CHARLES UNIVERSITY

FACULTY OF SOCIAL SCIENCES

Institute of International Studies

Department of Political Science

UNIVERSITY COLLEGE LONDON

SCHOOL OF SLAVONIC AND EAST EUROPEAN STUDIES

IMESS: Economics & Business

Master's Thesis

2024 **ZIXI NING**

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The Determinants of Non-Performing Loans in Banking Sectors in Central and East European Countries

Master's Thesis

Author of the Thesis: Zixi Ning

Study programme: International Masters in Economy, State and Society

Supervisor: Mgr. Karel Svoboda, Ph.D.

Year of the defence: 2024

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In Prague on the 29th April Zixi Ning

References

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Abstract

This article investigates the determinants of non-performing loans (NPLs) across 52 commercial banks in 11 Central and Eastern European (CEE) countries, including Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia, over the period from 2007 to 2022. The study employs both static and dynamic panel data analyses, utilizing fixed effects, random effects, one-step system Generalized Method of Moments (GMM), and two-step system GMM models to evaluate the influence of macroeconomic and bank-specific factors on NPLs. The findings reveal that GDP growth, unemployment rates, share price indices, return on assets, and loan loss reserves significantly influence NPL ratios. The study substantiates existing literature while contributing new insights into managing the risks associated with NPLs. It provides evidence-based recommendations for policymakers and commercial banks, aimed at mitigating potential risks and enhancing financial stability. The research uniquely combines various econometric models, offering a comprehensive evaluation of both macroeconomic impacts and bank-specific determinants on NPL ratios. This broad approach not only confirms the significant influence of identified variables but also highlights the complex interactions between different economic and operational factors within the banking sectors of CEE countries.

Abstrakt

Tento článek zkoumá determinanty nesplácených úvěrů (NPL) napříč 52 komerčními bankami v 11 zemích střední a východní Evropy (CEE), včetně Bulharska, Chorvatska, České republiky, Estonska, Maďarska, Lotyšska, Litvy, Polska, Rumunska, Slovenska, a Slovinsko, v období od roku 2007 do roku 2022. Studie využívá statické i dynamické panelové analýzy dat, využívající fixní efekty, náhodné efekty, jednokrokový systém zobecněné metody momentů (GMM) a dvoukrokové systémové modely GMM k vyhodnocení vliv makroekonomických faktorů a faktorů specifických pro banky na úvěry v selhání. Zjištění ukazují, že růst HDP, míra nezaměstnanosti, indexy cen akcií, návratnost aktiv a rezervy na ztráty z úvěrů významně ovlivňují ukazatele nesplácených úvěrů. Studie zdůvodňuje existující literaturu a zároveň přináší nové poznatky o řízení rizik spojených s nesplácenými úvěry. Poskytuje na důkazech podložená doporučení pro tvůrce politik a komerční banky, zaměřená na zmírnění potenciálních rizik a posílení finanční stability. Výzkum unikátním způsobem kombinuje různé ekonometrické modely a nabízí komplexní vyhodnocení jak makroekonomických dopadů, tak specifických bankovních determinant na ukazatele NPL. Tento široký přístup nejen potvrzuje významný vliv identifikovaných proměnných, ale také zdůrazňuje složité interakce mezi různými ekonomickými a provozními faktory v rámci bankovních sektorů zemí CEE.

Keywords

Non-performing Loans, Banking Sector, Central and Eastern European Countries, Panel Data Estimation, Fixed Effects Model, System GMM Model

Klíčová slova

Nesplácené Úvěry, Bankovní Sektor, Země Střední a Východní Evropy, Odhad Panelových Dat, Model s Fixními Efekty, Systémový Model GMM

Title

The Determinants of Non-Performing Loans in Banking Sectors in Central and East European Countries.

Název práce

Determinanty Nesplácených Úvěrů v Bankovních Sektorech v Yemích Střední a Východní Evropy.

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Introduction

Over the past few years, the Central and Eastern European (CEE) economies have been experiencing a period of growth. However, this growth has been relatively slow compared to other European Union (EU) nations, particularly in sectors such as banking. The financial crisis of 2008 inflicted significant damage on the CEE banking sectors, setting off a prolonged period of economic recovery. This fragile recovery was further challenged by the global outbreak of infectious diseases in early 2021, delivering a significant setback to the already struggling economies of the region.

The banking sector is vital to the economic growth of the CEE countries, with lending activities forming the core of bank operations. According to Capiga et al. (2005), these activities not only generate income to meet operational and financial costs but are essential for the economic vitality of the region. In turn, Kil et al. (2020) highlight that banks are the sole entities authorized to issue loans, indicating their integral role in the financial system. Traditional banking models prevalent in most CEE countries focus primarily on deposits and loans. This approach places a significant emphasis on credit risk management, crucial for maintaining financial stability (Kil & Miklaszewska, 2017). While active participation in lending can promote bank profits, Catturani (2016) suggests that it also enhances the risk of microeconomic instability and could increase the proportion of non-performing loans (NPLs) in the future.

Lessons from the 2008 financial crisis also tell us that the main factor affecting the banking system and and financial crisis is the deterioration of bank loans. An increase in defaulted loans connects macro-financial disturbances to tangible impacts on credit markets and financial market instability. As a consequence, NPLs have emerged as a significant concern and an area of increasing academic focus. Hou (2007) suggests that high levels of NPLs can diminish economic efficiency and impede economic growth, delivering a shock to the financial system and adversely affecting credit markets.

Moreover, NPLs serve as a critical indicator of a bank's credit risk and asset quality. Research into bank insolvency has shown that asset quality is a crucial factor in determining a bank's risk of failure (Demirguc-Kunt, 1989; Barr and Siems, 1994). Typically, before a bank becomes insolvent, it will have sustained high levels of impaired loans. Effective credit policies and maintaining low levels of NPLs are therefore vital for ensuring a bank's financial stability. Conversely, inappropriate policies or an uncontrolled banking system can lead to bank insolvency, as evidenced by the major bankruptcy within the Polish cooperative banking sector. The presence of high NPL levels on bank balance sheets can negatively impact the overall health of the banking system and its capacity to extend credit to the broader economy. This impact is primarily observed as high NPLs necessitate larger provisions, which reduce bank profits and increase the risk weights, leading to higher capital requirements. Additionally, managing NPLs can divert significant managerial resources from core, more profitable activities, further straining the financial health of banks.

The main goal of this paper is to utilize panel data to investigate the effects of both macroeconomic and bank-specific determinants on the levels of NPL across 52 commercial banks in 11 CEE countries that are members of the EU. The countries included in this study are Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia. While there is a substantial body of literature exploring these topics, our study distinguishes itself from previous work in several significant ways. Firstly, this paper is the first empirical study that analyzes both static and dynamic using a variety of econometric models, including the fixed effects (FE) model and the random effects (RE) model, as well as both the one-step and two-step Generalized Method of Moments (GMM) models. This comprehensive approach allows for a detailed understanding of the factors affecting NPLs within the context of CEE countries, providing a novel contribution to the field of financial analysis. Moreover, our research separately examines the effects of macroeconomic and bank-specific factors on NPL ratios, employing a comparative analysis using the methodologies mentioned earlier. This approach enhances our understanding of the variables influencing fluctuations in NPLs within the CEE banking sectors.

Additionally, it adopts a comprehensive approach by encompassing all 11 CEE countries that are members of the EU, analyzing the period from 2007 to 2022. This period, extending from the global financial crisis to the present, is critical for understanding the evolution of NPLs in these countries. Including the entire CEE region in the analysis provides significant academic value and offers practical insights that could inform policy decisions and banking strategies in these nations. This wide temporal and geographical scope ensures that the study’s findings are robust and reflective of the diverse economic and regulatory landscapes within the CEE. Besides, the selection of 52 commercial banks across these countries for the study’s analysis introduces a bank-centric perspective to the examination of NPLs. This approach is strategically advantageous, offering nuanced insights into how individual banks can more effectively manage NPLs. This perspective is particularly vital for developing tailored strategies that address the specific challenges and opportunities faced by these institutions in mitigating NPLs. Finally, our results are consistent with existing research, showing that both bank-specific and macroeconomic variables significantly impact the NPL ratio.

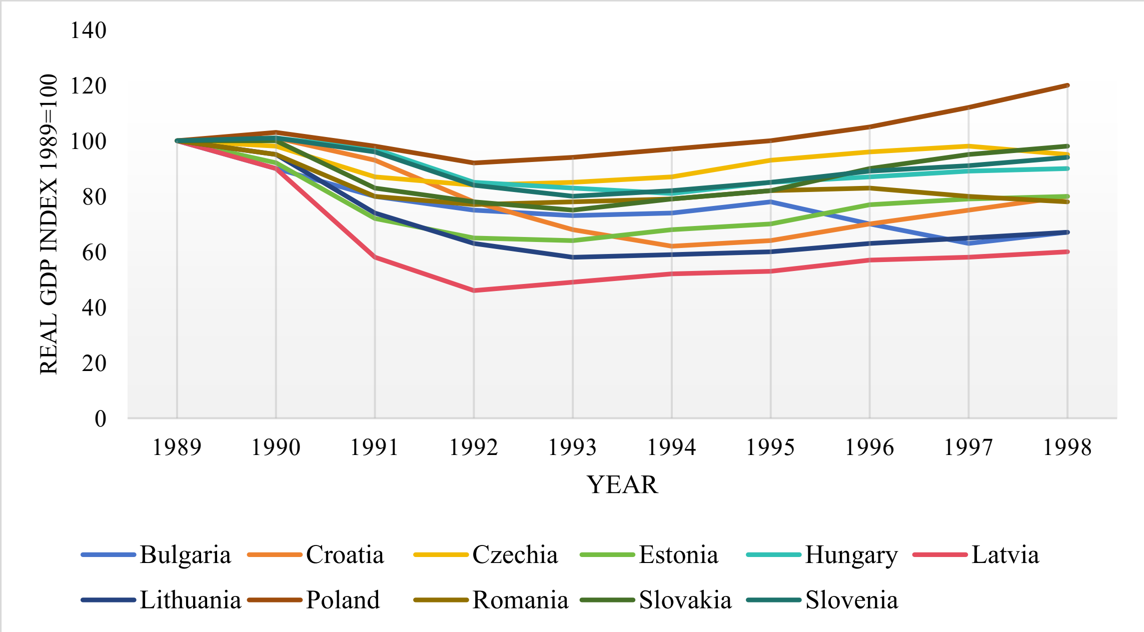
The remainder of the article is structured as follows. Section two offers a comprehensive examination of the economic and banking developments within the eleven CEE countries spanning the years 2007 to 2022. It also reviews relevant scholarly work, summarizing the literature on the determinants of NPL ratios and outlining the methodologies employed to analyze these determinants. Section three provides a detailed description of the data sources used in the article. It introduces the variables considered and discusses their potential impacts on NPLs. This section also details the statistical techniques used to analyze both static and dynamic panel data, including methods for pre- and post-estimation analysis. Section four presents the empirical findings of the study, discussing how each variable influences NPL ratios. The insights drawn from these analyses are critical for understanding the dynamics affecting NPLs in the region. The subsequent section identifies existing limitations within the current research, which could serve as direction for future studies. The final section offers conclusions and implications derived from the study. It provides theoretical insights that could inform policy-making and guide the development of the banking sector in the CEE region.

1 Background Information and Literature Review

1.1 Economic Evolution and Contemporary Challenges in CEE Countries

Following the end of World War II, the post-1945 global political landscape limited the developmental prospects of CEE nations. With communism's collapse in the early 1990s, these countries commenced a substantial economic restructuring, aligning more closely with the global market as their economies progressively improved. This shift from centrally planned economies to market-driven ones initiated widespread changes across various economic sectors. Initially, the CEE nations encountered a transitional downturn, primarily characterized by a decrease in Gross Domestic Product (GDP) (Figure 1). During this time, the real GDP index saw an overall decline, particularly notable in Latvia, Lithuania, and Estonia. At the same time, these nations faced a significant reduction in external demand and suffered extensive losses of both human and material resources (Antal, 2004; Blanchard - Kremer, 1997; Myant & Drahokoupil, 2013).

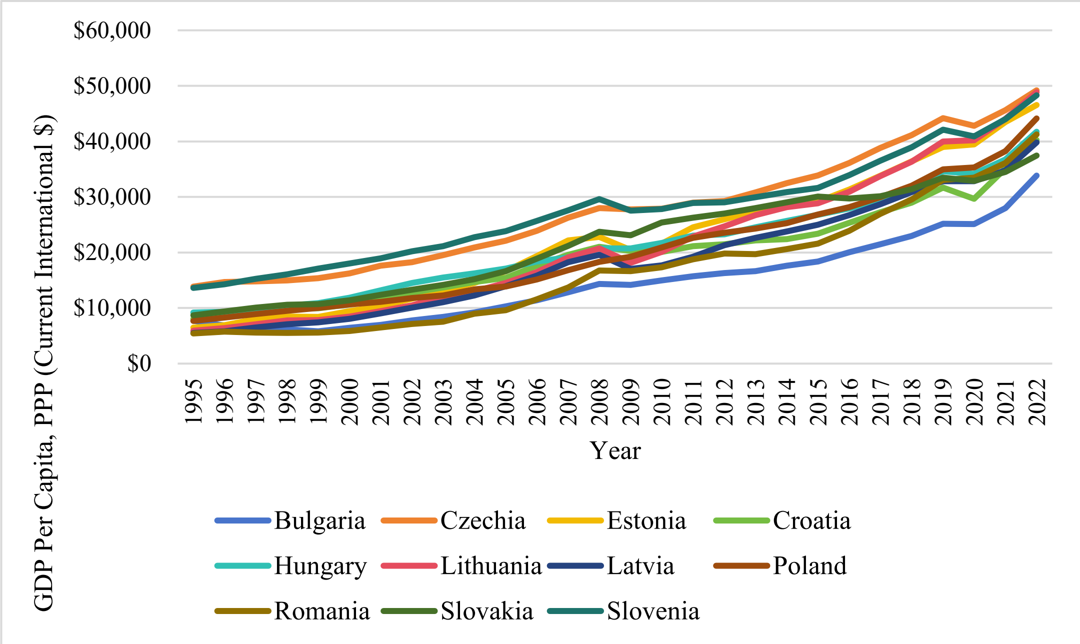
Figure 1 Real GDP Index (1989=100) across CEE countries from 1989 to 1998



Source: International Monetary Fund

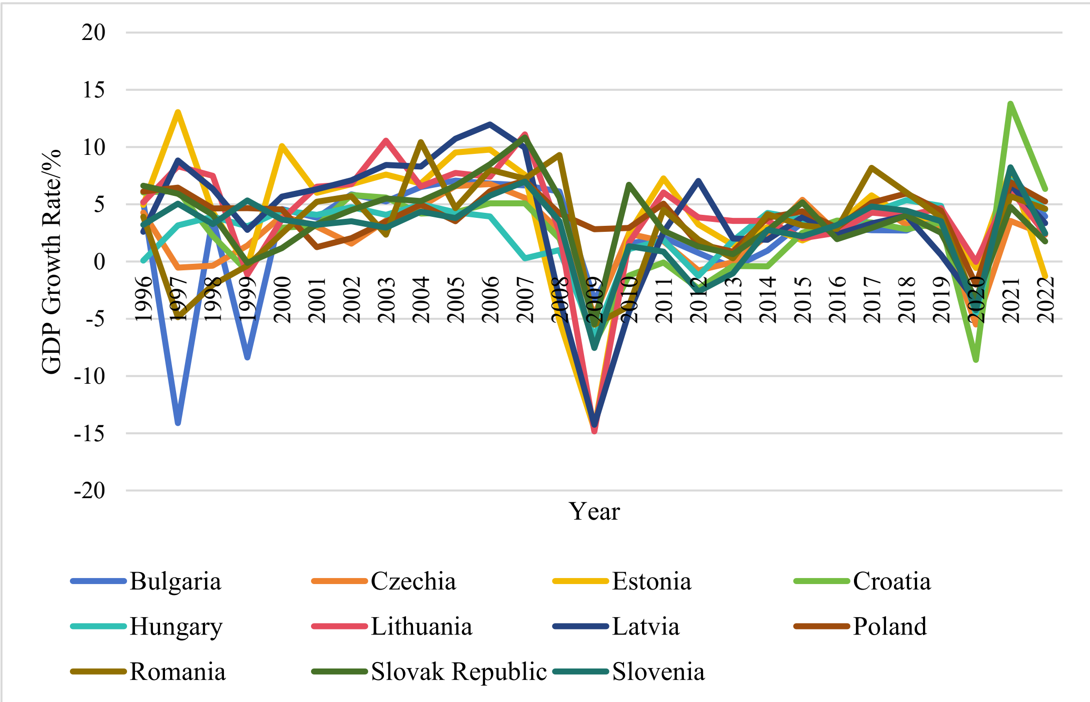
Between 1995 and 2007, following an initial phase of adjustment during their transition, the CEE economies experienced significant growth, positioning them among the most rapidly evolving regions globally (Dombi 2013). This era of vigorous expansion and convergence saw the transition economies not only recovered but also advance at an accelerated rate due to the swift implementation of reforms. According to Figure 2, there was a similar and steady upward trend in GDP per capita across all CEE nations throughout this period. The average GDP growth rate in these countries rose from 2.5% to 6.8%, allowing them to significantly narrow the development gap with more developed nations (Dombi, 2013). Estonia, Lithuania, and Latvia, as indicated in Figure 3, demonstrated a particularly strong growth trajectory, closing the developmental divide with other countries.

Figure 2 GDP Per Capita at Purchasing Power Parity (PPP) across Countries from 1995 to 2022



Source: World Bank Database

Figure 3 Annual GDP Growth Rate over Countries from 1996 to 2022

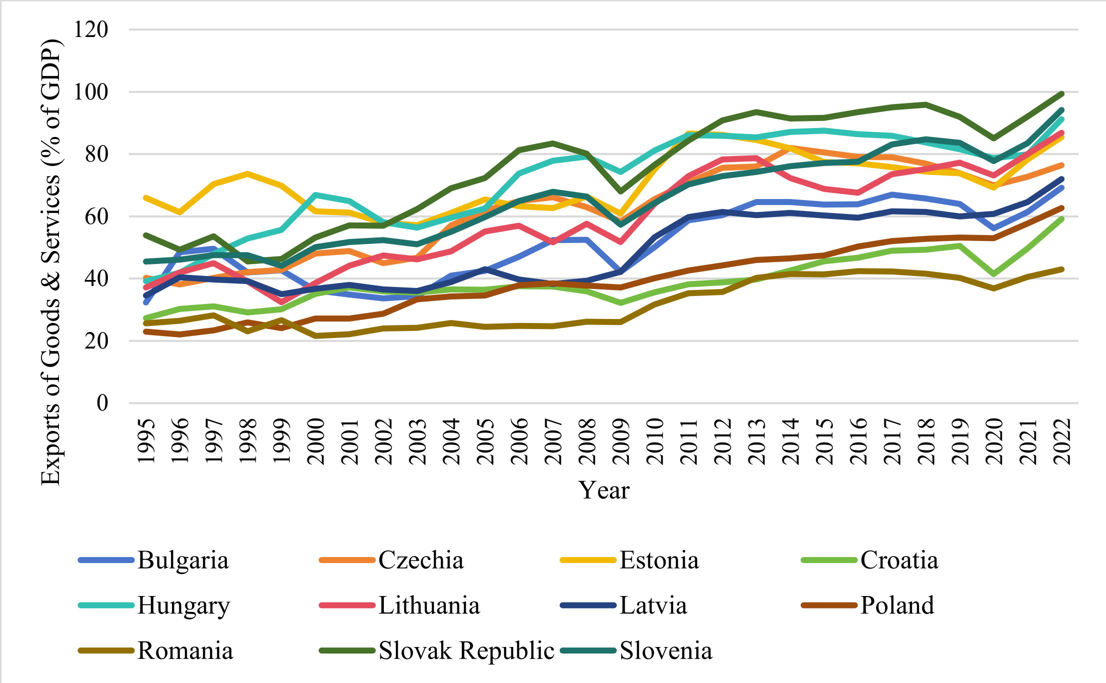


Source: World Bank Database

In addition to their overall economic progress, CEE countries face challenges that are distinctly influenced by regional factors, leading to regional variations in their development. Despite originating from similar economic systems, the development levels among these nations have increasingly diverged over time, leading to variations in economic performance and income inequality (Bayar, Gavriletea & Danuletiu, 2021; Anton, 2019). Countries with a high level of industrialization, which underwent significant de-industrialization and structural changes at the beginning of their transition, such as Poland, the Czech Republic, Hungary, etc., have witnessed dynamic developments in their economic sectors. This dynamism is largely attributed to their diversified socioeconomic frameworks and strong regional connections, particularly in sectors that are knowledge-intensive and globally interconnected, like tourism, management, and finance. However, the transformation and revitalization of old industrial areas present a complex and prolonged challenge, particularly in countries like Romania. This difficulty is exacerbated by reduced urbanization paces, substandard living conditions, and a workforce that lacks specialization. The disparity in the pace and nature of development highlights the regional dimension of the challenges faced by CEE countries, indicating the need for tailored approaches to address the unique obstacles within each nation's context.

