# Bank Non-Performing Loans – a Panel Data-Based Analysis in European Context. Study Case: Germany

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## Abstract

Humanity has recently been crossed by periods of great crises, and banks have had a particularly important role in keeping the economy afloat and in relaunching economic activities in these difficult periods. If we refer to the stability, health and efficiency of the banking system, one of the important factors mentioned in the specialized literature is the size of Non-Performing Loans. The present work carries out a time and space analysis of this indicator for the EU member countries, observing its behavior during major crises. Thus, in the distribution of European countries there was a decrease in the median level of the indicator and in its variability, but also an increase in the predominance of countries with low non-performing loans ratio. At the same time, the case of Germany is studied, with the strong and weak points of its banking system and the key determinants of the rate of non-performing loans, for the main commercial banks in Germany are identified, using a panel data regression model. The results revealed that the indicator-level is negatively and significantly correlated with the loan-deposit ratio and the degree of financial profitability and positively and significantly correlated with the total value of assets and the degree of capital adequacy. From this emerges the need to promote policies to stimulate the prudent behavior of banks in granting loans, in order to ensure the stability and health of the banking system in European countries.

## Keywords

Bank Non-Performing Loans to Total Gross Loans, Total Assets, Return on Average Equity, Loan-to-deposit ratio, Total Capital Ratio.

## Introduction

In specialized literature "Bank nonperforming loans to total gross loans are the value of nonperforming loans divided by the total value of the loan portfolio (including nonperforming loans before the deduction of specific loan-loss provisions). The loan amount recorded as nonperforming should be the gross value of the loan as recorded on the balance sheet, not just the amount that is overdue." (World Bank, 2023). Nonperforming loans influence banks' ability to grant and allocate loans efficiently, as well as banks' risk aversion, potentially affecting the stability of the financial system and economic growth (Foos, Norden and Weber, 2010). Studies reveal that the size of Non-Performing Loans - in absolute or relative terms - is linked to the stability, health and efficiency of the banking system, being often identified as one of its key factors (Khan, Siddique and Sarwar, 2020; Ludwian and Soekarno, 2022). The present paper proposes a temporal and territorial analysis of this indicator for the EU member countries, observing its behavior during major crises and identifying the key determinants of the non-performing loans ratio, based on data collected from the main commercial banks in Germany. The work is structured in three sections, as follows:

in the first section, a review of the most representative studies in the specialized literature in this field and their main results is carried out; the second section presents the statistical-econometric methods applied and the statistical variables included in the analysis; the third section contains the main results obtained from the analysis, followed by discussions and conclusions.

## 1. Review of the scientific literature

Foos, Norden and Weber (2010) study the relationship between loan growth and banks' risk-taking behavior, based on a sample of commercial banks from European countries, for the period 1992-2004. The main conclusions of the study are: the existence of a direct correlation between the increase in loans and the bank risk-taking behavior, a more obvious correlation in the case of small banks, which are more likely to take excessive risks when faced with a pronounced increase in loans. The connection between the two indicators is more obvious in periods of economic expansion, characterized by high economic growth.

Khan, Siddique and Sarwar (2020) identify the main determinants that lead to the emergence of non-performing loans in the banking sector in developing countries, taking Pakistan as a case study. The analysis is based on panel data from 22 commercial banks in Pakistan, in the period 2005-2017 and examines the impact of different variables, specific to the banking field, on Non-Performing Loans. The authors come to the conclusion that the bank profitability, the operating efficiency, the bank capital and the income diversification have a significant and negative impact on the variability in the Non-Performing Loans.

Viswanadham and Nahid (2015) identify several factors that have a significant influence on the level of Non-Performing Loans in commercial banks, among which we mention: interest rate, concentration of credit, supervision activity of bank loans, but they also highlight a series of macroeconomic factors that can affect the level of Non-Performing Loans, for example the GDP growth. The authors used the data collected from a survey with 152 respondents, to assess the impact of these factors on Non-Performing Loans.

