szarowska (2018)	11 CEE	1999–2015	Dynamic FE	Ratio	(−)	(+)	(−)	.	No
Mazreku et al. (2018)	10 transition	2006–2016	OLS, FE, RE, GMM	Ratio	(−)	.	.	.	No
Pop et al. (2018)	7 emerging European	2007–2016	PSTR	Ratio	.	(+)	.	.	Yes
Bayar (2019)	Emerging markets	2000–2013	Sys-GMM	Ratio	(−)	(+)	.	(−)	No
Lee et al. (2019)	28 EU	2007–2016	Sys-GMM	Ratio	(−)	(+)	.	(−)	No
Ciukaj and Kil (2020)	7 high-NPL EU	2011–2017	Static FE	Ratio	(−)	(+)	.	(+)	No
Kil et al. (2020)	CEE (EU)	2008–2017	Sys-GMM, RE	Ratio	(−)	.	.	.	No
Tătărici et al. (2020)	12 EEC	2005–2017	FE, Sys-GMM, BVAR	Logit	(−)	(+)	(+)	(−)	No

Table 1. Cont.

Study	Region	Period	Estimation	DV Form	GDP	IR	FX	Inst.	Threshold
Ristevska (2020)	5 SEE	2008–2017	Diff-GMM, DOLS, VECM	Ratio	(−)	(+)	.	.	No
Ayhan and Kartal (2021)	23 countries	2006–2018	AMG	Ratio	(−)	.	n.s.	.	No
Shala et al. (2022)	17 CEE	2006–2017	FE	Ratio	n.s.	.	.	(−)	No
Sfakianakis et al. (2022)	51 OECD/EU	2005–2020	Panel EGLS-FE	Ratio	(−)	(+)	n.s.	.	No
Bischof et al. (2022)	16 European	2007–2016	FE-OLS, RE-logit, DiD	Ratio	(−)	.	.	(−)	No
Milenković et al. (2024)	18 Eurozone	2015–2020	FE, PMG	Ratio	(−)	.	(+)	.	No
Tmava and Spahiu (2025)	6 Western Balkans	2012–2023	OLS, Sys-GMM	Ratio	(−)	(+)	.	.	No
This paper	14 CESEE	2008–2023	BC-FE, FE-DK, Threshold	Logit	(−)	(+)	(+)	n.s.	Yes

Notes: (−) = negative and significant; (+) = positive and significant; n.s. = tested but not significant; (.) = not tested or not reported. “DV form” denotes the transformation applied to the NPL ratio: Ratio = untransformed level; Log = natural logarithm; Logit = log-odds transformation; Change = first difference or growth rate. Column headers: “GDP” refers to a real GDP growth measure, “IR” to the real or nominal interest rate, and “FX” to an exchange-rate depreciation measure. “Inst.” refers to whether an institutional or governance variable was included and found significant. “Threshold” indicates whether a formal threshold or regime-switching test was conducted.

Three gaps are evident in the accumulated evidence. The majority of CESEE research studies either omit institutional variables entirely or include them as additive controls; only Tanasković and Jandrić (2015), Lee et al. (2019), Tătărici et al. (2020), Shala et al. (2022), Bayar (2019), and Erdinç and Abazi (2014) include institutional measures, and none test whether institutional quality conditions the slope of macroeconomic shock transmission. Of the studies reviewed, only Pop et al. (2018) use a formal threshold framework, and their threshold variable is bank-level liquidity, not system-level profitability. The vast majority of the studies model the NPL (non-performing loan) ratio in levels or logs, and only Moinescu (2012) and Tătărici et al. (2020) use the logit transformation that respects the bounded support of the variable. Taken together, the CESEE literature supports an empirical design organized around macroeconomic shocks, banking-sector resilience characteristics, and institutional conditions, while leaving unresolved whether institutions operate additively or as shock transmitters and whether transmission is state-dependent.

2.3. Institutional Quality, Enforcement, and Regulatory Transmission

For the purposes of this paper, institutional quality has been defined as the legal and regulatory environment in which macroeconomic stress is converted into banking outcomes: the quality of regulation, the enforceability of contracts, the credibility of the rule of law, and the predictability of the operating environment.

Tanasković and Jandrić (2015) show that institutional conditions still maintain explanatory power in addition to macroeconomic factors in a CEEC/SEE panel. Bayar (2019) finds that economic freedom indices are associated with lower non-performing loan ratios even after macro and bank-specific controls are included. Lee et al. (2019) associate certain WGI dimensions with non-performing loan outcomes in 28 EU countries. Goyal et al. (2023) document similar associations in the BRICS, and Abaidoo and Agyapong (2025) demonstrate that governance facilitates financial institution development in sub-Saharan Africa, and macroeconomic volatility acts as a negative moderator. Kanapickienė et al. (2023) find that institutional environment factors are risk-decreasing for consumer loan credit risk in 11 CEE economies.

Most of these studies, however, focus on whether institutions are important for the level of credit risk. The more important question is whether institutional quality affects the speed with which adverse shocks convert into banking outcomes. A better rule of law can help improve the enforcement of contracts and reduce strategic default. Similarly, improved regulation may improve the responsiveness of supervision and facilitate early intervention. Moreover, better insolvency frameworks can help resolve such cases more quickly rather than letting impaired assets pile up (Bischof et al., 2022; Zoller, 2023). Beirne and Panthi (2022), working with 12 Asian economies, find that high-quality institutions help to support macrofinancial resilience in times of stress, while the buffering effect disappears in countries with weaker governance. Kawalec (1999), in an earlier assessment of the transition-economy banking crisis, noted that institutional capacity for crisis resolution was a key differentiator between countries that stabilized quickly and those that did not.

An additive specification cannot test for the moderating effect of institutions on the transmission of shocks. What is needed is an interaction design in which the marginal effect of exchange-rate depreciation is allowed to vary with the level of institutional quality. That is the approach adopted in this paper.

2.4. Nonlinear and Threshold Dynamics

If the marginal impact of macroeconomic shocks is affected when the level of resilience in the banking sector falls below a critical level, a linear specification could underestimate the risk amplification precisely when financial stability is an issue of concern. The economic logic behind this is straightforward: low profitability means low capacity for a banking system to absorb deterioration, to provision without straining the balance sheet, and to resolve impaired assets in a timely manner. Under such conditions, a shock that in a high-profitability environment might be manageable can lead to a disproportionately large increase in non-performing loans.

Hansen (2000) gives the canonical framework of the threshold for panel data. Gong and Seo (2022) are an extension of the bootstrap treatment of dynamic-panel threshold models. In the non-performing loan literature, Pop et al. (2018) find a liquidity-based threshold in emerging European banks of around 0.95 for the loan-to-deposit ratio. Bardhan et al. (2019) find that capital adequacy has a nonlinear effect on impaired assets below 10–12 percent capital adequacy. Bolarinwa et al. (2021) report thresholds in the NPL-profitability relationship of 3.5 percent ROAA and 5.0 percent ROAE. Despite this accumulating evidence, formal threshold tests remain rare in the CESEE non-performing loan literature. The current analysis helps to fill that gap by employing lagged return on equity as the regime variable, based on the fact that it is directly related to the banking system's ability to absorb losses without impairment to its balance sheet.

2.5. Hypotheses

A simple conceptual framework organizes the strands reviewed above. Macroeconomic disturbances, comprising real income contractions, higher real borrowing costs, and currency depreciation, first reduce the debt-service capacity of households and firms. Whether that pressure surfaces as measured credit risk depends on the absorptive capacity of the banking system, meaning its profitability, capital, and liquidity buffers, and on the institutional environment that governs how quickly impaired exposures are recognized, restructured, and resolved. Persistence closes the loop, because unresolved credit risk feeds back into lending capacity and future fragility (Huljak et al., 2022). The hypotheses map directly onto this chain: H1, H2a, and H2b test the shock stage, H3 tests institutional conditioning of the pass-through, and H4 tests whether absorptive capacity generates regime-dependent transmission.

The theoretical arguments and empirical evidence reviewed above lead to four testable hypotheses.

H1 (Growth channel). *Lower real GDP per capita growth increases banking-sector credit risk, operating through the repayment-capacity mechanism (Beck et al., 2015; Ćurak et al., 2013; Jakubík & Reininger, 2014; Klein, 2013; Makri et al., 2014).*

H2a (Interest-rate channel). *Higher real interest rates increase banking-sector credit risk, operating through the debt-servicing channel (Jakubík & Reininger, 2014; Moinescu, 2012; Tătărici et al., 2020).*

H2b (Exchange-rate channel). *Exchange-rate depreciation increases banking-sector credit risk, operating through the external-balance-sheet channel, which is especially relevant in CESEE economies with significant foreign-currency exposure (Beck et al., 2015; Jakubík & Reininger, 2014; Tătărici et al., 2020).*

H3 (Institutional moderation). *Stronger institutional quality moderates the pass-through of macroeconomic shocks, particularly exchange-rate depreciation, to banking-sector credit risk. The claim is not that institutions improve outcomes, on average, but that they reduce the marginal sensitivity of credit risk to adverse conditions (Beirne & Panthi, 2022; Goyal et al., 2023; Lee et al., 2019; Tanasković & Jandrić, 2015).*

H4 (Threshold state dependence). *The transmission of macroeconomic shocks to banking-sector credit risk differs across regimes of banking-sector resilience. This is tested, rather than assumed, with lagged profitability as the primary threshold variable and liquidity, capital, and institutional quality as alternatives (Bardhan et al., 2019; Bolarinwa et al., 2021; Pop et al., 2018).*

H1, H2a, and H2b test the standard macro-financial transmission channels in a dynamic environment that takes account of persistence. Meanwhile, H3 goes one step further in the analysis by moving the institutional variable from being additive to being conditioning. Finally, H4 tests whether the data support regime-dependent behavior. The scenario module then converts the estimated coefficients into paths of projected credit risks under standardized adverse conditions, which converts the statistical evidence so that it is directly interpretable from a macro-financial surveillance perspective. Operationally, H1 to H4 imply a specification with macroeconomic shock variables, banking-sector controls, and a profitability threshold variable, with institutional quality entering both as a level term and as an interaction with exchange-rate depreciation.

3. Data, Variables, and Empirical Strategy

The empirical design of this paper is determined by the two features of the setting. The cross-sectional dimension is small, which enforces the discipline on the number and choice of regressors and the estimators, respectively. Meanwhile, the research questions require a framework that supports persistence, institutional interaction, threshold nonlinearity, and scenario projection within an integrated structure. This section outlines the sample and construction of the variables, specifies the baseline and augmented models, justifies the estimator, and sets out the threshold and scenario designs.

3.1. Sample, Country Coverage, and Data Sources

The empirical analysis is carried out on the banking systems of 14 countries in Central, Eastern, and Southeastern Europe, on an annual basis. The estimation window extends from 2008 to 2023, so that lags can be constructed consistently and time-series continuity

can be verified before fixing the estimation sample. The balanced baseline panel includes 224 country–year observations ($N = 14$ countries observed over $T = 16$ years). The estimation sample of complete case, with the restriction that all lagged regressors are available at the same time, includes 192 observations (85.7 percent of the baseline panel), and has an average usable time dimension of 13.7 years per country. The sample comprises five EU-member banking systems (Bulgaria, Croatia, Estonia, Latvia, and Lithuania) and nine non-EU emerging European systems (Albania, Bosnia and Herzegovina, Georgia, Moldova, North Macedonia, Montenegro, Serbia, Türkiye, and Ukraine). Appendix A Table A3 lists the full classification. Türkiye is included as a large emerging European banking system whose foreign-currency exposure profile matches the transmission mechanism under study, and Georgia as a small, open post-transition system with comparable credit-risk dynamics and complete data coverage. Both are classified as comparator emerging systems, rather than CESEE core members, and the results are robust to restricting the sample to the emerging-market group and to excluding Türkiye (Section 5.3).

The unit of analysis is the banking sector for each country observed on an annual basis. The paper does not deal with fluctuations in loan performance at individual institutions, but rather with how macroeconomic shocks are transmitted to aggregate credit risk. Country-level aggregation is also consistent with the institutional quality variables, which differ across countries as well as over time but not across banks within a single jurisdiction.

The dataset is constructed from four groups of publicly available sources. Banking-sector indicators are drawn from the IMF Financial Soundness Indicators (FSIs) database, and include the non-performing loan ratio, regulatory capital to risk-weighted assets, the liquidity ratio, return on equity, and total banking-sector assets. Macroeconomic variables are obtained primarily from the World Bank’s World Development Indicators (WDIs) database, and include real GDP per capita growth, exchange-rate change, and the real interest rate. The real interest rate is defined as the lending rate adjusted for the GDP deflator inflation. Where the WDI series is incomplete or yields implausible observations for particular CESEE countries, the relevant nominal rate or exchange-rate observations are taken from national central bank publications and reconstructed using a uniform definition across countries. Institutional variables, namely Rule of Law and Regulatory Quality, are taken from the World Bank’s Worldwide Governance Indicators (WGIs). Financial deepening is measured by private sector credit to GDP from the World Bank’s Global Financial Development Database (GFDD).

3.2. Variable Construction

Consistent with these hypotheses, the explanatory variables are organized into macroeconomic, banking-sector, and institutional blocks. The dependent variable is banking-sector credit risk, which is measured as the ratio of non-performing loans to the total of all gross loans. Since this ratio is bounded on $[0, 100]$ and typically right-skewed, the baseline analysis is conducted using a logit transformation:

$$npl_logit_{i,t} = \ln \left[\frac{npl_{i,t}}{(100 - npl_{i,t})} \right]$$

where $npl_{i,t}$ is the NPL ratio in percent for country i at time t .

This transformation maps the bounded ratio onto the real line and deemphasizes the extreme observation in the tails, which is also compatible with the transformation used by Moinescu (2012) and Tătărici et al. (2020) in the CESEE samples. The econometric analysis is presented with results in logit space and then transformed back to non-performing loan ratios, where econometric interpretation is required.

The explanatory variables are separated into three blocks. Table 2 presents all the variables, their precise definitions, origins, and roles in the construction of the empirical study.

Table 2. Variable definitions, sources, and empirical roles.

