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Master Program in Statistics and Information Management

The main drivers of a rise in the non-performing loans ratio

Case study for Portugal banking sector

Maria Catarina Silva Maltez Santos

Dissertation presented as partial requirement for obtaining the Master's degree in Statistics and Information Management

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THE MAIN DRIVERS OF A RISE IN THE NON-PERFORMING LOANS RATIO: CASE STUDY FOR PORTUGAL BANKING SECTOR

by

Maria Catarina Silva Maltez Santos

Dissertation presented as partial requirement for obtaining the degree in Statistics and Information Management, with a specialization in in Analysis and Risk Management

Advisor: Professor Rui Gonçalves

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RESUMO

O principal objetivo deste estudo é compreender os principais determinantes dos empréstimos em incumprimento em Portugal para o período de 2016-2021, para reduzir o impacto do risco de crédito vencido tanto no sector bancário como no estado económico e financeiro do país, uma vez o risco de crédito é considerado uma das maiores ameaças à estabilidade financeira (Kil K., & Miklaszewska, E., 2017).

Este ensaio pode ser particularmente pertinente uma vez que inclui um período peculiar, com dados a partir de 2016, quando ainda existiam ligeiros vestígios da crise da dívida soberana de 2010, uma das crises mais profundas e longas do país - consequência da crise financeira global de 2008 - até 2021, incluindo a crise pandémica do Coronavírus (COVID-19), cuja determinação do impacto é crucial.

O conjunto de dados tinha na sua composição variáveis macroeconómicas e variáveis específicas do setor bancário, nomeadamente o crescimento do PIB, a taxa de juro de obrigações governamentais a 10 anos e a taxa de desemprego, a rentabilidade dos ativos, a rentabilidade dos capitais próprios, o total dos empréstimos, a cobertura da exposição ao incumprimento, o custo do risco de crédito, o rácio de cobertura de liquidez e o rácio crédito em incumprimento, numa base trimestral, sendo que as variáveis específicas do setor bancário foram recolhidas dos seis maiores bancos portugueses. Foi então avaliado o impacto de cada variável num modelo de regressão linear produzido no SAS Miner e através de uma matriz de correlação. Finalmente, foram realizados quatro modelos de regressão combinados com variáveis diferentes para analisar o teste de significância, adequação do modelo e a sua qualidade, face aos resultados obtidos.

Os resultados mostraram que o aumento no nível de crédito vencido pode ser explicado tanto por variáveis macroeconómicas como microeconómicas. Foi possível concluir que o crescimento do PIB, o rácio NPL dos bancos, o ROA e o rácio LCR têm uma forte ligação com o rácio de crédito vencido em Portugal e explicam 38% do aumento da variável dependente (rácio de crédito vencido em Portugal).

PALAVRAS-CHAVE

Crédito vencido; Portugal; risco de crédito; setor bancário.

ABSTRACT

The main purpose of this paper is to understand the main determinants of non-performing loans in Portugal for the period of 2016-2021, to reduce credit risk on the banking sector and overall country's financial and economic, as credit risk it is classified one of the greatest threats to the financial stability of banks (Kil, K., & Miklaszewska, E., 2017).

This study can be particularly pertinent since it includes a unique period, from 2016, when there were still slight traces of the 2010 sovereign debt crisis, one of the most profound and long crises in the country – consequence of the 2008 global financial crisis – to 2021, including the Coronavirus (COVID-19) pandemic crisis, whose determination of impact is crucial.

The data consisted in both macro and specific variables, namely GDP growth, long-term government yield and unemployment rate, return on assets, return on equity, total loans, non-performing exposure coverage, credit risk cost, liquidity coverage ratio and NPL ratio, on a quarterly basis, with banking sector-specific variables collected from the five largest Portuguese banks. It was then evaluated the impact of each variable in a linear regression model produced in SAS Miner and through a correlation matrix. Finally, it was performed four combined regression model with different variables to analyze the significance test, model fit and quality from the results obtained.

The results showed that the high level of NPLs can be explained mainly by both macroeconomic and microeconomic factors. It was possible to conclude that GDP growth, banks NPL ratio, ROA and LCR ratio have a strong link with the NPL ratio in Portugal and explain 38% of the rise of the dependent variable.

KEYWORDS

Non-performing loans; Portugal; Credit risk; banking sector.