Ludwian and Soekarno (2022) analyze the relationship between the rate of non-performing loans and the operational efficiency of the bank, based on data taken from the Banking Statistical Reports in Indonesia, and covering the period January 2010 - September 2021. The results show that each banking group (cluster) in the banking system of the country behaved differently in terms of the association between problematic loans and operational efficiency, and the bad management and bad luck hypotheses were tested separately for each cluster. The authors suggest the need for the authorities to develop clear, relevant and individualized regulations for each group (cluster) separately, depending on its behavior.

Banks have a particularly important role in keeping the economy afloat and in relaunching economic activities in times of crisis. Karadima and Louri (2020) think that the consolidation of the banking sector manifested itself as a common trend in the Euro area countries after the global-financial crisis of 2007-2008. Thus, throughout this period, the phenomenon of fragmentation in the banking industry has been maintained, and the presence of large stocks of Non-Performing Loans contributes to the fragmentation between the countries of the Euro area. In a document of the European Commission (2022) on non-performing loans it is shown that the banks also played a key role in mitigating the effects of the pandemic crisis in 2020, because - due to the impact of this pandemic on the economy, it is expected that in the period following the crisis, the size of non-performing loans to grow in EU countries.

In the McKinsey&Company Report (2021) – "German banking returns to the playing field", *Global Banking Practice* it is shown that although the banking industry has over time had a key role in supporting the country's economy, offering support in relaunching economic activities in times of crisis, the relevance of this sector is decreasing, say some specialists. Others are of the opinion that the renowned resistance of the German banking system will speak for itself, and the banking system will adapt - through successful transformations and a solid strategy - to the new economic-social realities, to the new technologies. In this sense, Hock and Giebe (2022) show that the integration of Big Data analysis in the German banking industry is a possible solution to current challenges, such as increasing competition or changing customer requirements. At the same time, the McKinsey&Company Report (2021) provides a brief characterization of the German banking system, with German banks having a reputation for being stable, reliable and providing essential services at competitive prices. After the period of the global financial crisis of 2008, these banks acted prudently, performing a good risk management. Although the number of banking branches has registered a continuous decrease after the global financial crisis, there is still a considerable density of banking units, higher than many other European countries. Some banks lost their market share, but the banking industry still remained quite fragmented and characterized by low efficiency. A similar idea can be found in the report of the International Monetary Fund: "Germany: Financial Sector Assessment Program, Technical Note—The Determinants of Bank Profitability" (2022). The authors estimate that German banks are

less profitable than the global standard and than those in Europe, despite better risk-adjusted measures, which is partly explained by the complex structure of the German banking system, which favors fragmentation and prioritizes the well-being of shareholders over profits. The authors suggest that a mix of cost-cutting and revenue-generating measures should be taken to develop sustainable business models.

## 2. Data and methodology

In order to quantify the risk in bank loans, the variable *Non-Performing Loans to Gross Loans* (%) was selected, with values recorded at macro level (of European countries) and micro level (of commercial banks), allowing a more detailed analysis of the degree of risk that accompanies the banking activity from a double perspective. The macro-level values of the indicator refer to 27 European countries (26 EU member countries, to which Great Britain is added), and are recorded over a period of approximately one decade (2010-2021), being provided by the World Bank database. The micro-level values of the indicator refer to the 18 most important commercial banks in Germany, a country with a robust banking system, recognized for its stability, even if it is below European profitability standards. The micro data were recorded for the period 2013-2021 and were provided by the ORBIS database. In order to determine some significant influencing factors that explain the variation in risk when granting credits, five other financial indicators were selected, presented in Table no. 1.

