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DETERMINANTS OF LOAN LOSS PROVISIONS IN SERBIAN BANKS: THE EFFECT OF COVID-19 AND GEOPOLITICAL TURMOIL

Determinante kreditnih gubitaka u bankarskom sektoru Srbije - uticaj kovida-19 i geopolitičkih previranja

Abstract

In 2014, the IASB introduced IFRS 9 with the innovative ECL model, allowing for more timely and accurate credit loss recognition. While existing research has examined ECL during the COVID-19 crisis, there is limited focus on its behavior amid geopolitical instability. Our study addresses this gap by extending the analysis to include recent conflicts such as the Russia-Ukraine war and the Israeli-Palestinian conflict. Covering the period from 2019 to 2023, our empirical analysis is based on 95 bank-year observations from 19 banks over five years. Findings reveal a significant shift of loans from Stage 1 to Stage 2, with no substantial increase in Stage 3 loans. The average cost of risk tripled during global disruptions, highlighting the substantial impact of these crises on credit risk and loan loss provisions. The results show that higher proportions of unsecured household loans and investment corporate loans significantly increase loan loss provisions. However, government measures mitigated this effect for unsecured household loans during downturns, while the impact remains for investment corporate loans. Additionally, banks with a larger share of mortgage loans during distress periods are generally expected to incur lower losses compared to peers.

Keywords: *IFRS 9, credit risk, ECL model, expected credit losses, loan loss provisions, loan loss allowance, loan portfolio, COVID-19, geopolitical instability.*

Sažetak

U 2014. godini, Odbor za međunarodne računovodstvene standarde usvojio je novi standard MSFI 9 sa inovativnim modelom očekivanih kreditnih gubitaka (ECL), koji omogućava pravovremenije i preciznije priznavanje kreditnih gubitaka. Prethodna istraživanja uglavnom su se fokusirala na kretanje ECL tokom pandemije kovid-19, dok je zabeležen nedostatak detaljnih analiza u okviru uslova globalne geopolitičke nestabilnosti. Naš rad ima za cilj da popuni ovu prazninu u literaturi proširenjem perioda analize i uključivanjem uticaja skorašnjih geopolitičkih sukoba, poput sukoba između Rusije i Ukrajine, kao i izraelsko-palestinskog sukoba. Empirijska analiza obuhvata period od 2019. do 2023. godine. Naš uzorak se sastoji od 95 jedinica posmatranja (19 banaka posmatrane tokom perioda od 5 godina). Rezultati istraživanja ukazuju na značajan prelaz kredita iz stejdža 1 u stejdž 2, dok povećanje učešća kredita u okviru stejdža 3 nije zabeleženo. Vrednost *cost-of-risk* pokazatelja se utrostručila tokom perioda globalnih poremećaja, čime je istaknut značajan uticaj ovih kriza na kreditni rizik i povećanje kreditnih gubitaka. Rezultati istraživanja takođe pokazuju da veće učešće neosiguranih kredita stanovništvu i investicionih kredita privredi dovodi do povećanja iznosa gubitaka od obezvređenja, uz mogućnost njihovog smanjenja putem mera pomoći donetih od strane vlade. Pored toga, banke sa većim učešćem stambenih zajmova tokom perioda krize uglavnom procenjuju da će pretrpeti manje kreditne gubitke u poređenju sa konkurentima.

Ključne reči: *MSFI 9, kreditni rizik, ECL model, očekivani kreditni gubici, gubici od obezvređenja plasmana, ispravka vrednosti plasmana, kreditni portfolio, kovid-19, geopolitička nestabilnost.*

Introduction

The accounting treatment of financial instruments is regarded as one of the most complex and controversial areas of financial reporting. Following the outbreak of the subprime mortgage crisis, which triggered the financial crisis in 2007, significant shortcomings in accounting standards related to financial instruments were revealed. These deficiencies contributed to the erosion of confidence in the banking system [28] [32], thereby necessitating a reevaluation of the accounting treatment of financial instruments, particularly with respect to the recognition of credit losses.

The Incurred Credit Loss (ICL) model, developed under International Accounting Standard 39 (IAS 39), was based on the premise that credit losses should only be recognized when objective evidence of default by a counterparty existed. This approach resulted in insufficient and belated recognition of loan loss provisions (LLPs), especially during periods of economic downturn and increasing uncertainty. Consequently, IAS 39 was viewed as a significant contributor to the global financial crisis due to its procyclical behavior [10]. Banks were not permitted to recognize losses until the actual occurrence of a loss event or until there was a probability of default nearing or equal to 1 [26]. Such a circumstance highlighted a critical temporal mismatch between the recognition of credit losses and the actual quality of the loan portfolio, raising significant concerns about the reliability of financial reporting within banks.

In July 2014, in response to these challenges, the International Accounting Standards Board (IASB) issued International Financial Reporting Standard 9 (IFRS 9), which replaced the previous IAS 39. A significant innovation of IFRS 9 was the introduction of the Expected Credit Loss (ECL) model, fundamentally altering the methodology for determining and recognizing loan loss provisions. Effective January 1, 2018, IFRS 9 was designed to amend the shortcomings of IAS 39, particularly its procyclical ICL model that recognized credit losses 'too little, too late', resulting in unreliable forecasts of future credit risks. In contrast to the premise of IAS 39, which posited that no loan is considered impaired until definitive evidence suggests otherwise, IFRS 9 is based on a fundamentally different principle. Specifically, IFRS 9 asserts that every loan inherently carries a risk of impairment and requires ongoing evaluation for signs of such impairment, without waiting for objective evidence of default to be present. By employing a framework based on ECL, IFRS 9 seeks to enhance the timeliness and accuracy of credit loss recognition, thereby improving financial reporting related to credit risk [7].

The ECL model requires banks to classify and disclose loans across three stages of impairment, contingent upon changes in credit risk exposure that have occurred since their initial recognition [18]. *Stage 1* contains existing loans that have not experienced a significant increase in credit risk since initial recognition ("performing" loans), with interest revenue calculated on the gross carrying amount without deducting ECL. For loans in this stage banks recognize 12-month ECL for potential defaults within the next year and establish a corresponding loss allowance. *Stage 2* occurs when there is a significant increase in credit risk (SICR) since initial recognition ("underperforming" loans), at which point lifetime ECL are recognized, while the calculation of interest revenue remains the same as in Stage 1. To determine whether a SICR has occurred, a bank must assess any changes in the risk of default over the expected life of the loan, emphasizing the probability of default rather than the amount of ECL. Therefore, this assessment focuses on the probability of default (the occurrence of a loss event), rather than the likelihood of losses arising [31]. Assessment if SICR event has been realized involves comparing the default risk at the reporting date with that at the time of initial recognition [6]. Finally, in *Stage 3*, if a loan is classified as credit-impaired ("non-performing" loans), interest revenue is calculated based on the amortized cost (the gross carrying amount minus the loss allowance), and lifetime ECL are recognized, similar to Stage 2 [5].