Block	Variable	Definition	Source	Role
Dependent	NPL ratio (logit)	$\ln [NPL / (100 - NPL)]$, where NPL = non-performing loans in relation to total gross loans (%)	IMF FSI	Dependent variable
Macro shock	Real GDP p.c. growth	Annual growth rate of real GDP per capita (%)	World Bank WDI	Core regressor (H1)
Macro shock	Real interest rate	Lending rate adjusted for GDP deflator inflation (%)	World Bank WDI	Core regressor (H2)
Macro shock	FX depreciation	Year-on-year depreciation of local currency per USD, corrected for euro-adoption breaks (%)	World Bank WDI, national sources	Core regressor (H2)
Banking resilience	Regulatory capital/RWA	Regulatory capital in relation to risk-weighted assets (%)	IMF FSI	Lagged control
Banking resilience	Liquidity ratio	Liquid assets in relation to total assets (%)	IMF FSI	Lagged control
Banking resilience	Return on equity	Net income in relation to average equity (%)	IMF FSI	Lagged control; threshold variable (H4)
Banking structure	Private credit/GDP	Domestic credit in relation to the private sector as a share of GDP (%)	World Bank GFDD	Lagged control
Banking structure	Log bank assets	Natural logarithm of total banking-sector assets (USD)	IMF FSI	Lagged control
Institutions	Institutional composite (z)	Standardized mean of rule of law and regulatory quality	World Bank WGI	Level term; interaction with FX (H3)
Interaction	FX depreciation $\times$ Inst. quality	Product of lagged FX depreciation and lagged institutional composite	Derived	Tests H3 directly

The macroeconomic block comprises three variables, each addressing a transmission channel in H1, H2a, and H2b. The income and repayment-capacity channel is represented by Real GDP per capita growth, whereas the debt-servicing channel is represented by the real interest rate. The channel of international transmission that works via currency pressure, balance-sheet effects, and global financial tightening, on the other hand, is reflected in exchange-rate depreciation. These will be the core mechanisms of transmission to be studied, in harmony with the channels found in the CESEE literature (Beck et al., 2015; Jakubík & Reininger, 2014; Klein, 2013).

The block that deals with the banking industry holds five variables. The internal resilience is captured by return on equity, which is also used as the threshold variable in the nonlinear analysis (Section 3.6). Also, the ratio of the credit cycle and the extent of financial deepening is represented by the ratio of private credit to GDP, and the banking-sector assets are introduced in the logarithmic form to absorb the scale effect.

The institutional composite is constructed as the mean of two World Governance Indicator dimensions that are standardized, which are rule of law and regulatory quality. Each component is standardized to zero mean and unit variance before averaging. The resulting variable is the legal and regulatory environment in which financial intermediation operates. Its purpose is to test whether the institutional environment conditions the transmission of exchange-rate shocks to credit risk, as H3 posits. The augmented specification, therefore, adds a level term for the institutional composite and its interaction with exchange-rate depreciation.

The explanatory variables are all introduced in the baseline specification, with a one-period lag. Construction of the lag is done using the entire source window of 2007–2024, and then the panel is filtered to the estimation period of 2008–2023, so that the 2008 observations maintain valid lagged information from 2007. The one-period lag limits contemporaneous simultaneity and reflects the lagged response of asset quality to macroeconomic conditions. Table 3 presents descriptive statistics of the analysis panel.

Table 3. Descriptive statistics (analysis panel, 2008–2023).

Variable	N	Mean	SD	Min	Median	Max
NPL ratio (%)	220	9.94	9.17	0.40	6.53	54.82
NPL logit	220	−2.57	1.00	−5.50	−2.66	0.19
Real GDP p.c. growth (%)	224	2.78	5.02	−22.75	3.51	15.66
Real interest rate (%)	224	2.12	6.76	−45.27	2.55	20.44
FX depreciation (%)	224	4.45	12.61	−14.40	0.32	86.98
Regulatory capital/RWA (%)	224	19.53	4.18	11.00	18.76	35.65
Liquidity ratio (%)	223	32.11	13.19	7.30	28.50	72.28
Return on equity (%)	224	7.91	11.47	−53.10	8.86	42.23
Private credit/GDP (%)	209	50.81	15.56	18.65	49.99	101.38
Log bank assets	223	23.71	1.37	21.48	23.66	27.37
Institutional composite (z)	224	0.02	0.98	−1.74	−0.19	2.32

Figure 1 displays the pairwise correlations among all baseline variables.

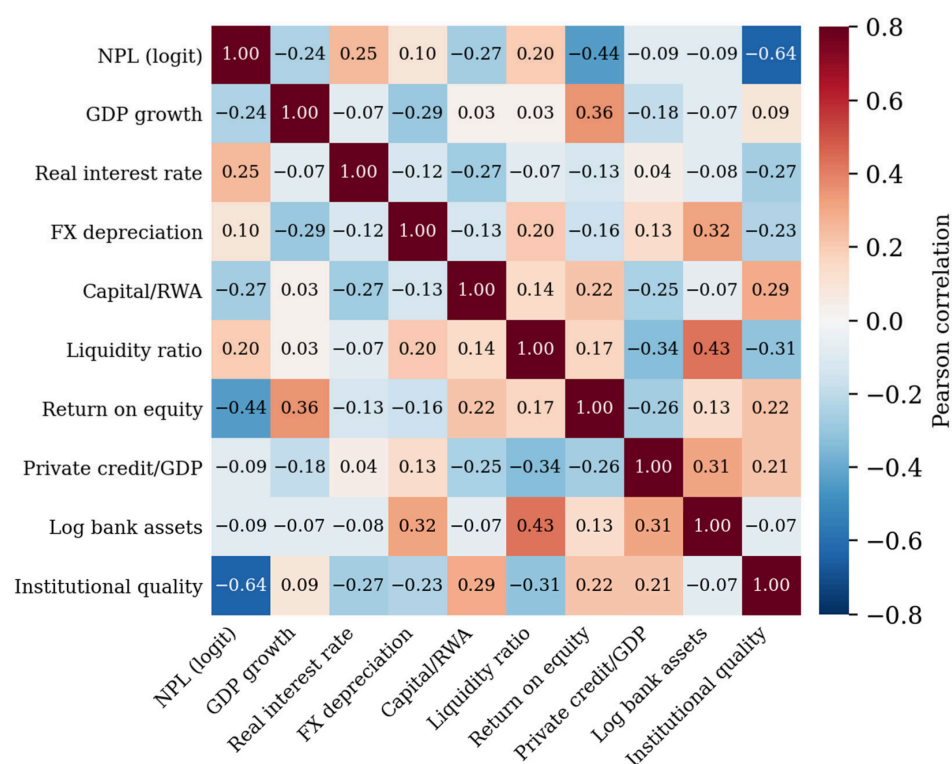


Figure 1. Pairwise correlation heatmap for baseline variables. Cell entries are Pearson correlation coefficients computed on the full estimation sample of 14 CESEE banking systems over 2008–2023. The dependent variable (NPL) is shown in its logit transformation. Source: authors' calculations based on data from the IMF Financial Soundness Indicators, World Bank World Development Indicators, World Bank Worldwide Governance Indicators, and central-bank statistical databases.

The descriptive statistics support the empirical design at several points. The average non-performing loan ratio stands at 9.94 percent, with a median of 6.53 percent, which validates the tight-skewed distribution based on the occurrence of distressing episodes in a few countries. The maximum is over 54 percent, which means that this panel has areas of severe sector-wide impairment, and the bounded and skewed character of this distribution is just why we want to apply the logit transformation. The growth in real GDP per capita is between approximately -22.75 and 15.66 percent, illustrating the deep contractions of the global financial crisis and the pandemic, as well as rapid recoveries. The FX depreciation is 4.45 percent, and the standard deviation is 12.61 , which is in line with the high exchange-rate volatility that is a typical feature of the region. The institutional composite varies between 2.32 and -1.74 , indicating strong heterogeneity in governance across the sample, which is critical in establishing the interaction effects in H3.

3.3. FX Correction Procedure

Before estimation, the exchange-rate series needed an explicit correction. Four countries in the sample adopted the euro during the observation window: Estonia (2011), Latvia (2014), Lithuania (2015), and Croatia (2023). In raw official exchange-rate data, these transitions produce mechanical discontinuities in the computed year-on-year depreciation because the reporting unit changes abruptly. If left untreated, the resulting series might contain values exceeding 80 percent in absolute terms, which do not represent real macroeconomic or financial stress. Since the exchange-rate variable is central to the paper's contribution to international financial transmission, this problem cannot be dealt with informally. Corrections applied are reported in Table 4.

Table 4. FX break corrections for euro-adoption years.

Country	Year	Raw FX Depreciation (%)	Corrected FX Depreciation (%)
Estonia	2011	-93.92	-4.80
Latvia	2014	42.19	0.04
Lithuania	2015	-65.34	19.69
Croatia	2023	-87.08	-2.75

The correction replaces the unadjusted depreciation value for the euro-adoption year with the same-year depreciation of the Bulgarian lev against the USD. The lev has operated under a currency board since 1997, fixed first to the Deutsche Mark and subsequently to the euro, so its movement against the USD mirrors the EUR/USD exchange rate one for one. Because each of the four adopting currencies was pegged to, or tightly managed against, the euro in the years preceding adoption, the lev-based value reproduces the depreciation that the domestic currency would have recorded had the reporting unit not changed. The procedure thus preserves the underlying macro-financial signal, which for these economies is EUR/USD movement transmitted through the peg, while removing the accounting discontinuity caused by the change in reporting unit. The corrected value for Lithuania (19.69 percent) remains large because the euro depreciated sharply against the USD during 2015 and the euro-pegged litas would have recorded a movement of the same magnitude. The correction removes only the mechanical break, not this real currency movement. According to Beck et al. (2015) and Jakubík and Reininger (2014), exchange-rate movements play a crucial role in the evolution of non-performing loans, particularly in financially exposed systems. That argument is economically meaningful only if the depreciation series reflects actual currency stress, as opposed to a change in reporting convention. The current correction does exactly that.

3.4. Baseline Dynamic Specification

Credit risk in the banking sector is very persistent, and once non-performing loan ratios rise, resolution is typically slow, especially in banking systems with poor coping frameworks or uncertain legal environments. Without this persistence in our specification, we would risk confounding inherited banking distress with the effect of current macroeconomic conditions. The baseline model is thus dynamic, and links current credit risk to its own lag, lagged macroeconomic shocks, lagged banking-sector controls, and institutional quality:

$$y_{i,t} = \alpha_i + \lambda_t + \rho y_{i,t-1} + \beta_1 g_{i,t-1} + \beta_2 r_{i,t-1} + \beta_3 f_{i,t-1} + \gamma' X_{i,t-1} + \delta Inst_{i,t-1} + u_{i,t} \quad (1)$$

where

- $y_{i,t}$ is the logit-transformed NPL ratio for country i in year t ;
- α_i denotes country fixed effects;
- λ_t denotes year fixed effects;
- $y_{i,t-1}$ is the lagged dependent variable with autoregressive parameter ρ ;
- g , r , and f are real GDP per capita growth, the real interest rate, and FX depreciation, respectively;
- $X_{i,t-1}$ is a vector of lagged banking-sector controls (regulatory capital, liquidity, return on equity, private credit to GDP, and log bank assets);
- $Inst_{i,t-1}$ is the institutional quality composite;
- $u_{i,t}$ is the idiosyncratic error.

Country fixed effects control for all stable, long-run differences between banking systems, including well-established institutional features and financial structures that are not reflected in the variables that change over time. Year fixed effects absorb common shocks that affect all countries at the same time, such as deterioration in global financial conditions, region-wide macroeconomic stress, or changes in the external risk environment. The joint significance of year fixed effects is formally tested in the diagnostic analysis in Section 5.

The specification recognizes variation over time, rather than cross-sectional differences in levels within selected countries. It poses the question of how changes in macroeconomic and institutional conditions are associated with changes in future credit risk, accounting for persistence and common shocks.

To test H3, i.e., whether institutional quality changes the pass-through of exchange-rate shocks, the baseline is supplemented with an interaction term:

$$y_{i,t} = \alpha_i + \lambda_t + \rho y_{i,t-1} + \beta_1 g_{i,t-1} + \beta_2 r_{i,t-1} + \beta_3 f_{i,t-1} + \gamma' X_{i,t-1} + \delta Inst_{i,t-1} + \dots + \theta(f_{i,t-1} \times Inst_{i,t-1}) + u_{i,t} \quad (2)$$

The parameter θ is central to our H3, and its negative value would indicate that stronger institutional quality dampens the pass-through of exchange-rate depreciation to banking-sector credit risk, while a zero or imprecisely estimated value of θ would show that the linear moderation channel is weak or difficult to identify in the available sample. The introduction of institutional quality as a transmission modifier, rather than as a passive background control, is driven by the theoretical argument developed in Section 2 and by empirical evidence that governance conditions influence the propagation of adverse shocks to financial performance (Abaidoo & Agyapong, 2025; Beirne & Panthi, 2022; Lee et al., 2019; Tanasković & Jandrić, 2015).

3.5. Estimation Strategy

The primary specification is a bias-corrected dynamic-panel fixed-effects estimator. The motivation for this is based on the data's dimensions. The standard within-groups estimator for a dynamic specification with $N = 14$ and $T = 16$ is subject to Nickell bias (Nickell, 1981),

which is of order $O(1/T)$ and can be non-negligible when T is moderate. Moreover, GMM estimators developed for large- N panels, whether in the difference form of [Arellano and Bond \(1991\)](#) or the system form of [Blundell and Bond \(1998\)](#), are not necessarily preferable in a setting with a small cross-sectional dimension. To be precise about what is implemented: the estimator is a two-way fixed-effects model in which the autoregressive coefficient receives a first-order Nickell-type correction of order $O(1/T)$, applied after estimation, while the remaining coefficients are within-group estimates. This is in the spirit of, but simpler than, the full-vector analytical corrections derived by [Kiviet \(1995\)](#) and extended to unbalanced panels by [Bruno \(2005\)](#). As a complementary correction that applies to the full coefficient vector, Section 4.3 additionally reports a half-panel jackknife estimate in the sense of [Dhaene and Jochmans \(2015\)](#). [Judson and Owen \(1999\)](#) provide Monte Carlo evidence that bias-corrected fixed-effects estimators perform well compared to GMM alternatives in panels with small N and moderate T , which is exactly the configuration encountered here.