**Table no. 1. List of statistical variables included in the analysis.**

| Indicator name | Measurement unit | Space/time coordinates | Source |
|---|---|---|---|
| Non Performing Loans / Gross Loans (macro-level) | % | 27 European countries 2010-2021 | World Bank database https://data.worldbank.org/indicator/FB.AST.NPER.ZS |
| Non Performing Loans / Gross Loans (NPL_GL) (micro-level) | % | 18 commercial banks (Germany) 2013-2021 | ORBIS - https://www.bvdinfo.com/en-gb/our-products/data |
| Total assets (TA) | thousand USD | | |
| Return on Average Equity (ROAE) | % | | |
| Loan-to-deposit ratio (Net Loans / Dep. & ST Funding) (NL_STF) | % | | |
| Total Capital Ratio (TCR) | % | | |
| Listing status (LS) (1=listed, 0=non-listed) | Binary variable | | |

*Source: authors' selection.*

The applicative part of the research begins with an analysis over time and in territorial profile of the variable *Non-Performing Loans to Gross Loans*, the variable that characterizes the risk that banks take when granting loans. Both statistical methods specific to time and territorial series were used, as well as descriptive statistical analysis of univariate data, in order to characterize the central tendency, the variability and the shape of the distribution of European countries by the rate of non-performing loans, as well as the changes that occurred over time in this distribution during economic or health crises.

The next stage of the analysis aimed to identify the main determinants of *Bank nonperforming loans to total gross loans*, using a regression model on panel data at the level of commercial banks in Germany (balanced panel). The dependent variable is *Bank nonperforming loans to total gross loans*, while the variables: *Total assets* (thousand USD) – standardized by z-scores, *Loan-to-Deposit-Ratio* (Net Loans / Dep. & ST Funding) (%), *Return on Average Equity* (ROAE) (%), *Total Capital Ratio* (%) and *Listing status* (binary variable) were considered independent variables. The sample included 18 cross-sections (commercial banks from Germany) and 9 time-units (9 years, from 2013 to 2021), summing up a total of 162 observations for each of the 6 variables included in the model.

In order to verify the validity of including the 6 variables in the panel data regression model, the stationarity of the time series was tested with the Levin, Lin, Chu test. The null hypothesis ($H_0$) and the alternative hypothesis ($H_1$) of this test are: $H_0$: the series has a unit root (non-stationary series); $H_1$: the series does not have a unit root (stationary series). If Prob. $> 0.05$ => the null hypothesis $H_0$ is accepted, the series is non-stationary, and if Prob. $< 0.05$ => there is insufficient reason to accept the null hypothesis $H_0$, therefore accept the alternative hypothesis $H_1$, that the series is stationary. To analyze the existence of the multicollinearity phenomenon between the explanatory variables, the correlation matrix was used, detecting the existence of strong correlations between two variables, in which case one of these variables can be

excluded from the model. The fixed effects regression model and the random effects one were applied, then the best model between the two was selected. In the model with fixed effects, it is assumed that the differences between individuals (in this case between banks) can be explained by the specific conditions of the individual (bank), the specific individual effect being a random variable that can be correlated with the explanatory variables. On the contrary, in the random effects model this specific individual effect represents a random variable that is not correlated with the explanatory variables (Zulfikar, 2018; Schmidheiny, 2022). To identify the best regression model (with fixed or random effects), the Hausman test was applied, whose null hypothesis is: $H_0$: the unobserved effects of the model are not correlated with the causal variables. If Prob. > 0.05 => $H_0$ is accepted, the best model is the one with random effects, and if Prob. < 0.05 => not enough reason to accept $H_0$, therefore accept $H_1$, the best model is the fixed-effects model.