The ECL is determined according to the following formula:

$$ECL = PD*LGD*EAD$$

Probability of Default (PD) represents an estimation of the likelihood of default on financial obligations [8]. PD is a critical component of the relevant formula and is regarded as one of the most complex parameters to calculate, as it depends on the assessment of various factors and indicators related to both macroeconomic conditions and the specific characteristics of the debtor. It is crucial to highlight that change in the level of credit risk cannot be simply discerned by comparing the absolute change in PD over observed periods. Consideration must also be given to the maturity of the loan and its initial quality. Loss Given Default (LGD) refers to the rate of loss incurred in the event of a default. It is derived from the difference between the contractual cash flows due and those that the lender expects to receive, including any proceeds from the realization of collateral. This is typically expressed as a percentage of the Exposure at Default (EAD) [14]. Essentially, LGD determines the magnitude of the expected credit loss. As previously noted, the assessment of a significant increase in credit risk exposure emphasizes the probability of default rather than the magnitude of expected losses, indicating that changes in LGD are not factored into evaluations of whether a SICR event has occurred. Consequently, LGD is generally considered to be constant. Therefore, variations in PD have the most substantial impact on the calculation of ECL [26]. EAD is also a critical parameter in the ECL formula, representing an estimate of the extent of a bank's exposure to the borrower at the time of default [31].

It is essential to highlight that the implementation of the ECL model requires a thorough assessment by management to collect information relevant to future projections that will be integrated into the modeling process [11]. Additionally, the new model demands enhanced quality disclosures within the annual financial statement notes to mitigate information asymmetry and minimize and reduce the risk associated with potential fluctuations in reported earnings due to credit losses [37]. The fundamental requirement outlined in IFRS 9 mandates that expected credit losses must represent an unbiased and probability-weighted amount, determined by evaluating a range of potential outcomes [3]. The use of different assumptions can lead to significantly varied estimates of ECL. Additionally, the inclusion of forward-looking macroeconomic scenarios entails considerable management judgment which introduces discretionary and subjective elements into loan loss provisions, thereby creating opportunities for earnings management.

Contextual background and research objectives

At the time of the issuance of IFRS 9, it was believed that the assessment of the quality and effectiveness of the new impairment model could only be made in the context of a substantial crisis and economic downturn. Consequently, we can assert that the COVID-19 pandemic represented the first major test for IFRS 9 and the ECL model, occurring shortly after its initial implementation. The first and most significant effects of the crisis were observed in 2020, although in some countries, the repercussions extended into 2021. Following the initial distress triggered by

Table 1: ECL vs. ICL model

Aspect	ICL model	ECL model
Key concept	No loan is deemed impaired until definitive evidence of default is provided	Every loan carries an inherent risk of at least some impairment
Impairment assessment	Applicable exclusively to loans with historical evidence of losses and corresponding objective evidence of impairment	Applicable to all loans, irrespective of historical evidence of losses or objective evidence of impairment
Nature of losses	Incurred losses	Expected losses
Loss assessment period	Recognized at the time of impairment determination	12 month or lifetime expected credit losses
Effective interest rate	Inflated, as it does not reflect anticipated losses	Reduced compared to the ICL model, adjusted for expected losses
Impact on capital adequacy	Delayed provisioning for losses and increased procyclicality	Timely provisioning for losses and reduced procyclicality due to the earlier recognition of credit losses
Transparency	Inadequate, with limited disclosure requirements that do not provide sufficient transparency and detail	Enhanced, featuring a robust and comprehensive set of disclosure requirements
Judgmental discretion	Relatively limited	Fairly high

Source: Authors` presentation

the pandemic, a separate geopolitical shock arose from the Russia-Ukraine war in February 2022. This conflict has since experienced further escalation. Additionally, the Israeli-Palestinian conflict intensified during the fourth quarter of 2023. Therefore, it appears that IFRS 9 was implemented at a particularly opportune moment, considering the myriad challenges facing the global economy from 2020 to the present. Numerous entities in the global economy have encountered significant disruptions due to the pandemic and geopolitical turmoil. These challenges have led to increased commodity prices, disruptions in production and supply chains, elevated production costs, slowed economic growth, and heightened inflationary pressures [30]. As a result, the risk of borrowers facing challenges in loan repayment increased markedly. Various governments have announced measures to provide both financial and non-financial assistance to the disrupted industry sectors and the affected business organizations. Consequently, banks were required to assess their exposure to external shocks, particularly regarding credit risk and potential credit losses.

Loan loss provisions calculated using the ECL model consist of two distinct components: the normal component and the abnormal component. The normal component represents the objective and systematic portion of loan loss provisions, reflecting the actual impact of economic and financial factors on credit risk assessment. This component is usually influenced by macroeconomic factors and various bank-specific indicators (e.g., loan portfolio composition). In contrast, the abnormal component represents the discretionary portion of loan loss provisions, which may arise due to managerial discretion, earnings management practices, model misapplication, or other non-economic factors. This component can lead to deviations from the true risk profile of a financial institution's loan portfolio, potentially influencing reported earnings. The identification of normal versus abnormal components within any accrual has long been a prominent challenge in accounting literature, particularly in the context of loan loss provisions, which represent the largest accrual for banks [9]. This process becomes significantly more complex under the ECL model compared to the ICL model due to the increased discretionary leeway in calculating loan loss provisions. This complexity is further exacerbated during economic downturns and periods of heightened uncertainty, as bank management may be motivated to engage in aggressive earnings management practices, particularly income smoothing [1] [38].

One of the primary objectives of this paper is to examine the determinants of the normal component of loan loss provisions. Specifically, this research aims to analyze the impact of macroeconomic conditions and regulatory measures, along with bank-specific factors such as the composition of a bank's loan portfolio, on the level of loan loss provisions during economic downturns and periods of heightened uncertainty. By analyzing the interplay between these variables, the study seeks to provide a deeper understanding of how external economic and regulatory circumstances, in conjunction with internal bank characteristics, influence the level of loan loss provisions in commercial banks in Serbia.