The baseline model uses country-block bootstrap inference with 500 replications ($B = 500$). The block structure preserves the serial dependence within a country and results in interval estimates that do not depend on large-sample approximations to the distributions. In this setting, bootstrap-based inference is essential rather than optional, because standard asymptotic formulas show signs of reduced reliability when the cross-sectional dimension is small. Because conventional cluster-robust inference can over-reject when the number of clusters is as small as 14 ([Cameron & Miller, 2015](#)), the two core macro-financial coefficients are additionally tested with a restricted wild cluster bootstrap (Rademacher weights drawn at the country level, $B = 999$, null imposed), reported in Section 4.3. The estimation is implemented in Python 3.11 (v. 3.11.15) using the linearmodels (v. 7.0) PanelOLS routine with entity and time effects on the unbalanced complete-case panel, with all regressors treated as predetermined one-period lags, and all bootstrap procedures using fixed seeds recorded in the replication package.

The identification limits of this design deserve explicit statement. All regressors enter as one-period lags and are treated as predetermined, which addresses contemporaneous simultaneity but not feedback over longer horizons, since credit risk influences subsequent growth, lending conditions, and bank profitability ([Cangombe et al., 2025](#); [Huljak et al., 2022](#)). Credible external instruments do not exist at the country-banking-system level, and the GMM alternative fails numerically in this configuration, so all estimates are reported as predictive associations, rather than causal effects. Two design features bound the concern. Country and year fixed effects absorb time-invariant heterogeneity and common shocks, and the exchange-rate result is robust to excluding the four euro-adoption observations whose depreciation values were corrected in the data construction (coefficient 0.009, $p = 0.020$), so the headline channel is an artifact of neither the correction nor any single country.

The baseline results are complemented by two alternative inferential approaches that have the same within-group point estimates but under different standard error corrections. Driscoll–Kraay standard errors ([Driscoll & Kraay, 1998](#)) are valid under general forms of cross-sectional and temporal dependence. The standard Pesaran CD test is not a valid check in this design: on two-way fixed-effects residuals, whose yearly cross-sectional means are zero by construction, the statistic is biased and can indicate spurious dependence ([Juodis & Reese, 2022](#)). A weighted CD test with Rademacher unit weights, which remains valid under two-way fixed effects ([Juodis & Reese, 2022](#)), does not reject cross-sectional independence of the residuals (statistic -1.25 , $p = 0.21$). Driscoll–Kraay inference is therefore retained as a conservative complement, rather than as a correction demanded by a diagnostic. Country-clustered standard errors serve as a conventional benchmark. Reporting these alternatives demonstrates that the main interpretation of the core coefficients does not depend upon one specific inferential convention.

Dynamic-panel GMM is retained as a diagnostic exercise, rather than as a competing estimator. With only $N = 14$ cross-sectional units and a highly persistent dependent variable, GMM estimators developed for large- N panels face well-documented finite-sample problems: instrument proliferation, singular weighting matrices, and weak over-identification test behavior (Roodman, 2009). In our implementation, the two-step System GMM weighting matrix was singular, and a parsimonious one-step Difference GMM attempt produced a persistence coefficient of 1.005 with macro-financial coefficients that lost all precision, alongside further generalized-inverse warnings. Because these estimates are numerically unreliable rather than merely imprecise, no GMM results are reported. The exercise, documented in the replication package, illustrates the small- N instability that motivates our choice of the bias-corrected fixed-effects estimator as the primary specification.

There are no serious multicollinearity issues in the baseline set of regressors. The maximum variance inflation factor is 2.06, comfortably below conventional thresholds (Milenković et al., 2024). This means that the interaction term and the institutional composite enter the system without creating a mechanical identification problem.

3.6. Threshold Design

The threshold analysis is used to test H4—that is, whether the slope of the macro-credit-risk relationship changes when banking-sector profitability falls below a critical level. Our specification is based on the panel threshold framework of Hansen (1999, 2000). Inference on the linearity null uses a wild sign-flip bootstrap under the null, in which the threshold is re-estimated by full grid search in every bootstrap replication, as the Hansen procedure requires. Two caveats bound what this design can establish. The specification includes a lagged dependent variable, while the Hansen framework is static, and the dynamic threshold estimators of Seo and Shin (2016) and the bootstrap theory of Gong and Seo (2022) address exactly this configuration, but require a cross-sectional dimension that $N = 14$ cannot provide. The threshold results are therefore reported as descriptive evidence of regime heterogeneity, rather than as inference from a dynamic-panel-valid threshold estimator. The estimating equation is

$$y_{i,t} = \alpha_i + \rho y_{i,t-1} + \beta'_L M_{i,t-1} \cdot I(q_{i,t-1} \leq \gamma) + \beta'_H M_{i,t-1} \cdot I(q_{i,t-1} > \gamma) + \phi' W_{i,t-1} + u_{i,t} \quad (3)$$

where

- $q_{i,t-1}$ is the threshold variable (lagged return on equity);
- γ is the threshold parameter to be estimated;
- $I(\cdot)$ is the indicator function;
- $M_{i,t-1}$ contains the macroeconomic shock variables whose coefficients are allowed to differ across regimes (GDP growth and FX depreciation);
- $W_{i,t-1}$ contains the remaining controls, whose coefficients are constrained to be equal across regimes.

By minimizing the concentrated sum of squared residuals over a grid of 300 candidate values, we estimated the threshold γ (gamma). Additionally, we have used a 15 percent parameter to ensure adequate observations in each regime.

The reason for using return on equity as a threshold variable is its direct link with the ability to absorb shocks. A banking system operating with weak profitability has less room to absorb asset-quality deterioration through retained earnings, less capacity to provision against losses without balance-sheet impairment, and weaker incentives to resolve impaired exposures promptly (Bolarinwa et al., 2021). The threshold model does not replace the linear baseline. It tests whether the average relationship estimated in Equation (1) masks a steeper transmission mechanism in low-profitability states.

Inference for the threshold parameter and the test of linearity against the threshold alternative is performed using 999 replications ($B = 999$), following the recommendation in Hansen (1999) for bootstrap-based p -values in threshold models.

3.7. Scenario Simulation Design

The final element of our empirical strategy is to translate the estimated coefficients into scenario-based projections of credit risk. The scenario module is an interpretive extension of the baseline dynamic panel, which aims to show what the estimated macro-financial sensitivities would suggest for the path of credit risk in the banking sector under alternative adverse conditions.

The scenario recursion operates in the same logit space as the econometric model:

$$\hat{y}_{t+h} = \bar{c} + \hat{\rho}\hat{y}_{t+h-1} + \hat{\beta}'S_h \quad (4)$$

where

- $\hat{y}_{t+h}$ is the projected logit NPL at horizon h ;
- $\hat{\rho}$ and $\hat{\beta}$ are the estimated persistence and shock parameters from Equation (1);
- S_h is the scenario-specific vector of macroeconomic conditions;
- $\bar{c}$ is the intercept calibrated so that the baseline no-shock path remains anchored at its observed starting level, rather than drifting mechanically.

Projected values are translated back into non-performing loan ratios, using the inverse logit transformation.

There are six scenarios that are analyzed over a five-year projection horizon. The baseline path assumes all macroeconomic variables are at their sample means. This baseline path is complemented by three single-shock scenarios, including a one-standard-deviation decline in GDP growth, an increase in the real interest rate, or a depreciation of the exchange rate. We also assume a combined adverse scenario, where all three shocks happen simultaneously at one standard deviation, and a severe combined scenario in which all occur at two standard deviations. Uncertainty around the projected paths is captured using the bootstrap distribution of estimated coefficients from the BC-FE procedure, ensuring internal consistency between the scenario projections and the inferential framework applied to the baseline model.

This module is driven by the fact that coefficient estimates convey direction and average magnitude, but policy institutions operate in a different register. The financial stability authorities and central banks make their reasoning based on the projected vulnerabilities and medium-run asset-quality paths. The results of Huljak et al. (2022) show that elevated non-performing loan ratios depress bank lending and real activity in the euro area, which means that the medium-run dynamics of credit risk have consequences well beyond the banking sector itself. In systems with high persistence, even relatively small single-period shocks may accumulate considerably, across multiple years. The scenario module renders this accumulation explicit by transforming econometric estimates into outputs that are readily interpretable from a macro-financial surveillance viewpoint.

The combination of data construction, estimator hierarchy, threshold design, and scenario module constitutes a cohesive empirical strategy adapted to the scale and configuration of the panel dataset.

4. Baseline Results

This section presents the stylized facts and the baseline dynamic-panel estimates. Section 5 discusses threshold dynamics, robustness diagnostics, and scenario analysis.

4.1. Stylized Facts

The descriptive data in Section 3 (Table 3) show that the credit risk in the banking sector is both persistent and unevenly distributed. Specifically, the mean non-performing loan ratio of 9.94 percent is higher than the median of 6.53 percent, consistent with a right-skewed distribution, influenced by periods of extreme shocks in a subset of countries. The timeline of the non-performing loan ratio for each country is shown in Figure 2. The analysis identified the following patterns. Primarily, the panel shows substantial cross-country divergence during the years after the global financial crisis. Moreover, the pace of improvement in credit quality after the mid-2010s varied significantly across banking systems. Finally, severe shocks in the banking sector were mainly limited to a group of countries where the non-performing loan ratio increased sharply and maintained persistence for years, while, in comparison, others remained stable throughout. These trajectories are in accordance with the strong macro-financial interconnections and asymmetric post-shock adjustment documented in CESEE by Klein (2013) and Jakubík and Reininger (2014), highlighting why a dynamic specification with country fixed effects is the appropriate starting point.

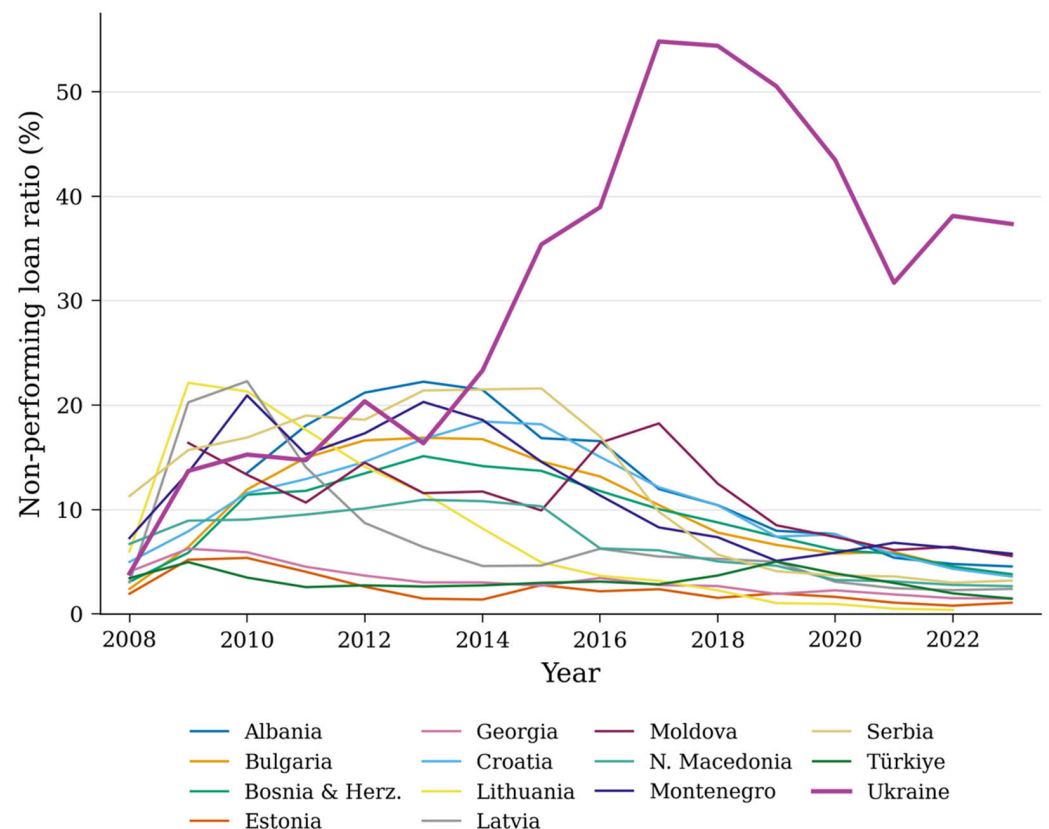


Figure 2. Banking-sector NPL ratio by country, 2008–2023. Source: authors' compilation from the IMF Financial Soundness Indicators and national central-bank publications.

4.2. Baseline Dynamic-Panel Results

Table 5 presents the baseline estimates for the two bias-corrected specifications. The preferred specification is a bias-corrected fixed-effects (BC-FE) model estimated with block-bootstrap inference. We then consider an augmented BC-FE version that includes an interaction term between exchange-rate movements and institutional quality. Because uncorrected within-group estimates are subject to Nickell bias, they are no longer displayed alongside the corrected ones: the within-group estimates under Driscoll–Kraay (FE-DK) and country-clustered (FE-Cluster) standard errors are relegated to Appendix A Table A4 for reference, and the restricted wild cluster bootstrap in Section 4.3 provides the preferred

few-cluster inference. All specifications include country and year fixed effects and the full set of lagged regressors. Both columns report bias-corrected point estimates with country-block bootstrap standard errors. Figure 3 documents that the inference conclusions for the macro-financial channels are unchanged across standard-error conventions (estimates in Appendix A, Table A4), and Figure 4 plots the BC-FE estimates with 95 percent bootstrap confidence intervals.

Table 5. Baseline estimation results (dependent variable: logit NPL ratio).

Variable	BC-FE		BC-FE + Int.	
	Coef.	SE	Coef.	SE
Lagged NPL (logit)	0.944 ***	(0.108)	0.926 ***	(0.090)
Real GDP p.c. growth	−0.014 *	(0.008)	−0.018 **	(0.007)
Real interest rate	0.004	(0.009)	0.002	(0.010)
FX depreciation	0.009	(0.006)	0.012 **	(0.006)
Regulatory capital/RWA	0.001	(0.022)	0.000	(0.024)
Liquidity ratio	0.004	(0.005)	0.005	(0.005)
Return on equity	0.002	(0.003)	0.002	(0.003)
Private credit/GDP	0.003	(0.005)	0.004	(0.004)
Log bank assets	−0.089	(0.209)	−0.160	(0.221)
Institutional composite	0.140	(0.175)	0.110	(0.167)
FX × Inst. quality	-	-	0.003	(0.003)
Country FE	Yes		Yes	
Year FE	Yes		Yes	
Observations	192		192	

Notes: BC-FE denotes the bias-corrected fixed-effects estimator with country-block bootstrap ($B = 500$). BC-FE + Int. adds the FX-institutional quality interaction. Bootstrap standard errors in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All regressors are lagged one period. Uncorrected within-group estimates under Driscoll–Kraay and country-clustered standard errors are reported for reference in Appendix A, Table A4, and restricted wild cluster bootstrap inference appears in Section 4.3.