The integration of CEE nations into the EU in 2004 significantly bolstered their reform initiatives, leading to notable enhancements in both their economic landscape and institutional frameworks. This integration allowed the economies of most CEE countries to align more closely with the growth patterns observed in Western European nations (Bostan et al., 2023). Since their accession, these countries have fostered strong connections and collaborative efforts with other European nations across various domains such as trade, finance, and education. This period also saw a strategic reallocation of resources from Western to CEE countries. Concurrently, there has been a marked increase in the exports of goods and services from CEE countries, accelerating significantly post-2004 (Figure 4).

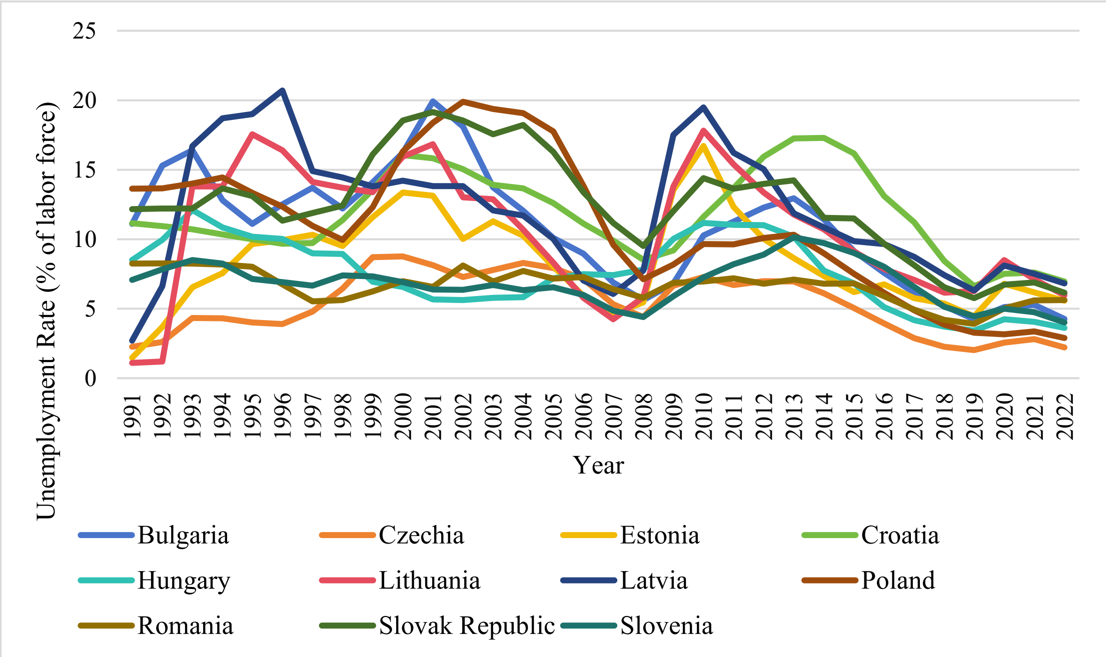
Figure 4 Export of Goods and Services over Countries from 1995 to 2022



Source: World Bank Database

Following the period of economic expansion triggered by their transition, the global financial crisis in 2007 dealt a significant blow to the economies, with effects that were more devastating than those of the Great Depression in 1930 and the Southeast Asian financial crisis in 1997 (Dhameja 2010). This era was characterized by economic contraction, reductions in GDP, rising unemployment, and capital depletion, among other challenges. The CEE economies, on average, saw their GDP fall by 2-2.6% (European Bank Report, 2009). Figure 3 illustrates a sharp downturn in the GDP growth rate during 2008-2009, indicating the severe impact of the recession, which affected economies to different extents. Lithuania, Latvia, Estonia and Slovenia, in particular, faced even more profound challenges with their economies shrinking by 14.84%, 14.25%, 14.63% and 7.55% respectively in 2009. Poland's economy was the least affected by the recession due to the liberalization of the economy since 1990. In addition, there was a decrease in the exports of goods and services from 2009 to 2010 in CEE countries (Bjelić, Jaćimović & Tašić, 2013), which is shown on Figure 4. Subsequent to this downturn, the CEE countries entered a prolonged phase of recuperation, during which governmental efforts were concentrated on revitalizing the economy and tackling employment issues. This resulted in a gradual decrease in unemployment rates (Figure 5).

Figure 5 Unemployment Rate over Countries from 1991 to 2022



Source: World Bank Database

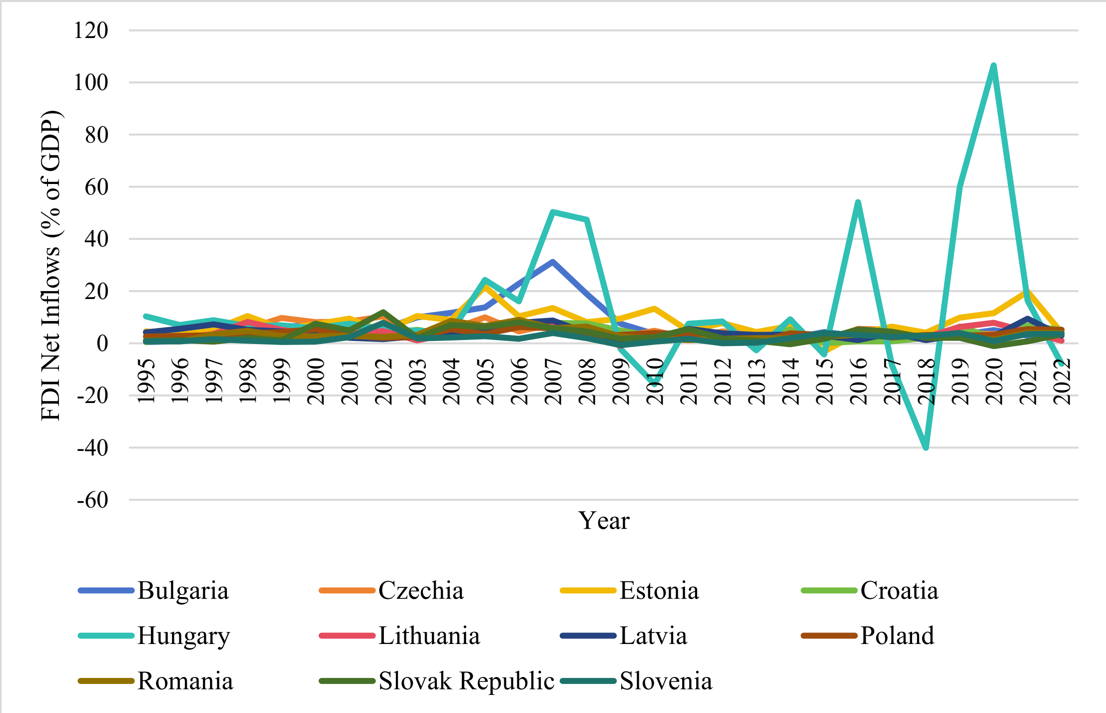
However, the 2020 global outbreak of Covid-19 delivered a substantial setback to the economies across the globe, with CEE countries experiencing particularly significant impacts. This was predominantly manifested through a severe contraction in the real economy, undermining years of economic progress. The resurgence of these economies prior to the pandemic was notably driven by their successful integration into global value chains and the relocation of numerous industries from Western to Eastern Europe, highlighting a strategic shift in economic dynamics. Foreign Direct Investment (FDI) played a crucial role in this context, serving as a primary channel for introducing innovation and facilitating technology transfer throughout the CEE region. For example, since the transition period, FDI inflows have been regarded as a crucial component of Hungary's economy, serving as the main driver of capital accumulation, industrial restructuring and economic growth. A 2011 press released from the Hungarian National Bank indicated that capital in transit[1] transactions represented about 83% of total inflows. These transactions frequently led to wide fluctuations, as seen in 2016, where the majority of changes were due to these short-term capital movements. In contrast, the surge in FDI inflows to Hungary by 2018 could be associated with a decline in divestments, as detailed in the 2017 UNCTAD World Investment Report, suggesting a more stable and attractive environment for long-term investments.

However, the global recession caused by the pandemic severely disrupted the complex supply chains essential to the operational base of the CEE economies. These networks were severely disrupted, leading to widespread economic consequences. A telling example of this disruption can be seen in Hungary, where the FDI net inflows for 2020 dramatically decreased, dropping from a robust 109% to a mere 20%, as illustrated in Figure 6. This decline is indicative of the broader economic challenges faced by the region in the wake of the pandemic.

As the CEE countries navigate through the latter stages of the Covid-19 crisis, their economies remain in a phase of ongoing recovery. This process is characterized by efforts to rebuild and strengthen the damaged supply networks and to re-establish the conditions conducive to attracting FDI. The path to recovery is complex, requiring strategic adaptations to the new economic realities imposed by the pandemic. The resilience and adaptability of these economies are being tested as they strive to regain their pace and continue their journey toward sustainable economic growth and integration into the global economy.

[1] Capital in transit describes situations where local Hungarian companies receive financing or a loan from an affiliated entity or a multinational corporation, only to quickly transfer these funds to another foreign entity within the same corporate group (MNB, 2011).

Figure 6 FDI Net Inflows over Countries from 1995 to 2022



Source: World Bank Database

1.2 Banking sectors and NPLs in CEE countries

Financial investment is crucial for economic growth and stands as a primary marker of economic progress, significantly contributing to the efficiency of the economic system. The banking system is crucial in financial markets for gathering and distributing financial resources, serving as a foundational element for domestic investment. Economic development indicators, such as GDP growth rates and the distribution of the nation's real income across financial institutions, trade balances, etc., significantly impact the composition of a bank's portfolio (Umantsiv & Ishchenko, 2017). Furthermore, the globalization of the economy and the increasing interconnection of financial markets have partially driven the evolution of the banking system.

In Europe, the establishment of the EU, the introduction of a unified currency system, and the founding of the European Central Bank have significantly propelled the growth of national economies, financial markets, and particularly the banking sector. The banking sector within the CEE countries exhibits a notably high level of financial integration (Fischer et al., 2008). The shift of these nations from centrally-planned to market economies marked the onset of a comprehensive and challenging reform and integration of their financial sectors. Despite varied experiences in reform, a common characteristic among the banking systems in CEE countries is the extensive presence of foreign banks. The presence of foreign banks in host economies contributes to increasing competitiveness, improving business efficiency, and stabilizing financial systems within those countries (Jeon et al., 2013). This is also a reflection of their deep economic and financial interconnection with more economically advanced European nations (Efthyvoulou & Yildirim, 2014).

The process of reforms across political, social, and economic dimensions led countries in CEE to gradually open their banking sectors to international investments. This trend was marked by the privatization of numerous state-owned banks, which were acquired by foreign investors. For example, in Hungary, this period was characterized by a substantial expansion in the operations of financial institutions. As a result, there was a significant increase in cross-border financial services and foreign ownership of banks within the CEE region (Horvatova, 2018). The continuous efforts to liberalize and privatize the banking industry provided avenues for foreign investors to buy shares in national banks through various methods and at different points in time (Chumachenko et al., 2021).

However, at the same time, the evolution of banking systems in CEE countries encountered various structural obstacles (Jokipii et al., 2020). These financial systems underwent profound changes, facing several challenges, including shortages of capital, a lack of banking expertise, political interventions, and widespread efforts towards privatization and restructuring. In the early phases of their economic transitions, state-owned banks began to divert their commercial activities to newly formed commercial banks, catalyzing the development of the private banking sector. This phase was succeeded by a concentrated effort on significant asset restructuring and the liquidation of non-performing assets (Felice et al., 2006). These series of transformations and reforms highlight the complex and adaptive nature of the banking sector in the CEE region, illustrating its pivotal role within the broader framework of economic and financial integration across Europe.

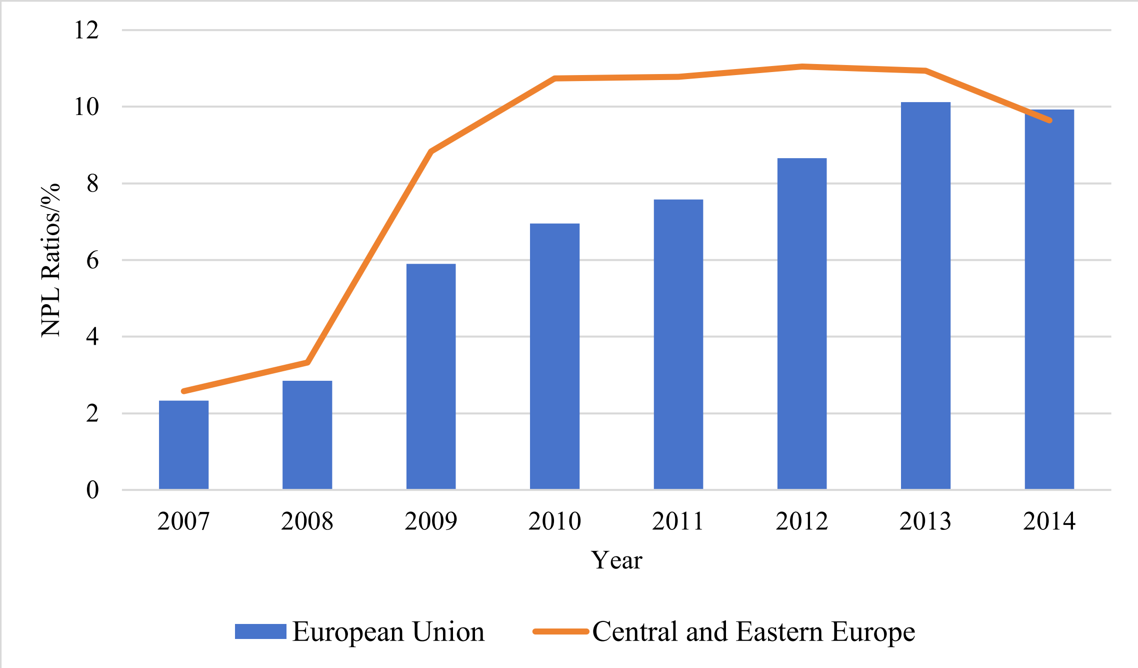
Moreover, the financial crisis that occurred between 2007 and 2008, triggered by the downfall of the real estate market in the United States, profoundly impacted financial markets globally, affecting both developed and emerging economies. Throughout the crisis, confidence among investors in the banking sector diminished, and the banking system in the CEE region suffered significantly due to the intensifying European debt and banking turmoil. The level of credit availability was closely linked to the globalization of the banking system, resulting in foreign banks conveying economic shocks from their home nations to the countries where they operated (Giannetti et al., 2012). Western European banks, due to their extensive reach and influence in the CEE markets, left the region's credit flows to businesses and consumers exposed to external disruptions (Popov et al., 2012). As such, the prevailing ownership structure within the CEE banking sector made these countries particularly prone to risk and the spread of shocks, especially during periods of crisis (Shah & Shaikh 2011). With the sudden halt of credit expansion, there was a downturn in financing demand and a diminished propensity to lend by European banks (Škarica, 2014). During this period, lending practices garnered considerable attention. There was a marked deterioration in the quality of bank loan portfolios. The surge in risky loans led to a higher number of defaulted loans and the need for provisions against potential losses, adversely affecting the profitability of the banking sector at large (Kil et al., 2020).

Banks employ a variety of tools to evaluate the quality of their loan portfolios, with the majority of these approaches targeting the estimation of associated risks. Among these, the NPL ratio is widely recognized as a key metric (Kjosevski & Petkovski, 2021). A rise in the NPL ratio is indicative of a decline in the performance of the banking sector (Mörttinen et al., 2005). The uncertainty that high levels of NPLs introduce often hinders banks' lending capabilities, which in turn negatively impacts investment and overall economic demand. Additionally, when borrowers are excessively leveraged and unable to resolve their NPLs, it leads to the inefficient use of economic resources and a decrease in economic activity. A swift escalation in the NPL ratio is also a significant factor in triggering banking crises (Demirguc-Kunt & Detragiache, 1998). Historical financial disruptions have highlighted the importance of financial sector reform as a foundational element for sustainable economic recovery. The recent economic downturn has resulted in a notably tepid recovery process. This phenomenon was particularly pronounced in the CEE region during the financial crisis, where there was a marked surge in the NPL ratios, reflecting the acute financial stress experienced by these countries.

The growth of NPL ratios exhibits variation among different clusters of nations (Tanasković & Jandrić, 2015). Remarkably, even with substantial intervention from regulatory bodies and concerted efforts within the banking sector, CEE countries have struggled to reduce NPL ratios to levels comparable to their Western European counterparts, as evidenced by Figure 7. During the financial crisis, the prevalence of NPLs in the CEE region outpaced that found within the EU[2]. There was a significant escalation in NPL ratios during 2008-2009, with the figures nearly doubling for the CEE countries, soaring from 2.85% to 5.90%, and more than doubling for the EU, jumping from 3.32% to 8.83%. These statistics highlight the acute financial challenges faced in the CEE during this period, with a noteworthy impact on the banking sector's stability and performance compared to other regions in Europe.

[2] The classification of country groups is based on the World Bank Database. There are 27 countries in EU: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden.