Literature review

The literature includes studies that have examined the dynamics and determinants of ECL during the COVID-19 pandemic. However, there is a notable lack of research addressing ECL analysis during periods of uncertainty stemming from recent geopolitical upheavals, such as the Russian-Ukrainian war and the Israeli-Palestinian conflict. In our study, we extend the timeframe of analysis to encompass these events. We consider this extension to be a significant contribution of our study.

Financial institutions, notably banks, faced some of the most profound effects of the uncertainty brought about by the COVID-19 pandemic [38].Top of Form The literature reveals mixed findings regarding the dynamics of ECL during COVID-19, with significant variations observed among banks. These divergences can be attributed to several factors, including the nature of financial products offered, the customer base, and the overall business mix. Furthermore, banks' exposure to sectors particularly impacted by the pandemic, coupled with the implementation of government support measures, has played a critical role in shaping ECL dynamics. Additionally, variability in macroeconomic projections and the weights assigned to

different scenarios contribute to these observed differences. Together, these drivers illustrate the complex landscape influencing credit risk outcomes.

Ozili and Arun (2023) discuss how worldwide governmental measures, such as grace periods and payment moratoriums, pose challenges for banks in identifying relevant information for ECL scenarios. The authors highlight that banks often rely on judgment-based assessments, using models developed by large global institutions that consider various economic variables including unemployment rates, GDP growth, and interest rates. Adapting these models to reflect the pandemic's extreme conditions is critical to avoid misestimating credit risk and ensure accurate ECL calculations [27].

According to Salazar, Merello, and Zorio-Grima (2023) provisions moratoria implemented during the COVID-19 pandemic mitigated the volatility in impairment losses among banks, stabilizing reported earnings quality. However, these moratoria also diminished the effectiveness of key drivers like LLPs and Stage 2 Loan Loss Allowances (LLAs) in anticipating overall banking credit risk. Despite the uncertain environment, credit risk parameters used to calculate LLPs remained stable, limiting their ability to accurately reflect the true level of risk associated with loan portfolios [34].

Brouwer, Huttenhuis, and Hoeven (2021) examined the dynamics of ECLs among 27 global systemically important banks over a three-year period (2018-2020). Their findings indicate a significant increase in ECL during the pandemic, particularly evident in the household sector when compared to the corporate sector. The authors attributed this disparity to the targeted government support for businesses, which effectively reduced loss probabilities within the corporate segment. Conversely, the lack of similar support for households led to heightened risks for banks engaged in that sector [7].

Engelmann and Lam Nguyen (2023) conducted an analysis involving 71 global banks listed in the S&P 100, comparing data from the pre-crisis year of 2019 with that of the pandemic year in 2020. Their findings revealed a significant increase in ECL, primarily due to a shift in loan classifications from Stage 1 to Stage 2, necessitating a transition from 12-month to lifetime ECL calculations. They also reveal that changes in the distribution of Stage 3 clients were minimal, with the highest concentration of Stage 3 clients located in Eastern Europe, Latin America, and Africa [13].

Nkomombini et al. (2022) conducted an analysis focusing on the five largest banks within the South African banking sector. Analyzing data from 2019 and 2020, their findings indicate a deterioration in credit quality, characterized by reductions in Stage 1 loans alongside increases in Stage 2 and Stage 3 loans. Consequently, ECL rose significantly by 41%. The study concluded that, despite the implementation of government measures, SICR levels remained largely unchanged [24].

In a comparative study of Polish banks versus European banks, Slazak and Skwarzec (2022) reported a significant rise in ECL, highlighting differences in responses. Polish banks increased Stage 3 provisions markedly during the pandemic, while European banks adjusted their provisions in line with Stage 3 portfolio values [36]. Hladika (2021) studied the Croatian banking sector, assessing non-performing loans and ECL from 2017 to 2020. Contrary to expectations, the share of Stage 3 loans decreased slightly during the pandemic, suggesting that government interventions may have stabilized credit quality. Hladika noted a 37.66% increase in ECL, primarily due to growth in the Stage 2 segment [20].

In early 2021, EY assessed ECL among 18 European Global Systemically Important Banks (G-SIBs), revealing that average ECL reached €3.9 billion in 2020, doubling the previous year. Notably, variances in sensitivity among banks were influenced by factors including portfolio structure and geographic location. This increase in ECL was largely driven by additional provisions for performing clients in Stage 1 and Stage 2 categories, which rose from 10% to 43% of total provisions. The cost of risk, calculated as the ratio between the ECL charge and gross loans to customers, doubled in 2020 (81 basis points) compared to 2019 (38 basis points), with half of the banks concentrated within a ratio of 40 to 100 basis points. The differences in outcomes can be attributed to several key factors, including the types of products offered, particularly those more sensitive to economic fluctuations, such as corporate and commercial loans, credit cards, and unsecured personal

lending, along with exposure to vulnerable sectors and significant individual Stage 3 losses in 2020 compared to 2019 [15]. According to the European Central Bank (ECB), the overall cost of risk for significant banking institutions rose throughout 2020, ultimately reaching 0.67% in the fourth quarter, an increase from 0.50% observed in the corresponding period of the previous year [16]. At the aggregate level, the cost of risk remained stable at 0.47% in the fourth quarter of 2022 while in 2023, cost of risk was 0.45%, close to the levels reported in the last 2 years [17].

As previously mentioned, this paper aims to investigate the determinants of loan loss provisions, focusing on the impact of macroeconomic conditions, regulatory measures, and bank-specific factors, such as loan portfolio composition, during economic downturns and heightened uncertainty related to COVID-19 pandemics and recent geopolitical turmoil. The movement of ECL cannot be viewed in isolation from the specific characteristics of individual banks, as these characteristics dictate the sensitivity of ECL to changes in macroeconomic conditions [9] [12] [19] [22]. In this context, Dejuan-Bitria and Gómez Biscarri (2024) identify credit risk, portfolio structure, and loan maturity as key characteristics. For banks facing high credit risk or those with poor portfolio quality, changes in ECL may be more pronounced under the influence of macroeconomic shocks [25].

Additionally, the structure of the portfolio, specifically the representation of various types of loans within the total lending, significantly impacts PD and LGD. The influence of portfolio structure is manifested through the specific characteristics of each loan type, which shape the behavior patterns of ECL components in response to shocks. For instance, mortgage loans, which are secured by collateral, are typically associated with lower LGD, while unsecured loans such as credit card debt and consumer loans demonstrate higher PD and LGD.

