DETERMINANTS OF CORPORATE NON-PERFORMING LOANS IN THE UKRAINIAN BANKING SECTOR

by

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Abstract

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The share of non-performing loans is a key indicator of bank asset quality and the overall health of the banking system. Globally, NPLs are usually linked to economic activity and banks' own behavior. In Ukraine, however, their persistently high level was long driven by related-party lending. After the banking reform and the withdrawal of many insolvent banks, the NPL share started to decline after 2020, but remains the highest in Europe.

This thesis investigates the main determinants of NPL accumulation in Ukrainian banks in 2020–2025, focusing on corporate exposures, which dominate banks' loan portfolios. Using GMM estimation, the study examines whether NPLs are driven mainly by their own persistence, external shocks such as war and economic activity, or bank-level characteristics.

The results suggest that NPL dynamics are primarily driven by persistence, while changes in IPI and CAR also show stable significance across specifications. Although the estimated coefficients are small, the findings mainly show which factors are related to changes in NPL shares, rather than the size of their economic effects.

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AI USE DECLARATION

During the preparation of this thesis, Generative AI (ChatGPT) was used as a supplementary tool to:

support the identification of appropriate Python packages and libraries for the implementation of Generalized Method of Moments (GMM) models;

summarize publicly available package documentation and technical descriptions related to the implementation of econometric models in Python.

Any suggestions produced by the AI tool were critically evaluated and substantially modified* by the author before being incorporated into the thesis.

The tool was not used to generate research findings, produce literature summaries used directly in the thesis, create citations, or conduct any form of data analysis. All research questions, theoretical framing, methodology, analysis, interpretation of results, and conclusions were developed independently by the author. The author takes full responsibility for the originality, validity, and academic integrity of the work presented in this thesis.

* substantially modified for code – implies complete understanding and ability to reproduce without support

* substantially modified for text – implies no AI generated text was used in the thesis

LIST OF ABBREVIATIONS

CAR. Capital Adequacy Ratio

CIR. Cost to Income Ratio

EAD. Exposure at Default

NBU. National Bank of Ukraine

NIM. Net Interes Margin

NPL. Non-Performing Loan

ROA. Return on Assets

ROE. Return on Equity

SSSU. State Statistics Service of Ukraine

Chapter 1

INTRODUCTION

The key role of the banking sector in supporting economic activity is providing payment and settlement services, channeling funds from savers to borrowers, and creating liquidity in the financial system. However, this role can be successfully fulfilled only if banks remain financially stable, meaning capitalized and liquid enough to meet their obligations and absorb possible losses. Otherwise, especially if financial instability affects numerous banks in the economy simultaneously, problems may develop into a systemic economic crisis.

Modern central banks and supervisory authorities use numerous indicators to assess the financial stability of individual banks and the banking system as a whole. One of the most closely monitored indicators is the ratio of non-performing loans (NPLs). This is because high volumes of NPLs may affect nearly all aspects of banking activity. First, they deteriorate bank capital, since banks are forced to recognize losses and create additional provisions when borrowers fail to repay their loans. Second, high levels of NPLs may create liquidity pressures, as banks do not receive the expected cash inflows from loan repayments. Finally, NPLs may constrain lending activity, as banks become more cautious, tighten their lending standards, and allocate more resources toward covering potential losses.

Because of these effects, understanding the factors associated with the accumulation of NPLs remains an important issue both for regulators and for academic research.

This issue is particularly relevant in the Ukrainian context. During the past two decades, the Ukrainian banking system experienced persistently high levels of

NPLs, largely driven by connected lending practices and the widespread presence of captive banks, which primarily served the business interests of their owners rather than operating as independent financial institutions. All these eventually culminated in the large-scale banking crisis of 2014-2016. It resulted in the withdrawal from the market of nearly 100 insolvent banks and the nationalization of one of the largest banks in Ukraine, PrivatBank. According to NBU reports, the overall fiscal cost of the crisis reached approximately 38% of GDP, including nearly UAH 155 billion of the recapitalization of PrivatBank (NBU).

The introduction of a stricter NPL definition in line with international supervisory practices, together with the recognition of NPLs by PrivatBank after its nationalization, sharply increased the reported NPL ratio in Ukraine, making it the highest in Europe (see Figure 1).

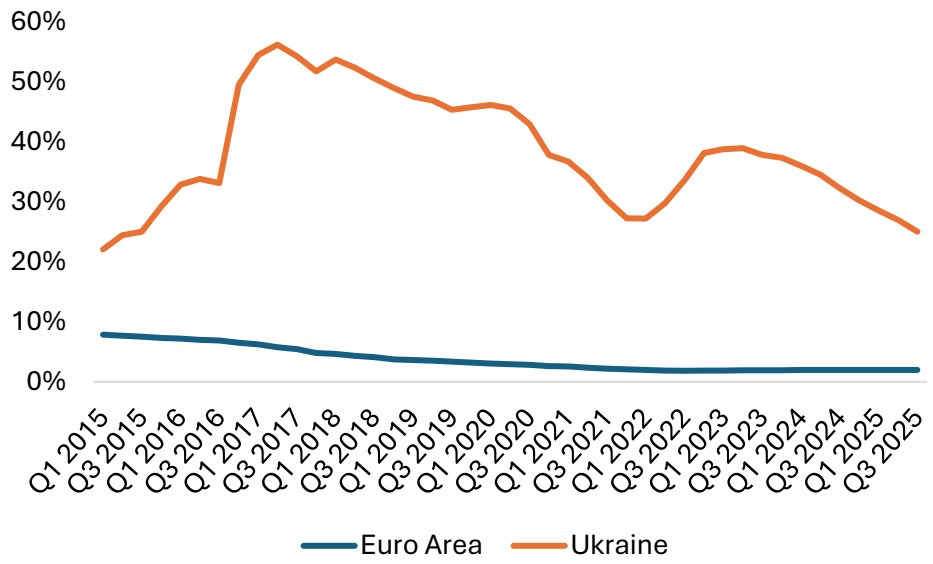


Figure 1. NPL ratio for Ukrainian and Euro Area banks, 2017-2025, %

Source: ECB data portal, NBU

Earlier studies of the Ukrainian banking system identified connected lending practices as one of the main drivers of NPL accumulation (Vyshnevskyi and Sohn, 2023). Koziuk (2017) also noted that, during the pre-reform period, NPL dynamics were weakly associated with broader macroeconomic conditions, reflecting structural problems within the banking sector itself.