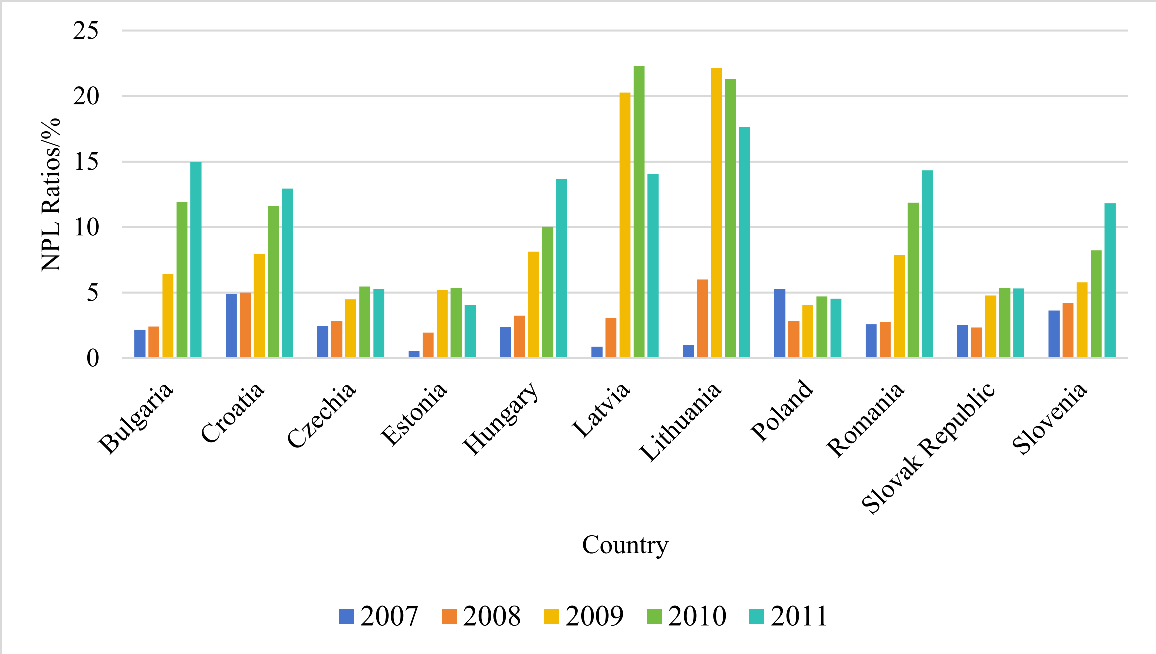
Figure 7 Bank NPL Ratios (%) from 2007 to 2014



Source: World Development Indicators

Moreover, within the CEE countries itself, the scale of NPLs was not uniform. Based on data presented in Figure 8, it was observed that the NPL ratios improved during the crisis in the CEE countries and the impact of the global financial crisis peaked around 2008-2009. Latvia and Lithuania witnessed especially sharp increases in their NPL ratios, increasing from 3.04% to 20.27% and 5.99% to 21.31% respectively. On average, the CEE countries saw an alarming average growth rate of NPLs at 165.96%. However, countries such as Czechia, Poland, and the Slovak Republic managed to keep their NPL ratios at bay, suggesting potentially resilient financial institutions or a more robust economic backdrop that afforded them greater protection against the crisis's consequences.

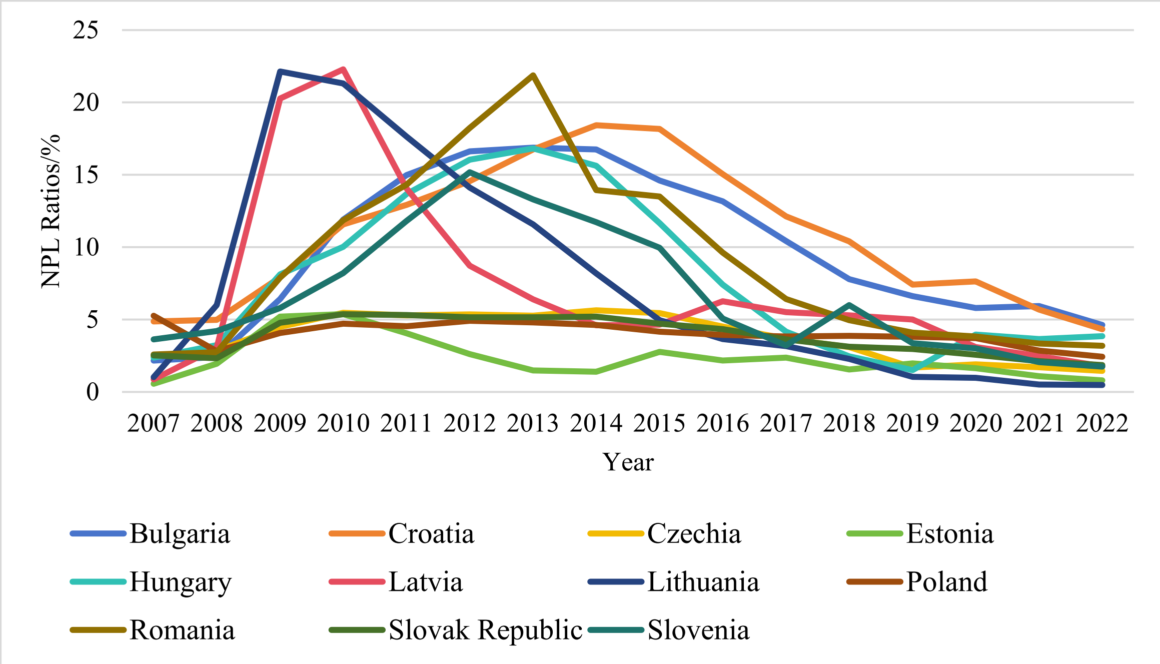
Figure 8 NPL Ratios across the CEE Countries from 2007 to 2011



Source: World Bank Database

Following the financial crisis, a period of recovery unfolded over several years. Starting in 2013, there was a noticeable downward trend in NPL ratios across the majority of countries (Figure 9). This decline might signal a phase of recovery or a reflection of enhanced strategies for handling NPLs. While the Covid-19 pandemic in 2020 exerted a moderate effect on the NPL ratios in some countries, by 2022, the trajectories of NPL ratios across the countries demonstrated a tendency to align more closely, suggesting a trend towards a unified state of financial stability within the banking sectors of these nations. This convergence could imply that the disparities in banking sector health that were once pronounced are now diminishing. Additionally, this pattern hints at the possibility that these countries have not only emerged from the shadow of the crisis but also may have adopted more consistent and effective banking practices, contributing to a collective bolstering of their financial systems.

Figure 9 NPL Ratios across the CEE Countries from 2007 to 2022



Source: World Bank Database

1.3 Literature Review

Academic research has extensively explored the diverse factors influencing NPL ratios, leading to significant discussion regarding the causes of financial instability across different nations. This interest has grown in recent years, with scholars like Khemraj & Pasha (2009), Saba et al. (2012), Sorge (2014), Radivojevic & Jovovic (2017), Mazreku (2018), as well as Saliba (2023), highlighting the importance of understanding financial vulnerabilities through indicators like NPL ratios and loan loss provisions. This section aims to summarize the literature on the determinants of NPL ratios, with a particular emphasis on empirical studies that form the majority of research in this area.

The variability in NPL ratios can be attributed to numerous factors, varying across regions, time frames, databases, and the variables considered in different studies, leading to a wide range of empirical findings. The existing literature on NPLs can broadly be categorized into two primary groups. The first examines the impact of macroeconomic factors—such as GDP growth rate, unemployment rate, and share price index (SPI)—on NPL ratios. The second group delves into bank-specific determinants, including but not limited to the return on assets (ROA), the equity-to-total assets (ETA) ratio, and the net interest margin (NIM). This paper will review the literature from both of these aspects, subsequently delving into the methodologies employed in prior research to provide a comprehensive overview of the empirical landscape surrounding NPL ratios.

1.3.1 Macroeconomic factors

A substantial body of research highlights the robust link between the NPL ratios and numerous macroeconomic factors. The consensus among these studies points to variables associated with GDP as the primary determinants of NPL ratios. Among various GDP-related metrics, such as per capita GDP, the real GDP growth rate, and production gap, the real GDP growth rate emerges as the most frequently utilized indicator in these analyses. Numerous scholarly articles have established a negative relationship between NPLs and real GDP growth (Espinoza & Parad, 2010; Jakubik & Reininger, 2013). Beck et al. (2015) further reinforced this perspective by demonstrating that an upswing in GDP significantly contributed to a decrease in the ratio of NPLs within the overall loan portfolio. Their research, which spanned 75 banks from 2000 to 2010, highlighted the crucial role of economic expansion in bolstering the resilience and health of the banking sector. Similarly, Nkusu (2011) posited that economic growth leads to an uptick in the general income level and mitigates financial pressures. Consequently, an inverse relationship is expected between GDP growth and the net borrowing recovery rate. This suggests that as economies expand and income levels rise, the financial health of individuals and businesses improves, thereby reducing the likelihood of loans becoming non-performing. Such insights underline the pivotal influence of economic dynamics on the stability and performance of the banking industry.

Extensive research has also focused on the impact of the unemployment rate on NPL ratios, drawing parallels across multiple studies that indicate a positive correlation between these two variables. Notably, Messai & Jouini (2013) delved into the factors affecting NPLs within a dataset comprising 85 banks from Italy, Spain, and Greece over the period of 2004 to 2008. Through their panel data analysis, they found a direct positive link between the unemployment rate and the prevalence of problem loans. This observation was further supported by Dimitrios et al. (2016), who utilized the GMM model to assess quarterly data from banks in the euro area from 1990 to 2015. Their research concluded that an increase in unemployment significantly degrades the quality of bank loan portfolios. This conclusion is consistent with findings from Škarica (2013) and Makri et al. (2014), suggesting a widespread consensus across various studies regarding the impact of unemployment on NPL ratios.

The annual inflation rate's effect on NPL ratios has also been a point of interest, though findings in this area remain inconclusive. Donatah et al. (2014) investigated the relationship between inflation rates and NPL ratios in the Baltic States[3] and Romania from 2000 to 2013, uncovering a generally negative relationship between the two, with the exception of Lithuania. Similarly, Staehr & Uusküla (2017) highlighted inflation as a key macroeconomic determinant in lowering NPL ratios through their analysis of panel data from the EU spanning 1997 to 2017. Conversely, Kavkler & Festic (2010) identified a significant positive correlation between inflation rates and NPL ratios in the Baltic States. Furthermore, research conducted by Aver (2008) and Bofondi & Ropele (2011) on the banking systems in Slovenia and Italy revealed no noticeable effect of inflation on credit risk, highlighting the diverse results found in studies within this field. These findings underscore the complex interplay between inflation and its influence on NPL ratios.

[3] The Baltic States: Estonia, Latvia and Lithuania.

In the realm of research on macroeconomic factors affecting bank NPL ratios, the impact of FDI and exports on the incidence of unpaid loans has been notably studied. Given the EU's economic structure, FDI has garnered considerable attention. Festić et al. (2011) employed both fixed and RE models to examine various macroeconomic variables within the banking sectors of five EU countries. Their analysis revealed that FDI in the financial intermediation sector is associated with a rise in NPLs. On the other hand, an increase in the export of goods and services plays a crucial role in enhancing the resilience and reducing NPLs within the banking sectors of these nations. Clichici & Colesnicova (2014) share a similar viewpoint, highlighting how export growth rates can shed light on the broader economic impacts. A downturn in exports could lead to lower firm revenues, which in turn, hampers their loan repayment capabilities, thereby elevating the NPL ratio. Echoing this viewpoint, Kavkler & Festic (2010) investigated 12 variables in the Baltic States from 1997 to 2007. Through the application of the ordinary least squares (OLS) method, they found that a downturn in exports correlates with an increased NPL ratio.

Moreover, several studies have explored the effects of real interest rates and the SPI on NPLs. Berge & Boye (2007) found a strong sensitivity of problem loans to real interest rates within the Nordic banking system between 1993 and 2005. Following this, Espinoza & Prasad (2010) carried out a dynamic panel study on approximately 80 banks in the Gulf Cooperation Council region from 1995 to 2008. Their observations indicated that NPL ratios generally increase as interest rates rise. When it comes to the impact of the SPI on NPLs, the findings are less clear-cut. Škarica (2013) applied a FE model to analyze data from seven CEE countries from 2007 to 2012, concluding that SPI's effect on NPL ratios was negligible. Contrarily, Beck et al. (2015) indicated that a decrease in SPI significantly influences NPL ratios, revealing a negative correlation between the two. This divergence in findings highlights the complex dynamics between market indicators and loan performance.

Other macroeconomic variables have also been explored by scholars. Ozili (2019) conducted an analysis using data from 103 countries over the period from 2003 to 2014, employing an unbalanced panel approach. This study found that an increase in foreign bank activity and financial intermediation was associated with higher rates of NPLs. Additionally, it identified a positive correlation between the frequency of NPLs and factors such as banking crises and bank concentration. Buncic & Melecky (2012) observed a positive connection between lending rates and NPL ratios, indicating that higher lending rates may lead to increased NPLs. Similarly, Dimitrios et al. (2016) investigated the impact of public debt, concluding that an increase in public debt puts additional fiscal pressure on citizens, reducing their capacity to service debts. Their findings support a positive link between high public debt levels and a greater incidence of NPLs. Khemraj & Pasha (2009) extended the scope of analysis to include the real effective exchange rate, uncovering a positive association with NPL ratios. This body of research highlights the complex interplay between various macroeconomic variables and the health of the banking sector, specifically in relation to loan repayment performance.

1.3.2 Bank-specific factors

Regarding bank-specific factors, numerous studies have delved into the link between financial system profitability and NPL ratios (Salas et al., 2024). Kjosevski & Petkovski (2021), have found a negative relationship between profitability and NPL ratios. Boudrig et al. (2009) observed that banks with lower profit margins might pursue riskier and less secure investment strategies either to boost their profitability or to meet regulatory demands. This observation was earlier confirmed by Godlewski (2005), who, using ROA as a measure of profitability, identified a negative correlation between bank profitability and NPL ratios. In a more recent study, Ciptawan (2023) conducted a regression panel model analysis on 36 Indonesian commercial banks listed between 2008 and 2015, concluding that profitability inversely relates to NPLs.

Similarly, Melly (2023) further supported these conclusions in a study of 46 listed financial institutions in Indonesia, again demonstrating a negative correlation between profitability and NPL ratios.

NIM is another critical factor influencing the NPL ratios, serving as a reflection of the bank management's quality. According to Klein (2013), banks that manage their resources more efficiently generally possess better asset quality and report higher profits. Espinoza & Prasad (2010) observed that NIM ratios adversely impact NPLs, indicating that a reduction in NIM might prompt banks to revise their lending policies, thereby elevating the risk of defaults in their loan portfolio over time. A different finding was reported by Chowdhury et al. (2023), who, through their research covering the years 2007 to 2018, examined the factors affecting NPL ratios in Bangladesh. Their study concluded that a decline in the interest margin is associated with a reduction in the NPL ratio, suggesting an intricate link between NIM performance and loan repayment success.

The relationship between ETA ratio and NPL ratios has been extensively explored in numerous studies, yet the findings remain equivocal. Keeton & Morris (1987) introduced the concept of the "moral hazard" hypothesis, suggesting that banks with lesser capital levels might be more inclined to assume higher risks in their loan portfolios due to moral hazard incentives. This inclination often results in an increase in the average number of NPLs, leading to the observation of a negative correlation between NPL ratios and bank capital. This perspective is supported by the research of Salas & Saurina (2002) and Klein (2013), among others, who found evidence of this negative relationship. On the other hand, the analysis by Louzis et al. (2012) challenges the "moral hazard" hypothesis in the context of the Greek banking system, failing to find supporting evidence. Additionally, Quagliarello (2007) presented a contrasting viewpoint, arguing for a positive correlation between these variables. The rationale is that banks showing a preference for higher risk may increase the capital allocated to their current shareholders as a means to attract further investment and support from other shareholders. This approach, based on a higher risk preference, essentially seeks to bolster the bank's financial stability and growth prospects by leveraging the confidence and additional capital from shareholders. The ambiguity in conclusions highlights the complexity of banking behavior and the impact of external and internal factors on the risk-taking decisions of banks. The varied findings across different studies underscore the necessity for a nuanced understanding of the dynamics between bank capital levels and NPL ratios, considering the specific context and regulatory environment of each banking system.

In a detailed examination of the loan losses suffered by the banking sector in the United States, Sinkey & Greenwalt (1991) proposed that banks anticipating substantial capital losses may opt to increase their loss provisions. This strategic move is aimed at reducing the volatility of earnings and bolstering medium-term solvency. Additionally, Ahmad et al. (1999) have indicated that managers could use loss provisions as a strategic tool to project an image of financial stability and strength of their banks to stakeholders. This utilization of loss provisions underscores the tactical aspect of financial management within banks, where signaling financial health becomes a key operational strategy. Expanding on the theme of risk management, Messai & Jouini (2013) have identified Loan Loss Reserves (LLR) as a crucial metric reflecting the banking system's general stance towards managing risk. Moreover, in an international context, Hasan & Wall (2004) conducted a comprehensive study across banks in 24 countries spanning the years 1993 to 2000. Their findings revealed a positive correlation between LLR and NPL ratios, underscoring the importance of LLR as a financial safeguard and a reflection of a bank's exposure to credit risk.

Podpiera & Weill (2008) have explored the significant link between cost efficiency and NPL ratios, uncovering a negative correlation between the two by studying the Czech Republic's banking sector from 1994 to 2005. Their research suggests that improving the stability of the financial system involves focusing on managerial performance. This insight is followed by the findings of Espinoza & Prasad (2010), Koju et al. (2018), and Khan et al. (2020), who have also observed a similar relationship. Despite these findings, the connection between cost efficiency and NPL ratios remains somewhat ambiguous. While banks that decrease their short-term investments in evaluating the creditworthiness of borrowers and in risk monitoring may see an immediate increase in profitability, such strategies might result in an increase in NPLs over a longer period. This contrast highlights the complex relationship between immediate financial efficiency measures and their impact on long-term loan performance.

Discussions around how a bank's size[4] affects its NPL ratios have brought forward notable insights. El-Maude et al. (2017) found a corresponding relationship among listed commercial banks in Nigeria during 2010-2014. Similarly, Salas & Saurina (2002) discovered a significant link between bank size and NPL ratios by examining the performance of Spanish commercial banks from 1985 to 1997. Ghosh (2015) pointed out that larger banks may tend to overextend their lending activities by leveraging financial tools, a strategy that often results in lowered lending standards and, consequently, an increased likelihood of loan defaults. Echoing this observation, Ahmed et al. (2021) found that the scale of a banking institution is directly and positively related to its NPL ratios in the context of commercial banks in Pakistan. This body of research underscores the critical impact of a bank's size on its risk profile and the quality of its loan portfolio.

Scholars have delved into various internal factors within banks, including the dynamics between credit growth and the NPL ratios, yielding varied outcomes. Dash & Kabra (2010) identified a positive correlation between credit growth and NPL ratios, suggesting that as banks expand their lending, NPLs tend to increase. Conversely, Swamy (2012) found a negative relationship between these variables, attributing this divergence to the distinct characteristics, regulatory frameworks, and

[4] The bank size is measured by the bank's total assets.

operational environments of different banking systems, which may prompt banks to proceed more cautiously in extending credit, following the recommendation by Quagliarello (2007). Furthermore, significant attention has been paid to the capital adequacy ratio (CAR), which evaluates a bank's equity relative to its risk exposure. However, the impact of CAR on NPL ratios is not uniformly agreed upon across studies. While some research suggests that lower CAR is associated with higher NPL levels, indicating a potential vulnerability to loan defaults, other studies propose that a higher CAR might lead banks to assume riskier loans, thereby possibly elevating NPLs (Rime, 2001). The diverse outcomes shown in these studies highlight the complex interaction between the internal strategies adopted by banks, the regulatory contexts within which they operate, and the subsequent risk profiles that emerge.

1.3.3 Review on Econometric Models

A diverse array of econometric models have been employed by various researchers to dissect the effects of both external and internal factors on NPL ratios, showcasing the multifaceted nature of this financial phenomenon. For instance, Festic & Repina (2009) explored the interconnection between macroeconomic conditions and specific banking factors on the NPL ratios within the Baltic States. Their investigation utilized panel regression techniques over a period stretching from the first quarter of 1998 to the third quarter of 2008. The outcomes of their study highlighted a direct correlation between economic downturns and a swift rise in NPL ratios, underscoring the vulnerability of NPLs to broader economic fluctuations. Using a multiple linear regression model, MANÇKA (2012) evaluated how national currency instability and the global financial crisis affected systemic credit risk in Albania. Her findings highlighted the significant influence of these variables on the country's credit risk landscape, suggesting a pronounced sensitivity of the financial sector to macroeconomic and external shocks. Moreover, Otašević's (2013) analysis provided a detailed look into the Serbian banking sector by examining panel data from 33 commercial banks from 2008 to 2012 on a quarterly basis. The study unveiled how adverse business cycles and exchange rate depreciation played a critical role in deteriorating the quality of loan portfolios in Serbian banks. Furthermore, it suggested that inflation spikes could lower the real value of outstanding loans, leading to temporary relief for debt servicing, thereby offering a potential buffer against short-term credit risk.