## 3. Results and discussions

The first part of the analysis focuses on a statistical indicator that quantifies the degree of risk that banks take on loans: *Bank nonperforming loans to total gross loans* (%). The purpose of this analysis is to characterize the stability in the banking industry of the different EU member countries and to see what was the behavior of the banking systems in these countries during the major crises, from this indicator point of view. Based on the World Bank data for the period 2010-2021 and for 27 EU member countries (UK included, although the country officially left the EU in 2020) it can be observed that – at EU level - there were two sub-periods in which the indicator had opposite trends. Thus, in the first part of the analyzed period (2010-2013), the period that immediately followed the global financial crisis of 2008-2009, Bank nonperforming loans to total gross loans registered an increase from 6.36% to 9.07%, which affected the stability of the banking activity. After 2013, the level of the indicator followed a downward slope, which was maintained until 2021, when *Bank nonperforming loans to total gross loans* decreased 3.5 times compared to the maximum level in 2013. During the COVID-19 pandemic crisis the indicator continued its decline, reaching only 2.57% in 2021 (EU-average level). There was, however, a great variation in territorial profile, between the EU member countries throughout this period. The record regarding the rate of non-performing loans was held by Southern European countries, led by Greece and Cyprus (countries where in 2016-2017 almost half of the loans granted by banks were non-performing), followed by Italy and Portugal. At the opposite pole, with a low bank loan-risk were Switzerland, Luxembourg, Finland and Sweden, countries with a recognized stability of the banking industry and with maximum values of the indicator that barely exceeded 1%.

In the next stage of the analysis, the distribution of European countries was characterized by *Bank nonperforming loans to total gross loans* in three years: 2011 (immediately after the global financial crisis of 2008-2009), 2019 (before the COVID-19 pandemic crisis) and 2021 (immediately after the pandemic crisis, although at that time it had not completely ended). The purpose of this analysis was to identify possible significant changes in the behavior of European countries from the perspective of risk in the bank activity, which could jeopardize the stability of the banking systems in those countries. Following the descriptive analysis of the indicator, a reduction of the central tendency was observed (the average level decreased from 6.9% in 2011 to 4.27% in 2019 and to 2.57% in 2021), indicating a reduction in the risk of loans and an increase in the stability of banking activity. The variation in the territorial profile was greater in 2011 and in 2019, then decreasing in 2021, which shows a prudent behavior of banks when granting loans, after the pandemic crisis. The shape of the distribution of countries by this statistical variable have changed significantly, while in 2011 the distribution was moderately positively skewed and close to the normal distribution, in the years before and after the pandemic crisis the skewness grew strongly, countries with low shares of non-performing loans predominated. At the same time, in the period immediately following the financial-global crisis from 2008-2009 the distribution was platykurtic, but during the pandemic crisis it became leptokurtic (with a higher degree of kurtosis in 2019), the indicator values are concentrated around the mean to a greater extent than in the normal distribution, and the probability occurrence of outlier values is higher (indeed, outlier values were recorded in Greece and Cyprus) (Figures no. 1 and 2).
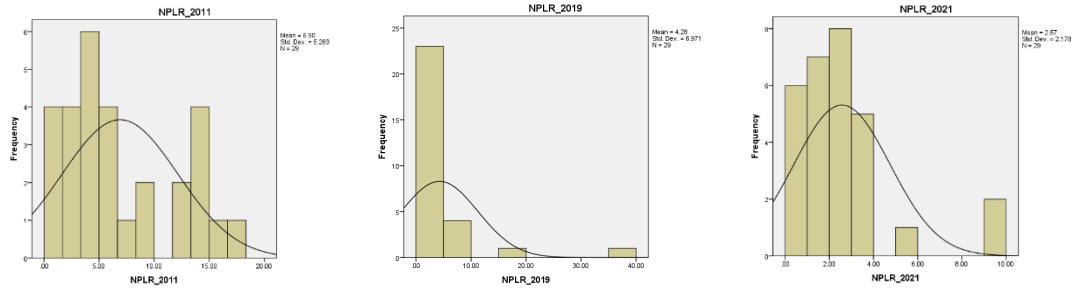
**Figure no. 1. Histogram of EU-member countries by the Bank nonperforming loans to total gross loans (%) in 2011, 2019 and 2020.**
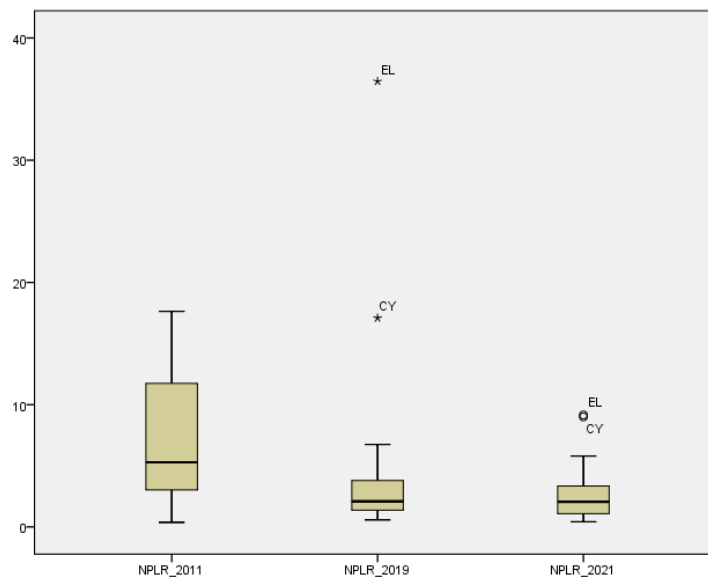*Source: authors' contribution, based on World Bank data.*