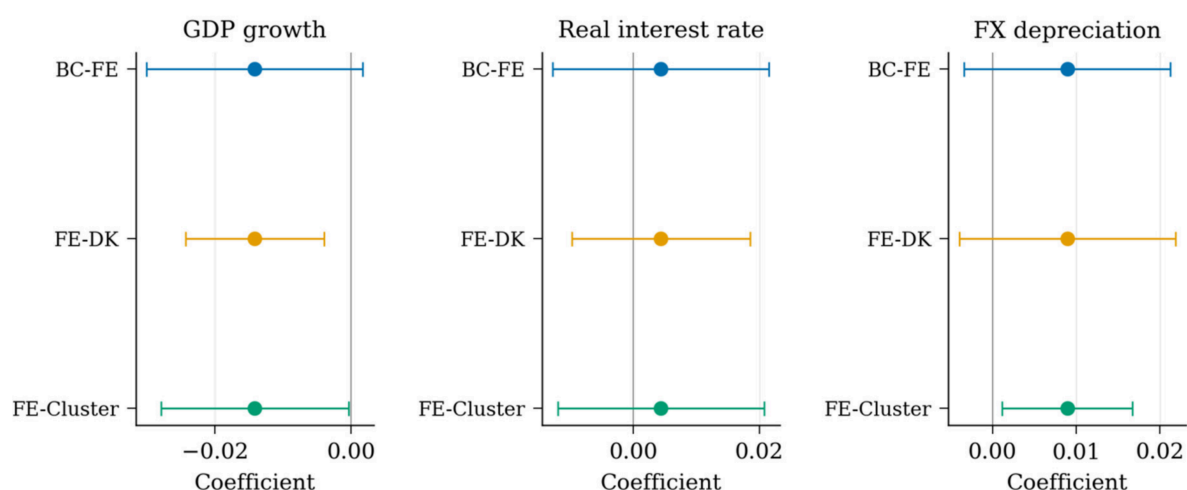


Figure 3. Inference robustness of the macro-financial channel coefficients: identical within-group point estimates under alternative standard-error conventions, shown for reference only (estimates in Appendix A, Table A4), compared with BC-FE. Source: authors' calculations.

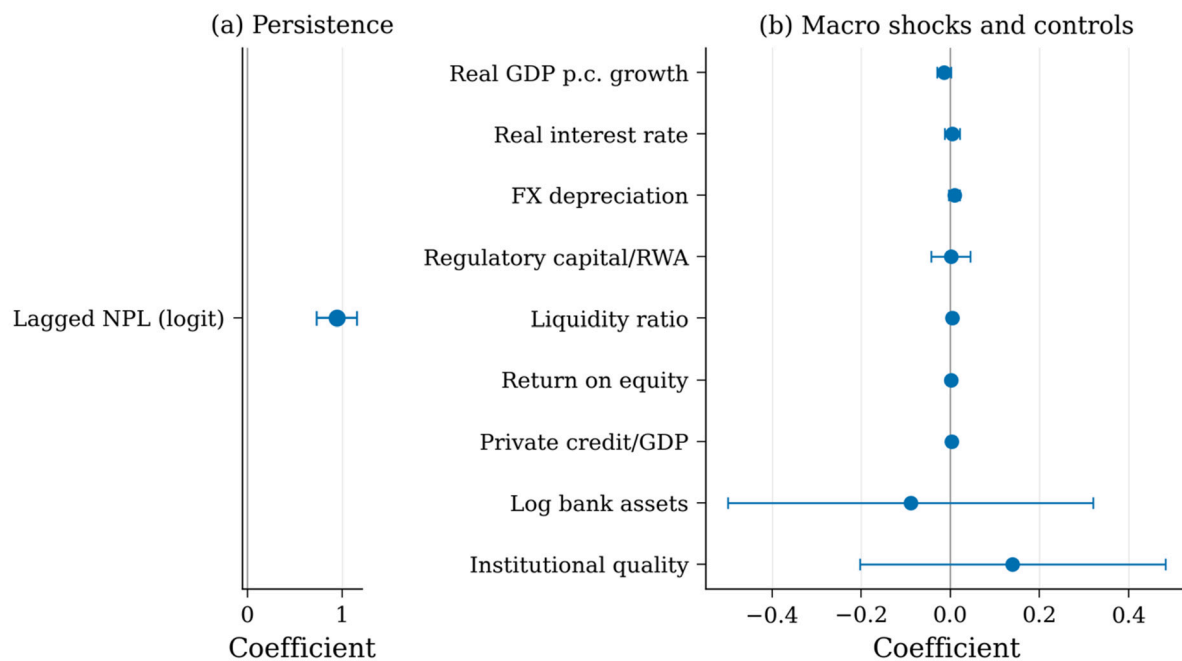


Figure 4. BC-FE coefficient estimates with 95% bootstrap confidence intervals. Source: authors' calculations.

Figure 4 complements this presentation by reporting the BC-FE point estimates for the full coefficient vector, together with their bootstrap confidence intervals.

4.3. Persistence and the Macro-Financial Channels

The dominant characteristic of the estimates is the magnitude of persistence. The BC-FE autoregressive coefficient of 0.944 (SE = 0.108) shows that the current credit risk is being carried forward to the next period at a rate of approximately 94 percent.

This corresponds to a half-life of 12.0 years. Even the lower, uncorrected within-group estimate of the persistence coefficient, 0.802 (Appendix A, Table A4), corresponds to a half-life of 3.1 years. The inertia of banking-sector credit risk under both sets of estimates means that the effects of macroeconomic shocks persist well after the year in which they occurred. The high degree of persistence is consistent with the slow loan-resolution dynamics documented in CESEE by Klein (2013), Tătărici et al. (2020), and Milenković et al. (2024), and with the broader evidence that elevated stocks of non-performing loans can depress bank lending and real activity for extended periods (Huljak et al., 2022).

The uncertainty around the persistence estimate is substantial, and must be stated plainly. The bootstrap 95 percent confidence interval for the bias-corrected coefficient is 0.601 to 1.048, so the interval does not exclude unity, and 13 percent of the bootstrap draws lie above one. A split-panel jackknife sensitivity analysis in the spirit of Dhaene and Jochmans (2015), constructed on each country's longest contiguous span with country-specific almost-equal partitions and length-weighted averaging, and correcting the full coefficient vector rather than only the autoregressive parameter, yields a persistence estimate of 1.037 (1.039 under equal weighting), with calendar-split checks ranging from 0.86 to 1.09. These are point corrections without accompanying distribution theory, and no established result covers this unbalanced odd-length configuration, but they consistently point toward, without precisely locating, unit-root territory. A CIPS panel unit-root test (Pesaran, 2007), computed on the contiguous 2010 to 2022 panel and evaluated against finite-sample critical values simulated under a documented common-factor null, does not reject the panel unit root (statistic -2.09 , simulated $p = 0.15$), consistent with the country-

level ADF evidence. Taken together, the evidence supports describing banking-sector credit risk as highly persistent, while any statement about long-run convergence, including the implied half-life, is conditional on stationarity that the data cannot confirm. Few-cluster inference reinforces the channel ranking: under a restricted wild cluster bootstrap with Rademacher weights at the country level (Cameron & Miller, 2015), the exchange-rate coefficient remains significant ($p = 0.028$), while the growth coefficient becomes marginal ($p = 0.060$), against country-clustered p -values of 0.026 and 0.046, respectively.

The growth channel is negative and stable across all four specifications. The BC-FE estimate of -0.014 ($p = 0.081$) gains precision in the interaction model (-0.018 , $p = 0.012$) and attains conventional significance under both FE-DK ($p = 0.006$) and FE-Cluster ($p = 0.044$) inference on the within-group regression (Appendix A, Table A4) inference. A 5-percentage-point decline in real GDP per capita growth is associated with an increase of about 0.07 in the logit credit-risk measure in the preferred specification. Due to the persistence of the system, this one-period effect compounds over time. The long-run multiplier implied by the BC-FE estimates is -0.252 , which means that a permanent one-percentage-point decline in growth would eventually raise the logit NPL by approximately 0.25 units. The results are consistent with the repayment-capacity channel emphasized across the CESEE literature (Beck et al., 2015; Bilan & Roman, 2016; Ćurak et al., 2013; Klein, 2013; Makri et al., 2014).

The coefficient on the real interest rate is positive in all specifications, which is in line with the debt-servicing channel and indicates that tighter real borrowing conditions are associated with higher future credit risk. The impact is relatively weak, and the coefficient is estimated with low precision in all four models (p -values from 0.545 to 0.870), which means that the interest-rate channel is present but less precisely estimated than the growth and exchange-rate channels in this sample. This is reasonable in a regional panel with heterogeneity in the pass-through of interest rates, which depends on the refinancing structure, contract structure, and distribution of existing balance-sheet stresses across regions. The result is consistent with Szarowská (2018), and Jakubík and Reininger (2014), who also find that the interest-rate effect is present, but smaller and less stable than the growth effect in CEE panels. The exchange-rate channel produces economically significant estimates. The BC-FE coefficient of 0.009 increases to 0.012 ($p = 0.030$) in the interaction model, and is significant at the 5 percent level under cluster-robust inference ($p = 0.025$). A 10-percentage-point depreciation is associated with an increase of 0.09 to 0.12 in the logit credit-risk measure, depending on specification. The long-run multiplier implied by the BC-FE estimates is 0.159, suggesting that exchange-rate pressure can have significant long-term effects on banking-sector credit risk. These effects arise after the exchange-rate series has been adjusted for euro-adoption breaks, which reinforces the argument that the estimated coefficient captures genuine macro-financial transmission through the channels identified by Beck et al. (2015) and Jakubík and Reininger (2014), rather than a measurement error.

The banking-sector controls, such as regulatory capital, liquidity, profitability, private credit to GDP, and banking-sector scale, do not individually reach significance in the baseline specification. This does not mean that these variables are not important, but that in a dynamic model dominated by a lagged dependent variable with a coefficient near unity the marginal explanatory contribution of additional regressors is compressed. The banking-sector controls have a conditioning function. They absorb variation in banking system structures across countries that could otherwise distort the estimated effects of the macro-financial channels. This function is more pronounced in the threshold analysis (Section 5), where the profitability of banks, in particular, determines the regime in which macro shocks are multiplied.

4.4. Institutions as a Moderator of FX Transmission

The enhanced specification (Equation (2) in Section 3) tests H3, which posits an interaction of exchange-rate depreciation and the institutional quality composite. The estimated interaction coefficient is 0.003 (SE = 0.003, $p = 0.253$). This is not the dampening pattern that a simple reading of H3 might suggest. A negative interaction would have indicated that stronger institutional quality reduces the pass-through of exchange-rate shocks to credit risk. However, the positive but insignificant estimate does not support that interpretation in this particular specification. The insignificant interaction between exchange-rate depreciation and institutional quality therefore indicates that H3 is not supported in this sample.

To establish whether this null reflects the aggregation of the composite rather than the absence of moderation, the interaction is re-estimated separately for each of its two components. Appendix A, Table A1 reports the results, and Appendix A, Figure A1 traces the implied marginal effect of exchange-rate depreciation across the institutional distribution. The conclusion is unchanged. The Rule of Law interaction is 0.0035 (bootstrap SE = 0.0031, 95 percent confidence interval -0.0027 to 0.0097) and the Regulatory Quality interaction is 0.0030 (bootstrap SE = 0.0028, 95 percent confidence interval -0.0031 to 0.0084). Both are positive, both are statistically insignificant, and the marginal effect of depreciation on credit risk remains positive across, essentially, the entire observed range of institutional quality. The null is therefore not an artifact of the composite. Two considerations qualify, rather than overturn, this conclusion. In a panel with $N = 14$ and country fixed effects already absorbing permanent cross-country institutional differences, the within-country variation available to identify the interaction effect is limited, and the institutional channel can operate through mechanisms that a single linear-interaction term cannot describe, such as supervisory responsiveness, restructuring capacity, or the credibility of the legal environment. Bischof et al. (2022) found that legal efficiency has different importance depending on the stage of the economic cycle, which points in the same direction.

The baseline model and the interaction model have a main-effect coefficient of 0.140 (SE = 0.175) and 0.110 (SE = 0.167), respectively, which are imprecisely estimated. Without considering the broader context, these coefficients should not be over-interpreted. In small annual panels, level effects for broad institutional variables are inherently noisy (Bayar, 2019; Tanasković & Jandrić, 2015). This is why the paper does not base its institutional argument on these coefficients. Instead, the institutional dimension enters the analysis at several points: through the direct term, the interaction term, the threshold design (where profitability proxies a dimension of institutional and balance-sheet resilience), and the scenario interpretation. One dimension-level regularity deserves note. The Regulatory Quality-level term is positive and significant at the 5 percent level in the dimension model (0.162, cluster $p = 0.042$), a pattern more plausibly read as reform timing (since governance reforms in the region frequently follow episodes of banking distress) than as a causal effect of better regulation on credit risk.

The results of the baseline model can be summarized concisely in the following way. Banking-sector credit risk is highly persistent, with an implied half-life that ranges from 3.1 to 12.0 years, depending on the estimator. Greater future credit risk is always linked to weaker real income growth and exchange-rate depreciation, and both are consistent across the correction of the exchange-rate series of euro-adoption breaks. Real interest rates carry the expected sign, but lack precision. The linear moderation of the FX channel by institutional quality is not supported, whether institutions are measured by the composite or separately by its Rule of Law and Regulatory Quality components. These findings are the basis for the nonlinear, diagnostic, and scenario-based evidence developed in Section 5.

5. Nonlinearities, Robustness, and Scenario Analysis

The baseline model results point to a linear transmission mechanism dominated by persistence, output growth, and exchange-rate depreciation. The question is how stable those findings are and what they suggest once nonlinearity, specification sensitivity, and adverse scenarios are introduced into the analysis.