The evolution of stress testing methodologies in the banking sector has witnessed a significant transformation from the early static balance sheet approach, a method documented in initial research by Čihák (2007), to a more nuanced and dynamic approach. This modern methodology enables modifications to specific components of the balance sheet over time, adapting to the dynamic nature of banking operations. Such flexibility enhances the precision of evaluating the impacts of shifts in lending practices -- be it an escalation or a reduction -- on the financial health of banks, particularly in terms of capital adequacy and NPL ratios. This dynamic perspective is especially critical for analyzing the consequences of banks' strategies to either decrease or increase their leverage, highlighting its relevance as pointed out in studies by Schmieder et al. (2011) and Jakubík & Schmieder (2008). Similarly, Louzis et al. (2010) delved into the Greek banking sector, examining the variables that influence NPLs across various loan types from 2003 to 2009. By employing a dynamic panel data approach, their investigation cast light on the significant role of macroeconomic indicators. It was found that the prevalence of impaired loans was closely linked to various macroeconomic variables, such as GDP and unemployment rates, as well as the management quality of banks. Moreover, their research noted that mortgage-related NPLs were relatively less affected by macroeconomic changes, suggesting different sensitivities among loan categories to broader economic conditions.

Further expanding the scope of analysis, some researchers have utilized both static and dynamic panel data methods to offer a comprehensive view of the determinants affecting NPL ratios. For example, Klein (2013) conducted an extensive study on the NPL ratios in the regions of Central, Eastern, and Southeastern Europe (CESEE) over the period from 1998 to 2011. His research incorporated three distinct analytical models: the FE model, system GMM, and difference GMM. The conclusions drawn from this study underscored the significant influence of macroeconomic variables, including GDP growth and inflation rates, on the dynamics of NPL ratios.

Some significant insights are revealed through the use of Panel Vector Autoregressive (PVAR) and Autoregressive Distributed Lag (ARDL) models. Nkusu (2011) employs the PVAR methodology to analyze the interconnection between NPLs and macroeconomic determinants, emphasizing the crucial role NPLs play in the connection between credit market frictions and macro-financial vulnerabilities. The study outlines a situation where rising NPLs lead to a downturn in macroeconomic performance, which subsequently triggers a prolonged adverse cycle affecting GDP growth and unemployment. This highlights the PVAR's ability to capture the dynamic feedback mechanisms across various time periods, demonstrating a nearly linear response to economic shocks that persists over several years. Moreover, Adebola et al. (2011) utilize the ARDL approach to investigate the determinants of NPLs in Islamic banks within Malaysia, focusing on the period from 2007 to 2009. The ARDL model proves effective in identifying long-term relationships between NPLs and key macroeconomic variables such as industrial production, interest rates, and producer price indices. Their findings indicate that higher interest rates significantly exacerbate the proportion of bad loans, whereas lower producer prices seem to mitigate them. The ARDL model's strength lies in its flexibility to estimate short- and long-term dynamics simultaneously from integrated and non-integrated variables, providing a comprehensive view of economic interactions over time.

In a complementary strand of research, Fainstein & Novikov (2011) ventured beyond the confines of VAR analysis by integrating a vector error correction model (VECM) into their study, with the aim of providing a nuanced empirical evaluation of how macroeconomic variables alongside real estate market factors influence NPLs in the Baltic states, utilizing quarterly data for their analysis. Their research findings underscore the pivotal role of real GDP fluctuations as the initial driver for escalations in NPL levels across these nations. Notably, their study also reveals that other analyzed variables typically display a delayed response to shifts in real GDP, indicating a period of adjustment that is directly proportional to the increase in NPL levels.

Together, these studies highlight the evolving nature of financial analysis, demonstrating the application of sophisticated econometric models to dissect the complex network of relationships between the banking sector's performance, macroeconomic variables and NPLs. Through such detailed investigations, these research efforts contribute valuable insights into the dynamics of financial stability and economic health, underscoring the criticality of understanding these interactions for policy-makers and financial institutions alike.

Despite considerable research on the determinants of NPLs globally, a significant research gap persists regarding the influence of various factors on NPLs within CEE countries. This study aims to fill this research gap by offering empirical analysis specific to the CEE context. Additionally, the study spans from 2007 to 2022, offering the most up-to-date analysis of NPL determinants in CEE countries. It examines 12 variables in total, placing a primary focus on three extensively researched variables, namely GDP growth rate, unemployment rate, and ROA, as well as two additional variables, SPI and LLRs, which have significant influence during the selected period for Central and Eastern European countries. For other variables, such as the inflation rate and NIM ratio, the article conducts a basic study and analysis. Based on the literature review and the research of previous scholars, the main hypotheses of this article are proposed as follows.

H1: There's a negative relationship between GDP growth rate and NPL ratios.

H2: There's a positive relationship between unemployment rate and NPL ratios.

H3: There’s a negative relationship between SPI and NPL ratios.

H4: There’s a negative relationship between ROA and NPL ratios.

H5: There’s a positive relationship between LLRs and NPL ratios.

This research is the first to integrate FE models with both one-step and two-step system GMM models in its analysis. Therefore, this paper significantly enriches the body of knowledge on NPLs in the CEE region. By offering a detailed exploration of the issue through a methodologically robust framework and by providing actionable insights for both policymakers and banking institutions, the study not only fills a critical gap in the existing literature but also lays down a foundation for future research and practical application in the management of NPLs within the CEE banking sector.

2 Data and Methodology

2.1 Data

2.1.1 Data Sources

In this study, we focus on 52 commercial banks across eleven CEE countries to examine the effects of both macroeconomic factors and bank-specific characteristics on NPL ratios. The selection process for these banks involved using The Banker Database to rank commercial banks within each CEE country according to their Tier 1 capital[5], descending from highest to lowest. Tier 1 capital was chosen as a selection criterion because it not only reflects the amount of capital available to be distributed among shareholders but also serves as an indicator of the bank's overall size and the level of banking development within each country. Moreover, the availability and completeness of data from 2007 to 2022 for each bank were considered crucial for inclusion in the study. Initially, 151 CEE commercial banks were identified as potential subjects for this research. However, after excluding those with incomplete data records, the final sample was narrowed down to 52 commercial banks. For a detailed list of the banks included in this study, refer to Appendix 1.

Table 1 Observations per Country

Country	Number of Observations
Bulgaria	8
Croatia	3
Czech Republic	6
Estonia	2
Hungary	4
Latvia	3
Lithuania	2
Poland	10
Romania	6
Slovakia	4

[5] Tier 1 capital represents the primary funds maintained in a bank's reserves, serving as the essential financial support for the bank's client-related business operations.

Slovenia	4
Total	52

Source: Authors' compilation.

In this research, NPL ratio has been chosen as the dependent variable to assess the health and risk management of the banking sector. Instead of focusing on the NPL ratios of individual banks, we have selected to analyze aggregated data across the entire banking sector of each country. This approach addresses the challenge of limited availability of detailed, bank-level data in CEE countries. Moreover, it enhances the significance of our findings to a broader, macroeconomic scale, providing insights that are crucial for policy adjustments within the entire banking industry. The primary sources for our data include the World Bank Database, from which we have gathered most of our information, and the Global Financial Development Database (GFDD), which supplied data for the year 2007.

Regarding the independent variables, our study incorporates a selection of seven macroeconomic factors and five bank-specific factors. The selection of these variables is based on several considerations. First, previous research has demonstrated their potential impact on NPLs. Second, these variables, including GDP growth, unemployment rate, inflation rate, ROA, and ETA ratio, are commonly studied in research on the determinants of NPLs. Third, our article aims to also explore certain variables that have received less attention in past studies, such as the SPI, bank concentration, NIM, LLRs, and the net loans ratio. The macroeconomic variables were sourced primarily from the World Bank Database, the GFDD and the OECD database, ensuring consistency and reliability. The bank-specific data, on the other hand, were extracted from the BankFocus Database, offering detailed insights into the operational and financial status of the banks under consideration. We concentrate primarily on five variables in our study: GDP growth rate, unemployment, and ROA, which are the most frequently examined in the literature, as well as SPI and LLRs, which, despite being less studied, are crucial for understanding the changes in NPL ratios in CEE countries during the 2007-2022 period.

2.1.2 Data Specification

2.1.2.1 NPL Ratio

In the study, the logarithm of NPL ratio was used as dependent variable. The NPL ratio is a key financial metric, derived by dividing the amount of NPLs by total gross loans. NPLs are defined, according to the Report of the Working Group on NPL ratios in CESEE (2012), as significant lending obligations that have not been serviced for more than 90 days. Nevertheless, it's important to note that there is variance in how different countries classify NPLs. For instance, some nations report loans as non-performing if they are overdue by more than 31 days, while others set this threshold at more than 61 days. Despite these discrepancies in some national standards for reporting NPLs, our analysis adopts a standardized approach. Specifically, for the purpose of this study involving 11 countries in the CEE region, we applied a consistent criterion across all jurisdictions, treating any loan that remains unpaid for over 90 days as NPLs. This uniform standardization is crucial for ensuring comparability and coherence in our analysis of NPL ratios across the diverse banking landscapes of the CEE countries.

2.1.2.2 GDP Growth Rate

The annual growth rate of GDP is frequently cited as the most significant indicator influencing NPL ratios in the literature. A broad consensus among scholars indicates a negative correlation between GDP growth rate and NPL ratios. This relationship is based on empirical research, which demonstrates that a rise in the real GDP growth rate usually corresponds with higher income levels among the population. This rise in income improves the ability of borrowers to fulfill their debt obligations, subsequently leading to a reduction in the occurrence of bad debts within the banking sector. Conversely, during economic downturns, marked by reduced or negative growth in GDP, often result in an increased rate of bad debts. During such periods, the diminished economic activity affects income levels adversely, impairing borrowers' capacity to service their debts and increasing the likelihood of loans turning non-performing.

2.1.2.3 Unemployment Rate

Unemployment rate is defined as the proportion of the labor force that is not currently employed but is actively seeking work and available to start. There is a well-established consensus in academic research indicating a direct positive correlation between the unemployment rate and NPL ratios. Obviously, for individuals and households, an increase in unemployment typically results in a significant drop in income. People who find themselves jobless, or those who must settle for part-time work due to the lack of full-time opportunities, face a steep decline in their earnings. This reduction in income directly affects their ability to fulfill various financial commitments. The struggle to keep up with these payments can lead to an increase in NPLs, as more individuals are unable to meet the terms of their debt agreements. From a macroeconomic perspective, increasing unemployment rates are often a symptom of broader economic downturns in consumer spending and a decrease in demand for goods and services. This reduction in economic activity can result in further job losses across multiple sectors, creating a feedback loop that intensifies unemployment and, consequently, the difficulty for many borrowers to pay off their debts.

2.1.2.4 Share Prices Index

SPI are derived from the trading prices of common stocks of companies listed on national or international stock exchanges. These indices provide a glimpse into market trends and investor sentiment by tracking the changes in the market capitalization of a selected group of stocks. A basic price index reflects the aggregate value changes of these stocks, while a total return index further incorporates the dividends issued by these companies, assuming these dividends are reinvested back into the stocks. The dynamics of SPI can subtly influence the landscape of NPLs.

Market volatility, particularly when share prices are on a downward trajectory, can significantly alter the risk landscape perceived by investors and financial institutions. This shift in risk perception can prompt banks to adopt more conservative lending policies, prioritizing financial stability over loan growth, which could result in tighter credit conditions, making it increasingly challenging for both businesses and consumers to secure new loans or credit lines. Initially, this cautious approach may lead to a decline in the formation of new NPLs, as reduced lending opportunities limit the potential for borrowers to take on unmanageable debts. However, the tightening of credit standards can also exert pressure on existing borrowers. Those in need of refinancing or additional credit to navigate through financial difficulties may find themselves without viable options. In such cases, the failure to restructure or extend their debt obligations could trigger a rise in NPLs, as borrowers struggle to meet their repayment terms under the prevailing economic conditions.

2.1.2.5 Inflation Rate

Inflation, as a significant macroeconomic factor, is measured by the annual percentage change in consumer prices, typically captured through the consumer price index (CPI). The relationship between inflation and NPL ratios is ambiguous and has been subject to varied interpretations in existing literature. On one side, higher inflation rates can lead to a decrease in the real value of outstanding debts. Therefore, the money that borrowers owe is worth less in terms of purchasing power, which can potentially ease the burden of debt repayment. This dynamic suggests that inflation could indirectly contribute to reducing the proportion of NPLs by making existing debts more manageable for borrowers. Conversely, inflation can have a detrimental effect on borrowers' capacity to service their debts by eroding their real income. When inflation rates are high, the purchasing power of money declines, meaning that individuals and households may have to spend more to maintain the same standard of living. This increase in living costs without a corresponding rise in nominal income reduces the disposable income available for repaying debts. For borrowers already close to their financial limits, higher inflation can exacerbate their debt servicing challenges, potentially leading to an increase in NPL ratios.

2.1.2.6 Exports of Goods and Services

In the study, the logarithm of exports of goods and services was used as independent variable. The role of exports in influencing NPL ratios is a significant area of study within financial analysis. While prevailing research tends to highlight a negative correlation between exports and NPL ratios, this paper introduces a nuanced perspective by dissecting the impact of exports on NPL ratios into two distinct aspects. Initially, a decrease in exports can negatively affect the financial health of firms by reducing their revenue streams. This reduction in income can directly impair the ability of these firms to fulfill their debt obligations on time, potentially leading to an increase in NPL ratios within the financial system. This aspect underscores the direct link between export performance and the financial stability of businesses, illustrating how downturns in international demand can escalate financial distress and enhance NPL ratios.

Conversely, a decrease in exports can also prompt government and monetary authorities to implement various economic policies aimed at mitigating the adverse effects of reduced export earnings on the national economy. Such policy measures may include monetary easing to lower interest rates and make borrowing more affordable, fiscal stimulus packages to boost domestic consumption and investment, or structural reforms designed to enhance economic efficiency and competitiveness. These interventions can enhance the overall liquidity within the financial system, providing essential support to both businesses and households. By improving the economic environment and financial conditions, these measures help in reducing the NPLs, thus mitigating the potential rise in NPL ratios triggered by the initial downturn in exports.

2.1.2.7 Foreign Direct Investment

FDI represents a significant flow of capital into a country, aimed at acquiring a lasting interest and management control in enterprises operating outside the investor's home country. FDI serves as a fundamental pillar of international economic integration, playing an indispensable role in weaving the global economic fabric tighter. In the context of CEE countries, which are marked by their ongoing processes of economic and financial integration, FDI emerges as a critical element supporting their economic dynamics. The influence of FDI on these economies is multifaceted, warranting a detailed analysis.

On one hand, FDI acts as a catalyst for economic revitalization, channeling capital, cutting-edge technology, and managerial expertise into the host economy. This infusion of resources not only propels economic growth but also enhances the financial resilience of the economy. Consequently, businesses and individuals alike find themselves better positioned to fulfill their financial obligations, potentially reducing the volume of NPLs within the banking sector. Conversely, the injection of FDI can also accelerate economic growth to a pace that may not be sustainable in the long term, especially when it leads to a surge in banking sector lending. This scenario often occurs in emerging markets, where the desire to harness the benefits of rapid growth can sometimes result in a loosening of lending standards. When the expansion of credit is not aligned with a corresponding increase in the borrowers' ability to repay, the outcome can be a rise in the incidence of NPLs.

2.1.2.8 Bank Concentration

Bank concentration is measured by the share of total assets that the three largest commercial banks hold in relation to the overall assets in the commercial banking sector. A high level of bank concentration indicates that a few banks dominate a large portion of the market share in the banking industry, creating significant entry barriers for new competitors and influencing NPLs ratios in different manners. In such markets, larger banks often possess the capacity to allocate more resources towards advanced risk management systems, enhancing their ability to identify and mitigate the risks associated with loan defaults. Additionally, these banks' capability to spread their lending and investment activities across various sectors may contribute to a decreased aggregate risk of NPLs. Furthermore, a high degree of concentration in the banking sector can encourage more cautious lending behaviors. With fewer incentives to pursue aggressive market share expansion, leading banks may opt for a more prudent approach, favoring loans to individuals and businesses with solid credit histories. This prudent lending strategy tends to lower the occurrence of NPLs, as the focus shifts towards borrowers deemed more financially reliable.

2.1.2.9 ROA

The ROA is widely recognized as a crucial metric for evaluating a bank's profitability, indicating the efficiency with which a bank or any entity generates profits from its total assets. According to existing literature, there is a general agreement that there is a negative correlation between ROA and NPL ratios. Berger & DeYoung (1997) elaborate on their "bad management" hypothesis through the lens of ROA. They suggest that a company's poor performance can often be attributed to managerial shortcomings, which negatively impact ROA. This decline in profitability may compel managers to seek higher returns by extending credit to riskier borrowers, ultimately contributing to an increase in NPL ratios. Moreover, when profitability is constrained, banks might struggle to allocate funds for advanced risk management technologies or to hire experienced risk management professionals. This lack of investment can hinder a bank's capacity to accurately evaluate and mitigate loan default risks, increasing the likelihood of a rise in NPLs.

2.1.2.10 Loan Loss Reserves

In the study, the logarithm of LLRs was used as independent variable. LLRs serve as critical financial buffers that banks allocate to address potential losses arising from NPLs. These reserves play a crucial role in a bank's approach to risk management and are fundamental to maintaining its financial health, influencing how NPLs are managed and perceived. According to scholarly research, a consensus exists among many researchers about the positive correlation between LLR and NPL ratios. As the volume or percentage of NPLs escalates, banks find it necessary to bolster their LLRs to sufficiently mitigate the anticipated losses stemming from these distressed loans. In essence, the enhancement of LLRs is coordinated with increases in NPLs, a strategy that is crucial for ensuring a bank's financial resilience and its capacity to handle the impacts of loan defaults.

2.1.2.11 Equity-to-Assets Ratio

In the study, the logarithm of ETA ratio was used as independent variable. The ETA ratio is a crucial indicator of a bank's financial leverage and stability, reflecting the extent to which a bank's assets are funded by shareholder equity as opposed to debt. Research on the effects of the ETA ratio on NPL ratios presents mixed findings. On one side, a higher ETA ratio could lead banks to adopt more conservative lending behaviors. This conservatism stems from the bank's reliance on equity financing over debt, with equity investors shouldering the residual risks. Consequently, these banks might lean towards extending credit to individuals and businesses with robust credit histories and financially viable projects, thus diminishing the incidence of loan defaults. On the other side, a substantial ETA ratio can position banks more attractively for securing additional investments and support, enhancing their ability to leverage and positively influence their NPL ratios. The capital influx resulting from a higher ETA ratio provides banks with greater means to effectively address and mitigate the challenges associated with NPLs.

2.1.2.12 Net Interest Margin

NIM serves as a critical financial benchmark for banks, quantifying the spread between the revenue generated from loans and other assets and the costs incurred on deposits and other liabilities, as a proportion of the bank's total earning assets. It stands as an important measure of a bank's profitability and the efficiency of its operations. The relationship between NIM and NPL ratios can be examined from two perspectives. On one side, the increased earnings from a higher NIM provide banks with the opportunity to bolster their risk management capabilities. This financial advantage facilitates investments in superior credit evaluation technologies and methodologies, enhancing the early detection and proactive management of potential

NPLs. On the other side, within the context of a highly competitive banking environment, certain banks might differentiate themselves by offering higher interest rates on deposits to attract clients, alongside imposing higher loan interest rates to preserve their NIM. This strategy, however, may compress profit margins unless banks resort to issuing loans with a higher risk profile. While such an approach can improve NIM, it concurrently raises the probability of escalating NPLs.