However, the situation may have changed substantially after the banking sector clean-up was completed in 2020, when prudential regulation and supervisory standards became significantly stricter. Nevertheless, the determinants of NPLs in the post-reform Ukrainian banking system, as well as the impact of the full-scale Russian invasion on NPL dynamics, remain insufficiently studied, especially in the context of corporate lending, which constitutes the largest share of bank lending in Ukraine and therefore remains crucial for financial stability.

Against this background, the first research question of this study is what determines corporate NPLs in the Ukrainian banking system during the post-reform period of 2020–2025. The second research question concerns the effect of the full-scale Russian invasion on NPL dynamics. The results may contribute to a better understanding of NPL formation in the post-reform banking sector and provide additional evidence for the broader discussion on financial stability in emerging economies under wartime conditions.

The remainder of the thesis is organized as follows. The introduction presents the research context and highlights the importance of studying NPLs in the context of banking system stability. Chapter 2 reviews the relevant literature and approaches to analyzing the determinants of NPLs. Chapter 3 outlines the methodology. Chapter 4 describes the data used in the analysis, including the key variables, their definitions, and data sources. Chapter 5 presents the estimation results and interprets the effects of various factors on NPL shares. Finally, Chapter 6 concludes with a summary of the findings and policy implications.

Chapter 2

LITERATURE REVIEW

Non-performing loans have been widely examined and still attract substantial academic interest. Most of the existing literature examines the determinants on NPLs analyzing bank-specific characteristics such as profitability ratios (ROA, ROE, NIM), macro-economic conditions and institutional settings influence their accumulation.

In this section, I provide a review of the existing empirical papers from all strands to identify the key factors through which NPLs emerge and accumulate in the banking system.

2.1. Review of the Key Determinants of NPLs

The most influential foundation for studies of NPLs determinants is provided by Berger and DeYoung (1997), whose work focuses on banks' cost efficiency as a key channel linking managerial quality and risk-taking behavior to the evolution of NPLs. They were also first who systematized and operationalized for previously discussed hypotheses on determinants of NPLs. Basically, they proposed next four hypotheses of NPLs formation:

1. The "bad luck" hypothesis: suggests that adverse economic conditions weaken borrowers repayment capacity, which results in decrease in NPLs share;

2. The "bad management" hypothesis: suggests that poor managerial quality results in weaker credit standards, more aggressive and careless credit expansion and, therefore, increasing the likelihood of loan portfolio deterioration;

3. The "skimping" hypothesis: states that banks which deliberately cut costs on screening and risk monitoring in order to boost profits, may face higher volumes of NPLs in the future;

4. The "moral hazard" hypothesis: states that weakly capitalized banks may engage in excessive risk taking, which results in accumulation of problem loans.

Empirical results of Berger and DeYoung (1997) themselves, provide the strongest support for the "bad management" hypothesis. The authors applied Granger-causality models to annual observations of U.S. commercial banks from 1985 to 1994. The strongest results were provided in support of the "bad management" hypothesis, but with relatively small economic impact: a one standard deviation in cost-efficiency predicts a cumulative increase in NPL ratio over four years only at 1.8% depending on a bank. They also found that relatively risky loan portfolios will eventually increase NPLs. Their results also provide support for the "moral hazard" hypothesis, suggesting that, on average, poorly capitalized banks take increase portfolio risk, resulting in higher NPL ratios.

Building on this framework, further empirical studies mainly test those four hypotheses across different economies and time periods. First who introduced macroeconomic variables into NPL models were Salas and Saurina (2002). The authors examined the panel of Spanish commercial and savings banks in 1985-1999 with dynamic panel model. They found evidences that GDP growth has a significant effect on NPLs, supporting "bad luck" hypothesis.

Several later empirical studies also demonstrated that business cycle plays important role in NPL accumulation, although the strength and magnitude varies across studies. Quagliarello (2007) employed panel data for Italian banks from 1985 to 2002 and found evidence that business cycle, measured as change in GDP, is significantly associated with banks' portfolio riskiness and NPL ratio. Specifically, higher GDP growth is associated with lower NPL ratio. Later

findings of Makri, Tsagkanos, and Bellas (2014) also support the countercyclical nature of NPLs. Using a difference GMM estimator on a panel of 14 Eurozone countries over the period 2000–2008, the authors found a negative relationship between GDP growth and NPL ratios, suggesting that stronger economic performance in Eurozone is associated with improved loan portfolio quality. Finally, Ozili (2015) employed the multivariate model on the sample of banks' from 16 European countries with the interaction term between NPLs and the state of the business cycle and found evidence for procyclical behavior of NPLs.

By contrast, some empirical studies argue that NPLs exhibit countercyclical behavior and may themselves be a factor of the economic downturn. Schnattinger finds that high NPL ratios are associated with lower investment and weaker capital reallocation, suggesting that NPLs may contribute to persistent economic slowdowns. The most recent studies also provide evidence supporting countercyclical nature of NPL stocks.

Espinoza and Prasad (2010) estimated a dynamic panel of around 80 banks found evidences that lower economic growth triggers an increase in NPLs. Authors also found that higher interest rates and lagged credit growth are positively related with NPLs. Using IMF data on banks from 34 countries., Kauko (2012) finds that credit growth, trade and current account deficit, and money stock are significantly associated with variation in NPLs.

Louzis, Vouldis, and Metaxas (2012) adopted a dynamic panel model for the nine largest Greek banks from 2003Q1 until 2009Q3 and found that the real GDP growth rate, unemployment and lending rates have significant negative correlation with the level of NPLs. The recent results of Anastasiou, Louri, and Tsionas (2016) indicate that unemployment and economic growth have strong and statistically significant influence on NPLs.

Beck, Roland, Jakubik, and Piloiu (2013) estimated panel regression on a banks over 75 countries (including Ukraine) and found evidence that real GDP growth is the dominant driver of NPLs. In addition to this, they found significant negative relationship between NPL and share prices, exchange rate depreciation and lending interest rates.

Results of Anastasiou et al. (2019) indicate that unemployment and economic growth exert a strong influence on NPLs, while cyclical indicators such as output gap are also found to be significant. In addition, the authors found association between personal income taxation and NPLs, highlighting the relevance of fiscal conditions.

Several studies also highlight the importance of bank-level factors in explaining NPL dynamics. These variables are frequently examined in the context of the bad management, moral hazard, and skimping hypotheses. In particular, the literature focuses on measures of profitability (ROA, ROE, NIM), efficiency (CIR), capitalization (CAR, Tier 1 capital ratio), and lending behaviour (credit growth).