5.1. Threshold Results

The threshold analysis utilizes lagged banking-sector profitability, measured by return on equity, as the conditioning variable. The rationale is that a banking system that enters a shock episode with weak profitability may have less capacity to absorb losses, less room to provision without balance-sheet strain, and weaker incentives to resolve impaired exposures promptly. The threshold model allows the slopes of the macroeconomic shock variables to vary across regimes of low and high profitability while holding the remaining controls to be equal across regimes, as described in Equation (3) of Section 3. Table 6 presents the threshold test summary, and Figure 5 traces the concentrated sum of squared residuals across the candidate threshold grid.

Table 6. Threshold-model summary.

Item	Value
Threshold variable	Lagged return on equity (%)
Estimated threshold (γ (gamma))	1.80
Linear-model SSR	8.055
Threshold-model SSR	7.562
Likelihood-ratio statistic	12.527
Bootstrap replications	999
Bootstrap p -value (threshold re-estimated in each replication)	0.218
Bootstrap p -value (fixed threshold, original submission)	0.046
Low-regime observations ($\text{ROE} \leq 1.80\%$)	32
High-regime observations ($\text{ROE} > 1.80\%$)	160

Under the corrected bootstrap, in which the threshold is re-estimated by a full grid search in every replication, the p -value is 0.218 and the null of a fully linear specification is not rejected at conventional levels. The fixed-threshold bootstrap used in the original version of this paper yielded $p = 0.046$, an artifact of comparing a sup-type statistic against a pointwise null distribution. The threshold is estimated at approximately 1.80 percent return on equity, which separates 32 low-profitability observations from 160 high-profitability observations. The concentrated sum of squared residuals decreases from 8.055 under the linear model to 7.562 under the threshold specification, a reduction consistent with the estimated likelihood-ratio statistic. This result does not support H4. Once the threshold search is accounted for in the bootstrap, the data do not provide statistically significant evidence that macro-financial transmission differs across profitability states. The regime-specific estimates below are presented as descriptive.

Appendix A, Table A3 reports the full robustness analysis under the corrected bootstrap. No trimming window produces a rejection. The corrected p -value is 0.093 at a 10 percent trim, 0.218 at the baseline 15 percent trim, and 0.415, 0.536, and 0.528 at 20, 25, and 30 percent trims, with the estimated cutoff migrating to the boundary of the admissible window under the wider trims. The 95 percent confidence interval for the threshold location, obtained by inverting the likelihood-ratio statistic, spans 1.0 to 9.8 percent return on equity. The smallest p -values arise when the trimming window retains the acute-distress

tail of the ROE distribution, and the regime composition shows why: the low-ROE regime consists mainly of crisis episodes in Ukraine, Montenegro, Serbia, Bosnia and Herzegovina, and Georgia. Hansen (1999) points out that threshold inference is inherently contingent on the relative size of the regimes, and the present configuration is not generous in that respect. The correct reading is that the data do not establish a statistically significant regime split in profitability, and that whatever state dependence exists appears concentrated in acute-distress episodes, rather than in a broad low-profitability regime.

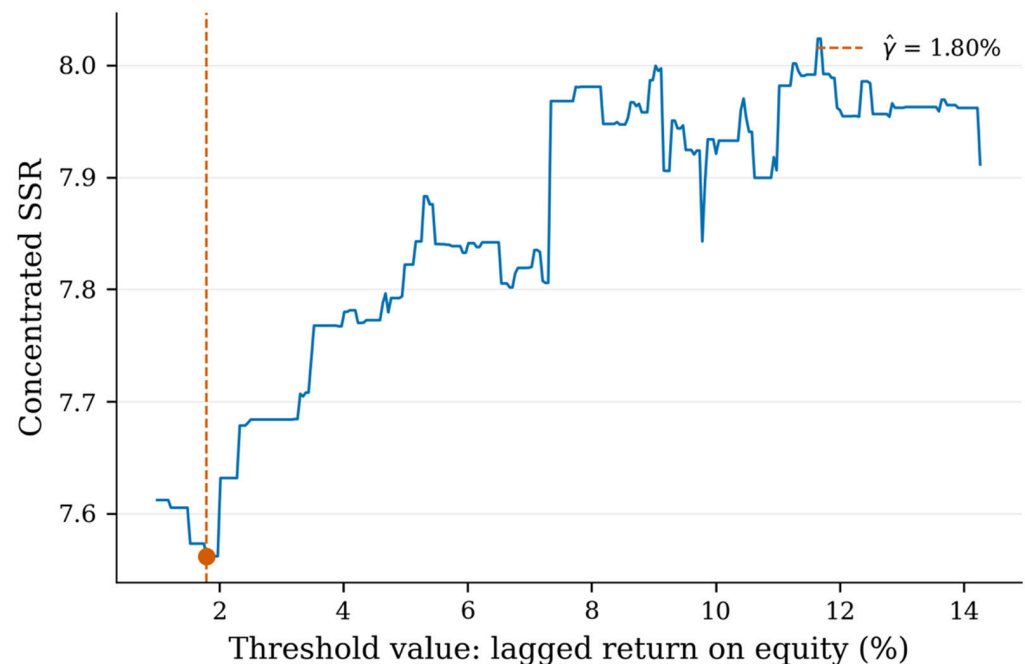


Figure 5. Threshold SSR profile and estimated profitability cutoff. Source: authors' calculations.

The same corrected testing standard applied to alternative threshold variables leads to the same conclusion. No configuration rejects linearity at the 5 percent level. The minimum corrected p -value across the 14 configurations reported in Appendix A, Table A2 is 0.071 for an institutional regime split at the 15 percent trim, the liquidity-ratio thresholds range from 0.079 to 0.154, and regulatory capital shows no threshold effect at all ($p = 0.750$). Among the candidates, the liquidity cutoff near 41.5 percent of liquid assets to total assets is the most stable across trimming windows and produces the sharpest regime contrast in point estimates, with an exchange-rate coefficient of 0.016 (SE = 0.003) in the high-liquidity regime against 0.005 (SE = 0.004) in the low-liquidity regime, but this contrast is not statistically established. Appendix A, Figure A2 summarizes the corrected p -values across the three threshold variables.

The composition of the high-liquidity regime explains this initially counterintuitive point pattern. The regime is dominated by Türkiye (15 observations), Ukraine (12), Moldova (8), and Latvia (6), banking systems that hold large liquid-asset buffers precisely because they operate in risky, foreign-currency-exposed funding environments. High measured liquidity in this sample is therefore a symptom of exposure, rather than an indicator of safety. The pattern is consistent in spirit with the liquidity-based threshold documented for emerging European banks by Pop et al. (2018), although that finding, like the original version of this paper, rested on bootstrap inference that did not re-estimate the threshold within each replication, and our corrected results suggest such estimates deserve re-examination. Because the regime split partially overlaps a country-group split, and is not statistically

significant under corrected inference, these patterns indicate where transmission appears strongest, not a structural parameter.

5.2. Regime-Specific Coefficients

Table 7 reports the regime-specific coefficient estimates from the threshold model with cluster-robust standard errors.

Table 7. Threshold regime coefficients (dependent variable: logit NPL ratio).

Variable	Coefficient	SE (Cluster)
Lagged NPL (logit)	0.788 ***	(0.066)
Real interest rate	0.006	(0.008)
Regulatory capital/RWA	−0.000	(0.017)
Liquidity ratio	0.004	(0.003)
Private credit/GDP	0.004	(0.004)
Log bank assets	−0.147	(0.154)
Institutional composite	0.192 *	(0.110)
Regime-varying coefficients	Low ROE	High ROE
Real GDP p.c. growth	−0.004 (0.011)	−0.018 ** (0.009)
FX depreciation	0.005 (0.003)	0.014 *** (0.004)

Notes: Low-ROE regime: $ROE \leq 1.80\%$ ($n = 32$). High-ROE regime: $ROE > 1.80\%$ ($n = 160$). The persistence parameter, the real interest rate, the banking-sector controls, and the institutional composite are constrained to be equal across regimes. Standard errors (cluster-robust) in parentheses. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Threshold tests fail to reject the null of linearity, and the regime-specific coefficients are presented for descriptive purposes only.

The regime contrast requires careful interpretation. The growth effect is more negative in the high-profitability regime (−0.018, SE = 0.009) than in the low-profitability regime (−0.004, SE = 0.011). The exchange-rate effect follows the same pattern, being larger in the high-profitability regime (0.014, SE = 0.004) than in the low-profitability regime (0.005, SE = 0.003). This is not the simple amplification narrative that the strongest version of H4 might suggest, in which weak profitability mechanically magnifies every shock coefficient.

The pattern is, however, consistent with an alternative reading that we consider the most defensible interpretation. In the low-profitability regime, banking systems are already in a state of accumulated distress. The stock of impaired loans is elevated, workout dynamics are ongoing, and the marginal response of the non-performing loan ratio to additional macroeconomic deterioration may be compressed by reporting inertia, restructuring delays, or the fact that the most vulnerable exposures have already migrated into non-performing status. In the high-profitability regime, the system operates closer to normal transmission: shocks hit a portfolio that still contains performing loans with the capacity to deteriorate, and the standard macro-financial channels, repayment capacity, and balance-sheet effects are more clearly measurable.

This interpretation is not unprecedented in the literature. Pop et al. (2018) identify a liquidity-based threshold that separates different risk regimes in emerging European banks, with the more liquid regime exhibiting distinct sensitivity to risk factors. Bolarinwa et al. (2021) document nonlinearities in the NPL-profitability relationship that do not reduce to a simple monotonic story. Bardhan et al. (2019) find that the effect of capital adequacy on impaired assets changes character once a critical level is breached. The common thread is that threshold effects in banking outcomes can take forms more nuanced than uniform amplification. Once the bootstrap accounts for threshold search, the present data cannot reject the assumption that the macro-credit-risk relationship is constant across states of the

banking system at conventional significance levels. The regime-specific point estimates, nevertheless, display a consistent qualitative pattern across every split considered, profitability, liquidity, and institutional quality: transmission appears compressed in distressed or structurally weak states and stronger in systems that still function normally. That descriptive consistency motivates future work with larger panels and dynamic-panel-valid threshold estimators, but it is not a statistically established result, and we present it in this way.

5.3. Robustness and Referee Diagnostics

The baseline findings are subjected to four categories of specification checks: alternative inference, coefficient stability across robustness specifications, leave-one-out sensitivity, and formal diagnostic tests. Table 8 consolidates the key results.

Table 8. Robustness and diagnostic summary.

Panel A: Coefficient stability across logit-DV specifications (4 specifications)			
Variable	Min	Mean	Max
Persistence (lagged NPL)	0.726	0.783	0.807
Real GDP p.c. growth	−0.017	−0.015	−0.014
Real interest rate	0.003	0.007	0.016
FX depreciation	0.008	0.010	0.014
Panel B: Leave-one-country-out sensitivity (14 exclusions)			
Coefficient	Min	Median	Max
FX depreciation	0.007	0.009	0.014
Real GDP p.c. growth	−0.018	−0.014	−0.010
Persistence (lagged NPL)	0.726	0.806	0.823
Panel C: Diagnostic tests			
Test	Statistic	Interpretation	
Weighted CD (valid under two-way FE)	−1.25 ($p = 0.210$)	No residual cross-sectional dependence detected; FE-DK retained as conservative complement	
Maximum VIF	2.06	No multicollinearity concern	
Year FE joint F-test	6.78 ($p < 0.001$)	Common time shocks are jointly significant	
Country-level ADF rejections at 10%	1 of 14	Mixed unit-root evidence; persistence should be discussed carefully	

Figure 6 summarizes coefficient stability across the four logit-DV specifications.

Three patterns were maintained through all checks. The persistence coefficient remains large and positive across every specification and every country exclusion (range: 0.726 to 0.823). The growth coefficient remains negative throughout (range: −0.018 to −0.010). The FX depreciation coefficient remains positive throughout (range: 0.007 to 0.014). These three sign patterns, the empirical core of the paper, are not an artifact of a single estimator, a single inferential convention, or a single influential country. Figure 7 displays the leave-one-country-out estimates for the growth and FX depreciation coefficients; the largest single movement, produced by excluding Ukraine, raises the FX coefficient to 0.014 without changing its sign.

The weighted CD test of Juodis and Reese (2022), which remains valid on two-way fixed-effects residuals, does not reject cross-sectional independence (statistic = −1.25, $p = 0.21$). The standard CD statistic of Pesaran (2004) is reported in the replication package for reference only, because it is biased in this design. Driscoll–Kraay inference is retained as a conservative complement to the bootstrap-based BC-FE baseline. The maximum variance inflation factor of 2.06 is well below conventional concern thresholds (Tmava & Spahiu,

2025), indicating that multicollinearity does not compromise the coefficient estimates. The year fixed effects are jointly significant ($F = 6.78, p < 0.001$), confirming that common time shocks matter in the panel and should be retained. The unit-root evidence is mixed: only 1 of 14 country-level ADF tests rejects at the 10 percent level, which is not unusual in short annual panels with a highly persistent dependent variable but does mean that the paper should avoid claiming more time-series certainty than the panel can support.

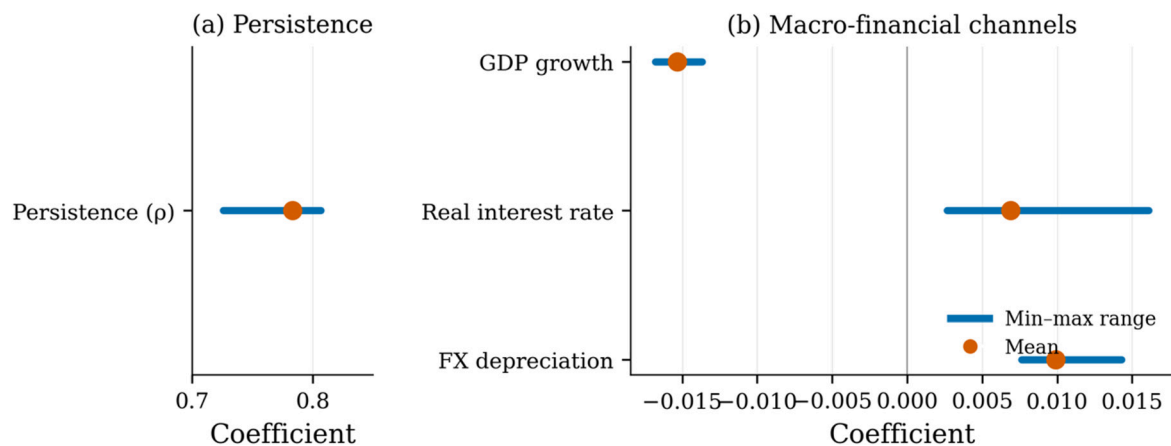


Figure 6. Coefficient stability across four dynamic logit-DV specifications. Panel (a) shows the persistence coefficient ρ ; Panel (b) shows the macro-financial channel coefficients (real GDP per capita growth, real interest rate, FX depreciation). Blue bars indicate the min-max range across the four specifications; orange markers show the mean. Source: authors' calculations based on the panel summarized in Table 8.