2.1.2.13 Net Loans

This factor is represented by the ratio of net loans to total assets, serving also as a measure of liquidity. The interaction between net loans and NPLs indicates a bank's lending operations, its approach to risk management, and the inherent quality of its loan portfolio. A significant amount of net loans points to an extensive lending activity within a bank. Such an expansion of the loan portfolio can indeed improve the bank's potential for earning interest income but simultaneously enhances its vulnerability to credit risk. Without rigorous credit evaluation and ongoing monitoring, an enlarged loan portfolio might lead to the occurrence of NPLs, particularly when the growth in lending lacks comprehensive risk assessment procedures. On the other side, a surge in net loans could also show a bank's strategy to broaden its loan portfolio over diverse sectors and categories of borrowers. This strategy of diversification is capable of mitigating the impacts of downturns specific to certain sectors or defaults by individual borrowers, thereby contributing to a diminished overall ratio of NPLs.

Table 2 Explanation of Determinants

Determinants	Symbol	Specification	Expected relationship	Source
Dependent Variable				
Logged NPL Ratio	ln_npl	The logarithm of (NPLs/total gross loans)		World Bank Database & GFDD
Macroeconomic Determinants				
GDP growth Rate	gdpg	Annual growth rate of GDP	Negative	World Bank Database
Unemployment Rate	unemp	Unemployment/total labor force	Positive	World Bank Database
Share price index	spi	Overall changes in stock prices	Negative	OECD Database
Inflation Rate	infl	Increase in prices over a period of time	Positive/Negative	World Bank Database

Logged Exports of Goods & Services	ln_exp	The logarithm of (exports of goods & services/GDP)	Positive/Negative	World Bank Database
Foreign Direct Investment	fdi	FDI/GDP	Positive/Negative	World Bank Database
Bank Concentration	bankcon	Assets owned by the three largest commercial banks/total assets in banking sector	Negative	GFDD
Bank-specific Determinants				
Return on Assets	roa	Net income/total assets	Negative	BankFocus Database
Logged Loan Loss Reserves	ln_llr	The logarithm of (LLR/gross customer loans & advances)	Positive	BankFocus Database
Logged Equity-to-Assets Ratio	ln_eta	The logarithm of (equity/total assets)	Positive/Negative	BankFocus Database
Net Interest Margin	nim	Net interest income/(average interest - earning assets)	Positive/Negative	BankFocus Database
Net Loans	nl	Net loans/total assets	Positive/Negative	BankFocus Database

Source: Author's compilation.

2.2 Methodology

2.2.1 Methodology for Static Panel Estimation

This study employs both static and dynamic panel data methods to explore the factors influencing NPL ratios. The utilization of panel data presents numerous advantages (Hsiao, 2022), including the provision of a richer dataset, which leads to less covariance among variables, greater variability, and increased degrees of freedom. Additionally, panel data enhance the analysis of data dynamics post-adjustment. They also enable the development of more sophisticated behavioral models compared to either time series or cross-sectional data. Lastly, panel data usage facilitates the control of individual heterogeneity, allowing for more precise analyses.

Our analysis starts by employing the Pearson Correlation Matrix to determine whether the data suffer from multicollinearity, a condition indicated by a high correlation among any of the independent variables. Multicollinearity may mask the unique effects of individual variables in regression analyses, resulting in uncertain statistical conclusions (Farrar & Glauber, 1967). According to Ouhibi & Hammami (2015), a positive correlation coefficient suggests a positive relationship between two variables, and the opposite holds true for a negative coefficient.

Subsequently, it is crucial for panel data analysis to conduct a stationarity test. Rinaldi & Sanchis-Arellano (2006) note that NPL ratios and other independent variables might be subject to a unit root process, implying their statistical properties could change over time. To mitigate issues that arise from non-stationary variables, a unit root test (URT) is essential in our research. Accordingly, we apply the Im-Pesaran-Shin (IPS) and Levin-Lin-Chu (LLC) URTs. These tests are particularly adept at detecting stationarity, an insight which is not typically obtained through univariate analysis methods. The IPS URT, introduced by Im et al. (2003), is favored in scenarios with a large number of panels (N) due to its stronger statistical power. Conversely, the LLC test operates under the assumption that all panels share a common autoregressive parameter, overlooking the potential for some country-specific time series data to possess unit roots while others do not. Both URTs aim to examine the core hypothesis, namely whether all panels exhibit unit roots, while the alternative hypothesis proposes that some panels are stationary.

Following the application of URTs, we identified non-stationarity issues among several variables, including NPL ratios, exports of goods and services, ETA ratios, and LLRs. Non-stationarity in data can significantly undermine the validity of econometric models, as it implies that the statistical properties of these variables, such as mean and variance, could change over time, leading to unreliable predictive models. To mitigate this problem and enhance the stability of further model building, we apply the logarithmic transformation to these variables, namely ln_npl, ln_exp, ln_eta and ln_llr. This mathematical alteration often normalizes data distributions, reduces the effect of outliers, linearizes relationships among variables, thereby simplifying the underlying patterns in the data. To enhance the evaluation of the reliability of these chosen variables, we apply the Pedroni (1999, 2004) panel cointegration test (PCT). This method allows us to analyze the long-term equilibrium relationships between the variables using their original forms. By avoiding the first-differenced versions, we maintain the validity of the data's long-term information, providing a clearer insight into the underlying dynamics among the variables.

In the analysis of static panel data, the bank FE model is initially used to account for unobserved heterogeneity among banks. There are several benefits of using FE model. Firstly, assuming strict exogeneity, the FE model focuses on the disparities between banks. It accommodates the unique, unobserved characteristics of each bank, allowing these traits to have correlation with the factors affecting NPL ratios (Wooldridge, 2002). This flexibility is crucial for capturing the complex interaction between bank-specific situations and the determinants of NPL ratios. Secondly, by incorporating controls for bank-specific effects, the FE model directly tackles the problem of omitted-variable bias. Subsequently, further tests are required to decide if time FE should be included. We analyze the model that includes both bank and time FE to control for any unobserved effects related to these factors. The static relations are as follows:

$$\ln\_NPL_{i,t} = \alpha + \beta_1 Macro_{i,t} + \beta_2 Bank_{i,t} + \varepsilon_{i,t} \qquad (1)$$

$$\varepsilon_{i,t} = \nu_i + \lambda_i + \mu_{i,t}$$

Here, $Macro$ indicates macroeconomic variables and $Bank$ denotes the bank-specific variables. Additionally, i is the bank in the sample, t is the year. ε represents the error term, ν_i indicates the unobserved bank-specific effects, λ_i signifies the unobserved time-specific effects and μ is the idiosyncratic error.

To delve deeper into the issue of unobserved heterogeneity and better understand the impacts of independent variables on NPL ratios, we additionally employ the RE model. To assess the suitability of the RE model for our static panel data estimation, we apply the Hausman test (Hausman, 1978). This test helps us to decide whether the RE model provides a better fit for our analysis compared to FE model. Specifically, the Hausman test's null hypothesis is that the RE model is the appropriate choice for estimating our panel data.

To verify the reliability of our model, we conduct several post-estimation analyses.

We employ the Modified Wald test to evaluate the presence of heteroskedasticity, ensuring that the variance of the residuals is consistent across observations. Additionally, we use the Wooldridge (2010) test to determine if there are any issues with autocorrelation, which would indicate that the residuals are correlated with themselves over time. Lastly, we apply Pesaran's test (2007) to check for cross-sectional dependency in the previous model, assessing whether the residuals are correlated across different sections or groups in the dataset. These tests help ensure that our model provides accurate and robust results.

2.2.2 Methodology for Dynamic Panel Estimation

To precisely capture the growing trends in NPL ratios, we incorporates a dynamic model. This framework includes the previous period's logarithmic changes of the NPL ratios as a lagged dependent variable within our econometric model. The inclusion of this lagged variable is crucial for monitoring the persistence of NPL ratios' growth over time. However, the lagged dependent variable may be endogenous, meaning it could be correlated with unobserved FEs within the error term that also affect the NPL ratios, thus resulting in the econometric bias. To mitigate these issues and ensure the reliability and consistency of our findings, the GMM model is employed in this study for the analysis of dynamic panel data. This approach allows us to achieve unbiased and consistent results, enhancing the validity of our analysis.

When dealing with dynamic panel data, two variants of GMM model are commonly employed: the First Difference (FD) GMM and the System GMM. The FD GMM model, despite its utility, has been critiqued for its lack of precision in cases where the sample data exhibits a high degree of persistence, leading to potentially unreliable estimates (Blundell & Bond, 1998). This limitation is particularly pronounced in analyses where the dependent variable's past values significantly influence its current value.

To address this limitation and enhance the robustness of our analysis, our study employs both the one-step and two-step system GMM approaches, as developed by Arellano & Bover (1995). It operates under the assumption that bank-specific factors from earlier periods can be considered as predetermined, meaning they are not entirely independent of future error terms but are not perfectly correlated either. Simultaneously, macroeconomic variables are considered strictly exogenous, based on the premise that these variables are external to the individual banks and hence unaffected by the banks' internal dynamics. As a result, these variables can be effectively used as instrumental variables to help isolate the effects of other independent variables on NPL ratios, thereby mitigating potential sources of bias (Roodman, 2009).

In employing the system GMM approach for our analysis, we operate under the assumption that NPL ratios show a tendency to persist across time periods. Therefore, we incorporate the lagged logarithm of NPL ratios (ln_NPLt-1) as an independent variable in our model. The inclusion of this lagged term allows us to directly examine how past levels of NPL ratios continue to impact their present values, thereby providing a quantifiable measure of their persistence over time. The dynamic relationships within our model can be represented as follows:

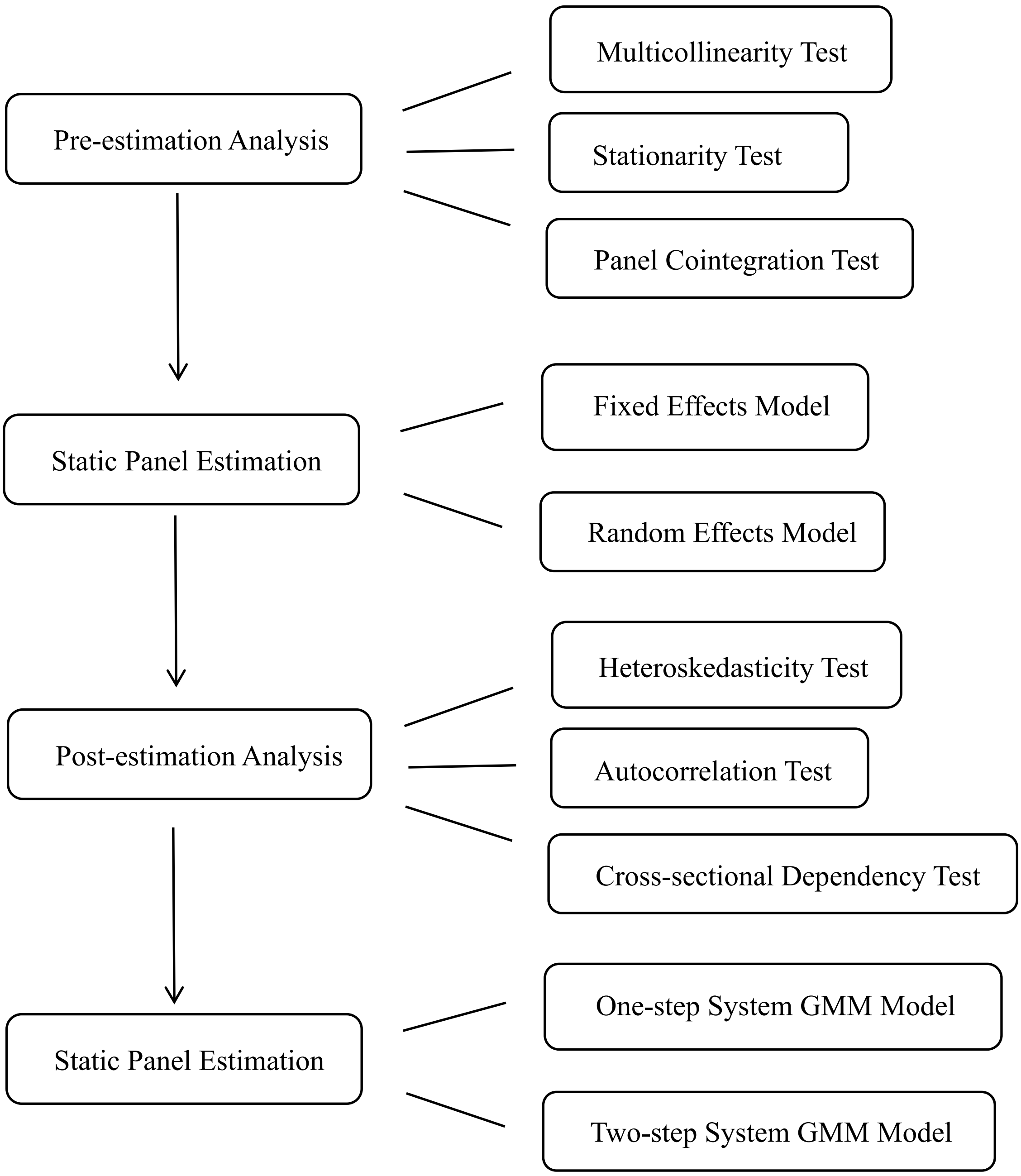
$$\ln\_NPL_{it} = \alpha_i \ln\_NPL_{i,t-1} + \alpha_i Macro_{i,t} + \alpha_i Bank_{i,t} + \varepsilon_{it} \tag{2}$$

Following the establishment of our dynamic model using the system GMM approach, we further test the reliability and appropriateness of our selected instrumental variables through the application of the Hansen test of overidentifying restrictions, as outlined by Arellano and Bond (1991). This statistical test is critical for ensuring that the instruments employed in our analysis are indeed valid and do not correlate with the error terms, which would otherwise bias our results. The null hypothesis for the Hansen test is that the instruments chosen for the model are appropriate and valid.

In addition, our analysis also strictly examines the presence of autocorrelation within the model, which is a common concern in dynamic panel data analyses. To this end, we specifically look for first-order (AR1) and second-order autocorrelation (AR2) in the residuals of our model. The detection of AR1 is generally expected in panel data models that incorporate lagged dependent variables, and thus, it does not necessarily indicate a defect in the model. However, the presence of AR2 would suggest that the model's error terms are correlated across time, implying that our estimates may be inconsistent.

To thoroughly analyze the relationships among the independent variables in our study, we adopt a comprehensive approach by estimating Equations (1) and (2) across three different models, each designed to isolate and then combine the effects of different sets of variables. Initially, in Model 1, we focus exclusively on macroeconomic factors. By doing so, we aim to assess the direct impact of broader economic conditions on NPL ratios. This model serves as a baseline to understand how general economic trends influence the outcomes. Following that, Model 2 shifts the focus entirely towards bank-specific factors. This model allows us to delve into the internal, operational aspects of banks, examining how their unique attributes affect NPL ratios. Finally, Model 3 combines both macroeconomic and bank-specific factors, offering a complete view of all determinants. This comprehensive model allows us to observe the interaction between internal bank dynamics and external economic conditions. In this way, we can also compare the impact of both sets of factors on NPL ratios.

Figure 10 Model Specification Tests



Source: Created by author.

3 Empirical Results and Discussion

3.1 Descriptive Analysis

Table 3 provides a comprehensive overview of the descriptive statistics for 52 commercial banks across 11 CEE countries, covering the period from 2007 to 2022. This table presents key financial indicators, including their mean values, standard deviations, minimum values and maximum values. For instance, the NPL ratio, on average, stands at 6.58%, with the lowest observed value being 0.48%. This suggests a generally strong performance in the banks' loan portfolios. However, the maximum NPL ratio reported is 22.29%, indicating potential issues with loan management or the impact of policy changes within the respective countries.

The ROA averages at 1.04%. This metric shows a wide range, from a low of -13.52% to a high of 7.43%, highlighting the variability in banks' profitability and operational efficiency. Such disparity suggests that banks experience either profitable or challenging periods, reflecting different levels of success in their operations. Variable NIM, which also measures the profitability of banks, averages at 3.50%. Like the large disparity in ROA, this figure exhibits a broad range, from -0.35% to 22.52%, pointing to significant differences in how banks earn from their interest-bearing assets compared to their interest-bearing liabilities. Moreover, Variable LLR varies widely among the banks, ranging from -56.62% to 48.83%, with an average of 5.79%. This wide range indicates diverse approaches to loan loss provisioning, reflecting the banks' varying strategies in managing potential loan losses.

The mean value of Variable ETA across the dataset is 11.27%. This figure suggests that, on average, about 11.27% of the banks' assets are financed through equity, which is capital provided by shareholders. The maximum ETA value observed is 35.05%, indicating a substantial level of financial leverage where 35.05% of the bank's assets are funded by shareholders. This scenario reflects a stronger reliance on shareholder funding rather than external debt. Conversely, the minimum ETA value is 2.86%, pointing to a lower financial leverage situation where a mere 2.86% of assets are equity-funded, implying that the majority of the banks' assets are funded by debt. In addition, the average for Variable NL stands at 61.24%. The range for this variable stretches markedly, from as low as 7.44% to as high as 95.53%. This wide spread indicates a substantial diversity in the banks' lending activities, with some institutions having a low proportion of their assets in loan form, suggesting a conservative lending approach or a diversified asset portfolio. On the other hand, banks at the higher end of the range demonstrate a heavy concentration in loan assets, potentially indicating a more aggressive lending strategy or a focus on loan generation as their primary business activity.

Table 3 Descriptive Statistics of All Variables

Variable	Obs	Mean	Std. dev.	Min	Max
country	832	5.961538	3.324194	1	11
bank	832	26.5	15.01736	1	52
year	832	2014.5	4.612545	2007	2022
npl	832	6.576156	4.936892	.4768343	22.28973
spi	832	116.1394	44.77752	39.1	317.5
bankcon	832	60.91811	12.64632	38.56158	98.82536
gdpg	832	2.496754	3.845023	-14.83861	13.78495
unemp	832	7.48101	3.343135	2.02	19.48
fdi	832	4.972291	11.16809	-40.08635	106.5942
infl	832	3.363136	3.790025	-1.544797	19.70505
exp	832	61.46797	17.7272	24.71083	99.36478
roa	832	1.035035	1.468916	-13.5189	7.4301
llr	832	5.789451	7.058658	-56.61514	48.82923
eta	832	11.26697	3.795163	2.856322	35.04815
nim	832	3.50254	2.08647	-.3505697	22.52108
nl	832	61.23719	14.67173	7.4445	95.53015
ln_npl	832	1.627244	.7229306	-.7405863	3.104126
ln_exp	832	4.073176	.3096446	3.207242	4.598798
ln_eta	832	2.370339	.3197675	1.049535	3.556723
ln_llr	832	1.433626	.8935375	-1.920547	3.888329

Source: Compiled by author using STATA 18.0.

In order to conduct a comprehensive analysis of macroeconomic trends, a detailed descriptive statistics has been established, capturing a wide collection of macroeconomic variables as detailed in Appendix 2. This framework is designed to provide a whole view of the economic situation spanning various countries. Within this context, a particular focus has been placed on NPL ratios. Over the period from 2007 to 2022, Croatia has been identified as having the highest average NPL ratio, recorded at 10.80%. This denotes a high level of credit risk within the Croatian banking sector. Moreover, notable peaks in NPL ratios have been observed in Latvia and Lithuania, where the ratios have surged to 22.29% and 22.14%, respectively. These figures show significant variances in credit health and financial resilience across different economies.

Besides, an examination of the GDP growth rates reveals that Poland stands out with the most rapid average increase in GDP (3.83%), coupled with the lowest level of variability, as denoted by its minimal standard deviation of 2.26. This implies that Poland's economic expansion not only outpaced that of its peers but also maintained a remarkable consistency, exhibiting fewer fluctuations and thus indicating a more stable economic environment. Conversely, Latvia experienced the greatest fluctuation in its GDP growth rate, indicative of an economic landscape that was marked by instability and unpredictability throughout the observed time frame.