Among the most commonly used explanatory variable is the lagged NPL ratio itself, as it reflects the highly persistent nature of NPLs, whereby past loan portfolio quality strongly influences current levels of NPL share (Pancotto, ap Gwilym, and Williams 2024). As a result the lagged dependent variable is almost always included in empirical models of NPL determinants.

As proxies for the bad management hypothesis, most studies employ profitability indicators, primarily ROA and ROE. However, the empirical evidence regarding their significance remains inconclusive. Louzis et al. (2010) found ROA and ROE to be significantly negatively associated with NPL ratios in mortgage and consumer loan portfolios, while the relationship was insignificant for business loans. Makri et al. (2014), as well as Pancotto et al. (2024), also found ROE to be

a significant determinant of NPL ratios, supporting the bad management hypothesis.

Salas and Saurina (2002) found that effect of lagged efficiency on NPLs is statistically insignificant. At the same time, they provided evidence that lagged solvency ratio may negatively influence NPLs, which support moral hazard hypothesis. In addition, they provided evidence of "size effect" according to which large banks seem to have fewer NPLs.

Podpiera and Weill (2008) used similar approach as Berger and DeYoung (1997) on Czech banks during the period 1994-2005. They provided evidence on the causal relationship between NPLs and banks' cost efficiency in Czech market, supporting "bad management" hypothesis. However, authors didn't find support to the "bad luck" hypothesis, which suggests that accumulation of NPLs is associated with lower cost efficiency.

At the same time, Pancotto et al (2024) estimated dynamic panel model with application of GMM estimators on the sample of the Italian banks over the period 2011 to 2017. Their findings show support for moral hazard hypothesis, as better capitalized banks in their model tend to have lower levels of NPLs. As Louzis et al (2010), they also found no evidence on Italian sample that strong credit expansion drives NPL levels and explain this with possible higher demand rather than excessive risk-taking behavior.

A particularly influential contribution is Balgova, Nies, and Plekhanov (2016), who examine episodes of high and declining non-performing loans using a large cross-country dataset covering more than 190 countries over roughly the period from the early 1990s to the mid-2010s. The authors show that the most effective strategy for reducing NPL ratios involves a combination of asset management companies (AMCs) and public recapitalization measures. Their evidence suggests that successful resolution episodes typically begin with a sharp initial decline in

NPLs, driven by write-offs and transfers of impaired assets to AMCs. In the following years, the downward trend continues as improved bank balance sheets support the recovery of credit growth.

While the issue of NPLs has been widely examined in the European context, research on Ukraine remains limited and most of them are rather descriptive than quantitative. However, one research that provides us with valuable evidence is by Vyshnevskyi and Sohn (2023), who studied the Ukrainian data on NPLs and found that NPLs are positively related to the volume of related-party lending. Their findings are also consistent with earlier evidence that accumulation of NPLs in the Ukrainian banking system is rather the result of deep-rooted institutional problems (Koziuk 2017), and do not follow the conventional countercyclical relationship between NPLs and credit growth observed in most of economies (Beck et al. 2013).

2.2. Empirical Modeling Approaches and Variable Selection

Most empirical studies on NPL determinants rely on panel data techniques, often using dynamic specifications to account for the persistence of NPL ratios over time. For example, Ozili (2015) applies a multivariate dynamic regression framework in order to account for the interaction between NPL and business cycle, while Cifter, Yilmazer, and Cifter (2009) use dynamic model with 2SLS estimation to address potential endogeneity in the model specification. However, most of the researchers emphasize that NPL ratios are highly persistent over time (Klein 2013; Pancotto et al. 2024) meaning that the current level of NPL is strongly related to their past values, as deterioration of the portfolio quality tends to unfold gradually and may remain on banks' balance sheet for a long time due to the lengthy and complex process of loan write-offs. For this reason, most studies include the lagged NPL ratios in explanatory variables.

However, the inclusion of lagged dependent variable in panel models may lead to biased and inconsistent estimates when conventional estimators are used. Therefore the common approach in recent studies is to use GMM approaches, such as Difference GMM (Arellano-Bond 1991) or System GMM (Blundell-Bond 1998). Those approaches account for persistence in GMM dynamics as well as for bank-specific effects and potential endogeneity between NPLs and explanatory variables. For instance, Makri et al. (2014) use Difference GMM to estimate the determinants of NPLs in Eurozone, while Pancotto et al. (2024) use System GMM model.

The most commonly used dependent variable is NPL ratio (Ozili 2015; Pancotto et al. 2024; Makri et al. 2014), since it reflects the relative quality of the loan portfolio and allows to compare it across banks of different sizes. In contrast, some empirical research use changes in NPL volume as dependent variable (Karadima and Louri 2019), however this estimate may be more sensitive to bank size or portfolio growth, which makes them less comparable across different banks.

As explanatory variables, most studies use contemporanous macroeconomic and bank-level indicators as the lagged dependent variables already captures the persistence of NPLs, while contemporaneous variables are used to identify current association between economic conditions, bank characteristics, and loan portfolio quality.

In addition, empirical models often include control variables such as bank size, usually measured as the logarithm of total assets, and indicators of systemic importance, since larger or systemically important banks may differ from other banks in terms of risk profile, regulatory treatment, and balance sheet structure.

This study contributes to the ongoing discussion by providing new evidence from the Ukrainian banking system. In particular, it focuses on the post-crisis period following a large-scale banking sector reform. We aim to investigate the determinants of NPLs with a specific focus on corporate loans, which allows for a more granular analysis of credit risk. Moreover, the analysis of NPL determinants across borrower segments (namely households and corporate clients) remains largely underexplored in the empirical literature, and this study seeks to address this gap.

Finally, the study relies on a unique monthly panel dataset obtained directly from the National Bank of Ukraine. This enables a more precise identification of credit exposures, as well as a clear segmentation between corporate and household NPLs, thereby allowing the analysis to better capture underlying credit risk rather than relying solely on accounting-based measures that may not fully reflect it.

Chapter 3

METHODOLOGY

In order to study determinants of NPLs in Ukrainian banking system, we employ a dynamic panel data model, which is similar to Pancotto et al. (2024), Anastasiou (2017) and Klein (2013) and is expected to capture both bank-specific and macroeconomic drivers of the NPL dynamics.