Ryan (2011) further emphasizes that during periods of economic crises, loans granted to businesses exhibit more volatile credit risk [33]. Additionally, Benbachir and Habachi (2018) highlight the necessity for careful selection of models for estimating ECL in the case of loans extended to small and medium-sized enterprises (SMEs), as this group of borrowers is heterogeneous in terms of creditworthiness and the availability of reliable data for assessing ECL components [4]. Lastly, loan maturity has a dual but opposing effect on ECL [19]. Longer maturities imply higher PD due to increased uncertainty. However, they simultaneously mitigate this prior effect on PD as they reflect the bank's confidence in the borrower's ability to meet obligations over a longer timeframe.Top of Form

Research design

Our empirical analysis covers the period from 2019 to 2023, with 2019 designated as the pre-crisis reference year, while the period from 2020 to 2023 represents a phase of increased uncertainty and global economic disruptions, driven by the COVID-19 pandemic and geopolitical instability, including war-related conflicts (e.g., the Russian-Ukrainian war and the Israeli-Palestinian conflict). Although the implementation of IFRS 9 and the ECL model became mandatory in 2018, this year was excluded from the analysis as it represented the initial phase of implementation. This exclusion was intended to mitigate potential distortions arising from transitional adjustments to the new methodology for estimating credit losses. The analysis concludes with 2023, as it was the most recent year for which data were available at the time of the study.

Our sample comprises only those banks that operated continuously throughout the entire study period. Additionally, data from banks that were acquired and merged during the analyzed period were aggregated with data from the successor acquirer banks. This resulted in the identification of 20 banks. However, due to the distinctive nature of its business model and asset structure, one bank was excluded from the analysis. Consequently, the final sample comprised 19 commercial banks operating within the Republic of Serbia, resulting in 95 bank-year observations (19 commercial banks over a 5-year period). Data were hand-collected from publicly available financial statements and various reports issued by the National Bank of Serbia covering the period from 2019 to 2023.

The methodological recommendations presented by Dejuan-Bitria and Gómez Biscarri (2024) served as the foundation for the development of our model. They recommend that modeling loan loss provisions should focus

on several dimensions. First, they suggest incorporating either time-fixed effects or a set of macroeconomic indicators to capture systematic expected credit losses. Second, they recommend including proxies for bank-specific expected credit losses or approximating these losses through heterogeneous effects of macroeconomic conditions based on banks' credit quality and portfolio composition. Finally, they advocate incorporating loan growth as a determinant of changes in loan loss allowances. Below, we outline the development of our model based on these ideas and guidelines. Our model examines the determinants of normal loan loss provisions during economic downturns caused by global turmoil.

Given that the primary objective of the paper is to examine the determinants of the normal component of loan loss provisions, the dependent variable is defined as the ratio of loan loss provisions to lagged gross loans, referred to as the lagged cost of risk ratio (CoR_LAGGED). The cost of risk measures a bank's potential credit risk exposure, with a higher ratio signifying an increased expectation of loan defaults and leading to greater provisions for loan losses. Additionally, it reflects the overall quality of the bank's loan portfolio. The use of lagged gross loans mitigates the distorting effects of newly originated loans during the reporting period. Such loans may be granted at any time within the period and are typically classified under Stage 1, as no significant increase in credit risk is expected at inception. Including these loans in the denominator for the same year in which LLPs are recognized could lead to an underestimation of the cost of risk ratio. Our analysis centers on gross loans to customers at amortized cost, while gross loans to banks and other financial institutions are excluded from this examination [15]. This exclusion is justified by their relatively marginal contribution to the total assets and overall loan portfolios of the banks, coupled with their consistently low and predominantly stable exposure to credit risk over time. Such loans are primarily classified within Stage 1, and the corresponding loan loss provisions are typically minimal.

In analyzing the loan portfolio structure, we specify the regressors as the values of individual loan categories scaled by total assets. We adopt this methodological choice for two primary reasons. First, scaling by total assets mitigates multicollinearity that occurs when loan values are based on the total portfolio, where the sum of all loan shares equals one. Addressing multicollinearity would require excluding at least one variable of interest, which could diminish the model's explanatory power and complicate result interpretation. Second, some banks, due to specific business models or other institutional factors, have little to no exposure to certain loan types. Therefore, scaling by total assets minimizes variation in the relative size of these categories across banks, thus enhancing the robustness of our analysis by reducing the influence of outliers and extreme values that can distort coefficient estimates. The relative proportions of different loan types serve as proxies for estimating bank-specific expected losses.

In our analysis, we define four variables that quantify the structure of the loan portfolio. The first variable, UNCOLAT, measures the level of uncollateralized household loans, which include cash and credit card loans characterized by the absence of collateral backing. This lack of collateral means that these loans depend solely on the borrower's ability to repay, thereby increasing their credit risk and the potential for loss in the event of default. Consequently, we anticipate a positive relationship between uncollateralized household loan share and loan loss provisions, reflecting higher ECL associated with these loans. Furthermore, we hypothesize that this influence will become even more pronounced during periods of economic downturn and heightened uncertainty. What could potentially weaken this relationship is the significant regulatory measures implemented by the National Bank of Serbia, aimed at supporting citizens in mitigating the adverse impacts of the crises mentioned earlier.

Another variable, HOUSING, represents the proportion of housing loans that are secured by a mortgage, which substantially mitigates exposure to credit risk and loss given default. However, these housing loans typically have longer maturities than other types of household loans, potentially leading to higher calculated lifetime ECL. While collateral reduces credit risk, the extended repayment periods may increase a bank's long-term exposure to changes in economic conditions and borrower default risk. Thus, the direction of the relationship between housing loans and

loan loss provisions cannot be definitively predicted. We also hypothesize that the influence of housing loan share on LLPs will become stronger and negative during the period of economic downturn and heightened uncertainty. During the period when real estate values remained stable amid the crisis, the solid collateral backing of housing loans, combined with targeted regulatory measures, likely contributed to lower expected credit losses compared to other household loans.

The third variable, INVEST, assesses the proportion of investment loans in the loan portfolio, which are primarily used to acquire and enhance long-term assets that drive business growth. Even if they are usually collateralized with long-lived assets, such loans often exhibit more volatile credit performance, particularly during economic downturns. Consequently, a positive relationship with loan loss provisions is anticipated due to the higher risk profile of these loans, with this relationship intensifying in times of economic stress.

Finally, the variable LIQWC measures the level of liquidity and working capital loans within a bank's portfolio. Designed to address short-term funding requirements for corporations, these loans typically feature shorter maturities compared to investment loans. Unlike investment loans, liquidity and working capital loans are often less secured, and any collateral involved primarily consists of current assets. Given these characteristics, we expect a positive relationship between this variable and loan loss provisions.