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LIST OF ABBREVIATIONS AND ACRONYMS

AIC………………………………………………………………………………………….. Akaike Information Criterion

BCBS………………………………………………………………………………Basel Committee on Banking Supervision

BIC…………………………………………………………………………………………. Bayesian Information Criterion

CNPE……………………………………………………………………………….… Coverage of Non-performing Exposure

DV……Dependent Variable

EBA…………………………………………………………...……………………………….….European Banking Authority

ECB……………………………………………………….……………………………………….….European Central Bank

GDP……………………………………………………………………………………………………Gross Domestic Product

GMM…………………………………………………………………………………….Generalized Method of Moments

IV………………………………………………………………………………………………………Independent Variables

LCR……………………………………………………………………………………………………Liquidity Coverage Ratio

NPL……………………………………………………………………………………………………Non-performing Loans

NPE……………………………………………………………………………………………… Non-performing Exposure

P&L…………………………………………………….……………………………………………...… Profits and Losses

ROA……Return on Assets

ROE……Return on Equity

VAR……. Value at Risk

RWA…………………………………………………………………………….………………… Risk weighted assets

INTRODUCTION

The perception of risk at both micro and macro levels materialized in the 1990s, which has led to a progressive increase of importance of risk management in the past decades, (Ali, A., & Daly, K., 2010) reaching its peak of importance immediately after the 2008 global financial crisis.

This global crisis was the turning point for risk management in the banking sector, which became much more aware of the consequences of financial risk and acted accordingly, with the elaboration of more precise banking systems regulating, namely the Basel III reforms.

This regulatory framework emerged as a response to the recent crisis, implementing the Basel III "for more resilient banks and banking systems" with the introduction of higher capital requirements as "It is critical that banks' risk exposures are backed by a high-quality capital base" (BCBS, 2010).

According to EBA definition, "non-performing loans or exposures are those that satisfy either of the following criteria: (a) material exposures that are more than 90 days past due; and (b) the debtor is assessed as unlikely to pay its credit obligations in full without realization of collateral, regardless of the existence of any past due amount or of the number of days past due."

Credit risk represent the leading cause for the increase of non-performing loans in the eurozone banking sector (Ciukaj, R. & Kil, K., 2020) and may consequently origin financial difficulties that can lead to insolvency and bankruptcy. This type of problems impacts not only the banking sector but also the overall country's economy, fragilizing the entire financial system (Konstantakis, K. N. et al., 2016).

Throughout the years several authors have been analyzing this topic and developing different approaches to identify the main correlations between the macroeconomic and bank-specific determinants and measure the impact on the quality of debt issuers, to prevent the occurrence of default. The main purpose of this research is to understand what is failing in the modelling of banks default probability such that there is an elevated level of NPL, and to apply to the practical case of Portugal during the 2016-2021 study period.

The rest of this dissertation is arranged as follows: the first section describes the background, studies objective and problem identification and relevance. The second section includes the literature review, namely on credit risk, non-performing loans, and risk management. The third section highlights the data methodology and application. The fourth section contain the Results analysis and finally the fifth section is composed of the discussion and conclusions of the study.

Non-performing loans affect the quality level of the lending activity and the banking system and represent one of the main responsible factors for the bank's collapse, so, "understanding the determinant of NPLs is immensely crucial to ensure the efficiency and soundness of the overall economy" (Rachman, R. A., 2018).

Risk management became increasingly important for the banking sector, to closely analyze the reasons and further mitigate default credit risk. In Portugal, strict supervision and severe measures were taken by the European regulatory bodies that conducted analyses on behavior of the country's financial outlook and implemented NPL reduction strategies to improve loan credit quality.

Non-performing loans have been a relevant issue for Portugal, especially in the 2008-2016 period, reaching the peak of 17,9% in 2016, product of the sovereign crisis.

Distress in the financial system often led to crises, by inducing a similar increase in the unemployment rate and decrease of the GDP per capita. Nevertheless, in recent years the NPL ratio has been reducing, since the pronounced mid-2016 peak, as a result of procedures from European policymakers and supervisors that have been targeting this indicator (Marques, C., Martinho, R., & Silva, R., 2020).

The ratio has been steadily declining from 2016, having reached the lowest value of 4% in the third quarter of 2021, the most recent quarter with available data, according to Banco de Portugal data for studied period.