**Figure no. 2. Box-and-Whisker Plot of EU-member countries by the Bank nonperforming loans to total gross loans (%) in 2011, 2019 and 2020.**
*Source: authors' contribution, based on World Bank data.*

The next stage of the analysis aimed to identify the main determinants of *Bank nonperforming loans to total gross loans*, using a regression model on panel data at the level of commercial banks. For this, 18 commercial banks from Germany were selected, for which the following financial indicators relating to the period 2013-2021 were recorded: *Non-Performing Loans / Gross Loans* (%), *Total assets* (thousand USD), *Loan-to-Deposit-Ratio* (Net Loans / Dep. & ST Funding) (%), *Return on Average Equity* (ROAE) (%), *Total Capital Ratio* (%) and *Listing status* (binary variable). The selected explained variable was *Non-Performing Loans / Gross Loans*, the other variables being considered explanatory variables. In the first phase, the stationarity of the time series involved in the regression analysis was tested, using the Levin, Lin, Chu test. The results showed that - for a significance level of 5% - all time series are stationary and therefore can be integrated in the regression model (Table no. 2).

**Table no. 2. Stationarity test results for the variables included in the regression model**

| Null Hypothesis: Unit root (common unit root process) | | Newey-West automatic bandwidth |
|---|---|---|
| Series: NPL_GL, TA, NL_STF, ROAE, TCR | | selection and Bartlett kernel |
| Sample: 2013 2021 | | Total (balanced) observations: 126 |
| Exogenous variables: Individual effects, individual linear trends | | Cross-sections included: 18 |
| User-specified lags: 1 | | Method: Levin, Lin & Chu |
| Variable | Statistic | Prob |
| NPL_GL | -9.15474 | 0.0000 |
| TA | -10.1149 | 0.0000 |
| NL_STF | -6.53468 | 0.0000 |
| ROAE | -6.04313 | 0.0000 |
| TCR | -11.9302 | 0.0000 |

*Source: authors' processing results, based on ORBIS data - https://www.bvdinfo.com/en-gb/our-products/data.*

The multicollinearity phenomenon between the explanatory variables was analyzed using the correlation matrix. Since a strong correlation was observed between the variables *Listing status* (LS) and *Total assets* (TA), we selected the latter variable for the regression model, as we believe it generates more numerical information.