The econometric model is specified as follows:

$$NPL_{share_{i,t}} = \alpha + \rho NPL_{share_{i,t-1}} + \beta X_{i,t} + \gamma Z_t + \delta Controls_{i,t} + u_i + \varepsilon_t \qquad (1)$$

Where:

The dependent variable is the share of corporate non-performing loans ($NPL_share_{i,t}$), defined in accordance with NBU methodology:

$$NPL_share_{i,t} = \frac{Gross\ Corportate\ NPL_{i,t}}{Total\ Gross\ Corporate\ EAD_{i,t}} \qquad (2)$$

The inclusion the lagged NPL ($NPL_{i,t-1)}$ share into the regression is justified by both economic theory and the nature of the data, as past values of NPLs are likely to be correlated with their current values. This reflects the persistent nature of non-performing loans, as they are typically slow to resolve and may remain on banks' balance sheet for extended periods.

$X_{i,t}$ – a vector of bank-specific variables constructed from banks' monthly balance sheet data:

1. Loan Growth captures the dynamics of the gross corporate loan portfolio. The portfolio is measured in terms of exposure at default (EAD), as it reflects a broader measure of credit exposure compared to accounting loan values, which only capture currently outstanding amounts. The variable is constructed in accordance with NBU methodology. Growth is measured as the log-difference of the portfolio:

$$LoanGrowth_{i,t} = \ln\left(EAD_{i,t}\right) - \ln\left(EAD_{i,t-1}\right) \quad (3)$$

2. Return on Assets (ROA) reflects bank profitability and is used as proxy for managerial efficiency. As balance sheet variables are measured in stock terms, average total assets are used to ensure consistency over time:

$$ROA_{i,t} = \frac{Net\ Income_{i,t}}{(Total\ Assets_{i,t} + Total\ Assets_{t-1})/2} \quad (4)$$

3. Return on Equity (ROE) also reflects bank profitability and used as proxy for managerial efficiency:

$$ROE_{i,t} = \frac{Net\ Income_{i,t}}{(Total\ Equity_{i,t} + Total\ Equity_{t-1})/2} \quad (5)$$

4. Cost-to-income Ratio (CIR) is used as a proxy for bank cost efficiency:

$$CIR_{i,t} = \frac{Operating\ Expenses_{i,t}}{Operating\ Income_{i,t}} \quad (6)$$

5. Capital adequacy Ratio (CAR) is used as a measure of bank capitalization and reflects the adequacy of regulatory capital relative to risk-weighted assets. The indicator corresponds to the regulatory capital adequacy indicator defined by NBU.

Z_t is a vector of macroeconomic variables including policy rate and change in the IPI, and a war dummy variable;

To account for heterogeneity across banks, control variables commonly used in the empirical literature are included, namely bank size, measured as log(assets), and ownership type. In addition, a country-specific variable, systemic importance, is introduced. In accordance with the NBU definition, systemically important banks are those whose activities influence the stability of the entire national banking system.

i, t – subscripts identifying the bank and time period, respectively.

Estimating the model using OLS may be problematic due to the nature of the data. First, bank-level variables may have causal relationships that can run in both ways. Hence, bank-level variables are assumed to be endogenous. Second, time-invariant bank-specific characteristics (fixed effects) may be correlated with

explanatory variables, leading to omitted variable bias. Finally, the inclusion of a lagged dependent variable introduces additional bias in standard panel estimators.

To address these issues, the model is estimated using the Generalized Method of Moments (GMM), which allows controlling for potential endogeneity and produces consistent estimates, whereas OLS would yield biased results.

The GMM has two main specifications – Difference GMM and System GMM. For highly persistent and potentially endogenous data, System GMM is commonly used as it improves efficiency and helps to address the problem of weak instruments that often arises in Difference GMM. The System GMM estimator extends the Difference GMM by incorporating the equation in levels, and can be decomposed in two stages. First, the model is transformed into first differences to eliminate unobserved time-invariant bank-specific effects u_i, and lagged levels are used as instruments (Difference GMM specification). Second, the model is augmented with the equation in levels, where lagged differences are used as instruments. This additional step helps to mitigate the weak instrument problem by introducing additional instruments, and, therefore, exploiting additional variation in the data.

Another important aspect is the classification of explanatory variables. In the GMM framework, variables may be treated as strictly exogenous, predetermined, or endogenous, depending on their correlation with the error term (Arellano & Carrasco, 2003). In our dataset, as suggest previous empirical results, bank-level variables are likely to be jointly determined with NPL dynamics, and therefore should be treated as endogenous or predetermined. For instance, bank profitability (e.g. ROA) is unlikely to be strictly exogenous, because changes in asset quaility may directly affect profitability through provisioning or write-offs, while profitability itself may influence future risk-taking and, consequently, NPL

dynamics, which creates a potential two-way relationship between profitability and NPL share.

In our analysis we treat bank-level variables (except controls) as endogenous or predetermined. Due to limitations of the Python implementation of System GMM used in this study, we cannot explicitly differentiate between endogenous and predetermined variables. Instead, we address this issue indirectly through the choice of instruments, using sufficiently lagged values of the variables as instruments, under the assumption that deeper lags are less likely to be correlated with the current error term. Thus, variables treated as exogenous are instrumented using deeper lags, while predetermined variables may also rely on shorter lags.

Except abovementioned, the choice of lag depth in the instrument set reflects a trade-off between instrument relevance and exogeneity. While shorter lags may strongly correlate with the endogenous variables, they are also more likely to be correlated with the error term, violating the instrument validity conditions. Conversely, deeper lags are less likely to be endogenous but may provide weaker instruments.

In this study, we restrict the instrument set to deeper lags in order to reduce the risk of endogeneity while maintaining sufficient instrument strength. Accordingly, we typically use lag ranges of 2–3 in specifications including a single lag of the dependent variable, and lag ranges of 3–4 when a second lag is introduced.

Consistent estimates in the GMM framework depend on the validity of the instruments. In order to assess it, the Sargan/Hansen test of overidentifying restrictions should be performed. The null hypothesis of the test is that the instruments as a group are exogenous, therefore high p-value indicates that the

instruments are valid. In addition, the Arellano-Bond test for autocorrelation should be applied. The presence of first-order autocorrelation (AR(1)) and the absence of second-order autocorrelation (AR(2)) indicate validity correct model specification.

The goal of this study is to investigate hypotheses, following to previous empirical studies on determinants of NPLs:

1. "Bad management": banks with higher ROA are expected to have lower NPL ratios;
2. "Bad luck": adverse macroeconomic conditions are expected to be associated with higher NPL ratios;
3. "Moral hazard": banks with lower CAR are expected to have higher NPL ratios, reflecting weaker capital buffers and potentially riskier bank behavior;
4. "Skimping": banks with faster loan growth are expected to have higher NPL ratios, as rapid credit expansion may reflect weaker screening and monitoring standards.