What's more, the analysis reveals that Croatia had the highest mean unemployment rate, averaging at 11.31%. This persistent high unemployment suggests a longstanding challenge within the Croatian job market. The high unemployment levels can be attributed to the country's period of economic transition, as Croatia has been engaged in a process of restructuring its economy and transforming its industrial framework. During such transitions, it's common for shifts in employment to occur as industries undergo contraction or growth, compelling the workforce to adjust to evolving requirements. This dynamic is captured in the unemployment figures reported for Croatia.

From 2007 to 2022, Romania showed the highest mean inflation rate at 4.22%, highlighting its position as the economy most impacted by inflation during this period. On an individual peak basis, Lithuania experienced the most extreme inflation rate, reaching a staggering 19.71%, which signifies a significant surge in prices within 16 years.

Turning our attention to international trade, Slovakia boasted the leading average in terms of the exports of goods and services, accounting for 88.28% of its total economic output. This high figure suggests that Slovakia's economy is heavily reliant on external markets, with a substantial part of its production being distributed internationally.

In the context of FDI, Hungary emerges as the top country with its average FDI-to-GDP ratio hitting 17.44%. This figure presents that a considerable portion of Hungary's economic activity is driven by investments coming from abroad, highlighting its openness to international capital flows. Finally, Estonia's average bank concentration ratio is at 94.44%, with a range between 89.57% and 98.53%. Such a concentration indicates that Estonia's banking assets are dominated by a limited number of financial institutions, which could imply less competition and higher market control by the major banks.

From 2007 to 2022, Romania's average inflation rate is the highest, which is 4.22%. The highest inflation rate was Lithuania, which was 19.71%. Moreover, Slovakia's average exports of goods and services is the highest, which stands at 88.28%. This shows that the most of goods and services in Slovakia were from other countries. Hungary's average FDI-to-GDP ratio was the highest, with the value of 17.44%, whi ch indicates that FDI takes a large portion in GDP. Finally, Estonia's average bank concentration is 94.44%, which has the range of 89.57% to 98.53%. This shows that a large portion of assets is held by a smaller amount of banks.

3.2 Tests for Multicollinearity

In this section, Pearson Correlation Matrix (Table 4) is used to analyze the results of multicollinearity. The robustness of the regression model depends on the assumption that independent variables do not exhibit multicollinearity (Poole & O'Farrell, 1971). According to Kennedy (2008), a severe multicollinearity problem is indicated by a correlation coefficient that exceeds 0.8, which could undermine the validity of the regression outcomes. According to Table 4, NPL ratios are negatively correlated with GDP growth rate, inflation rate, exports, FDI, SPI, bank concentration and ROA, while are positively correlated with unemployment rate, ETA ratio, NIM, LLR and NL. Among these figures, the strongest correlation coefficient observed is between the NPL ratio and LLR. Additionally, the correlations among independent variables are generally weak, as indicated by most correlation coefficients being under 0.3.

In order to further ensure there's no multicollinearity issues exist among independent variables within our analysis, the variance inflation factor (VIF) tool is employed in the study. The results are shown in Table 5. O'Brien (2007) suggests that multicollinearity is not a concern when the VIF values are below 5, or equivalently, when the tolerance values (1/VIF) exceed 0.2. The data in Table 5 align with these criteria, showing that all VIF values fall below the threshold of 5, and correspondingly, all tolerance values are above 0.2. This evidence collectively confirms that multicollinearity does not pose an issue in this research, supporting the robustness of the statistical analysis conducted.

Table 4 Correlation Coefficient

	ln_npl	**gdpg**	**unemp**	**infl**	**ln_exp**	**fdi**	**spi**	**bankcon**	**roa**	**ln_eta**	**nim**	**ln_llr**	**nl**
ln_npl	1												
gdpg	-0.299***	1											
unemp	0.553*	-0.242	1										

	**	***											
infl	-0.403***	0.129***	-0.291***	1									
ln_exp	-0.194***	0.033	-0.069**	-0.028	1								
fdi	-0.175***	-0.004	-0.106***	0.105***	0.078**	1							
spi	-0.448***	0.321***	-0.320***	0.350***	0.191***	0.245***	1						
bankcon	-0.343***	-0.017	-0.018	0.131***	0.422***	0.059*	0.161***	1					
roa	-0.264***	0.257***	-0.147***	0.081**	-0.058*	0.070**	0.185***	0.069**	1				
ln_eta	0.137***	-0.018	0.158***	-0.168***	-0.016	-0.037	-0.026	-0.015	0.338***	1			
nim	0.209***	-0.001	0.039	0.050	-0.114***	0.008	-0.021	-0.072**	0.306***	0.337***	1		
ln_llr	0.662***	-0.148***	0.234***	-0.276***	-0.059*	-0.108***	-0.271***	-0.335***	-0.170***	0.217***	0.355***	1	
nl	0.076**	-0.104***	0.163***	0.013	-0.022	-0.005	-0.067*	-0.010	-0.079**	0.117***	0.053	-0.096***	1

Source: Compiled by author using STATA 18.0.

Table 5 Test of Multicollinearity

Variable	VIF	1/VIF
ln_llr	1.75	0.572512
roa	1.51	0.660484
nim	1.50	0.667048
spi	1.48	0.677146
bankcon	1.44	0.692801
ln_eta	1.38	0.722876
infl	1.33	0.752465
ln_exp	1.33	0.752546
unemp	1.28	0.781693
gdpg	1.23	0.815560
nl	1.12	0.892564
fdi	1.08	0.923947
Mean VIF	1.37	

Note: Dependent variables are NPL ratios and 1/VIF is the tolerance.
Source: Compiled by Author Using STATA 18.0.

3.3 Stationarity Testing

In the field of econometrics, the implementation of panel URT is increasingly recognized as a critical step to prevent suspicious regression and confirm the validity of regression analysis. The growing preference for URT, as suggested by Saidi & Mbarek (2017), can be attributed to its enhanced effectiveness in identifying true statistical relationships. Within our research, we utilize two specific types of URTs, namely the IPS and LLC tests, to rigorously evaluate the stability and reliability of our findings. The null hypothesis for these tests assumes that a unit root exists, suggesting that the data panels are non-stationary.

Initially, we undertake the IPS unit root test, with the outcomes detailed in Table 6. The findings indicate that variables such as GDP growth rate, unemployment rate, inflation, FDI, SPI, bank concentration, and ROA are significant stationary at the 1% significance level. What's more, the NPL ratio and LLR are identified as non-stationary. To address this, we transform these variables into their logarithmic forms, ln_npl and ln_llr, respectively. These transformed variables are found to be significantly stationary at the 1% level. Similarly, due to its non-stationarity, we also apply a logarithmic transformation to exports (ln_exp), which then shows significant stationarity at the 10% level. However, when it comes to ETA ratio, NIM, and net loans, neither the original nor their logarithmic transformations (ln_eta, ln_nim, and ln_nl) pass the stationarity test under the IPS methodology. As a consequence, we examined the stationarity of the first differences for variables that were initially either non-stationary or showed weak stationarity. The analysis revealed that, after taking the first differences, all variables had stationarity. Moreover, we also turn to the LLC test to further investigate the stationarity of their original forms, with these results presented in Table 7. This step is crucial for enhancing the rigor of our analysis by ensuring that all variables considered are appropriately stationary, thereby strengthening the validity of our regression findings.

Table 6 Im-Pesaran-Shin (IPS) Unit-root Test

AR parameter: Panel-specific	Asymptotics: T,N -> Infinity sequentially			
Panel means: Included	Cross-sectional means removed			
Time trend: Not included	ADF regressions: 0 lags			
Variables	**At level**		**At first difference**	
	W-t-bar Statistics	**p-value**	**W-t-bar Statistics**	**p-value**
npl	0.0777	0.5310		
ln_npl	-4.7930***	0.0000		
gdpg	-12.9435***	0.0000		
unemp	-4.6609***	0.0000		
infl	-8.4586***	0.0000		
exp	0.6182	0.7318	-12.7706***	0.0000
ln_exp	-1.5200*	0.0643	-14.1533***	0.0000
fdi	-13.3169***	0.0000		
spi	-8.0697***	0.0000		
bankcon	-7.0122***	0.0000		
roa	-5.2032***	0.0000		
eta	-0.2676	0.3945	-15.5607***	0.0000
ln_eta	-0.0119	0.4953	-15.6148***	0.0000
nim	1.2221	0.8892	-15.5915***	0.0000
ln_nim	-0.1095	0.4564	-14.1023***	0.0000
llr	3.0557	0.9989	-8.7824***	0.0000
ln_llr	-3.3970***	0.0003	-10.5225***	0.0000
nl	-0.5090	0.3054	-17.8312***	0.0000
ln_nl	-0.7063	0.2400	-17.3052***	0.0000

Note: ***,**,* donate the coefficient is significant at the level of 1%, 5% and 10% respectively.
Source: Compiled by author using STATA 18.0.

Based on the findings presented in Table 7, we observe that the logarithm of exports, as well as NIM, net loans, and the logarithm of net loans, all exhibit stationarity at the significant level of 1%. Furthermore, the analysis reveals that the logarithmic transformation of the ETA ratio achieves a significant stationarity at the 10% level. This indicates that while the confidence in its stationarity is slightly lower compared to the other variables, it still presents a statistically significant absence of a unit root, thereby utilizing in further analyses. In this way, our econometric investigation could be enriched the depth and breadth. To ensure that the ETA ratio and the logarithm of ETA exhibit stationarity, an analysis of their first differences is conducted. This analysis demonstrates that these first differences remain constant over time, indicating stationary behavior in both the ETA ratio and its logarithmic transformation.

Table 7 Levin–Lin–Chu (LLC) Unit-root test

AR parameter: Common	Asymptotics: N/T -> 0			
Panel means: Included	ADF regressions: 1 lag			
Time trend: Not included	LR variance: Bartlett kernel, 8.00 lags average			
Variables	**At level**		**At first difference**	
	Adjusted t-statistics	**p-value**	**Adjusted t-statistics**	**p-value**
ln_exp	-3.6750***	0.0001		
eta	-1.2687	0.1023	-9.4520***	0.0000
ln_eta	-1.6312*	0.0514	-8.9357***	0.0000
nim	-6.5512***	0.0000		
nl	-3.9843***	0.0000		
ln_nl	-4.0424***	0.0000		

Note: ***,**,* donate the coefficient is significant at the level of 1%, 5% and 10% respectively.
Source: Compiled by author using STATA 18.0.

In conclusion, our analysis proceeds with the logarithm of the NPL ratio serving as the dependent variable for in-depth examination. For the exploration of macroeconomic variables, we select a series of variables that include the GDP growth rate, unemployment rate, inflation rate, the logarithm of exports, FDI, SPI, and bank concentration. These variables have been chosen for their demonstrated stability and relevance to our econometric analysis, ensuring they accurately reflect broader economic trends. As for specific factors related to banking, such as the ROA, the logarithm of the ETA ratio, NIM, the logarithm of LLR, and net loans. This approach enhances the validity of our study by incorporating a diverse set of variables, each demonstrating significant stationarity and relevance to the financial domain under investigation.

3.4 Panel Cointegration Test

In IPS URT, it is noted that certain variables do not exhibit stationarity in their original forms. Nevertheless, by taking the first differences of these variables, stationarity is achieved. This transition from non-stationary to stationary states has distinct economic implications depending on whether variables are analyzed in their original levels or their first-differenced forms. Consequently, to include the original form of the variables within our analysis, while also ensuring the reliability of these variables being analyzed, we select the PCT. The PCT plays a crucial role in determining whether the indicators under consideration move towards a long-term equilibrium relationship. Various methodologies exist for conducting PCT, including those developed by Kao (1999), Westerlund (2005), and Pedroni (1999, 2004). For our research, we specifically employ the Pedroni (1999, 2004) PCT approach to adequately account for the heterogeneity observed across different banks. This selection is motivated by the need to consider the diverse characteristics and conditions present within our dataset, ensuring a comprehensive and detailed analysis.

The PCT is designed to test the null hypothesis that no cointegration exists among individuals in the panel. This test sets a limitation on the number of regressors, restricting them to no more than seven for effective analysis. To accommodate this constraint and effectively categorize our variables, we segmented them into two distinct groups, namely macroeconomic variables and bank-specific variables, which also aligns with the structure of our analysis, as outlined in Model 1 and Model 2 within our study. According to Table 8, the p-values for both Model 1 and Model 2 are 0.00 (below 0.01). This statistical outcome suggests that the variables within each panel are cointegrated at the 1% significance level. This finding essentially suggests that there are long-term equilibrium relationships among the variables examined in our study. Such a result is crucial, as it highlights the interconnection and the enduring equilibrium dynamics present among the macroeconomic and bank-specific indicators considered in our analysis.

Table 8 Pedroni Test for Cointegration

Model			
Model 1	Sets of variables: ln_npl gdpg unemp infl ln_exp fdi spi bankcon		
		t-statistics	P-value
	Modified Phillips–Perron	12.1877	0.0000
	Phillips–Perron	-6.0023	0.0000
	Augmented Dickey–Fuller	-5.2532	0.0000
Model 2	Sets of variables: ln_npl roa ln_eta nim ln_llr nl		
		t-statistics	P-value
	Modified Phillips–Perron	9.1531	0.0000
	Phillips–Perron	-6.8668	0.0000
	Augmented Dickey–Fuller	-6.6425	0.0000

Note: Since the number of regressors cannot exceed 7, we only tested Model 1 and Model 2.
Source: Compiled by author using STATA 18.0.

3.5 Results from Static Panel Data

3.5.1 Results from Fixed Effects model

In this section, we initially employed the bank FE to analyze static panel data. The influence of all variables in the bank FE model was examined, with findings presented in Table 9. This model has an R-squared value of 0.77, indicating that 77% of the variation in the dependent variable is explained by these independent variables. To assess the demand for including time FE, further testing is required. Therefore, Model 3 integrates time FE. The results show an F-statistic of 12.95 and a P-value of 0.00, significantly below 0.01. Consequently, it is essential to incorporate time FE into the model, suggesting that both bank and time fixed effects should be included.

Subsequently, we examined how different variables -- grouped into three distinct sets -- impact the NPL ratios. Specifically, Model 1 incorporates solely macroeconomic variables, Model 2 includes only bank-specific variables, and Model 3 combines all the variables from the first two models, offering a comprehensive view.

The results, as detailed in Table 9, present the R-squared values for each model, which stand at 0.775 for Model 1, 0.728 for Model 2, and 0.808 for Model 3. These figures suggest a varied degree of explanatory power across the models. For instance, Model 1, with an R-squared of 0.775, implies that the macroeconomic variables alone account for approximately 775% of changes in NPL ratios. Additionally, Model 2, which focuses on bank-specific factors with an R-squared of 0.728, indicating that 45.4% of changes in NPL ratios can be explained by bank-specific factors. The comparison between the models reveals that the macroeconomic variables have a more important effect on the NPL ratios than the bank-specific variables. The higher R-squared value of Model 3, at 0.808, further demonstrates the utility of combining both sets of variables for a more comprehensive understanding of the factors that drive changes in NPL ratios, showing the added value of an integrative approach in econometric analysis.

Table 9 Fixed Effects Model

	Bank Fixed Effects	**Bank and Time Fixed Effects**		
		Model 1	Model 2	Model 3
	ln_npl	ln_npl	ln_npl	ln_npl
gdpg	-0.015***	-0.043***		-0.034***
	(0.003)	(0.005)		(0.005)
unemp	0.086***	0.042***		0.036***
	(0.005)	(0.008)		(0.008)
infl	-0.033***	-0.049***		-0.051***
	(0.003)	(0.008)		(0.008)
ln_exp	0.759***	1.795***		1.436***
	(0.094)	(0.170)		(0.167)
fdi	-0.005***	-0.005***		-0.004***
	(0.001)	(0.001)		(0.001)
spi	-0.002***	-0.003***		-0.002***
	(0.000)	(0.000)		(0.000)
bankcon	-0.017***	-0.015***		-0.014***
	(0.002)	(0.002)		(0.002)
roa	-0.047***		-0.067***	-0.055***
	(0.010)		(0.011)	(0.009)

ln_eta	-0.118**		-0.057	-0.035
	(0.053)		(0.060)	(0.051)
nim	0.030***		0.010	0.019**
	(0.010)		(0.011)	(0.009)
ln_llr	0.185***		0.248***	0.139***
	(0.021)		(0.022)	(0.020)
nl	0.002		-0.001	-0.001
	(0.001)		(0.001)	(0.001)
_cons	-0.805*	-4.221***	1.020***	-3.010***
	(0.428)	(0.654)	(0.161)	(0.648)
N	818	832	818	818
r2	0.770	0.775	0.728	0.808
ar2				
F-statistic	13.10***	23.01***	10.90***	12.95***
P-value	0.000	0.000	0.000	0.000

Note: Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Compiled by author using STATA 18.0.

3.5.2 Results from Random Effects Model

Following the evaluation process, the RE model was applied to analyze the static panel data. This analysis also divides the variables into three distinct categories, each represented within separate models. The findings, as detailed in Table 10, reveal that the R-squared values for Model 1, Model 2, and Model 3 are 0.720, 0.452, and 0.759, respectively. These statistics indicate that macroeconomic factors alone account for 72% of the variability in NPL ratios, while bank-specific factors explain 45.2% of the changes in NPL ratios. Following the insights gained from the FE model analysis, these results further confirm the predominant influence of macroeconomic conditions over bank-specific variables in determining the changes in NPL ratios. This consistency across different model applications highlights the critical role that macroeconomic variables play in determining loan performance outcomes, far outweighing the influence of internal variables specific to each bank.

Table 10 Random Effects Model

	Model 1	Model 2	Model 3
	ln_npl	ln_npl	ln_npl

gdpg	-0.018***		-0.012***
	(0.004)		(0.003)
unemp	0.094***		0.079***
	(0.006)		(0.007)
infl	-0.032***		-0.030***
	(0.002)		(0.003)
ln_exp	0.620***		0.236***
	(0.091)		(0.091)
fdi	-0.007***		-0.005***
	(0.001)		(0.001)
spi	-0.003***		-0.002***
	(0.001)		(0.001)
bankcon	-0.020***		-0.014***
	(0.004)		(0.003)
roa		-0.089***	-0.049***
		(0.020)	(0.015)
ln_eta		0.095	-0.066
		(0.155)	(0.097)
nim		0.023*	0.030***
		(0.013)	(0.010)
ln_llr		0.514***	0.254***
		(0.056)	(0.041)
nl		0.009**	0.002
		(0.003)	(0.002)
_cons	0.217	0.139	0.972*
	(0.542)	(0.424)	(0.504)
N	832	818	818
r2	0.720	0.452	0.759
ar2			
Wald chi2	2115.16	161.98	2299.92
Prob > F	0.000	0.000	0.000

Note: Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Compiled by author using STATA 18.0.

3.5.3 Test for FE Model vs. RE Model

To select the most suitable model for our analysis, we employed the Hausman test, a statistical methodology designed to choose between the FE model and the RE model. This test helps in making an informed decision on which model better captures the dynamics of our dataset. The null hypothesis of the Hausman test assumes RE model is the preferable choice for the analysis. The results of this comparison are recorded in Table 11. According to the results, the P-value is 0.00, which falls significantly below the critical threshold of 0.01, indicating a strong statistical reason to reject the null hypothesis.

In conclusion, based on the results of the Hausman test, the FE model emerges as the more appropriate approach for analyzing our data. This conclusion highlights the importance of choosing the correct model based on statistical evidence to ensure the validity and reliability of the findings in our analysis. The preference for the bank FE model is rooted in its ability to better account for unobserved heterogeneity across banks, thereby providing a more accurate and insightful understanding of the factors influencing the results.