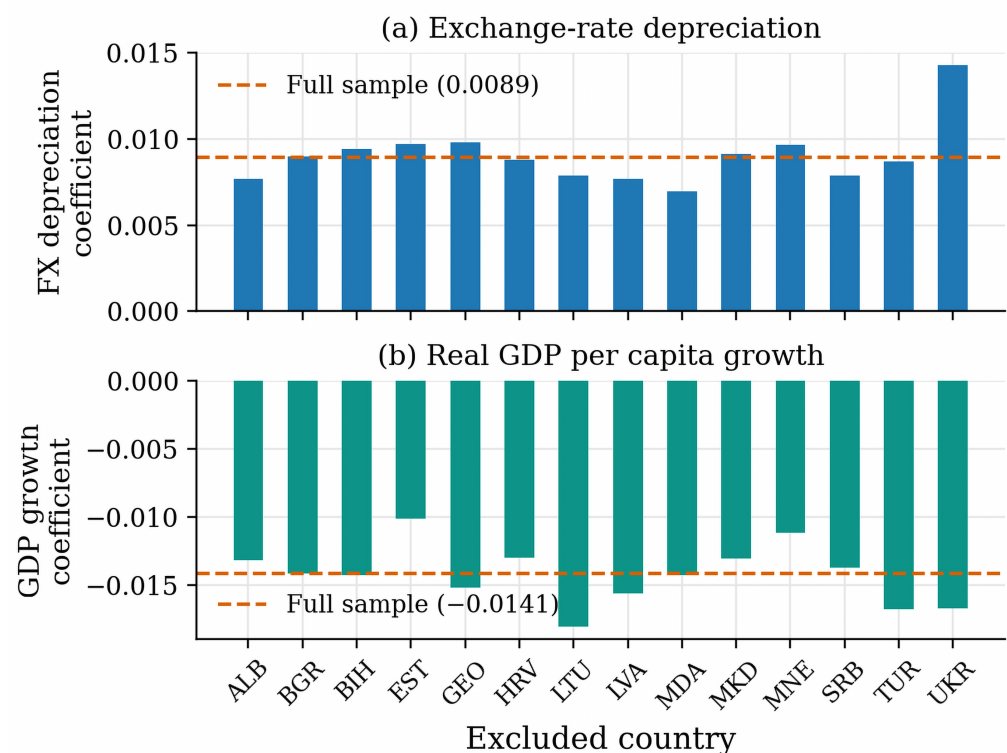


Figure 7. Leave-one-country-out sensitivity of the growth and FX depreciation coefficients. Source: authors' calculations.

The leave-one-out exercise provides the strictest single-country influence check. No country exclusion reverses the sign of either the growth or the FX depreciation coefficient. The FX coefficient ranges from 0.007 to 0.014, and the growth coefficient from -0.018 to

−0.010, across all 14 exclusions. This matters because small regional panels are always vulnerable to the criticism that one or two influential units may drive the results. That criticism is not supported by the evidence.

Dynamic-panel GMM was examined and discarded, rather than reported. A parsimonious one-step Difference GMM produced a lagged dependent-variable coefficient which is effectively at unity (1.005) with macro-financial coefficients that lost all precision, and both the System and Difference variants required generalized inverses of singular two-step weighting matrices. With $N = 14$, augmenting the instrument set magnifies the proliferation problem identified by Roodman (2009). We therefore treat GMM as infeasible in this configuration, and report no GMM estimates; the attempted specifications are documented in the replication package. This pattern clarifies why the primary estimator was chosen, rather than undermining the baseline findings.

5.4. Scenario Simulation

The scenario analysis translates the estimated coefficients into projected credit-risk paths under standardized adverse conditions. The simulation horizon is five years, and the shocks are set to one and two standard deviations of the respective macroeconomic variables. The baseline path is intercept-calibrated so that, in the absence of shocks, the projected non-performing loan ratio is anchored at its observed starting level. The projected results at the 5-year horizon are reported in Table 9.

Table 9. Scenario outcomes at the five-year horizon.

Scenario	Projected NPL Ratio (%)	Change vs. Baseline (pp)
Baseline	6.54	-
GDP shock (−1 SD)	7.29	+0.75
Real-rate shock (+1 SD)	6.84	+0.30
FX shock (+1 SD)	7.76	+1.22
Combined adverse (1 SD)	9.02	+2.48
Severe combined (2 SD)	12.32	+5.78

The scenario ranking is a reflection of the coefficient structure. The exchange-rate shock produces a larger medium-run effect (+1.22 pp) than either the GDP shock (+0.75 pp) or the interest-rate shock (+0.30 pp) in isolation, consistent with the relative magnitudes of the baseline coefficients. The combined negative scenario increases the projected non-performing loan ratio to 9.02 percent, which represents a 38 percent increase over the baseline. Under the severe combined scenario, the projected ratio nearly doubles, to 12.32 percent. Uncertainty around these paths is material. The 90 percent bootstrap interval for the severe scenario at the five-year horizon spans 8.2 to 24.6 percent, reflecting the persistence uncertainty documented in Section 4.3, and the projections should be read as an illustrative translation of the estimated sensitivities, rather than as a forecast. Figure 8 plots the projected non-performing loan trajectories in each scenario at the five-year horizon.

Two features of the scenario output are economically consequential. The first is the part that persistence plays. Even though the one-period macro coefficients are individually modest, their impacts are compounded by the autoregressive nature of the system over multi-year horizons. The 5.78 percentage-point deterioration in the severe combined scenario is not driven by large one-period shocks to the non-performing loan ratio. It is driven by the interaction between moderate annual shocks and a persistence coefficient near 0.94. Huljak et al. (2022) demonstrate that high non-performing loan ratios depress

bank lending and real economic activity in the euro area, and the scenario projections demonstrate the extent of deterioration that can set such feedback mechanisms in motion.

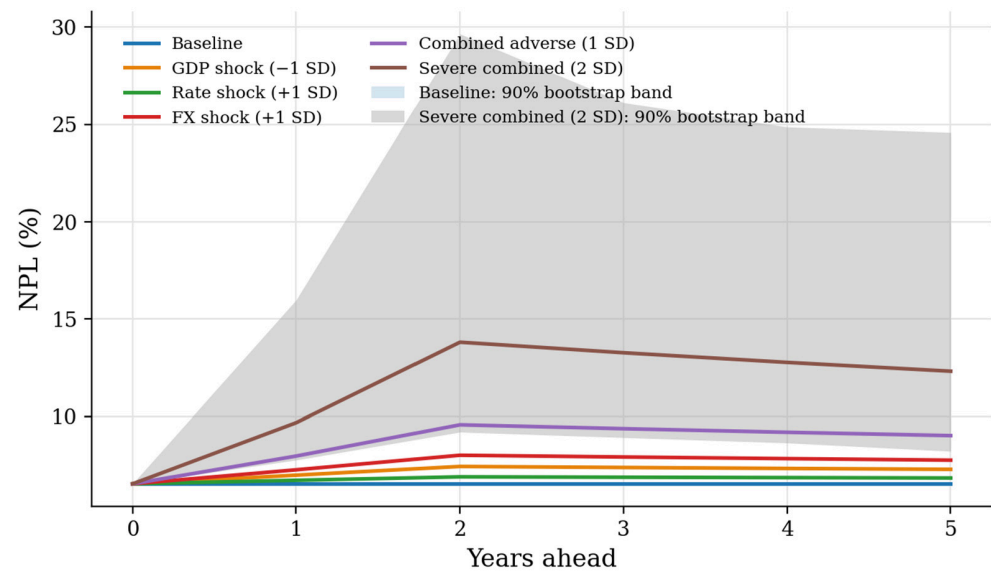


Figure 8. Projected NPL paths under baseline, single-shock, and combined adverse scenarios. Shaded areas show 90 percent bootstrap bands for the baseline and severe combined scenarios. Source: authors' calculations.

The second feature is the dominance of the exchange-rate channel. The FX shock has a bigger impact on the medium-run than the GDP shock, and it explains a significant proportion of the combined-scenario deterioration. This result reinforces the international-finance dimension of the paper. Exchange-rate movements are not a secondary feature of the macro-financial environment in CESEE; they are actually a primary transmission channel through which external monetary and financial conditions affect the domestic banking-sector credit risk (Beck et al., 2015; Jakubík & Reininger, 2014). Figure 9 decomposes the five-year impact by scenario.

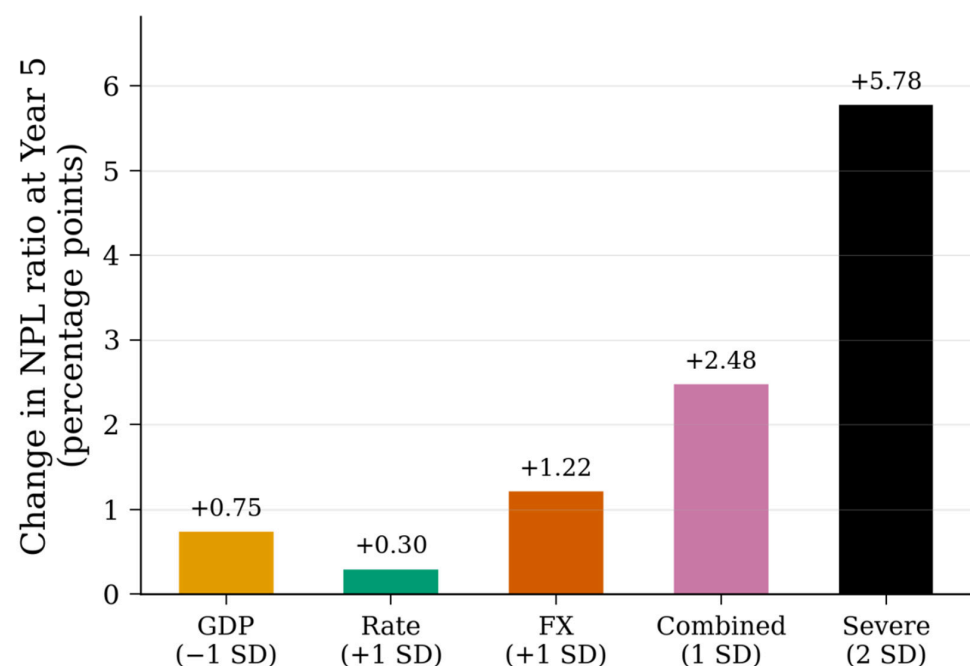


Figure 9. Scenario impact relative to baseline at the five-year horizon. Source: authors' calculations.

Figure 9 isolates the five-year impact of each scenario relative to the baseline, expressed in percentage points, to make the relative magnitudes more directly comparable.

5.5. Policy Implications

The combined evidence of the threshold model, robustness exercises, and scenario simulations have three implications for macro-financial surveillance.

The exchange-rate channel is to be considered as a core financial-stability mechanism in emerging Europe. The baseline estimates, the robustness checks, and the scenario projections all lead to the same conclusion: that the exchange-rate depreciation is a quantitatively significant driver in the banking-sector credit risk in the region, and its medium-run impact is amplified by the persistence of the non-performing loan process. For regulatory authorities, this means that exchange-rate stress is not just an external-price event. It is a banking-sector vulnerability channel that requires monitoring alongside the more conventional growth and interest-rate indicators (Beck et al., 2015; Tanasković & Jandrić, 2015).

Persistence suggests that delayed intervention is costly. Once banking-sector credit risk increases, it remains elevated for an extended period (Bischof et al., 2022). The scenario simulations show that a severe adverse shock can approximately double the non-performing loan ratio within five years. The policy implication is that resolution, provisioning, and restructuring frameworks need to operate early and effectively when deterioration sets in. In banking systems where workout capacity is limited or where insolvency frameworks are weak, the persistence mechanism converts short-term shocks into medium-run balance-sheet problems (Bischof et al., 2022; Zoller, 2023).

The institutional environment belongs within macro-financial surveillance, rather than outside it. The baseline interaction term is not significant, and the threshold regime contrast does not follow the simplest amplification story. But the broader pattern, that institutional quality is theoretically relevant to the transmission mechanism, that regime-specific point patterns are suggestive even though corrected threshold inference does not reject linearity, and that the scenario projections illustrate how macro-financial sensitivities compound over time, is consistent with the view that governance conditions shape the environment in which shocks propagate (Beirne & Panthi, 2022; Lee et al., 2019). The evidence is suggestive, rather than definitive, on the precise institutional channel, which is an honest limitation. It does not, however, support the conclusion that institutions are irrelevant to macro-financial transmission in CESEE.

Why these two null results arise deserves more than a statement of non-support. For institutional moderation, at least three mechanisms plausibly mute a linear interaction. Better institutions accelerate both the recognition of impaired loans, which raises measured NPL ratios during stress, and their resolution, which lowers them, and these opposing recognition and resolution effects can offset, within a net moderation coefficient, even when each channel is active. Institutional indices also move slowly within countries, so country fixed effects absorb most of their variation and leave little identifying signal in a 16-year window. Perception-based governance measures additionally record institutional quality with error, which attenuates interaction estimates toward zero. For the threshold results, the candidate low regimes are concentrated in a handful of crisis episodes, annual data can mask regime switching that occurs within a year, and 14 cross-sectional units offer limited power for detecting regime-dependent slopes even where they exist.

These explanations carry distinct implications. For research, bank-level panels would restore the cross-sectional variation that country aggregates suppress, higher-frequency supervisory data could capture within-year regime dynamics, and discrete institutional reforms offer quasi-natural experiments that slow-moving indices cannot. For policy, the nulls are informative, rather than empty: macro-prudential triggers should not be

conditioned on profitability or liquidity cutoffs that formal testing cannot validate, and the exchange-rate channel deserves monitoring universally, rather than only in supposedly vulnerable regimes. A null result established under corrected inference protects policy design from acting on false positives.