The explanatory variables are grouped in accordance with the framework proposed by Berger and DeYong (1997). Expected signs and their detailed explanation are provided in Table 1.

Table 1. Variables and their definitions

Hypothesis/category	**Measurement**	**Expected sign**	**Rationale**
	Lagged NPL	+	Past NPLs tend to persist due to slow resolution (+)
"Bad management"	ROA	+/-	Higher profitability may reduce risk-taking incentives (−), but may also incentivize more aggressive lending behavior in pursuit of higher returns (+)
	ROE		
Skimping	CIR	+/-	Higher CIR may indicate pure cost efficiency (+) but may also capture greater expenses on monitoring and risk management (-)
	$\Delta ln(EAD)$	+	Increase in loan supply often leads to a loosening of credit standards and higher NPL shares in the future (+)
Moral hazard	CAR	-	Higher capitalization improves borrower monitoring and reduces risk-taking, leading to lower NPLs (-)

Table 1 - Continued

"Bad luck"	Policy rate	+	Higher policy rate often reflect tightening monetary conditions during periods of economic stress, which are associated with higher NPL share (+)
	Change of IPI	-	Higher industrial output reflects better economic conditions, reducing NPLs (-)
	War dummy	+	The war shock worsened borrowers' financial conditions, which may lead to higher NPLs (+)
Controls	Size	+/-	Larger banks may engage in riskier lending behavious accorging to "too-big-to-fail" hypothesis (+), but may also benefit from more advanced risk-management (-)
	Systemic importance	+/-	Systemically important banks may face stricter supervision (-), but they may also carry larger historical NPL portfolios due to legacy exposures (+)
	Ownership	+	State-owned banks in Ukraine historically exhibit higher NPL ratios (+)

Overall, the model incorporates bank-level and macroeconomic variables to explain the dynamics of NPL formation in Ukraine in the period following the banking crisis resolution. The empirical strategy is designed to account for high persistence in NPLs, potential endogeneity of key bank-level variables, and the panel structure of the data with a relatively large cross-sectional dimension. The use of a dynamic System GMM framework allows us to capture both within-bank adjustment processes and broader macro-financial conditions affecting credit risk.

Chapter 4

DATA

Our analysis relies on bank-level panel data obtained from the NBU, combined with macroeconomic indicators sourced from the SSSU. The dataset covers the period from March 2020 to December 2025 at a monthly frequency and includes 74 banks.

Dependent variable, corporate NPL share, is constructed from loan-level dataset provided by the NBU, which contains detailed information on individual credit exposures, including borrower type and loan performance status in accordance with regulatory definitions. We restrict the sample to corporate borrowers and sole proprietors, include only exposures denominated in domestic currency, and aggregate the data at the bank level. In our analysis, NPLs are defined in line with NBU regulations. Prior to 2025, NPLs include all exposures classified as defaulted, as well as exposures that formally exited default but remain more than 30 days past due or have not completed one year since the date of exit. In addition, exposures meeting the POCI criterion are treated as non-performing. From 2025 onwards, NPLs are defined based on classification in class 10 under NBU Regulation No. 351.

From the same dataset, we construct gross corporate EAD denominated in domestic currency. Under the NBU reporting framework, it represents total on-balance-sheet corporate credit exposure, including outstanding principal, accrued interest, and revaluation adjustments. *Corporate credit growth* is then defined as the log-difference of corporate EAD. To mitigate the influence of extreme values driven by abrupt changes in credit volumes, that could originate from small base levels, we winsorized credit growth at the 1st and 99th percentiles.

The second data source is banks' balance sheet data reported to NBU on the monthly basis. These data are used to construct key bank-level indicators, including ROA, ROE, and CIR.

In our sample, bank-level indicators exhibit substantial variation over time. In particular, they display extreme values during bank liquidation periods, when some balance sheet items may sharply decline due to accounting write-offs, which mechanically distorts the reported ratios.

To address this issue, liquidation-month observations are exclude, while retaining the corresponding banks in earlier periods as exited banks may contain important information on pre-resolution NPL-dynamics. In addition, three out sixteen banks liquidated between 2020 and 2025 are excluded entirely due to persistently non-interpretable values of financial ratios. Also, to mitigate the extreme values, CIR was winsorized at the 99th percentile.

CAR is obtained from NBU supervisory and financial sector statistics reported on a monthly basis. However, CAR is unavailable for the period from February 2022 to June 2022, as the calculation of prudential ratios was temporarily suspended following the onset of the full-scale russian invasion.

Macroeconomic variable policy rate was taken from NBU and IPI (as a log-difference) from SSSU.

The final dataset constitutes an unbalanced panel of 4378 observations across 71 banks spanning from March 2020 to December 2025.

Table 2. Descriptive statistics of the selected variables

Variable	**Obs.**	**Mean**	**St. Dev.**	**Min**	**Max**
NPL Share	4378	21.54	25.49	0.00	100.00

Table 2 - Continued

Variable	**Obs.**	**Mean**	**St. Dev.**	**Min**	**Max**
Lag of NPL	4378	21.54	25.49	0.00	100.00
Change in EAD	4378	0.0049	0.15	-0.69	0.69
ROA	4378	1.25	2.65	-25.7	29.40
ROE	4378	6.76	15.34	-291.41	63.16
CIR	4378	83.2	47.2	16.46	334.34
CAR	4378	44.19	57.17	0.00	653.12
Log(assets)	4378	15.53	1.84	8.00	20.60
Change in IPI	70	-4.66	19.52	-53.5	44.1
Policy rate	70	13.9	6.54	6	25

After constructing the dataset, we examine the correlation of the variables by computing the correlation matrix. Although less central for GMM estimation, this step is informative for the baseline fixed-effects specification, where multicollinearity may affect the precision of the estimates.

As shown in Figure 2 the correlation matrix does not indicate severe multicollinearity among the explanatory variables. Most pairwise correlations are relatively low, suggesting that the regressors capture distinct bank characteristics and macroeconomic conditions. Among the explanatory variables, a relatively high correlation is present between ROA and ROE which is expected given that both variables measure bank profitability. In addition, log(assets) is positively correlated with the level the credit growth, reflecting differences between larger

and smaller banks. Overall, the correlation structure does not raise concerns about multicollinearity in the baseline specification.