Table 11 The Hausman Test

Test of H0: Difference in coefficients not systematic
chi2(12)= (b-B)'[(V_b-V_B)^(-1)](b-B) = 73.44
Prob > chi2 = 0.0000

3.5.4 Post Estimation Analysis

After conducting the regressions, this section would proceed with a series of post estimation analyses, including tests for heteroskedasticity, autocorrelation, and cross-sectional dependency in the bank and time FE model. This model was taken as more suitable model following the results of the Hansen test.

3.5.4.1 Heteroskedasticity Test

The Modified Wald Test, employed to evaluate heteroskedasticity in the bank and time FE model, operates under the assumption that ε_{it} and ε_{is} are not correlated. According to the results displayed in Table 12, the P-value was 0.00, falling below 0.01. Therefore, the null hypothesis was rejected with the significance level of 1%, confirming the presence of heteroskedasticity in the model.

Table 12 Heteroskedasticity Test

Modified Wald test for groupwise heteroskedasticity in fixed effect regression model
H0: sigma(i)^2 = sigma^2 for all i
chi2 (52) = 2402.87
Prob>chi2 = 0.0000

3.5.4.2 Autocorrelation Test

Following this, to identify autocorrelation in the residuals of the panel data, the Wooldridge test is applied. It is crucial to identify AR(1), as it can bias the estimated coefficients and lead to underestimation of their standard errors. This, in turn, might result in an inflated R-squared value. The findings, as reported in Table 13, revealed a P-value of 0.00, which was less than 0.01. As a result, we rejected the null hypothesis of no AR(1) at the 10% significance level, demonstrating the presence of AR(1) in the model.

Table 13 Wooldridge Test

Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
F(1, 51) = 170.084
Prob > F = 0.0000

3.5.4.3 Cross-sectional Dependency Test

To evaluate the presence of cross-sectional dependence in the panel data, we applied the Pesaran (2015) Test. Since cross-sectional dependence can introduce biases into the outcomes of statistical analyses, this test is essential. The null hypothesis for the Pesaran test is that there’s no cross-sectional dependency. The results, detailed in Table 14, showed a P-value of 0.192, which was above 0.1. Consequently, we cannot reject the null hypothesis at a 10% significance level. This indicates that there is no substantial evidence for cross-sectional dependence in the residuals.

Table 14 Cross-sectional Dependency Test

Pesaran's test of cross sectional independence = -1.306, Pr = 0.1915
Average absolute value of the off-diagonal elements = 0.361

3.5.5 Revised Fixed Effect Model

Following the post estimation analysis, it has been determined that the bank and time FE model exhibits both heteroskedasticity and AR(1). To address these issues, the model would be updated to include heteroskedasticity-robust standard errors, which help correct the standard errors of the coefficients, ensuring more reliable statistical inference. Modifications are necessary for the FE model to adequately manage these concerns. The results from the updated model, incorporating these adjustments, are detailed below.

Table 15 Revised Fixed Effects Model

	Model 1	Model 2	Model 3
	ln_npl	ln_npl	ln_npl
gdpg	-0.043***		-0.034***
	(0.006)		(0.005)
unemp	0.042***		0.036***
	(0.010)		(0.009)
infl	-0.049***		-0.051***
	(0.010)		(0.009)
ln_exp	1.795***		1.436***
	(0.171)		(0.169)
fdi	-0.005***		-0.004**
	(0.002)		(0.002)
spi	-0.003***		-0.002***
	(0.000)		(0.000)
bankcon	-0.015***		-0.014***
	(0.003)		(0.003)
roa		-0.067***	-0.055***
		(0.016)	(0.011)
ln_eta		-0.057	-0.035
		(0.068)	(0.058)
nim		0.010	0.019**
		(0.012)	(0.008)
ln_llr		0.248***	0.139***
		(0.031)	(0.025)

nl		-0.001	-0.001
		(0.002)	(0.001)
_cons	-4.221***	1.020***	-3.010***
	(0.689)	(0.206)	(0.674)
N	832	818	818
r2	0.841	0.810	0.865
ar2	0.826	0.792	0.851
Bank Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes

Note: Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: Compiled by author using STATA 18.0.

3.5.6 Results Discussion

Given that the FE model suits our study better, we focus solely on the analysis using the revised bank and time FE model. While our findings are consistent and robust across various models employed in our research, it's important to note that the value of the estimated coefficients varies among the different models we have utilized.

3.5.6.1 Macroeconomic Factors

In our analysis, both Model 1 and Model 2 showed a significantly negative correlation between the GDP growth rate and the NPL ratio. This finding is consistent with previous studies (Espinoza & Parad, 2010; Jakubik & Reininger, 2013), and it corroborates our estimated outcomes. Further examination indicates that when bank-specific variables are incorporated into the model, the impact of GDP growth on the NPL ratio is diminished. Specifically, the coefficient of -0.034 suggests that a one-unit increase in the GDP growth rate leads to a by 3.5%[6] reduction in the NPL ratio, assuming other factors remain constant.

The findings regarding the relationship between unemployment rate and the NPL ratio are consistent with the results of previous research, including studies by Messai &

[6] Exp (0.034) = 1.035.

Jouini (2013) and Dimitrios et al. (2016), as well as with our own estimated results. We observed a significant positive correlation between the unemployment rate and the NPL ratio. As for individuals, an increase in unemployment diminishes the capacity of people to earn income and fulfill their loan obligations, leading to a rise in NPLs for banks. As for institutions, a reduction in the workforce impacts the operational efficiency and productivity, which, in turn, contributes to an increase in NPLs. The result is indicated by a coefficient of 0.036, implying that for every percentage point increase in unemployment, the NPL ratio increases by 3.7%[7], holding other variables constant.

As for the inflation rate, our analysis indicates a significant negative correlation with the NPL ratio, following the findings of Donatah et al. (2014) and Staehr & Uusküla (2017). An increase in the inflation rate leads to higher prices, effectively diminishing the real value of money. Under these circumstances, borrowers are able to repay their loans using money that is worth less than it was at the time they borrowed it. Consequently, this dynamic results in a decrease in the NPL ratio. This relationship is captured by a coefficient of -0.051, signifying that for every one-unit increase in inflation, there is a corresponding reduction in the NPL ratio by 5.2%[8], all else being equal.

The relationship between the exports of goods and services and the NPL ratio exhibits a significant positive correlation. This finding is in line with the observations made by Kjosevski & Petkovski (2021). Specifically, in Model 3, the coefficient is 1.436, indicating that a 1% increase in the logarithm of exports leads to a 1.44% rise in the NPL ratio, assuming all other factors remain constant. This suggests that while exports contribute to economic activity, they may also be associated with increased risk or financial instability that affects loan repayment capabilities. Conversely, our study reveals a significant negative relationship between FDI and the NPL ratio. An

[7] Exp (0.036) = 1.037
[8] Exp (0.051) = 1.052.

influx of FDI is likely to enhance productivity, stimulate job creation, and raise income levels, contributing to a healthier economic environment. With these positive developments, both companies and individuals find themselves in better positions to fulfill their loan obligations, which in turn leads to a reduction in the NPL ratio.

As for SPI, there is a significant negative correlation with the NPL ratio at the 1% significance level. This aligns with the findings of Beck et al. (2015), reinforcing the insight that a rise in the SPI is beneficial for loan performance. The increase in the SPI may initiate a wealth effect, leading investors to feel wealthier as the value of their investment portfolios grows. This perceived increase in wealth may lead to higher levels of spending and investment by individuals and businesses alike, which, in turn, stimulates economic activity. Enhanced economic conditions can improve the ability of borrowers to service their debt, thus reducing the NPL ratio. Our analysis illustrates that a one-unit rise in the SPI is associated with a 0.2%[9] decrease in the NPL ratio, when all other factors are remain constant.

Our analysis of the effects of bank concentration on the NPL ratio aligns with both our estimated result and the research conducted by other scholars, such as Ferreira (2022) and Shala et al. (2022). A higher concentration within the banking sector can strengthen the market dominance and increase the profitability of the leading banks. This consolidation of market power and increased earnings serve as a financial "buffer" that can mitigate the impact of adverse economic events, enhancing the resilience of these banks to the risks associated with lending. The empirical results further indicate that a one-unit increase in bank concentration correlates with a 1.4%[10] reduction in the NPL ratio.

3.5.6.2 Bank-specific Factors

In Model 2 and Model 3, we discovered that the ROA is inversely correlated with the

[9] Exp (0.002) = 1.002
[10] Exp (0.014) = 1.014

NPL ratio, a relationship that is statistically significant at the 1% level. This finding is in line with the research conducted by Godlewski (2005) and Ciptawan (2023), etc. It is clear from these findings that banks exhibiting higher profitability have better capabilities to manage and mitigate the risks associated with lending, leading to a decrease in their NPLs. The empirical data further indicates that an increase in ROA by one unit is associated with a 5.7%[11] reduction in the NPL ratio.

Our analysis reveals a significantly positive correlation between the NIM and the NPL ratio, a finding that is consistent with the research conducted by Chowdhury et al. (2023). Specifically, within Model 3, this positive correlation between NIM and the NPL ratio is significant at 5% level, suggesting a robust relationship between the profitability from interest and the level of NPLs. However, this relationship is not significant in Model 2. Furthermore, our study also identifies a significantly positive relationship between LLRs and the NPL ratio, a relationship that has been previously confirmed by Hasan & Wall (2004) and aligns with our estimated result. Remarkably, our results indicate that a 1% increase in the logarithm of LLRs is associated with a 0.14% decrease in the NPL ratio, when controlling for other variables.

According to the results, there’s no significant relationship between the ETA ratio and NPL ratios, which diverges from what we initially anticipated in our estimates. It indicates that the ETA ratio does not have a direct impact on the levels of NPLs in our study. Moreover, a significant relationship between net loans and NPL ratios is detected only in Model 2, which indicates that net loans do not constitute a primary determinant influencing NPL ratios across the board.

[11] Exp (0.055) = 1.057

3.6 Results from Dynamic Panel Data

3.6.1 Results from One-step & Two-step System GMM Model

Table 16 presents the cumulative effect of various variables on the NPL ratio as determined through the one-step and two-step system GMM approach. Within this method, GDP growth rate and unemployment rate are treated as strictly exogenous variables. This treatment is based on the rationale that these indicators reflect broader macroeconomic conditions which remain unaffected by changes in the operational dynamics of individual banks. In contrast, other variables are considered to be either endogenous or predetermined, recognizing that they may be influenced to varying degrees by the banks' own actions. The impact of these variables on the NPL ratio varies, acknowledging the complexity of interactions within the banking sector's activities.

The lower section of Table 16 is dedicated to demonstrating the outcomes of tests for autocorrelation and the validity of the data presented. Specifically, the Arellano-Bond tests for AR(1) and AR(2) in first differences are employed to assess whether there is autocorrelation in the error terms of the first-differenced data within this dynamic panel dataset. For Model 1, the p-values associated with the AR(2) test are greater than 0.1, suggesting the absence of autocorrelation at a significance level of 10%. This implies that there is no statistically significant autocorrelation in the first-differenced errors for this model at the 10% level of significance. However, for Model 2, the AR(2) test yields p-values that are below 0.1 but above 0.01. This outcome indicates the presence of autocorrelation at the 10% significance level. For Model 3, the analysis reveals a more complex situation. The p-value obtained from the one-step system GMM for AR(2) lies between 0.05 and 0.1, while the p-value from the two-step system GMM exceeds 0.1. These results suggest that, under the one-step system GMM, there is evidence of autocorrelation at the 10% significance level but not at the 5% level. Meanwhile, the two-step system GMM indicates a lack of autocorrelation even at the 10% significance level for Model 3.

The Hansen test is the principal method for verifying the overall validity of the instruments used in the study. The outcomes of this test are represented by p-values, all of which exceed 0.1. This result implies that, at a 10% level of significance, there is insufficient evidence to reject the null hypothesis. As a consequence, based on this level of significance, it can be inferred that the instruments are collectively valid and can be considered exogenous. This means that they are appropriately external to the model, and their validity stands at traditionally accepted levels of statistical significance, reinforcing their reliability and applicability in the analysis.

Table 16 System GMM Model

Variables	One-step System GMM			Two-step System GMM		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	ln_npl	ln_npl	ln_npl	ln_npl	ln_npl	ln_npl
L.ln_npl	0.487^{***}	0.535^{***}	0.454^{***}	0.919^{***}	0.527^{***}	0.453^{***}
	(0.055)	(0.054)	(0.043)	(0.271)	(0.006)	(0.046)
gdpg	-0.029^{***}		-0.023^{***}	-0.023^{***}		-0.023^{***}
	(0.004)		(0.003)	(0.009)		(0.003)
unemp	0.031^{***}		0.028^{***}	0.051^{*}		0.029^{***}
	(0.011)		(0.008)	(0.030)		(0.009)
infl	0.007^{**}		0.004	0.039^{**}		0.004
	(0.003)		(0.004)	(0.016)		(0.005)
ln_exp	0.387^{*}		0.059	-2.795^{***}		0.047
	(0.214)		(0.152)	(0.925)		(0.162)
fdi	-0.001^{**}		-0.000	0.008^{**}		-0.000
	(0.001)		(0.000)	(0.003)		(0.000)
spi	-0.005^{***}		-0.004^{***}	0.002		-0.004^{***}
	(0.001)		(0.001)	(0.003)		(0.001)
bankcon	-0.006^{***}		-0.001	0.009		-0.001
	(0.002)		(0.003)	(0.009)		(0.003)
year	-0.026^{***}		-0.010	0.005^{***}		-0.009
	(0.007)		(0.008)	(0.001)		(0.008)
roa		-0.052^{**}	-0.026^{**}		-0.051^{**}	-0.027^{**}
		(0.023)	(0.011)		(0.024)	(0.011)
ln_eta		-0.092	-0.151		-0.093	-0.151
		(0.124)	(0.104)		(0.128)	(0.108)
nim		0.069	0.048		0.068	0.049
		(0.061)	(0.032)		(0.060)	(0.032)
ln_llr		0.368^{***}	0.213^{***}		0.381^{***}	0.213^{***}
		(0.075)	(0.042)		(0.092)	(0.044)
nl		0.026^{***}	0.009^{***}		0.026^{***}	0.009^{**}
		(0.006)	(0.003)		(0.006)	(0.004)
_cons	51.571^{***}	-1.326^{***}	20.554		-1.346^{**}	18.756
	(13.112)	(0.510)	(15.302)		(0.523)	(16.376)
Number of observations	780	766	766	780	766	766
Number of banks	52	52	52	52	52	52
Hansen test (p-value)	1.000	1.000	0.183	0.587	1.000	0.183
Test for AR(1) errors	0.000	0.000	0.000	0.014	0.000	0.000
Test for AR(2) errors	0.195	0.034	0.097	0.854	0.039	0.109

Note: Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Compiled by author using STATA 18.0.

3.6.2 Results Discussion

The analysis reveals that the lagged dependent variable not only holds statistical significance but also demonstrates a positive correlation in both methodologies applied, thereby confirming the dynamic properties of the models. Specifically, the values of this variable span from 0.45 to 0.92 across various models, indicating that any abrupt changes in NPL ratio are likely to have a sustained impact on the stability of the banking sector. This observation is consistent with findings from prior analyses, such as the study conducted by Jesus & Gabriel (2006) focusing on Spain, which identified the lagged NPLR at a value of 0.55, and the research by Kjosevski & Petkovski (2017), which examined the Baltic States and found the lagged NPLR values to range between 0.33 and 0.49. This series of findings highlights the importance of monitoring and managing NPLR levels within the banking industry to mitigate potential long-term adversities.

In terms of macroeconomic variables, our findings highlighted a consistent pattern regarding the GDP growth rate. Specifically, when employing both the one-step and two-step system GMM models, the GDP growth rate exhibited a significant negative correlation, which was similar to the results obtained using the FE model. The values reflecting this negative impact ranged between -0.023 and -0.029. This finding aligns with previous research outcomes, notably those conducted by Louzis et al. (2010) for Greece, where GDP growth values spanned from -0.25 to -0.46, and by Makri et al. (2014) for a group of 14 Eurozone countries, with reported values fluctuating between -0.053 and -0.071. Furthermore, our analysis also confirmed the positive correlation between unemployment rates and the dependent variable, as initially indicated by the FE model's results. This subsequent analysis revealed that the values of unemployment fall within a range of 0.028 to 0.051.

Regarding the SPI, our findings showed a significantly negative effect of SPI on the NPL ratio, following our hypothesis and the results obtained from the FE model. Specifically, the impact of SPI on the NPL ratio varied with a narrow range, from -0.004 to -0.005. In addition, when examining the dynamics between bank concentration and NPL ratios, a negative correlation emerged, but this relationship was statistically significant only at the 1% significance level in Model 1 using the one-step system GMM approach.

As for inflation, our analysis within Model 1 indicates a positive correlation between inflation rate and NPL ratios. However, this result contrasts with that obtained using the FE model. The difference may be attributed to the heterogeneity of banks in the static panel (Pelinescu, 2015). Moreover, this finding shifts when taking into account bank-specific variables. Upon integrating these determinants, the influence of inflation was not statistically significant in either the one-step or two-step system GMM model. The reasons behind the initial positive impact of inflation could be tied to the reduced real repayment capacity of bank borrowers. As inflation rises, the real value of borrowers' income may decline, adversely affecting their ability to service debt. This positive results were also confirmed by Klein (2013), who reported inflation impact values ranging from 0.006 to 0.38.

Regarding exports, we observed a positive correlation between exports of goods and services and the NPL ratio. However, this relationship achieved statistical significance exclusively in Model 1. Such a finding implies that within our sample, the variable of exports does not play a key role in influencing the NPL ratio of commercial banks using system GMM model. Furthermore, the case for FDI was similar to that of exports. The relationship between FDI and the NPL ratio was significantly negative, but again, this significance was limited to Model 1. When we considered the influence of bank-specific factors, the impact of FDI was not significant. Consequently, this indicates that FDI is not a crucial determinant affecting the NPL ratio within our analysis.

Analyzing bank-specific factors, our findings regarding ROA indicate that profitability exerts a significant negative influence on the NPL ratio, aligning with results observed using the FE model. In the context of the system GMM method, this negative impact is quantified with values ranging from -0.026 to -0.052. Such findings are consistent with the research conducted by Erdinc & Abazi (2014), who reported the values between -0.34 and -0.55, further validating our results. Additionally, the analysis revealed a significant positive relationship between LLRs and the NPL ratio when employing the system GMM approach. This suggests that higher LLRs, which reflect a bank's proactive measures to safeguard against possible loan defaults, correlate with increased NPL ratios. The range of values was between 0.213 and 0.381. Furthermore, our study identified a positive correlation between net loans and NPL ratios at a 1% significance level. Specifically, the increase in net loans is linked to a reduction in loan quality, with values ranging between 0.009 and 0.026. However, this positive relationship was not significant in FE model, which might be caused by heterogeneity.

However, in our sample, we did not find a statistically significant correlation between the ETA ratio and the dependent variable, which was consistent with the results derived from the revised FE model. Similarly, our analysis revealed no significant relationship between the NIM and the NPL ratio. These results imply that neither the ETA ratio nor the NIM emerged as key factors influencing the NPL ratio in the 11 CEE countries during the period spanning from 2007 to 2022.

4 Limitations

Firstly, this study examined 52 commercial banks, which may not be a sufficient sample size, leading to issues with representativeness. In selecting the sample, the study prioritized strictly balanced panel data, excluding any commercial banks that do not have complete data for the period from 2007 to 2022 or that have gaps in their data records. This criterion restricts the completeness of the sample and further widens the data gap. Consequently, the findings of this study may lack representativeness, highlighting one of its key limitations.