Taken together, the evidence from the baseline estimates, robustness exercises, threshold analysis, and scenario simulations reinforces the paper's central argument. The baseline results are robust, withstanding alternative inference procedures, sample perturbations, and diagnostic scrutiny. Threshold analysis, under corrected bootstrap inference, does not establish statistically significant nonlinearity in the transmission process, while scenario exercises demonstrate that the estimated sensitivities imply substantial medium-run consequences once persistence and joint shocks are accounted for.

6. Conclusions

This paper examined the cross-border transmission of macroeconomic shocks to credit risk in the banking sector in a panel of 14 CESEE and comparator banking systems over 2008–2023. The empirical design combined a bias-corrected dynamic-panel specification with threshold analysis, alternative inferential approaches, and a scenario simulation module. The analysis is based on three key findings.

Credit risk in the banking sector is highly persistent. The bias-corrected autoregressive coefficient is 0.944, which means that the half-life is 12.0 years. Even under the more conservative Driscoll–Kraay estimates, the persistence coefficient remains at 0.802, with a half-life of 3.1 years. The bootstrap interval for the persistence coefficient (0.601 to 1.048), a half-panel jackknife estimate above unity, and a CIPS test that does not reject a panel unit root, together imply that these half-life figures are conditional on stationarity that the data cannot confirm. Such a level of inertia means that macroeconomic shocks do not simply raise credit risk in the period in which they occur, but rather interact with a legacy of banking-sector weaknesses, and the resulting deterioration can extend over many years. The finding is consistent with the slow loan-workout dynamics documented across CESEE by Klein (2013) and Tătărici et al. (2020), with the larger body of evidence that high NPL ratios reduce bank lending and real activity in the long run (Huljak et al., 2022).

The macro-financial factors that most consistently predict future credit risk are lower real income growth and exchange-rate depreciation. The growth coefficient lies between -0.014 and -0.018 across specifications, with the FX depreciation coefficient between 0.008 and 0.012 , which compounds substantially over time. The exchange-rate effect survives the test of the explicit correction of the depreciation series breaks, which confirms the argument that it is the manifestation of the actual macro-financial transmission via the balance-sheet and competitiveness channels, and not a measurement error. The real interest-rate channel works in the anticipated direction, but is not as precisely predicted. The scenario simulations illustrate the practical implications of these relationships: in a combined adverse scenario calibrated at one standard deviation, the estimated ratio of non-performing loans increases from 6.54 percent to 9.02 percent at the five-year horizon, and in a severe combined scenario it nearly doubles, to 12.32 percent (90 percent bootstrap interval: 8.2 to 24.6 percent). Only the exchange-rate shock has a larger medium-run effect than the growth shock or the interest-rate shock, which underscores the international aspect of the banking-sector susceptibility in the region.

The paper contributes to the international financial markets and institutions literature in four ways. It shifts the emphasis from average determinants of non-performing loans to the transmission of macroeconomic shocks in a dynamic cross-country environment, with persistence modeled explicitly and its uncertainty stated plainly, rather than left in the residual structure. It documents which channels survive demanding verification:

exchange-rate depreciation and, more marginally, real income growth. It reports disciplined null results for institutional moderation, tested at the composite level and dimension by dimension, and for threshold nonlinearity, tested across 14 configurations under a bootstrap that re-estimates the threshold in every replication. And it provides a scenario module, with explicit uncertainty bands, which converts the estimates into a form directly readable for macro-financial surveillance, together with a fully reproducible replication package whose verification history is documented in its changelog.

However, several limitations must be acknowledged. The cross-sectional dimension of the panel is small ($N = 14$), which constrains the precision of all estimates and particularly affects the identification of interaction effects involving slowly moving institutional variables. The baseline interaction between exchange-rate depreciation and institutional quality does not reach conventional significance, and the simple linear moderation of the FX channel is not conclusively determined in this sample. Such a finding should be weighed against the theoretical relevance of the institutional channel, instead of being taken as evidence that governance is irrelevant to macro-financial transmission. Under the corrected bootstrap, in which the threshold is re-estimated in every replication, the threshold test does not reject full linearity ($p = 0.218$ at the baseline trimming, with a minimum of 0.071 across 14 configurations spanning profitability, liquidity, capital, and institutional threshold variables), and the regime-specific coefficients are reported as descriptive. Any state dependence is at most suggestive, and the limited number of observations in the low-profitability regime ($n = 32$) reinforces that reading. The annual frequency of the data restricts the possibility of capturing within-year adjustment dynamics. The mixed unit-root evidence, with only 1 of 14 country-level ADF tests rejecting at the 10 percent level, indicates that the high persistence estimates are to be viewed with due caution as to the difference between slow adjustment and near-unit-root behavior. Dynamic-panel GMM, which might in principle address some of these concerns, does not perform well in the present configuration: System GMM can be estimated only via a generalized inverse of its singular two-step weighting matrix, and a parsimonious Difference GMM fallback yields a persistence coefficient of 1.005 with macro coefficients that lose precision, consistent with the small- N instability documented by Roodman (2009).

These limitations indicate the natural directions of future research. At the bank-level, panels would enhance the cross-sectional aspect and allow identification of within-country heterogeneity in the response of individual institutions to macroeconomic stress. Incorporating foreign-currency lending shares directly into the estimation would allow a more precise test of the balance-sheet mechanism captured by the FX coefficient in reduced form. Higher-frequency data would help distinguish contemporaneous from lagged adjustment dynamics. Regime-switching models that allow the threshold to vary over time or across countries would provide a more flexible treatment of nonlinearity. On the institutional side, exploiting specific governance reforms as quasi-natural variation, rather than relying on broad composite indices with limited within-country movement, would offer a more credible identification strategy for the institutional moderation channel.

For CESEE banking sectors, the broader implication is that macro-financial surveillance must consider exchange-rate pressure, output weakness, and balance-sheet persistence as interdependent, not independent risks. In a persistent credit-risk process, even moderate disturbances can accumulate into lasting impairment (Jakubík & Reininger, 2013). The policy focus should fall not only on shock prevention, but also on supervisory responsiveness, resolution capacity, and the institutional conditions that determine how quickly banking systems absorb or prolong stress.

Author Contributions: Conceptualization, I.M.; methodology, I.M., A.T. and A.P.; software, A.P.; validation, A.P.; formal analysis, A.P.; investigation, I.M. and A.T.; resources, A.T. and A.P.; data

curation, I.M., A.T. and A.P.; writing—original draft preparation, I.M. and A.P.; writing—review and editing, I.M., A.T. and A.P.; visualization, A.P.; supervision, I.M.; project administration, I.M.; funding acquisition, I.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the University of Slavonski Brod through the institutional research project “Digital Center for Student Internships, Research and Collaboration of the University of Slavonski Brod” (Project id: NPOO-007), financed by the European Union—NextGenerationEU.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The replication data and code supporting the findings of this study are openly available in the Mendeley Data repository at 10.17632/825rpt6328.5.

Acknowledgments: The authors gratefully acknowledge the support of the Ministry of Science, Technological Development and Innovation of the Republic of Serbia, Contract Number 451-03-33/2026-03/200371. The views and opinions expressed in this paper are solely those of the authors and do not necessarily reflect the official position of the European Union or the European Commission; neither the European Union nor the European Commission can be held responsible for them. During the preparation of this manuscript, the authors used Grammarly for grammar, spelling, and punctuation checking. No generative AI tools were used to draft, analyze, or interpret any substantive content. The authors take full responsibility for the content of the publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Institutional decomposition of the FX x institutional quality interaction (dependent variable: logit NPL ratio).

Model	Interaction	Boot SE	95% CI	Cluster <i>p</i>	Level (<i>p</i>)
Institutional composite	0.0034	0.0030	[−0.0023, 0.0093]	0.179	0.110 (0.336)
Rule of Law	0.0035	0.0031	[−0.0027, 0.0097]	0.166	−0.029 (0.777)
Regulatory Quality	0.0030	0.0028	[−0.0031, 0.0084]	0.186	0.162 (0.042)

Notes: Each row is a separate bias-corrected fixed-effects estimation of Equation (2) with the institutional composite replaced by the indicated WGI dimension, standardized over the full sample. Bootstrap standard errors and percentile confidence intervals are from a country-block bootstrap with $B = 500$ replications. Cluster *p* denotes country-clustered *p*-values. All regressors are lagged one period. $N = 192$.

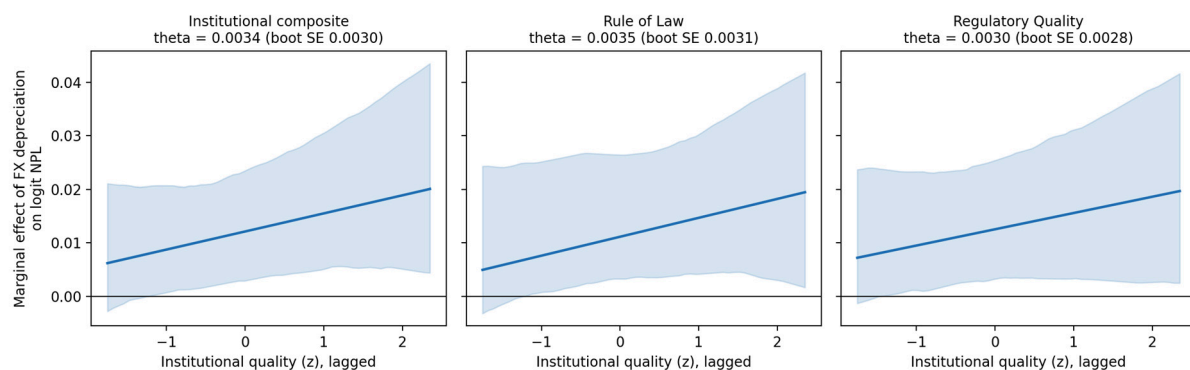


Figure A1. Marginal effect of exchange-rate depreciation on the logit NPL ratio across the institutional quality distribution, with 95 percent bootstrap confidence bands. Source: authors' calculations.

Table A2. Threshold robustness across trimming windows and alternative threshold variables (dependent variable: logit NPL ratio).

Threshold Variable	Trim	Gamma	Gamma 95% CI	Low/High n	LR	Boot <i>p</i> (Corrected)
Return on equity	0.10	−0.40	[−0.63, 3.25]	21/171	16.66	0.093
Return on equity	0.15	1.80	[1.00, 9.78]	32/160	12.53	0.218
Return on equity	0.20	3.34	[3.34, 12.77]	39/153	8.74	0.415
Return on equity	0.25	4.32	[4.32, 12.01]	48/144	7.04	0.536
Return on equity	0.30	6.66	[5.08, 11.16]	78/114	6.24	0.528
Regulatory capital/RWA	0.15	18.07	[15.74, 23.07]	85/107	5.92	0.750
Liquidity ratio	0.10	41.55	[20.20, 47.01]	151/41	19.99	0.154
Liquidity ratio	0.15	41.53	[21.26, 46.98]	151/41	19.99	0.119
Liquidity ratio	0.20	41.58	[22.35, 46.30]	151/41	19.99	0.096
Liquidity ratio	0.25	34.71	[31.13, 35.81]	142/50	18.23	0.079
Liquidity ratio	0.30	33.61	[24.54, 33.86]	134/58	14.93	0.115
Institutional composite	0.15	−0.83	[−0.83, −0.82]	29/163	16.62	0.071
Institutional composite	0.20	−0.63	[−0.76, 1.04]	53/139	6.21	0.573
Institutional composite	0.30	−0.53	[−0.57, 0.13]	67/125	6.14	0.389

Notes: Each row re-estimates the threshold specification of Equation (3) with the indicated threshold variable and trimming fraction. Confidence intervals for gamma are obtained by inverting the likelihood-ratio statistic with the Hansen (1999) 95 percent critical value of 7.35. Bootstrap *p*-values are based on *B* = 999 sign-flip replications with a fixed seed, with the threshold re-estimated by a full grid search in every replication, as the Hansen procedure requires. Under the fixed-threshold bootstrap of the original submission, these *p*-values ranged from 0.011 to 0.243; the replication package reports both sets. The return-on-equity row with trim 0.15 reproduces the Table 6 baseline. The reported confidence bounds are the convex hull of the LR no-rejection set, which is disconnected for several configurations (three components for the baseline configuration); the replication package reports every component. Estimated cutoffs are grid points, and any value between adjacent observed threshold-variable values (1.75 to 2.00 percent ROE for the baseline) yields an identical regime allocation. Threshold tests fail to reject the null of linearity in any configuration, and all regime-specific coefficients are presented for descriptive purposes only.

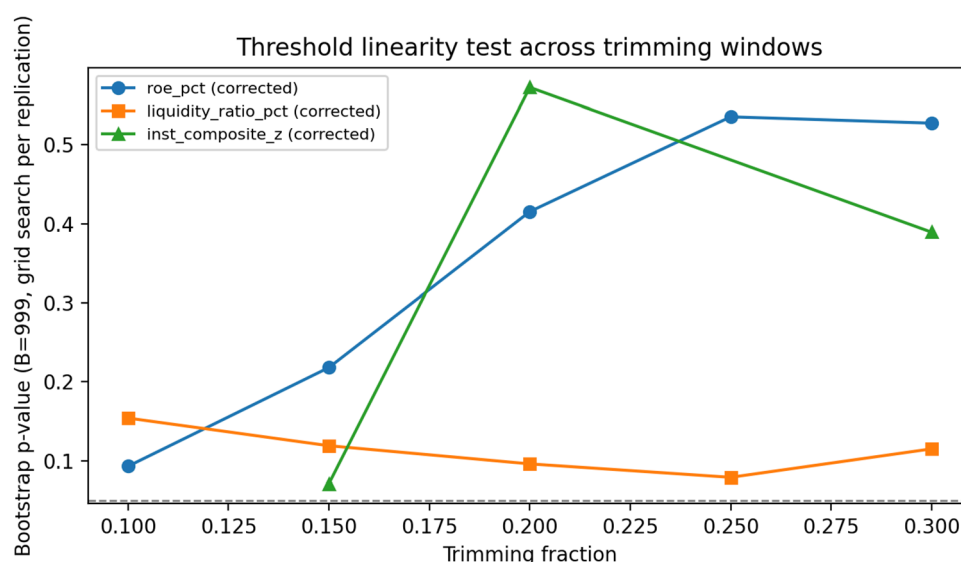
**Figure A2.** Bootstrap *p*-values of the threshold linearity test across trimming windows for the three threshold variables. The dashed line marks the 5 percent significance level. Source: authors' calculations.