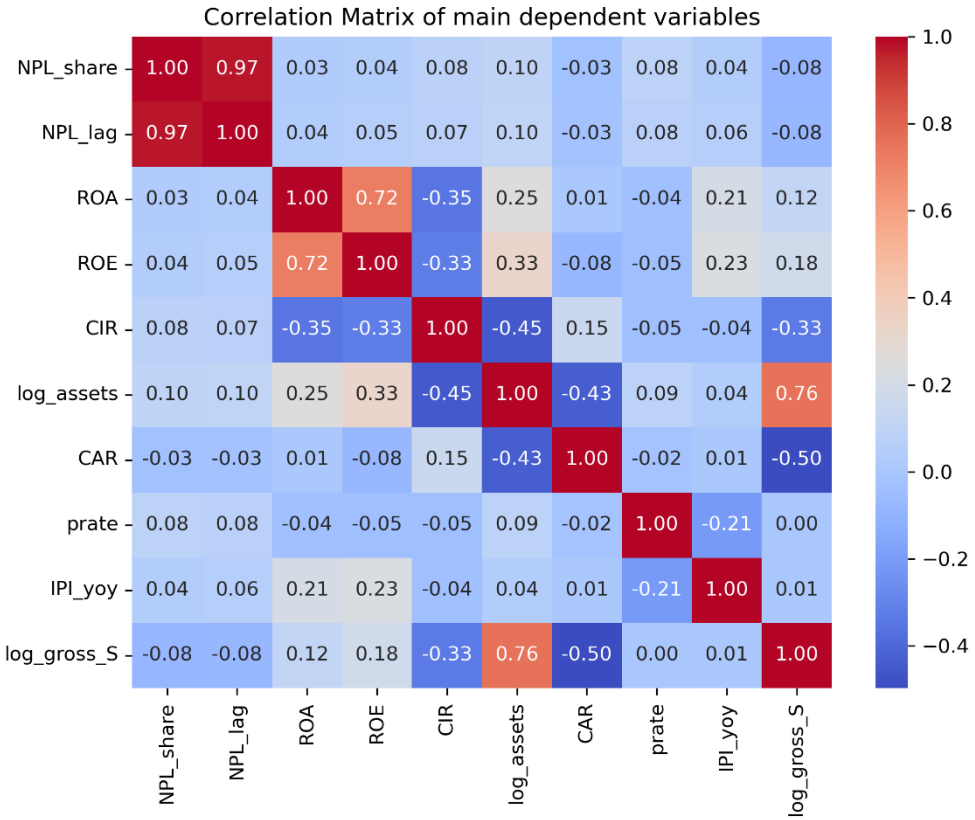


Figure 2. Correlation matrix of main variables

Before estimating the model, it is useful to examine the dynamics of the dependent variable, NPL_share, as preliminary evidences confirmed a high degree of persistence of NPLs in Ukrainian banking system. To isolate within-bank dynamics, the dependent variable is demeaned by bank and regressed on its lag. The estimated coefficient indicates a high degree of within-bank persistence, suggesting that adjustements in NPL ratios are gradual rather than adrupt. At the

same thime, around 37% of the total variation is driven by within-bank changes, indicating that meaningful dynamics remain even after controlling for bank-specific heterogeneity.

Figure 3 illustrates the evolution of the corporate NPL ratio over the period from February 2020 to February 2026. While changes in the median are relatively smooth, the interquartile range and the 10–90 percentile band reveal substantial cross-sectional dispersion throughout the sample period.

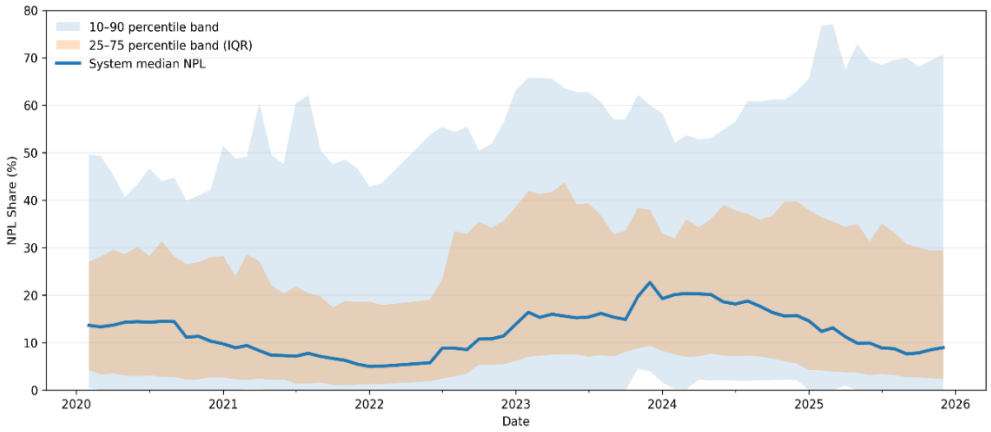


Figure 3. Median and Cross-Sectional Dispersion of corporate NPL ratio

To assess cross-bank heterogeneity, the standard deviation of NPL shares across banks was calculated for each time period. As Figure 4 suggests, cross-bank dispersion also varies considerably over time. We observe peak in 2022 which suggesting banks reacted differently on macroeconomic shock related to the beginning of full-scale russian invasion, and the subsequent decline indicates partial convergence in NPL share dynamics.

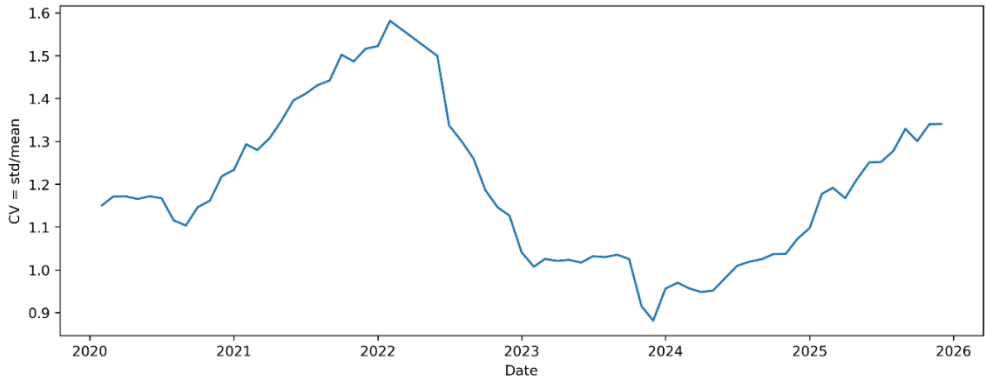


Figure 4. Median and cross-sectional dispersion of corporate NPL ratio

From the data analysis, we identify several key features of the sample. Although the NPL ratio exhibits a high degree of persistence, it remains suitable for empirical modeling, as a non-negligible portion of variation occurs within banks over time. In addition, the structure of the data is characterized by a relatively large cross-sectional dimension compared to the time dimension ($N > T$), and several key variables are likely to be jointly determined with NPLs, raising concerns about endogeneity. These patterns justify the use of the System GMM estimator, which is well suited to address the aforementioned features.