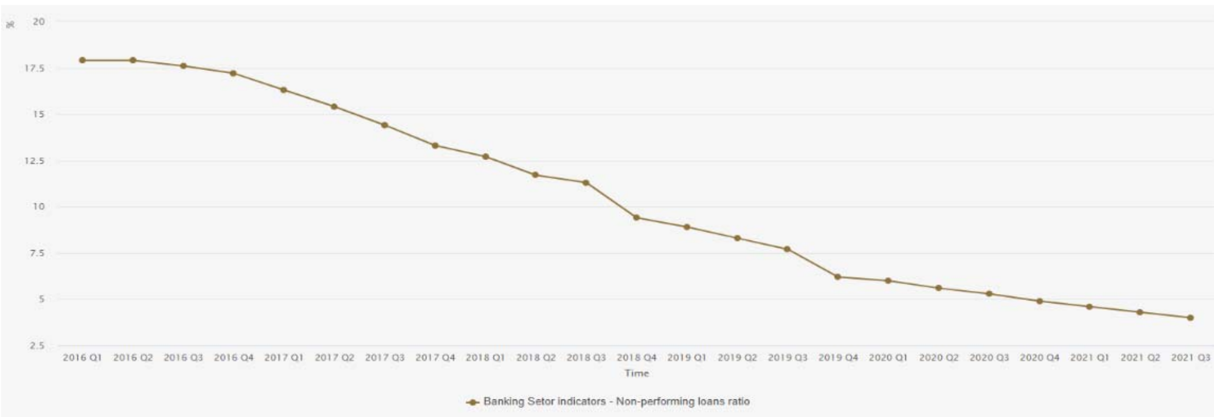

Figure 0 – NPL ratio for Portugal

Source: BP Stat, 2021

Several authors have studied the determinants of this occurrence for different countries and geographical areas that resulted in extensive literature on the topic. The link between the non-performing loans and the banks loss rates has been discussed for many decades, as it led to many recessions around the world.

The main objective of the study is to fully understand the causes of a rise in non-performing loans ratio in the banking sector, and in the whole economy of a country, namely in Portugal, as it is the most relevant indicator of financial stability and credit risk.

The main question, which the study aims to answer is:

What are the main drivers of a rise in the non-performing loans ratio in Portugal?

The sub-questions that are to be addressed on the dissertation are the following:

- **Which type of variables impact more severely the NPL ratio? Macro or bank specific?**
- **What type of credit risk management measures should be implemented to avoid a future rise of the non-performing loans ratio in Portugal?**
- **How did the Coronavirus pandemic affect the NPL ratio and the other macro and bank specific variables in Portugal?**

High NPL ratio can adversely affect the security of the banking system hence the relevance of this study relates with the importance of understanding credit risk so risk management techniques can be applied to banks, so it can be reduced their balance sheet exposure to great losses and to Portugal avoid future financial instability in the country.

The main purpose of the study is to have an understanding on the factors with higher relevance for the increase of the NPL rate in Portugal and furthermore assess the impact of crises in the NPL ratio based on the recent events of the Coronavirus pandemic.

By conducting this research, it is expected to obtain more insight on credit risk in the Portugal banking sector, by identifying the main variables causing the non-performing loans rate increase, and the principal measures that can avoid the negative results produced by it.

There are still very few articles evaluating the Portuguese non-performing loans ratio, which represents a breach in the state of art, and constitute the ideal opportunity to comprehend and develop a study with crucial information.

The acknowledgement of the importance of risk management in identifying and modelling the most relevant determinants of credit risk, aims to contribute to the knowledge of banking sector and financial ministry, specifically of risk managers and policy makers to further adequate financial laws and the credit risk models in continuous improvement.

This paper will consist of a theorical and practical approach to the problematic, which will expose the already existing evidence on the topic, to compose a more robust framework and extract conclusions from the model application, promoting progressively more informed decision-making.

The difficulties expected relates with the extraction of data with relevance and quality for given country and defined period, as well as the scientific uncertainty regarding the correlation of the variables in the application of the model, since this represents new additions to the state of art on the topic.

LITERATURE REVIEW

After the financial crisis of 2008, credit risk increased as *"many banks across Europe suffer from high levels of non-performing loans (NPLs), in particular in Cyprus, Greece, Portugal, Ireland, Italy and some Central and Eastern European countries."*[1], mainly due to the inability for the debt issuers to meet the payment deadlines.

Portugal levels of non-performing loans have been decreasing since 2016 peak, but due to the current pandemic crisis, the tendency is about to revert. Consequently, it is crucial to reevaluate the country's financial performance by focusing on supervising the most valuable indicators of the country, to prevent critical damages to the economy, considering Portugal's vulnerability to the matter.

Increases in NPLs' rate is pointed out as the key reason for the reduction in earnings of banks (Saba et Al., 2012), therefore it is instinctive that banks tend to protect themselves, by finding methods to neutralize this type of threats to the bank's normal function.

Credit Risk represents the threat that a borrower fails to meet its obligations in relation to the debt obtained. This risk can occur either if the payments are not made or in case they are not made in a timely manner.