Table A3. Country coverage and classification.

Country	ISO3	Classification (Group Variable: EU/EM)
Albania	ALB	Emerging (non-EU)
Bosnia and Herzegovina	BIH	Emerging (non-EU)
Bulgaria	BGR	EU member
Croatia	HRV	EU member
Estonia	EST	EU member
Georgia	GEO	Emerging (non-EU), comparator
Latvia	LVA	EU member
Lithuania	LTU	EU member
Moldova	MDA	Emerging (non-EU)
Montenegro	MNE	Emerging (non-EU)
North Macedonia	MKD	Emerging (non-EU)
Serbia	SRB	Emerging (non-EU)
Türkiye	TUR	Emerging (non-EU), comparator
Ukraine	UKR	Emerging (non-EU)

Table A4. Inference robustness: uncorrected within-group estimates under alternative standard-error conventions (reference only).

Variable	FE-DK Coef. (SE)	FE-Cluster Coef. (SE)
Lagged NPL (logit)	0.802 *** (0.049)	0.802 *** (0.061)
Real GDP p.c. growth	−0.014 *** (0.005)	−0.014 ** (0.007)
Real interest rate	0.004 (0.007)	0.004 (0.008)
FX depreciation	0.009 (0.007)	0.009 ** (0.004)
Regulatory capital/RWA	0.001 (0.016)	0.001 (0.017)
Liquidity ratio	0.004 (0.004)	0.004 (0.003)
Return on equity	0.002 (0.005)	0.002 (0.003)
Private credit/GDP	0.003 (0.003)	0.003 (0.003)
Log bank assets	−0.089 (0.094)	−0.089 (0.108)
Institutional composite	0.140 (0.125)	0.140 (0.114)
Observations	192	192

Notes: Point estimates are uncorrected within-group estimates subject to Nickell bias of order $O(1/T)$, and are reported solely to document that inference conclusions do not depend on the standard-error convention. FE-DK applies Driscoll–Kraay standard errors and FE-Cluster applies country-clustered standard errors to the same within-group regression. The preferred bias-corrected estimates appear in Table 5, and few-cluster restricted wild cluster bootstrap inference appears in Section 4.3. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

References

- Abaidoo, R., & Agyapong, E. K. (2025). Governance, regulatory quality and financial institutions: Emerging economies perspective. *Journal of Economic and Administrative Sciences*, 41(4), 1310–1331. [\[CrossRef\]](#)
- Ahmed, S., Majeed, M. K., Thalassinou, E., & Thalassinou, Y. (2021). The impact of bank specific and macro-economic factors on non-performing loans in the banking sector: Evidence from an emerging economy. *Journal of Risk and Financial Management*, 14, 217. [\[CrossRef\]](#)
- Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58, 277. [\[CrossRef\]](#)

- Ayhan, F., & Kartal, M. T. (2021). The macro economic drivers of non-performing loans (NPL): Evidence from selected countries with heterogeneous panel analysis. *MANAS Sosyal Araştırmalar Dergisi*, 10, 986. [CrossRef]
- Bardhan, S., Sharma, R., & Mukherjee, V. (2019). Threshold effect of bank-specific determinants of non-performing assets: An application in Indian banking. *Journal of Emerging Market Finance*, 18, 1–34. [CrossRef]
- Bayar, Y. (2019). Macroeconomic, institutional and bank-specific determinants of non-performing loans in emerging market economies: A dynamic panel regression analysis. *Journal of Central Banking Theory and Practice*, 8, 95. [CrossRef]
- Beck, R., Jakubík, P., & Piloiu, A. (2013). *Non-performing loans: What matters in addition to the economic cycle?* (ECB Working Paper No. 1515). European Central Bank. Available online: <https://hdl.handle.net/10419/153948> (accessed on 10 March 2026).
- Beck, R., Jakubík, P., & Piloiu, A. (2015). Key determinants of non-performing loans: New evidence from a global sample. *Open Economies Review*, 26, 525. [CrossRef]
- Beirne, J., & Panthi, P. (2022). *Institutional quality and macrofinancial resilience in Asia* (ADB Working Paper No. 1336). Asian Development Bank Institute. [CrossRef]
- Beka, A., & Abazi-Alili, H. (2023). The impact of economic growth on non-performing loans in Western Balkan countries. *InterEU LawEast: Journal for the International and European Law, Economics and Market Integrations*, 10, 117. [CrossRef]
- Bilan, I., & Roman, A. (2016). Effects of macroeconomic factors on bank loans quality: Evidence from Central and Eastern European countries. In *Eurasian studies in business and economics* (p. 571). Springer International Publishing. [CrossRef]
- Bischof, J., Rudolf, N., & Schmundt, W. (2022). How do non-performing loans evolve along the economic cycle? The role of macroeconomic conditions and legal efficiency. *European Accounting Review*, 31, 1149. [CrossRef]
- Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87, 115. [CrossRef]
- Bolarinwa, S. T., Olayeni, R. O., & Vo, X. V. (2021). Is there a nonlinear relationship between nonperforming loans and bank profitability? Evidence from dynamic panel threshold. *Managerial and Decision Economics*, 42, 649. [CrossRef]
- Bruno, G. (2005). Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models. *Economics Letters*, 87, 361. [CrossRef]
- Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources*, 50, 317. [CrossRef]
- Cangombe, E. L., Almeida, L. G., & Tavares, F. O. (2025). Determinants of banking profitability in Angola: A panel data analysis with dynamic GMM estimation. *Risks*, 13, 123. [CrossRef]
- Ciukaj, R., & Kil, K. (2020). Determinants of the non-performing loan ratio in the European Union banking sectors with a high level of impaired loans. *Economics and Business Review*, 6, 22. [CrossRef]
- Çifter, A. (2014). Bank concentration and non-performing loans in Central and Eastern European countries. *Journal of Business Economics and Management*, 16, 117. [CrossRef]
- Ćurak, M., Pepur, S., & Poposki, K. (2013). *Determinants of non-performing loans—Evidence from Southeastern European banking systems*. Available online: <https://doaj.org/article/d524cd361f7f4c97ad642765654e4eb2> (accessed on 10 March 2026).
- Dhaene, G., & Jochmans, K. (2015). Split-panel jackknife estimation of fixed-effect models. *The Review of Economic Studies*, 82, 991. [CrossRef]
- Driscoll, J. C., & Kraay, A. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics*, 80, 549. [CrossRef]
- Erdinç, D., & Abazi, E. (2014). The determinants of NPLs in emerging Europe, 2000–2011. *Journal of Economics Bibliography*, 1, 112–125.
- Gafsi, N. (2025). Machine learning approaches to credit risk: Comparative evidence from participation and conventional banks in the UK. *Journal of Risk and Financial Management*, 18, 345. [CrossRef]
- Gashi, A., Tafa, S., & Bajrami, R. (2022). The impact of macroeconomic factors on non-performing loans in the Western Balkans. *Emerging Science Journal*, 6, 1032. [CrossRef]
- Gong, W., & Seo, M. H. (2022). Bootstraps for dynamic panel threshold models. *arXiv*, arXiv:2211.04027.
- Goyal, S., Singhal, N., Prosad, J. M., & Mishra, N. (2023). Impact of institutional environment on banks' non-performing loans: Evidence from BRICS countries. *Finance: Theory and Practice*, 27, 67. [CrossRef]
- Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics*, 93, 345. [CrossRef]
- Hansen, B. E. (2000). Sample splitting and threshold estimation. *Econometrica*, 68, 575. [CrossRef]
- Huljak, I., Martin, R., Moccerro, D., & Pancaro, C. (2022). Do non-performing loans matter for bank lending and the business cycle in euro area countries? *Journal of Applied Economics*, 25, 1050. [CrossRef]
- Jakubík, P., & Reininger, T. (2013). Determinants of nonperforming loans in Central, Eastern and Southeastern Europe. *Focus on European Economic Integration*, 3, 48. Available online: https://econpapers.repec.org/article/onboenbf/y_3a2013_3ai_3a3_3ab_3a3.htm (accessed on 10 March 2026).
- Jakubík, P., & Reininger, T. (2014). *What are the key determinants of nonperforming loans in CESEE?* Econstor. Available online: <http://hdl.handle.net/10419/120422> (accessed on 10 March 2026).

- Judson, R., & Owen, A. L. (1999). Estimating dynamic panel data models: A guide for macroeconomists. *Economics Letters*, 65, 9. [CrossRef]
- Juodis, A., & Reese, S. (2022). The incidental parameters problem in testing for remaining cross-section correlation. *Journal of Business and Economic Statistics*, 40, 1191. [CrossRef]
- Kanapickienė, R., Keliuotytė-Staniulienė, G., Vasiliauskaitė, D., Špicas, R., Neifaltas, A., & Valukonis, M. (2023). Macroeconomic factors of consumer loan credit risk in Central and Eastern European countries. *Economies*, 11, 102. [CrossRef]
- Kawalec, S. (1999). *Banking sector systemic risk in selected Central European countries: Review of Bulgaria, Czech Republic, Hungary, Poland, Romania and Slovakia* (CASE Network Reports No. 23). CASE Center for Social and Economic Research.
- Kil, K., Ciukaj, R., Druhov, O., & Hrytsenko, N. V. (2020). Determinants of the non-performing loan ratio in the banking sectors of Central and Eastern Europe countries. *Financial and Credit Activity: Problems of Theory and Practice*, 2, 23. [CrossRef]
- Kiviet, J. F. (1995). On bias, inconsistency, and efficiency of various estimators in dynamic panel data models. *Journal of Econometrics*, 68, 53. [CrossRef]
- Klein, N. (2013). *Non-performing loans in CESEE: Determinants and impact on macroeconomic performance* (IMF Working Paper No. 13/72).. International Monetary Fund. [CrossRef]
- Lee, Y. Y., Yahya, M. H., Habibullah, M. S., & Ashhari, Z. M. (2019). Non-performing loans in European Union: Country governance dimensions. *Journal of Financial Economic Policy*, 12, 209. [CrossRef]
- Makri, V., Tsaganos, A., & Bellas, A. (2014). Determinants of non-performing loans: The case of Eurozone. *Panoeconomicus*, 61, 193. [CrossRef]
- Mazreku, I., Morina, F., Misiri, V., Jonathan, J., & Grima, S. (2018). Determinants of the level of non-performing loans in commercial banks of transition countries. *European Research Studies Journal*, XXI(3), 3–13. [CrossRef]
- Milenković, N., Kalaš, B., Mirović, V., & Andrašić, J. (2024). Static and dynamic modeling of non-performing loan determinants in the Eurozone. *Mathematics*, 12, 3323. [CrossRef]
- Moinescu, B.-G. (2012). Determinants of nonperforming loans in Central and Eastern European countries: Macroeconomic indicators and credit discipline. *Review of Economic and Business Studies*, 10, 47. Available online: <https://econpapers.repec.org/RePEc:aic:revebs:y:2012:i:10:moinescub> (accessed on 10 March 2026).
- Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, 49, 1417. [CrossRef]
- Pesaran, M. H. (2004). *General diagnostic tests for cross section dependence in panels* (CESifo Working Paper No. 1229). Center for Economic Studies and ifo Institute (CESifo). [CrossRef]
- Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22, 265. [CrossRef]
- Plikas, J. H., Kenourgios, D., & Savvakis, G. A. (2024). COVID-19 and non-performing loans in Europe. *Journal of Risk and Financial Management*, 17, 271. [CrossRef]
- Pop, I. D., Cepoi, C.-O., & Anghel, D. G. (2018). Liquidity-threshold effect in non-performing loans. *Finance Research Letters*, 27, 124. [CrossRef]
- Ristevska, M. (2020). *Determinants of non-performing loans and the relationship with macroeconomic factors: Evidence from Southeastern Europe*. Econstor. Available online: <https://hdl.handle.net/10419/298734> (accessed on 10 March 2026).
- Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71, 135. [CrossRef]
- Seo, M. H., & Shin, Y. (2016). Dynamic panels with threshold effect and endogeneity. *Journal of Econometrics*, 195, 169. [CrossRef]
- Sfakianakis, G., Agiomirgianakis, G., Ioakimidis, M., & Arvanitis, S. (2022). Determinants of NPLs revisited: The aftermath of two crises and the case of Greece. *Theoretical Economics Letters*, 12, 1577. [CrossRef]
- Shala, A., Toçi, V., & Mustafa, A. (2022). Macroeconomic, structural, and bank-specific determinants of non-performing loans in Central and Eastern Europe. *Ekonomický Časopis*, 70, 411. [CrossRef]
- Sharma, H., Andhalkar, A., Ajao, O., & Ogunleye, B. (2024). Analysing the influence of macroeconomic factors on credit risk in the UK banking sector. *Analytics*, 3, 63–83. [CrossRef]
- Szarowská, I. (2018). Effect of macroeconomic determinants on non-performing loans in Central and Eastern European countries. *International Journal of Monetary Economics and Finance*, 11, 20. [CrossRef]
- Škarica, B. (2014). Determinants of non-performing loans in Central and Eastern European countries. *Financial Theory and Practice*, 38, 37. [CrossRef]
- Tanasković, S., & Jandrić, M. (2015). Macroeconomic and institutional determinants of non-performing loans. *Journal of Central Banking Theory and Practice*, 4, 47. [CrossRef]
- Tătărici, L., Kubinschi, M., & Barnea, D. (2020). Determinants of non-performing loans for the EEC region. A financial stability perspective. *Management & Marketing*, 15, 621. [CrossRef]
- Tmava, Q., & Spahiu, M. J. (2025). Banking and macroeconomic drivers effects on non-performing loans: Insights from Western Balkan countries. *Financial and Credit Activity: Problems of Theory and Practice*, 2, 40. [CrossRef]

- Tuncay, C. M., & Grzegorzczak-Akin, E. (2025). Credit rationing, its determinants and non-performing loans: An empirical analysis of credit markets in Polish banking sector. *Econometrics*, 13, 51. [[CrossRef](#)]
- Zoller, C. B. (2023). Corporate restructuring laws under stress: Policy-making in uncertain times. *European Business Organization Law Review*, 24, 387. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.