Chapter 5

ESTIMATION RESULTS

This section presents the results of three different approaches: the entity FE model, Difference GMM, and System GMM, used to estimate the determinants of the NPL share in the corporate loan portfolio of the Ukrainian banking system over the period 2020–2025.

To ensure robustness, the same model specification is estimated using multiple econometric approaches, allowing for a comparison of results under different assumptions regarding endogeneity and dynamic structure. Table 2 represents the results of the three different approaches.

The fixed effects (FE) model is used as a baseline, as it provides a simple framework while controlling for unobserved bank-specific heterogeneity. The results already indicate strong persistence in the NPL share, as the lagged dependent variable is positive and highly significant. Credit growth enters with a negative and weakly significant coefficient, contrary to the initial hypothesis, but this result should be interpreted with caution due to potential dynamic panel bias and endogeneity.

The private ownership dummy is negative and significant, suggesting lower NPL ratios in privately owned banks, which is consistent with the historical concentration of corporate NPLs in state-owned banks in Ukraine. Finally, the war dummy is positive and significant, reflecting a deterioration in asset quality during the full-scale war.

However, since the FE model includes a lagged dependent variable, the estimates may be subject to Nickell bias — a mechanical correlation between the lagged dependent variable and the transformed error term after eliminating fixed effects. As a result, estimates in a dynamic panel FE model may be biased, especially when the time dimension is limited.

To address this limitation, the further analysis proceeds with GMM estimators. Compared to the FE model, the Difference GMM confirms the strong persisence of the NPL ratio, as the lagged dependent variable remains positive and significant. However, the Difference GMM does not reveal statistically significant effects for other explanatory variables. This may be due to weak instrument, an issue that was discussed in the methodology section.

Finally, the System GMM model is estimated to address the limitations of previous two models. Except that model confirmed strong persistence in NPL ratio, it shows a weak significance for systemic importance. Systemically important banks exhibit a higher NPL ratio, which may be explained that two banks with the highest NPL ratio are at the same time systematically important. Bank size has weakly significant negative coefficient, which indicates that larger banks tend to have less NPLs. Macroeconomic conditions, proxied by IPI growth, are negatively related to NPLs, indicating that better economic activity reduces credit risk. The policy rate is positive and significant, which may reflect both the countercyclical response of monetary policy to adverse macroeconomic conditions as well as the increase in borrowing costs that further deteriorates loan quality. CAR is negatively and statistically significant, in line with the moral hazard hypothesis, indicating that better-capitalized banks tend to have lower NPL ratios.

Table 3. Estimation Results from baseline FE, Difference GMM, and System GMM Models

	Entity FE Model	Diff-GMM	Sys-GMM
L1.NPL_share	0.9***	0.92***	1.020***
	(0.0245)	(0.21)	(0.021)
Sys_importance	-0.39	-0.14	0.829*
	(0.3913)	(0.373)	(0.438)
Log_assets	-0.52*	-0.26	-0.046*
	(0.2750)	(0.334)	(0.262)
Credit_growth	-0.075*	0.33	-0.26
	(0.0417)	(3.12)	(3.30)
IPI_yoy	-0.022	-0.007	-0.01***
	(0.0069)	(0.008)	(0.005)
ROA	0.0015	0.055	0.016
	(0.1023)	(0.156)	(0.174)
ROE	-0.015	-0.007	-0.032
	(0.0112)	(0.0267)	(0.028)
CIR	0.0048	-0.007	0.014
	(0.045)	(0.056)	(0.012)
CAR	-0.0074	-0.018	-0.02***
	(0.0114)	(0.012)	(0.007)
private	-7.53***	1.83	-0.83
	(1.169)	(1.624)	(0.553)
state	0.062	2.13	-0.37
	(1.174)	(2.773)	(1.07)
prate	0.78	3.31	5.364**
	(2.372)	(7.13)	(2.53)
War_dummy	1.45***	0.00	-0.015
	(0.4566)	(0.00)	(0.383)
Observations	4100	3864	3864
Groups		71	71
Lags		3-4	3-4
Instruments		19	26
AR(1) p-value		0.041	0.022
AR(2) p-value		0.824	0.815
Hansen J p-value		0.423	0.870

The analysis then proceeds with the System GMM estimator, which addresses both endogeneity and weak instrument issues. Although the model passes the standard specification tests, the coefficient on the lagged dependent variable exceeds unity, which raises concerns from an economic standpoint. In particular, a coefficient above one implies explosive dynamics in the NPL ratio, suggesting that shocks to asset quality would amplify over time rather than gradually dissipate. To address this issue, an additional lag of the dependent variable is introduced in the specification, allowing the persistence to be distributed across multiple periods and yielding more economically plausible dynamics. Table 4 presents the results of the two-lag System GMM specification, focusing on variables that are statistically significant for clarity.

Table 4. System GMM estimation results with two lags and alternative specifications

	2lags-SysGMM
L1.NPL_share	0.94***
	(0.169)
L2.NPL_share	0.06
	(0.165)
Sys_importance	0.923**
	(0.418)
Log_assets	-0.51*
	(0.265)
Credit_growth	2.00
	(5.516)
IPI_yoy	-0.012*
	(0.264)
ROA	0.152
	(0.178)
ROE	-0.354
	(0.028)

Table 4 - Continued

	2lags-SysGMM
CIR	0.013
	(0.013)
CAR	-0.02***
	(0.007)
Private	-0.899
	(0.498)
State	-0.339
	(1.029)
prate	6.615*
	(2.68)
War_dummy	-0.254
	(0.359)
Observations	3864
Groups	71
Lags	3-4
Instruments	19
AR(1) p-value	0.041
AR(2) p-value	0.824
Hansen J p-value	0.423

The System GMM model with two lags produces results that are generally in line with the baseline specification. The second lag of the dependent variable turns out to be insignificant, which indicates that most of the persistence in NPLs is already captured by the first lag. At the same time, introducing the second lag helps address the issue observed earlier, where the coefficient on the lagged dependent variable exceeded one. In this specification, the first lag remains

positive but stays below unity, suggesting more stable and economically reasonable dynamics.