[1] KPMG, 2018 "Non-performing loans in Europe: What are the solutions?"

After facing several financial distresses, banks felt an urge to minimize this event and therefore reduce and prevent the impact of potential losses, leading to the implementation of a method to assess the credit risk of each borrower, generally known as the 5 C's:

- Character – regarding the credit history of the borrower, its ability to repay previous loans;
- Capacity – considering the adequacy of the debt to the borrower's gross monthly income, the lower the debt-to-income ratio, the less is the credit risk;
- Capital – the larger the borrower presents as a down-payment the less is the perceived risk to the bank as it signals sense of concern;
- Collateral – provides security in the event of default, as it assures the payment;
- Conditions – external factors that affect the loan, such as the state of the economy at the moment or the reason for the borrower to ask for a loan.

This method requires adaptations to the specific characteristics of each bank, as well as to the causal temporal and socioeconomic framework, representing solely a standard help guide for credit risk procedures.

The bank's Balance Sheet on the asset side decomposes in two main items: Central bank money and Loans granted, marketable and non-marketable. While the liabilities are composed of Deposits and Loans from the Central Bank, Interbank loans and Repurchase agreements. Therefore, the banks should consider the possible complications from credit risk, as it will affect their lending ability, which impacts their overall business.

The expected loss from the event of default is based on several factors, namely:

- ✓ Probability of default – borrower likelihood to fail to meet its financial obligation.
- ✓ Exposure at default – the expected value of the loan at the moment of default.
- ✓ Loss given default – the amount of loss if there is a default, which depends on collateral.

Facing the rise on credit risk verified on the aftermath of 2008 financial crisis, Basel III regulatory accord have defined several procedures with the purpose of mitigation of risk in the banking sector, such as the minimum capital adequacy ratio of at least 8%, calculated using the RWA[2]. This ratio aims to intensify the strength of the banking sector by guaranteeing the financial trustworthiness of banks, by absorbing potential losses, protecting against unwanted leverage, insolvency, and overall financial

[2] Risk-weighted assets

distress (Fatima, N., 2014). Nevertheless, some authors consider that capital requirements should increase considerably more than suggested (Varroto S., 2011).

Loans are referred as non-performing loans when there are signs of the improbability of the issuer to repay the loan or if has passed 90 days without the payment of the agreed installments (BCE, 2016).

Non-performing loans, henceforth denominated NPL, constitute a problem for banks, as it debilitates the profitability and require the constitution of sturdy provisions for the losses they may incur, conditioning the bank's overall performance.

The fact that there is a strong correlation regarding the percentage of non-performing loans in the bank balance sheet with banks failures and countries financial crisis can be explained by the confirmation that a sharp increase in NPL weakens macroeconomic performance, triggering a vicious spiral that aggravates macro financial vulnerabilities (Nkusu, 2011), leading to the failing of entire banking ecosystems, as previously observed.

Through many decades, several authors have been investigating the causes of non-performing loans, to identify the main determinants of high NPL ratios, considering both macroeconomic and bank-specific variables, while more recently there have been taken efforts on understanding the consequences of the loan deterioration as well. The studies have been applied to different geographical areas, which translates in a broad spectrum of approaches due to the divergent finance cultures and therefore resulted in a robust state of art composed of relevant literature on the subject.

Early studies date back 40 years, where authors began to examine the reasons for bank failures (Keeton and Morris, 1987; Barr and Siems, 1994), and identified banks tendency for taking higher risks with the financial deregulation, increasing the "bad" loans as the leading cause. Immediately after, many authors focused on investigating the subjacent problem. The literature on the topic suggests that both non-performing loans can be affected by both macro and micro factors.

There is vast evidence, considering the macroeconomic determinants, consisting of external factors that potentially impact the borrower's ability to repay its loans. There is a broad indication of correlation between non-performing loans increase and the decrease of the GDP, the rise of bond yield rates and unemployment rate.

However, there are distinct levels of significance given to each variable, considering the geographic area under evaluation. In a study of the US sector, the main driver of high NPL ratio was the positive variation of interest rates (Saba et al., 2012), while on the Spanish banking sector the decrease of GDP growth of the country represented the more conclusive link between the NPL ratio and overall country's performance (Fernández L., 2000).