For the panel regression model with random effects that reveal the dependence of the Nonperforming loans ratio on the other explanatory variables, the following results were obtained (Table no. 3):

**Table no. 3. Panel regression model with random effects**

Dependent Variable: NPL_GL
Method: Panel EGLS (Cross-section random effects)
Sample: 2013 2021
Periods included: 9
Cross-sections included: 18
Total panel (balanced) observations: 162
Swamy and Arora estimator of component variances

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| NL_STF | -0.055614 | 0.014076 | -3.950948 | 0.0001 |
| ROAE | -0.312274 | 0.044625 | -6.997716 | 0.0000 |
| TA | -0.00000000358 | 0.00000000142 | -2.511712 | 0.0130 |
| TCR | 0.132894 | 0.006261 | 21.22567 | 0.0000 |
| C | 8.576508 | 1.498423 | 5.723689 | 0.0000 |
| Statistics | | | | |
| R-squared | 0.745630 | Mean dependent var | | 6.566123 |
| Adjusted R-squared | 0.739149 | S.D. dependent var | | 14.89409 |
| S.E. of regression | 7.606936 | Sum squared resid | | 9084.880 |
| F-statistic | 115.0529 | Durbin-Watson stat | | 0.742925 |
| Prob(F-statistic) | 0.000000 | | | |

*Source: authors' processing results, based on ORBIS data - https://www.bvdinfo.com/en-gb/our-products/data.*

The regression model with random effects is:

$$NPL\_GL_{it} = 8.57 - 0.055 * NL\_STF_{it} - 0.31 * ROAE_{it} - 0.0000000035 * TA_{it} + 0.13 * TCR_{it} + u_{it} \qquad (1)$$

Where: $i$=the bank, $t$=the year, $u$ = the residual.

In this random-effects regression model, all the parameters of the explanatory variables are statistically significant (having probabilities lower than 0.05), which means that all the independent variables have a significant influence on the variation of the dependent variable (NPL_GL). The loan-to-deposit ratio (NL_STF), financial return (ROAE) and total asset value (TA) have an inverse influence on the variation of the non-performing loans rate (NPL_GL) – their coefficients being negative. The capital adequacy ratio (TCR) is positively correlated with the dependent variable (NPL_GL) – the coefficient of this explanatory variable being positive. At a 1% increase in the loan-to-deposit ratio, it can be estimated that the non-performing loans ratio decreases, on average, by 0.055%, while a 1% increase in financial profitability will lead to an estimated average reduction in the non-performing loans ratio of 0.31%. Increasing total assets by 1 million USD leads to a decrease in the non-performing loans ratio by 0.00000358 % (on average), while a 1% increase in the capital adequacy ratio implies a 0.13% increase in the value of the explained variable (assuming that all other explanatory variables do not change). To identify the best regression model (with fixed or random effects), the Hausman test was applied and the results are as follows (Table no. 4):

**Table no. 4. Hausman test results**

Correlated Random Effects – Hausman Test
Equation: Untitled
Test cross-section random effects

| Test Summary | Chi-Sq. Statistic | Chi-Sq. d.f. | Prob. |
|---|---|---|---|
| Cross-section random | 201.974920 | 4 | 0.0000 |

*Source: authors' processing results, based on ORBIS data - https://www.bvdinfo.com/en-gb/our-products/data.*

For a 5% significance level it turns out that there are not enough reasons to accept the null hypothesis of the test, so the alternative hypothesis is accepted and the best model is the one with fixed effects (Table no. 5).

**Table no. 5. Panel regression model with fixed effects**

| Dependent Variable: NPL_GL | | | | |
|---|---|---|---|---|
| Method: Panel Least Squares | | | | |
| Sample: 2013 2021 | | | | |
| Periods included: 9 | | | | |
| Cross-sections included: 18 | | | | |
| Total panel (balanced) observations: 162 | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| NL_STF | -0.055347 | 0.019209 | -2.881306 | 0.0046 |
| ROAE | -0.059830 | 0.051005 | -1.173024 | 0.2428 |
| TA | 0.0000000039 | 0.00000000627 | 0.621671 | 0.5352 |
| TCR | 0.027562 | 0.009789 | 2.815678 | 0.0056 |
| C | 12.07211 | 2.263834 | 5.332593 | 0.0000 |
| Cross-section fixed | | | | |
| R-squared | 0.949828 | Mean dependent var | | 9.582804 |
| Adjusted R-squared | 0.942303 | S.D. dependent var | | 21.06118 |
| S.E. of regression | 5.058954 | Akaike info criterion | | 6.205848 |
| Sum squared resid | 3583.023 | Schwarz criterion | | 6.625151 |
| Log likelihood | -480.6737 | Hannan-Quinn criter. | | 6.376091 |
| F-statistic | 126.2105 | Durbin-Watson stat | | 1.793843 |
| Prob(F-statistic) | 0.000000 | | | |