In our regression model, we include two additional control variables to account for credit activity and bank size. The variable LOANGROWTH represents the annual loan growth rate. The rationale for the assertion that new credit impacts the level of loan loss provisions is based on the observation that rapid expansion in a bank's lending activities can result in reduced scrutiny during the loan approval process, as banks may relax their credit criteria to achieve growth objectives. It is expected that this dynamic will have a positive effect on the level of loan loss provisions. Recent regulatory requirements indicate that even newly originated loans classified under Stage 1 are subject to a 12-month ECL, which is recognized in profit and loss. Given that these loans are related to newly originated loans, it is likely that the associated LLPs will be minimal or nearly negligible. This raises significant questions regarding the extent of this influence, highlighting the need for further empirical analysis [35]. To examine the impact of bank size on LLPs, we employ the SIZE variable, measuring bank size as the natural logarithm of total assets. The literature presents mixed findings regarding the impact of bank size on LLPs. Anandarajan, Hasan, and Lozano-Vivas (2003) argue that larger banks may maintain higher LLPs to compensate for the risks associated with their higher levels of business activities [2]. Conversely, other studies indicate that larger banks may negatively influence LLPs, thanks to their superior information environments and access to advanced risk management tools. These advantages enhance screening and monitoring capabilities, leading to more effective credit risk management and ultimately reducing the probability and severity of credit losses (LGD). Additionally, the diversified loan portfolios of larger banks can further mitigate the impact of credit losses. Variations in bank size also result in differing levels of regulatory scrutiny, influencing risk-taking incentives and the composition of loan portfolios, which ultimately affects non-performing loans (NPL) and LGD dynamics [9].

In our analysis, we use time-fixed effects to incorporate the determinants of systematic expected credit losses associated with the macroeconomic and regulatory environment. To assess how the relationship between portfolio structure and loan loss provisions varies during economic downturns from 2020 to 2023, we introduce interactions between the time-fixed effects and the portfolio structure variables. This approach allows us to analyze the influence of a bank's portfolio structure on the cost of risk over time in the context of economic crises. In this context, we create a time dummy variable that equals 1 for the downturn period (2020-2023) and 0 for the reference pre-crisis year 2019.

Model specification is as follows:

$$CoR\_LAGGED_{it} = (\beta_1+\mu_i+\lambda_t) + \beta_2*UNCOLAT_{it} + \beta_3*HOUSING_{it} + \beta_4*INVEST_{it} + \beta_5*LIQWC_{it} + \beta_6*UNCOLAT_{it} \times \lambda_t + \beta_7*HOUSING_{it} \times \lambda_t + \beta_8*INVEST_{it} \times \lambda_t + \beta_9*LIQWC_{it} \times \lambda_t + \beta_{10}*LOANGROWTH_{it} + \beta_{11}*SIZE_{it} + u_{it}$$

Table 2: Model specification details

Dependent variable	Independent variables
CoR_LAGGED_{it} – the ratio of loan loss provisions to lagged gross loans	$UNCOLAT_{it}$ – share of uncollateralized household loans in total assets $HOUSING_{it}$ – share of housing loans in total assets $INVEST_{it}$ – share of investment corporate loans in total assets $LIQWC_{it}$ – share of liquidity and working capital corporate loans in total assets $UNCOLAT_{it} \times \lambda_t$ – interaction term between uncollateralized household loans and fixed-time effects $HOUSING_{it} \times \lambda_t$ – interaction term between housing loans and fixed-time effects $INVEST_{it} \times \lambda_t$ – interaction term between investment corporate loans and fixed-time effects $LIQWC_{it} \times \lambda_t$ – interaction term between liquidity and working capital corporate loans and fixed-time effects $LOANGROWTH_{it}$ – annual loan growth rate $SIZE_{it}$ – size of the bank measured by the natural logarithm of total assets
$\beta_1, \beta_{2, \ldots,} \beta_{11}$ – intercept and regression parameters μ_i, λ_t – time invariant and time effects u_{it} – random error	

Source: Authors` presentation

We employ a panel regression analysis to examine the determinants of the normal component of loan loss provisions. We estimate model specifications with both time invariant and time effects included – both FE and RE model specifications. According to the values of pairwise correlation coefficients and variance inflation factor (VIF), the correlation between regressors does not lead to harmful multicollinearity that could negatively affect the quality of the estimates obtained in the models (Table 3 and Table 4).

As the assumptions of homoskedasticity and cross-sectional independence are violated, when choosing between FE and RE models we have used the robust version of the Hausman specification test - the Sargan-Hansen statistics [29]. The values of the Sargan-Hansen statistics suggest the use of the FE model in our specification. Given the violation of assumptions in the FE model (Table 5), we have ended up with the Linear regression with correlated panel-corrected standard errors (PCSEs) for our model specifications (see Table 11). This approach incorporates time-fixed effects to control for factors that vary over time and includes interaction terms between loan portfolio structure variables and these effects, allowing us to assess how changes in economic conditions influence the relationship between loan portfolio structure and normal loan loss provisions. This methodological framework is also recommended as a viable alternative in the work of Dejuan-Bitria and Gómez Biscarri (2024). Additionally, we apply individual-fixed effects to control for unobserved heterogeneity in factors driving the abnormal (discretionary) portion of loan loss provisions, which may originate from managerial discretion, earnings management, model errors, or other non-economic influences. The results indicate that both time-fixed and individual-fixed effects are statistically significant, thereby providing a rationale for their use in the model (see Table 11).

Table 3: Pairwise correlation coefficients

Variable	CoR_LAGGED	UNCOLAT	HOUSING	INVEST	LIQWC	SIZE	LOANGR.
CoR_LAGGED	1.0000						
UNCOLAT	-0.1603	1.0000					
HOUSING	-0.2338	0.3007	1.0000				
INVEST	-0.1570	0.0123	0.0621	1.0000			
LIQWC	-0.0501	-0.2585	0.0250	-0.1040	1.0000		
SIZE	-0.2267	0.4055	0.7102	0.2525	-0.3200	1.0000	
LOANGR.	0.0907	0.1633	-0.0995	-0.0569	-0.3064	0.0692	1.0000

Source: Authors' presentation based on the Stata output

Table 4: Calculated values of VIF

Regressor	SIZE	HOUSING	LIQWC	UNCOLAT	LOANGROWTH	INVEST
VIF	2.98	2.49	1.41	1.26	1.15	1.12

Source: Authors' presentation based on the Stata output

Table 5: Calculated values of the relevant test statistics

Dependent variable	Homoskedasticity (modified Wald test)	Cross-sectional independence (Frees test)	Absence of autocorrelation (Wooldridge test)	Sargan-Hansen statistic
CoR_Lagged	1,697.36***	0.532*	2.808	1,559.027***

***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.
Source: Authors' presentation based on the Stata output

Research findings

Although this analysis primarily focuses on gross loans to customers measured at amortized cost, excluding gross loans to banks and other financial institutions, we observe a significant shift in the total loan portfolio over the period (see Table 6). Loans to banks and financial institutions rose from 7.97% in 2019 to 18.06% in 2023, while loans to customers declined from 92.03% to 81.94%. This transition was likely driven by the National Bank of Serbia's monetary policy measures, particularly the increase in interest rates on repurchase agreements (REPO), aimed at reducing excess liquidity and controlling inflation.