The signs of the main explanatory variables remain largely consistent with the baseline, although their statistical significance varies across specifications. This points to a certain degree of robustness in the underlying relationships, even if their precision depends on model design. The only coefficient that changes sign is credit growth, which becomes positive in the two-lag model; however, it is not statistically significant.

To further check robustness, several alternative specifications were estimated by excluding selected variables. In particular, ROA, ROE, and CIR were removed separately and jointly, as they reflect different dimensions of bank performance. In total, four additional models were considered. Contrary to expectations, model performance worsened in these cases, suggesting that even statistically insignificant variables may still contain useful information and contribute to the overall fit.

To check how sensitive the results are to the lag structure, several alternative specifications were tested. Both shorter and longer lag ranges were considered. In practice, the 3–4 lag specification turned out to be the most stable and economically interpretable. Other choices were less convincing: shorter lag structures (such as 2–3) produced coefficients that were mostly insignificant, while longer ones (3–6) sometimes made individual variables significant (for example, the war dummy), but at the cost of generating coefficients that were difficult to reconcile with economic intuition or with previous results. This suggests that the model is quite sensitive to how instruments are constructed. If the lag structure is too short, instruments may not be informative enough; if it is

too long, additional noise may be introduced, which weakens the overall reliability of the estimates.

To account for possible differences across banks, interaction terms with bank were introduced. In particular, interactions with ROA, CAR, and credit growth were examined, each entered separately into the model. Overall, these terms did not show statistical significance, with one partial exception — the interaction between size and CAR.

However, including this interaction brings back a familiar issue: the coefficient on the lagged dependent variable again exceeds one. This raises concerns about the implied dynamics, as such values may indicate unstable or explosive behavior. For this reason, the coefficient is not interpreted further and is treated as a modeling artifact.

Table 5. System GMM estimations with interaction term bank_sizexCAR

	Sys-GMM	**lnassets_car-SysGMM**
L1.NPL_share	1.020*** (0.021)	1.02*** (0.154)
Sys_importance	0.829* (0.438)	1.17** (0.586)
Log_assets	-0.046* (0.262)	-0.66*** (0.21)
Credit_growth	-0.26 (3.30)	-2.701 (3.945)
IPI_yoy	-0.01*** (0.005)	-0.02*** (0.005)

Table 5 - Continued

	Sys-GMM	lnassets_car-SysGMM
ROA	0.016	0.059
	(0.174)	(0.159)
ROE	-0.032	-0.015
	(0.028)	(0.019)
CIR	0.014	0.019*
	(0.012)	(0.009)
CAR	-0.02***	-0.22**
	(0.007)	(0.102)
privat	-0.83	0.397
	(0.553)	(0.578)
state	-0.37	0.531
	(1.07)	(1.125)
prate	5.364**	6.615*
	(2.53)	(2.68)
Logassets_car		0.018
		(0.006)
Observations	3864	3864
Groups	71	71
Lags	3-4	3-4
Instruments	26	19
AR(1) p-value	0.022	0.041
AR(2) p-value	0.815	0.824
Hansen J p-value	0.870	0.423

The results of this specification are broadly consistent with previous findings, with several key relationships remaining stable. However, the policy rate loses its statistical significance, suggesting that its effect may not be robust once interaction effects are taken into account. At the same time, the cost-to-income ratio (CIR) becomes positive and statistically significant, which is in line with the initial hypothesis. This indicates that lower operational efficiency, reflected in a higher CIR, is associated with a higher share of NPLs.

Chapter 6

CONCLUSIONS AND POLICY RECOMMENDATIONS

This study investigates the determinants of NPLs in the Ukrainian banking system using a dynamic panel model estimated via System GMM. First of all, the results confirm the strong persistence of NPLs, which is consistent with the previous literature and is also an expected in the Ukrainian context. Such persistence mainly reflects both regulatory and institutional factors. Since 2016, the NBU has repeatedly revised the rules for recognizing non-performing loans, substantially broadening this category. At the same time, state-owned banks often cannot remove legacy NPLs from their balance sheets quickly, as the resolution of problem exposures may involve lengthy legal procedures and debt recovery processes that can last for years.

The results give cautious support to the bad luck hypothesis. The negative coefficient on the industrial production index suggests that weaker economic activity is associated with a higher share of NPLs. However, the coefficient is small, so this result should be interpreted as evidence of the direction of the relationship rather than as a large economic effect. For the corporate loan portfolio, this means that deterioration in real-sector activity may contribute to NPL accumulation, but it does not explain NPL dynamics on its own. The policy rate also shows a weak positive relationship with NPLs. This link is not straightforward, as higher rates may capture both tighter monetary policy under worsening macroeconomic conditions and a direct increase in borrowers' debt-servicing costs. Therefore we tend to interpret the coefficient as evidence that NPLs are linked to tighter financial conditions, rather than as a clear causal effect of the policy rate.

However, none of the tested models, except for the fixed effects specification, finds a statistically significant coefficient for the war dummy. One possible explanation is that banks with high NPL shares already had a large stock of problem loans before the full-scale war, while the write-off and recovery process is slow and not necessarily directly linked to the war period. In addition, credit growth in Ukraine has remained limited since the beginning of the war, which may have reduced the direct effect of new wartime lending on NPL dynamics.

Our results also support the expected negative relationship between capital adequacy (CAR) and the share of non-performing loans. Better-capitalized banks tend to exhibit lower NPL ratios, which is consistent with the idea that stronger capital positions reduce incentives to engage in excessive risk-taking or poor lending practices. In this sense, higher capital buffers appear to be associated with more prudent credit allocation.

At the same time, none of the estimated models provide evidence in support of the bad management hypothesis in the context of Ukrainian banks. In all specifications, both ROA and ROE remain statistically insignificant, suggesting that variations in bank profitability do not systematically explain differences in NPL dynamics.

A similar conclusion applies to the skimping hypothesis. Only one specification yields a weakly significant positive relationship, which is in line with theoretical expectations. However, given that this result is not stable across models, it cannot be considered robust and should be interpreted with caution.

Overall, the results suggest that NPL dynamics in Ukraine are driven mainly by persistence, economic activity, and bank capitalization. Although the estimated coefficients are small, the findings help identify which factors are related to changes in NPL shares rather than the size of their economic effects. From a policy perspective, this implies that NPL reduction requires not only post-crisis

resolution measures, but also early monitoring of macroeconomic deterioration, close supervision of corporate credit risk, and the maintenance of adequate capital buffers in the banking sector.

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