Secondly, this study focused on commercial banks across 11 CEE countries, where variations in economic development levels pose challenges for analysis. The economic development disparities among these countries during transition period often reflected differences in industrial structures. Furthermore, each country prioritized different developmental goals, and not all placed equal emphasis on banking sector development. For instance, Poland, the Czech Republic, and Hungary boasted more advanced banking sectors compared to Latvia and Slovenia, where the sectors were less developed. This discrepancy was reflected in NPL ratios, which were notably lower in the Czech Republic and Poland between 2007 and 2022, and higher in Latvia and Lithuania. Consequently, the dataset used in this paper exhibits sample heterogeneity, complicating the application of the FE model and presenting another limitation of this study. To address these issues more effectively, it would be prudent to categorize the countries into clusters. These clusters could be defined either by the income level of the countries, such as high-income and low-income groups, or by the size of their banking sectors, categorized into high-banking asset and low-banking asset groups. This division would allow for a more detailed analysis of the banking sector across different economic environments.

Finally, in our study, the P-values for the Hansen test are close to 1 in most models, suggesting that the model may be overfitting in this region (Roodman, 2009), which could result in biased estimates of parameters (Windmeijer, 2005). Therefore, it is necessary to apply further estimations, such as the Roodman test. Additionally, the absence of subsequent tests for the GMM restricts the model's optimality, which in turn affects the interpretability of the data and leads to ambiguous results. For example, research indicates that the limited information maximum likelihood (LIML) estimator generally performs better than GMM estimators in addressing biases in small samples. For future research, it would be beneficial to use more precise estimation methods to enhance the robustness and accuracy of the findings.

Conclusion and Implications

This article analyzes the impact of two sets of variables, namely macroeconomic and bank-specific variables, on the NP ratios in eleven CEE countries over the period from 2007 to 2022. Initially, the study begins with a comprehensive review of the existing literature to frame the context of the analysis. We employed FE and RE models to estimate static panel data, identifying the most suitable model for our analysis. Supported by the Hausman test, our findings indicate that the bank and time FE model provides a more accurate framework for analyzing static panel data. Subsequently, the post-estimation analysis was conducted, leading to the revised FE model. We then extended our analysis to dynamic panel data. For this purpose, both one-step and two-step system GMM models were utilized.

In this study, we also analyzed the separate impacts of macroeconomic variables and bank-specific variables. A comparative analysis was carried out to determine which set of variables exerted a more significant influence on NPL ratios. To achieve this, we explored the impact of twelve different variables on the NPL ratios across various statistical models. During our estimation, certain variables showed significance in either the FE model or the system GMM model. However, these variables were not consistently significant across all models, indicating that they are not crucial determinants in the our study. For five variables mainly studied in our study, they consistently aligned with the previous hypotheses and demonstrated significant effects in all applied models, highlighting them as key factors in influencing NPL ratios. Our main findings are outlined as follows.

(1) There are three macroeconomic variables that significantly affect the NPL ratio. Firstly, the findings show a negative correlation between GDP growth rate and NPL ratio, suggesting that a higher GDP growth rate tends to decrease NPLs. Additionally, there’s a positive correlation between the unemployment rate and the NPL ratio,

indicating that lower unemployment rates can contribute to reducing NPLs. Lastly, a negative relationship exists between the SPI and the NPL ratio, demonstrating that an increase in share prices typically leads to a reduction in the NPL ratio.

(2) The study also highlights two bank-specific variables that significantly influence the NPL ratio. Firstly, the results indicate a negative correlation between ROA and the NPL ratio, suggesting that higher ROA is associated with lower NPLs. Additionally, there's a positive correlation between LLRs and the NPL ratio, showing that higher LLRs tend to correlate with higher NPLs.

(3) After categorizing all variables into two sets and evaluating their individual impacts on the NPL ratio using the bank and time FE model, our analysis had distinct results. When solely incorporating macroeconomic variables, the R-squared value was 0.826. In contrast, the R-squared value was 0.792 when only including bank-specific variables. Moreover, the R-squared value for the Model 3 that analyzed all variables combined was 0.851. These results clearly demonstrate that macroeconomic variables provide a more substantial explanation of the variations in our dataset, suggesting that the influences of macroeconomic factors are more significant.

(4) The analysis also indicates a positive correlation between lagged NPLs and current NPLs, highlighting the persistence of NPLs. This suggests that high levels of NPLs in the past are likely to continue unless proactive measures are taken to alter this trend. Consequently, using current NPL values can effectively predict future levels of NPLs. This insight allows regulators and banks to more effectively manage and mitigate the impact of NPLs.

After assessing the distinct impact of each variable, we derived several policy implications that can inform and enhance decision-making and strategic adjustments in the banking sectors of CEE countries. Particularly in the aftermath of the Covid-19 pandemic, effective management of NPLs would play a crucial role in facilitating economic recovery and development within these nations.

(1) To enhance GDP growth and reduce unemployment rates, both banks and regulatory bodies must take proactive actions and communicate effectively. Commercial banks should innovate lending practices and leverage financial technology (Fintech) to improve credit access, especially in underserved regions, which can stimulate local businesses and job creation. Additionally, banks can support micro-enterprises and startups to drive innovation and employment. For regulatory bodies, they should simplify and refine business regulations to facilitate the operations of new businesses and startups, thereby accelerating job creation and economic growth. Moreover, governments should invest in vocational training and higher education to build a workforce equipped for the changing needs of industries. They should also develop programs that efficiently match job seekers with vacancies, reducing the time spent unemployed and enhancing job suitability.

(2) To boost share prices, it's crucial to strengthen investor confidence. Regulators play a key role in this by consistently offering transparent updates about the financial markets and the banking sector, ensuring that investors are well-informed and actively engaged. Additionally, regulatory bodies should enhance investor protection laws to safeguard shareholders' rights and secure their investments. This not only helps protect investments but also encourages more robust investor participation, which can positively impact share prices. Strengthening such measures reassures investors about the stability and security of their investments, promoting a healthier investment environment.

(3) To improve ROA, commercial banks need to adopt comprehensive cost reduction strategies. This includes streamlining operations to eliminate redundancies, automating processes to reduce manual labor and errors, and optimizing the workforce to ensure that personnel costs are aligned with productivity. Such measures not only enhance efficiency but also improve profitability. Additionally, banks must

also strengthen their loan review and monitoring systems. By implementing more robust procedures, banks can better detect early signs of borrower distress to prevent the loan from becoming non-performing. These strategies are essential not just for improving financial performance but also for maintaining a healthy loan portfolio and minimizing risk exposure.

(4) Finally, it is crucial for regulatory bodies to enhance their oversight by tightening review standards and enforcing rigorous regulatory requirements for commercial banks. This effort should focus on enhancing transparency across the banking sector. Regulators should mandate that all operational, financial, and risk management practices meet high standards of clarity and accountability to maintain investor confidence and system integrity. For commercial banks, it is essential to uphold the highest standards of transparency in their financial reporting and risk assessments. Banks should ensure that their financial statements, risk management agreements, and operational reports are not only transparent but also align with international best practices.

Summary

Tento článek analyzuje dopad dvou souborů proměnných, konkrétně makroekonomických proměnných a proměnných specifických pro banky, na poměr NP v jedenácti zemích střední a východní Evropy v období od roku 2007 do roku 2022. Zpočátku studie začíná komplexním přehledem existující literatury, aby bylo možné zarámovat kontext analýzy. Použili jsme modely FE a RE k odhadu statických panelových dat a určili jsme nejvhodnější model pro naši analýzu. S podporou Hausmanova testu naše zjištění naznačují, že model banky a času FE poskytuje přesnější rámec pro analýzu statických panelových dat. Následně byla provedena post-estimační analýza, která vedla k revidovanému FE modelu. Poté jsme naši analýzu rozšířili na dynamická panelová data. Pro tento účel byly využity jak jednokrokové, tak dvoukrokové systémové modely GMM.

V této studii jsme také analyzovali samostatné dopady makroekonomických proměnných a proměnných specifických pro banky. Byla provedena komparativní analýza s cílem zjistit, který soubor proměnných má významnější vliv na ukazatele nesplácených úvěrů. Abychom toho dosáhli, prozkoumali jsme vliv dvanácti různých proměnných na poměry nesplácených úvěrů napříč různými statistickými modely. Během našeho odhadu některé proměnné vykazovaly významnost buď v FE modelu, nebo v systémovém GMM modelu. Tyto proměnné však nebyly konzistentně významné napříč všemi modely, což naznačuje, že v naší studii nejsou rozhodujícími determinanty. Nakonec jsme identifikovali pět proměnných, které konzistentně vykazovaly významné účinky ve všech aplikovaných modelech, a zdůraznili jsme je jako klíčové faktory ovlivňující poměry nesplácených úvěrů. Naše hlavní zjištění jsou nastíněna následovně.

(1) Existují tři makroekonomické proměnné, které významně ovlivňují poměr NPL. Za prvé, zjištění ukazují negativní korelaci mezi tempem růstu HDP a poměrem NPL,

což naznačuje, že vyšší tempo růstu HDP má tendenci nesplácené úvěry snižovat. Kromě toho existuje pozitivní korelace mezi mírou nezaměstnanosti a poměrem nesplácených úvěrů, což naznačuje, že nižší míra nezaměstnanosti může přispět ke snížení nesplácených úvěrů. Konečně existuje negativní vztah mezi SPI a poměrem nesplácených úvěrů, což dokazuje, že zvýšení cen akcií obvykle vede ke snížení poměru nesplácených úvěrů.

(2) Studie také zdůrazňuje dvě proměnné specifické pro banku, které významně ovlivňují poměr nesplácených úvěrů. Za prvé, výsledky naznačují negativní korelaci mezi ROA a poměrem NPL, což naznačuje, že vyšší ROA je spojena s nižšími NPL. Kromě toho existuje pozitivní korelace mezi LLR a poměrem NPL, což ukazuje, že vyšší LLR mají tendenci korelovat s vyššími NPL.

(3) Po kategorizaci všech proměnných do dvou souborů a vyhodnocení jejich jednotlivých dopadů na poměr NPL pomocí bankovního a časového FE modelu naše analýza přinesla jasné výsledky. Při pouhém začlenění makroekonomických proměnných byla hodnota R-squared 0,826. Naproti tomu hodnota R-squared byla 0,792, když zahrnovala pouze proměnné specifické pro banku. Navíc hodnota R-squared pro Model 3, který analyzoval všechny proměnné dohromady, byla 0,851. Tyto výsledky jasně ukazují, že makroekonomické proměnné poskytují podstatnější vysvětlení variací v našem souboru dat, což naznačuje, že vlivy makroekonomických faktorů jsou významnější.

(4)Analýza rovněž naznačuje pozitivní korelaci mezi zpožděnými úvěry v selhání a současnými úvěry v selhání, což zdůrazňuje přetrvávání úvěrů v selhání. To naznačuje, že vysoké úrovně nesplácených úvěrů v minulosti budou pravděpodobně pokračovat, pokud nebudou přijata proaktivní opatření ke změně tohoto trendu. V důsledku toho lze pomocí současných hodnot NPL účinně předpovídat budoucí úrovně nesplácených úvěrů. Tento přehled umožňuje regulačním orgánům a bankám efektivněji řídit a zmírňovat dopad nesplácených úvěrů.

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List of Appendices

APPENDIX 1 Observations in the Paper

Countries	Banks
Bulgaria	DSK Bank
	Unicredit Bulbank
	Eurobank Bulgaria
	First Investment Bank
	United Bulgarian Bank
	TBI Bank
	Investbank
	ProCredit Bank Bulgaria
Croatia	Zagrebacka Banka
	Privredna Banka Zagreb
	Erste & Steiermarkische Bank
Czech Republic	Ceska Sporitelna
	Komercni banka
	CSOB Czech Republic
	MONETA Money Bank
	PPF banka
	Ceska Exportni Banka
Estonia	Swedbank Estonia
	SEB Pank
Hungary	OTP Bank
	MBH Bank
	Erste Bank Hungary
	UniCredit Bank Hungary
Latvia	Swedbank Latvia
	SEB Bank Latvia
	Rietumu Banka
Lithuania	Swedbank Lithuania
	Siauliu Bankas
Poland	PKO Bank Polski
	Santander Bank Polska
	Bank Polska Kasa Opieki SA
	ING Bank Slaski
	mBank
	Bank BGZ BNP Paribas
	Millennium Bank Poland
	Bank Handlowy w Warszawie
	Bank Ochrony Srodowiska
	Deutsche Bank Poland

Romania	Banca Transilvania Banca Comerciala Romana BRD Groupe Societe Generale Raiffeisen Bank Romania CEC Bank Alpha Bank Romania
Slovakia	Slovenska Sporitel'na VUB Banka Tatra banka 365 Bank
Slovenia	Nova Ljubljanska Banka (NLB) Nova KBM SKB Banka Addiko Bank Slovenia

Source: Compiled by Author Using STATA 18.0.

APPENDIX 2 Descriptive Statistics of Macroeconomic Variables across Countries from 2007 to 2022

Country	Summary statistics	ln_npl	npl	gdpg	unemp	infl	exp	ln_exp	fdi	spi	bankcon
Bulgaria	Mean	2.110684	9.821553	2.360005	7.778125	3.747616	59.78293	4.083014	6.360535	123.6563	53.99081
	Max	2.826042	16.87852	7.661748	12.94	15.32526	69.194	4.236914	31.22753	317.5	65.72836
	Min	.7734793	2.167294	-3.966156	4.23	-1.418184	42.21885	3.742867	1.9133	66	43.96353
	SD	.6440313	5.065073	3.115876	2.90812	4.434924	7.100675	.1278192	7.522911	60.38708	6.314407
	N	128	128	128	128	128	128	128	128	128	128
Croatia	Mean	2.272652	10.80179	1.414095	11.31438	2.210827	43.24274	3.754338	3.678505	123.425	61.13365
	Max	2.913866	18.4279	13.78495	17.29	10.78058	59.16617	4.08035	7.831882	270.1	66.87838
	Min	1.465814	4.331069	-8.591424	6.62	-1.125	32.21966	3.472577	.0691693	96.8	53.35828
	SD	.4836071	4.755501	5.125143	3.717545	2.813241	6.981634	.1591244	2.528256	43.75287	4.664281
	N	48	48	48	48	48	48	48	48	48	48
Czechia	Mean	1.224554	3.768133	1.810706	4.633125	3.077069	72.8792	4.284549	3.931518	111.075	63.39612
	Max	1.729726	5.639108	5.570339	7.28	15.10017	81.95427	4.406161	7.264371	178	68.02515
	Min	.3753223	1.45546	-5.502968	2.02	.3093645	58.34543	4.066381	.904051	88.5	59.44337
	SD	.4782174	1.543518	3.102582	1.925862	3.455069	6.593604	.093914	1.450225	21.53454	2.196713
	N	96	96	96	96	96	96	96	96	96	96
Estonia	Mean	.6651046	2.312416	1.857689	7.856875	3.990068	75.98022	4.324968	7.775904	112.0875	94.44198
	Max	1.681849	5.375486	8.013463	16.71	19.39826	86.60379	4.461344	19.79294	209.7	98.53296
	Min	-.5730039	.5638292	-14.62906	4.45	-.492326	60.86438	4.108648	-3.125563	39.1	89.57411
	SD	.6082172	1.408328	5.473329	3.483844	4.95253	7.941496	.1077341	5.172648	47.05401	2.691268
	N	32	32	32	32	32	32	32	32	32	32
Hungary	Mean	1.788793	7.78915	1.870165	6.968125	4.129518	83.23896	4.420345	17.44405	135.825	68.19912

	Max	2.822909	16.82573	7.085721	11.17	14.60814	91.20826	4.513145	106.5942	234.5	86.72314
	Min	.4115259	1.509119	-6.597867	3.42	-.2275663	74.22425	4.307091	-40.08635	76.3	58.33648
	SD	.7627934	5.312351	3.534861	2.909772	3.512334	4.365351	.0529541	35.92078	52.31176	7.272031
	N	64	64	64	64	64	64	64	64	64	64
Latvia	Mean	1.639217	7.14251	1.388998	10.57062	4.035038	57.25285	4.03295	3.614218	144.6375	60.92469
	Max	3.104126	22.28973	9.941922	19.48	17.31028	71.98617	4.276474	9.434035	265.3	88.76881
	Min	-.1422929	.8673672	-14.26014	6.05	-1.084636	38.26159	3.644447	-.568031	54.4	48.68715
	SD	.8311633	6.189301	5.549529	4.167902	5.360838	9.170967	.1788157	2.496957	68.62652	11.5881
	N	48	48	48	48	48	48	48	48	48	48
Lithuania	Mean	1.344559	7.441034	2.73061	9.4325	4.073253	70.59137	4.246647	3.16273	110.5375	84.85289
	Max	3.097376	22.13979	11.10748	17.81	19.70505	86.84728	4.464151	7.909679	194.2	98.82536
	Min	-.7405863	.4768343	-14.83861	4.25	-.8840974	51.64121	3.94432	-.9634014	44.1	67.98005
	SD	1.299044	7.460834	5.218656	3.888163	4.925034	9.850002	.1488163	2.28132	42.5878	10.53081
	N	32	32	32	32	32	32	32	32	32	32
Poland	Mean	1.380571	4.047165	3.834785	6.79125	3.080112	47.62373	3.851952	3.369445	98.7625	46.60135
	Max	1.660848	5.263775	7.061535	10.33	14.42945	62.68512	4.138124	5.83445	129.7	58.02315
	Min	1.037475	2.822082	-2.020071	2.89	-.8741259	37.14225	3.614755	.1995106	61.5	38.56158
	SD	.1912853	.7302279	2.26356	2.747046	3.394529	7.21448	.1514225	1.366774	18.3925	4.645903
	N	160	160	160	160	160	160	160	160	160	160
Romania	Mean	1.954414	8.907917	3.042428	5.99125	4.229779	36.84952	3.590816	2.981049	102.6688	61.95193
	Max	3.085252	21.87297	9.307467	7.18	13.79549	42.97271	3.760565	6.377381	175.1	68.24536
	Min	.968991	2.635284	-5.517394	3.91	-1.544797	24.71083	3.207242	1.230493	48.8	54.6257
	SD	.700227	5.905274	4.216095	1.019442	3.483224	6.199049	.1861823	1.432364	33.33112	4.161915
	N	96	96	96	96	96	96	96	96	96	96
Slovakia	Mean	1.27872	3.821008	2.798946	10.11313	2.642671	88.28092	4.476214	2.585817	118.2438	71.93805
	Max	1.680558	5.368549	10.83203	14.39	12.77415	99.36478	4.598798	5.843347	166.2	79.25341

	Min	.61816	1.855511	-5.455533	5.76	-.5200102	68.03612	4.220039	-1.069697	73.5	67.62984
	SD	.365193	1.27421	3.679895	3.034167	3.0156	7.958311	.0954116	2.021478	29.88437	3.71685
	N	64	64	64	64	64	64	64	64	64	64
Slovenia	Mean	1.706672	6.769823	1.805552	6.6425	2.076735	75.68799	4.319507	2.157529	128.55	58.09994
	Max	2.719984	15.18008	8.2285	10.14	8.833699	94.14607	4.544847	4.013563	289.5	67.24356
	Min	.5597465	1.750229	-7.548438	4.01	-.5255523	57.26429	4.047677	-.6861517	76	51.43
	SD	.662843	4.235381	3.954954	2.047758	2.29694	8.986365	.1211439	1.510003	53.65889	4.884819
	N	64	64	64	64	64	64	64	64	64	64
Total	Mean	1.627244	6.576156	2.496754	7.48101	3.363136	61.46797	4.073176	4.972291	116.1394	60.91811
	Max	3.104126	22.28973	13.78495	19.48	19.70505	99.36478	4.598798	106.5942	317.5	98.82536
	Min	-.7405863	.4768343	-14.83861	2.02	-1.544797	24.71083	3.207242	-40.08635	39.1	38.56158
	SD	.7229306	4.936892	3.845023	3.343135	3.790025	17.7272	.3096446	11.16809	44.77752	12.64632
	N	832	832	832	832	832	832	832	832	832	832

Source: Compiled by Author Using STATA 18.0.