During the analyzed period, the customer loan portfolio exhibited dynamic shifts (see Figure 1). Investment loans decreased slightly from 29.87% to 26.13%, while liquidity and working capital loans increased from 24.52% to 28.94%, indicating an increased focus on short-term funding needs. Housing loans demonstrated a consistent upward trend, rising from 18.84% to 20.07%, highlighting a growing emphasis on real estate financing. Conversely, uncollateralized household loans gradually declined from 26.77% to 24.86%, suggesting changing borrower preferences or tighter lending standards. Overall, these shifts reflect evolving market conditions and strategic priorities within the lending landscape during increased uncertainty and global economic disruptions, driven by the COVID-19 pandemic and geopolitical turmoil. During the analyzed period, the customer loan portfolio underwent notable shifts (see Figure 1).

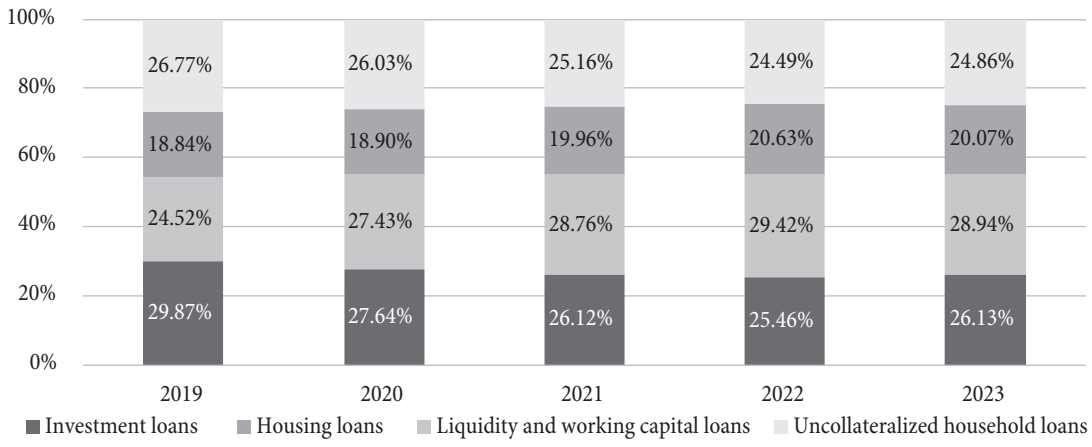
Our research findings indicate that during the period of escalating uncertainty associated with the COVID-19 pandemic and international conflicts, the proportion of loans classified as Stage 1 experienced a significant decline. Concurrently, there was a substantial increase in the share of loans classified as Stage 2, suggesting a notable shift from Stage 1 to Stage 2 during these crises. Importantly, our analysis revealed no significant increase in loans classified as Stage 3 (see Tables 7 and 8). In fact, this category saw a marginal decrease. These findings imply that, while there was a substantial rise in credit risk exposure reflected in the increased share of Stage 2

Table 6: Dynamics of the total loan portfolio

Gross loans	2019	2020	2021	2022	2023
Gross loans to banks and other financial institutions	7.97%	8.04%	9.78%	11.72%	18.06%
Gross loans to customers	92.03%	91.96%	90.22%	88.28%	81.94%

Source: Authors' calculation based on publicly available financial statements

Figure 1: Dynamics of the customer loan portfolio



Source: Authors' calculation based on publicly available financial statements

loans, the crises did not correlate with an increase in non-performing loans (NPLs). This observed trend during the COVID-19 pandemic can primarily be attributed to various government measures aimed at facilitating repayment for borrowers significantly impacted by the pandemic. Such measures may have played a critical role in mitigating a significant rise in loans classified as Stage 3. In the context of the Russo-Ukrainian conflict, Serbia's position relative to other EU countries regarding sanctions is underscored by an influx of Russian entrepreneurs and the maintenance of trade relations. Despite the geopolitical tensions and Western sanctions on Russia, Serbia continues to prioritize its energy security by relying on Russian supplies to meet domestic needs. Consequently, the classification of loans into Stage 3 largely depends on bank-specific characteristics and significant individual losses rather than general economic conditions and macroeconomic trends.

During analyzed period, National Bank of Serbia adopted significant regulatory activities and measures supporting citizens and the economy in overcoming the negative effects of the aforementioned events. These measures significantly influenced the parameter estimates of the ECL model, particularly the PD component, which in turn affected loan loss provisions and the overall cost of risk. In March 2020, the NBS enabled a 90-day moratorium for borrowers (citizens and businesses), and in July 2020, an additional moratorium was offered. In December 2020 the NBS introduced additional repayment facilities for debtors particularly affected by the pandemic. Measures were extended due to the persistent effects of the pandemic throughout 2021. Also, for debtors in the agricultural sector, since October 2022, the rescheduling of existing liabilities was enabled by postponing the repayment of principal liabilities for a period of six to twelve months. Considering that housing loans in Serbia are predominantly indexed in euros and contracted at variable interest rates, in response to the significant rise in EURIBOR rates, the NBS in September 2023 temporarily imposed a cap on the interest rates for housing loans in euros [23].