*Source: authors' processing results, based on ORBIS data - https://www.bvdinfo.com/en-gb/our-products/data.*

The fixed-effects regression model equation is:

$$\text{NPL\_GL}_{it} = 12.07 - 0.055 * \text{NL}_{\text{STF}_{it}} - 0.06 * \text{ROAE}_{it} + 0.0000000039 * \text{TA}_{it} + 0.027 * \text{TCR}_{it} + \alpha_i + \varepsilon_{it} \quad (2)$$

The fixed effects model has a higher explanatory power on the variability in the dependent variable (explaining almost 95% of the variability), compared to the random effects model (for which R_Square is 74.56%). At the same time, both models are statistically valid (the probability associated with the F test being less than 0.05).

The loan-to-deposit ratio (NL_STF) and the degree of financial return (ROAE) have an inverse influence on the variation of the non-performing loan ratio (NPL_GL), while the total value of assets (TA) and the capital adequacy ratio (TCR) have a direct contribution to NPL_GL variation. (the parameter estimators of the first two explanatory variables are negative, while those of the last two variables are positive). However, not all the parameters of the explanatory variables are statistically significant, respectively ROAE and TA do not significantly influence the NPL_GL variation (as their associated probabilities, Prob exceed the significance level of 0.05: Prob(ROAE)=0.2428>0.05, Prob(TA) =0.5352>0.05).

1% increase in the loan-deposit ratio (NL_STF), leads to an average decrease in the non-performing loans rate (NPL_GL) by 0.055% (assuming that the other explanatory variables remain constant). Similarly, a 1% increase in capital adequacy leads to an estimated average increase of 0.027% in the values of the explained variable (if all other explanatory variables do not change).

**Conclusions**

The bank risk-taking behavior has been studied for a long time by specialists, in connection to the state of health, stability and profitability of the banking system. The banks have offered real support in the recovery of the economy after periods of major crises of various types, in restarting the activity, and the application of a prudent bank strategy in granting loans is a necessity in such a context. The researchers correlated the risk-taking behavior of banks in granting loans with numerous variables, some correlations being more evident in periods of economic growth. In this paper, this behavior was analyzed through the variable *Bank Non-Performing Loans to Total Gross Loans*, from a double perspective: a macroeconomic perspective - at the level of EU member states and a microeconomic perspective - at the level of commercial banks. For the first perspective, the indicator was analyzed in a territorial and temporal profile, identifying significant changes in its behavior, in major crises time periods (the global financial crisis of 2008 and the COVID-19 pandemic crisis in 2020), in a comparative way between EU countries or compared to the average EU level. A change in the distribution of countries by the level of this indicator was observed in 2011 (after the global financial crisis), in 2019 (pre-pandemic crisis) and 2020 (post-pandemic crisis): a decrease in the central tendency of *Bank Non-Performing Loans to Total Gross Loans*, a decrease in the variability in territorial profile, an increase in (positive) skewness, which means a predominance of countries with low non-

performing loans ratio, an emphasis on the prudent behavior of banks in granting loans and an increase in the stability of the banking system. At the same time, the probability of the occurrence of extreme values of the indicator increases. Using a regression model on panel data provided by the main commercial banks in Germany for the period 2013-2021, the main determinants of *Bank nonperforming loans to total gross loans* were identified. Thus, following the application of the panel regression model with fixed effects, (which proved to be better than the random effects model), it turned out that the *Bank nonperforming loans to total gross loans* is negatively and significantly correlated with the loan-deposit ratio and the degree of financial profitability and positively and significantly correlated with the total value of assets and the degree of capital adequacy.

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