Our findings reveal a notable increase in the cost of risk ratio during periods of crisis (see Table 9). In 2020, the cost of risk rose to 0.81%, largely attributed to the economic disruptions caused by the COVID-19 pandemic. The upward trend persisted into 2021, reflecting the prolonged effects of the pandemic and the continued vulnerabilities in the economy. A marked increase in the cost of risk to 1.51% was observed in 2022, coinciding with the onset of the Russo-Ukrainian conflict, which introduced further economic uncertainties and pressures. By 2023, the cost of risk slightly decreased, indicating some degree of stabilization within the banking sector, with no significant impact from the Israeli-Palestinian conflict that commenced. Overall, the average cost of risk rose from 0.37% in the pre-crisis period to 1.15% during the global disruptions, emphasizing the marked influence of these overlapping crises on credit risk (see Table 10). The increase in the cost of risk coincided with the transition of loans from Stage 1 to Stage 2, reflecting a substantial rise in credit risk exposure, with no significant influence from Stage 3 loans, whose proportion remained relatively stable with a slight decline. Based on this analysis, we can conclude that had the ICL model established in IAS 39 been applied during the recent global turmoil, there would likely have been no increase in annual LLPs. In the context described, the rise in LLPs was not attributable to an increase in NPLs that demonstrate objective evidence of default. Instead, it arose from an increase in ECL as mandated by IFRS 9, reflecting both the 12-month ECL related to performing loans and the lifetime ECL associated with loans that have shown a significant increase in credit risk, based on forward-looking information regarding credit quality.

The positive coefficient for UNCOLAT is significant at the 0.01 level, indicating that an increase in the share

Table 7: Distribution of loans by stages

Year	Stage 1	Stage 2	Stage 3
2019	89.86%	6.19%	3.95%
2020	84.43%	12.06%	3.51%
2021	87.08%	9.44%	3.48%
2022	83.17%	13.88%	2.95%
2023	81.95%	14.94%	3.11%

Source: Authors' calculation based on publicly available financial statements

Table 8: Average loan share by stages: pre-crisis vs. crisis period

Year	Stage 1	Stage 2	Stage 3
Pre-crisis Period	89.86%	6.19%	3.95%
Period of Global Disruptions	84.16%	12.58%	3.26%

Source: Authors' calculation based on publicly available financial statements

Table 9: Cost of risk over the analyzed period

Year	2019	2020	2021	2022	2023
Cost of Risk	0.37%	0.81%	0.93%	1.51%	1.33%

Source: Authors' calculation based on publicly available financial statements

of uncollateralized household loans in a bank's portfolio is associated with higher loan loss provisions under the ECL model. This suggests that banks with a greater proportion of unsecured household loans, on average, recognize higher loan loss provisions compared to their peers. Additionally, the interaction term UNCOLAT x λ_t was positive but not statistically significant, suggesting that the relationship between uncollateralized household loans and loan loss provisions does not significantly intensify during economic downturns (2020-2023). While the uncollateralized nature of these loans theoretically presents higher risks during periods of increased uncertainty and disruption, the lack of significance suggests that these risks are effectively mitigated by the government measures implemented. As a result, these policies seem to reduce the potential for higher credit losses during such challenging periods.

The regression results indicate that the coefficient for HOUSING is negative but not statistically significant. However, the interaction term HOUSING x λt has a significant negative coefficient ($p < 0.01$), suggesting that this relationship changes during economic disruptions (2020-2023). Banks that hold a larger share of housing mortgage loans during periods of distress are likely to experience relatively smaller losses compared to their counterparts. This disparity indicates that the characteristics of mortgage loans, particularly their backing by real estate, provide a buffer against risks associated with fluctuating economic conditions, thus enhancing the stability of banks' financial performance during challenging times. This phenomenon likely results from the interplay between effective government support strategies and the inherent resilience of mortgage-secured properties, which have maintained their value despite crises stemming from the COVID-19 pandemic and geopolitical turmoil. Furthermore, this may suggest that banks operating in Serbia maintain strict approval policies for housing loans, resulting in lower loan loss provisions for these loans during economic turbulence compared to other types of credit.

Table 10: Average cost of risk – pre-crisis vs. crisis period

Period	Pre-crisis Period	Period of Global Disruptions
Cost of Risk	0.37%	1.15%

Source: Authors' calculation based on publicly available financial statements

The findings indicate that the share of investment corporate loans (the coefficient for INVEST) has a positive and statistically significant effect on recognized expected credit losses ($p < 0.05$). This suggests that, all else being equal, banks with a larger proportion of corporate loans tend to report higher expected credit losses. Furthermore, the macroeconomic and regulatory environment plays a crucial role in shaping this relationship, as evidenced by the statistically significant positive coefficient linked to the interaction between the share of investment corporate loans and fixed time effects. This positive coefficient indicates that during times of uncertainty, the disparity in recognized expected credit losses widens between banks with a higher proportion of investment loans and those with lower proportions. Specifically, banks holding a larger share of investment loans tend to incur relatively greater losses amid escalating macroeconomic instability. These findings imply that even though investment loans are typically collateralized with long-lived assets, they often exhibit more volatile credit performance due to their sensitivity to business cycle fluctuations. The adverse impacts of economic contractions seem to outweigh the mitigating influence of government support measures. Consequently, this underscores the necessity for banks to carefully evaluate their corporate loan exposure during periods of economic turbulence, highlighting the critical interplay between loan portfolio composition and external economic factors. Additionally, this may suggest that banks operating in Serbia have less stringent and more flexible policies regarding the approval of investment loans compared to housing loans. Both types of loans are secured by collateral, yet they demonstrate different behaviors in terms of loan loss provisions during periods of distress.

Finally, the coefficients for LIQWC and the interaction term LIQWC x λt are positive but statistically insignificant, suggesting a potential positive influence on loan loss provisions and a change in this relationship during economic disruptions, but the lack of statistical significance

indicates that these effects are not sufficiently robust to draw firm conclusions.

The coefficient for LOANGROWTH is positive, indicating that an increase in the growth rate of loans is associated with a slight rise in expected credit losses, although this effect is not statistically significant. This finding aligns with the hypothesis that loan growth could positively impact the level of loan loss provisions, but the effect is minimal due to recent regulatory requirements that mandate newly originated loans classified under Stage 1 to be subject to a 12-month ECL recognized in profit and loss. Consequently, since these new loans typically result in minimal or negligible loan loss provisions (LLPs), the overall impact on recognized expected credit losses remains insignificant.

The coefficient for SIZE is positive and statistically significant at the 0.01 level indicating that larger banks tend to report higher loan loss provisions (LLPs). This finding aligns with the perspective presented by Anandarajan, Hasan, and Lozano-Vivas (2003), who suggest that larger banks may maintain higher LLPs to compensate for the risks associated with their greater levels of business activities [2]. Besides, larger banks often benefit from higher-quality ECL models and financial reporting practices, undergo more rigorous audits, and face greater regulatory scrutiny. Additionally, larger banks operating in Serbia tend to be more profitable, and this higher profitability allows for greater room to recognize loan loss provisions (LLPs), as bank management may be motivated to engage in aggressive earnings management practices, such as income smoothing, particularly during economic downturns.

Table 11: Model Estimation Results

Dependent variable: CoR_Lagged#	
Regressor	**Coefficient**
UNCOLAT	0.0745199***
HOUSING	-0.0256179
INVEST	0.0727629**
LIQWC	0.0066213
UNCOLAT x λt	0.0078202
HOUSING x λt	-0.0925262**
INVEST x λt	0.0138106*
LIQWC x λt	0.0159665
LOANGROWTH	0.0043572
SIZE	0.0362787***
Intercept	-0.7422732***
Fixed effects	**Test of significance (p-value)**
time-invariant (individual)	575.64 (0.0000)
Time	462.17 (0.0000)
Regressors	**Joint F test**
UNCOLAT, UNCOLAT x λ_t	17.94***
HOUSING, HOUSING x λ_t	6.47**
INVEST, INVEST x λ_t	7.40**
LIQWC, LIQWC x λ_t	0.81
Model specification quality	**Values**
R^2	0.6788
Model significance (Wald χ^2)	1,010.52 (p=0.0000)

Linear regression, correlated panel-corrected standard errors (PCSEs)
***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.
Source: Authors' presentation based on the Stata output

Concluding remarks

The timing of IFRS 9's implementation coincided with significant global crises, including the COVID-19 pandemic and geopolitical conflicts, which dramatically increased credit risks worldwide. These events have served as a major test of the effectiveness of IFRS 9 and its ECL model. While existing research has examined ECL dynamics during COVID-19, there is limited analysis of how recent geopolitical crises (e.g., the Russian-Ukrainian war and the Israeli-Palestinian conflict) influence credit risk. Our study extends this understanding by incorporating these events, highlighting the complex interplay of macroeconomic, regulatory, and bank-specific factors that shape ECL responses in times of heightened uncertainty.

Our study analyzes the factors influencing loan loss provisions in Serbian banks from 2019 to 2023, focusing on macroeconomic conditions, regulatory measures, and bank-specific factors amid heightened uncertainty due to COVID-19 and geopolitical conflicts. Based on Dejuan-Bitria and Gómez Biscarri (2024), our model incorporates macroeconomic indicators, bank-specific factors, and loan growth to analyze the determinants of loan loss provisions during economic downturns caused by global crises.

Our analysis indicates that during periods of increased uncertainty from the COVID-19 pandemic and geopolitical conflicts, Serbian banks experienced a shift from Stage 1 to Stage 2 loans, with no significant increase in Stage 3 loans, likely due to effective government support measures. Stage 3 loan classification primarily depends on bank-specific factors and significant individual losses, rather than macroeconomic trends driven by geopolitical

turmoil. The cost of risk rose sharply during these crises, primarily driven by a significant shift of loans from Stage 1 to Stage 2. In banks operating in Serbia, a slightly lower level of expected credit losses (ECL) was observed in the year of the COVID-19 outbreak compared to European banks. However, in subsequent years ECL continued to increase in Serbia whereas it reverted to pre-pandemic levels among European banks. This divergence may be attributed to several factors including the implementation of numerous effective government measures in Serbia in 2020. The prolonged impact of the pandemic extending into 2021 was more significant in Serbia than in most European countries. Additionally, the initial use of more optimistic estimates and inputs by domestic banks in their ECL models during the early stages of the crisis may have contributed. Moreover, the worsening macroeconomic forecasts driven by geopolitical turmoil especially the high inflation rates in 2022 and 2023 likely played a role [21].

Our findings indicate that uncollateralized household loans are associated with higher expected credit losses. However, this relationship does not appear to significantly strengthen during the analyzed economic downturns, likely due to government measures that help mitigate potential losses. Conversely, housing mortgage loans backed by real estate proved to be more stable during crises, resulting in smaller credit losses. This stability may be attributed to the resilience of real estate values during the period, effective government support initiatives, and stringent approval policies. The share of corporate investment loans increases expected credit losses, especially during periods of economic uncertainty. This underscores their higher volatility and highlights the importance of thorough risk assessment. Overall, bank-specific factors and the characteristics of different loan types play a critical role in shaping credit risk and loan loss provisions during turbulent economic times.

The practical implications of our research suggest that banks should carefully manage their credit portfolios, paying particular attention to uncollateralized household loans such as cash and credit card loans, which pose higher risks during periods of economic uncertainty. Prioritizing collateralized loans, especially housing mortgages, can enhance resilience during downturns, particularly when supported by strict approval policies and government measures that help mitigate potential losses. Additionally, corporate investment loans, which tend to be more volatile during crises, require more stringent credit approval standards and continuous monitoring. The dynamics of the customer loan portfolio identified in our research (see Figure 1) indicate that, on average, banks operating in Serbia managed the portfolio as suggested. We also emphasize that regular stress testing, incorporating geopolitical and macroeconomic scenarios, is essential. Overall, adopting comprehensive risk management strategies across all loan types will better prepare banks to navigate periods of economic and geopolitical turbulence more effectively.

The key contribution of our research is providing empirical evidence on how different loan types and bank-specific factors influence loan loss provisions during economic downturns. It extends existing studies by incorporating recent geopolitical upheavals, such as the Russia-Ukraine war and the Israeli-Palestinian conflict, highlighting their impact on Serbian banks. The study emphasizes the importance of macroeconomic, regulatory, and internal bank factors, as well as the vital role of government support measures in mitigating credit risk during crises. Additionally, this paper represents a significant methodological advancement in ECL analysis by employing panel regression with time-fixed effects to accurately capture systemic expected credit losses driven by macroeconomic and regulatory factors. The introduction of interaction terms between these effects and loan portfolio structure enables a more detailed analysis of how portfolio composition influences loss provisions during economic downturns. Additionally, incorporating individual fixed effects enhances robustness by controlling for unobserved heterogeneity such as managerial discretion and ECL model misapplication.

However, this study has certain limitations. The reports from which data were collected lacked sufficient standardization, particularly concerning information on loan portfolio structure. Additionally, due to reliance on publicly available data, the research could not analyze the impact of internal policies specific to individual banks. Basing the analysis solely on the Serbian banking sector raises questions about the generalizability of the findings to

other countries. Therefore, comparative studies examining how differences in macroeconomic and regulatory environments influence outcomes are recommended. Future research could expand the time frame of analysis to examine potential delayed effects of regulatory measures on the development of ECL. Additionally, it is important to examine the extent to which Serbian banks may utilize the ECL model for earnings management and to investigate other factors influencing the abnormal component of loan loss provisions.

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