The difference in the results can also be an effect of the system statistical research system of study used. Considering, for example, Saba et Al., in 2012, in "Determinants of Non-Performing Loans: Case of US Banking Sector", the methodology selected was Pearson's' correlation and OLS research regression model for the period of 1985 to 2010, leading to the conclusion that GDP rate and Interest rates do affect the US banking sector, by the increase of the NPL, whereas Bofondi and Ropele (2011), using a single-equation time series approach reach to the conclusion that floating interest rate significantly affects the amount of bad debt in the Italian banking sector, for the period of 1990-2010. "This implies that the effect of interest rates should be positive, therefore there is an increase in the debt caused by the increase in payments of interest rates and hence the rise of non-performing loans."

But even using the same method as Saba et Al. (2012), Pearson's correlation matrix, Messai S. & Jouini F. (2013) reported different results.

Additionally, Louzis et al. (2010) has observed the GDP growth, the unemployment rate, and the real interest rate as determinants of the NPL, for the Greek banking sector, using the method of dynamic panel data for the period 2003 to 2009. The results show that "bad quality" loans are linked to the macroeconomic variables and to the quality of management.

On the other hand, focusing on the bank specific variables, some studies claim that these determinants impact more significantly the raise the NmPLs rate, consequently generating more loan losses. Salas and Saurina (2002), for the period of 1985–1997 in Spain, highlight bank size and capital ratio variables as more accurate explaining the increase in NPLs, and stating the noteworthy differences between commercial and savings banks in the management of credit risk.

Podpiera and Weill (2008) assessed the causality between non-performing loans and cost efficiency in order to examine if these were determinants of the failing of banks, by employing a dynamic panel estimator on a panel of Czech banks between 1994 and 2005. This study concluded that the lower the cost efficiency the higher is the correlation with the increase of non-performing loans, which in the long run leads to financial distress in the banking system, which is confirmed by Messai S. & Jouini F. (2013), in the study for 85 banks in Italy, Greece, and Spain, that stated a significant negative correlation between the return on assets (ROA) and the amount of NPLs. Contrary to that, Makris et Al. (2014), using GMM estimation[3] for fourteen countries banking system in the euro area, suggests that ROA has no effect and ROE has a negative effect on the Non-performing Loans. Abiola, I., & Olausi, A. S. (2014) states a positive relationship between non–performing loans and profitability of banks, in a study of seven commercial bank in Nigeria, using a panel regression model.

[3] Generalized method of moments.

For Chaibi, H. (2016), aiming to perceive if credit risk determinants are different through quantitative and qualitative proxies, concluded that cost inefficiency and bank profitability are the most frequent determinants for the loan quality deterioration in Tunisian banking sector, while Rajha, K., (2016) in the study of the Jordanian banking sector concluded that the more impactful bank-specific variable is the loans for total assets ratio.

Ultimately, some studies indicate that both macroeconomic and bank specific variables affect the NPL, such as Louzis D.P. et Al. (2015), that using a VAR model[4] have concluded that GDP, unemployment rate, interest rates, public debt and management quality were the most significant variables, while analyzing the Greek banking sector between 2003 and 2009, and Metin and Ali (2015) using linear regression models for Turkey banking sector during 2007-2013 have found that the most accurate determinants of high NPLs ratio are the increase of unemployment rate, return on equity (ROE), capital adequacy and inefficiency ratio of banks.

This variety of results can be considered an effect of the country banking sector in analysis, since deterioration of loan performance is uneven across countries (Beck et Al., 2015).

Boahene, S. H., Dasah, J., & Agyei, S. K. (2012) stated that "one of the major causes of serious banking problems continues to be ineffective credit risk management" therefore "credit risk management is very vital to measuring and optimizing the profitability of banks", confirming that it is imperative to recognize the need to implement effective risk management processes in the banking industry, regarding the mitigation of increasing loan losses deriving from higher default rates. This study points out that for Ghana banking sector, high profitability overpowers high credit risk, contrary to the normal view in previous studies.

As pointed out for some authors, credit risk management and financial performance have a strong correlation (Mwangi, G. N., 2012), as Capital adequacy ratio (CAR) and NPL ratio have a negative impact on Return on Equity (ROE), representing a reliably prediction of the ratio. On the other hand, the study presented by Boahene et Al. (2015), indicates that banks in Ghana enjoy high profitability in spite of high credit risk, disagreeing with other studies that state that credit risk indicators are negatively related to profitability.

The growth of non-performing loans ratio is considered an alarming sign, a threat for the bank system and country's financial and economic stability, therefore, it constitutes a crucial indicator of the sovereign financial health, usually taken in consideration by the rating agencies.

[4] Value at risk model.

Nevertheless, the observation of the indicator solo will not provide adequate perception of the current financial status of the country's overall outlook. Thus, it is essential to measure the impact of each variable in the ratio variance, to provides the regulators and risk departments in banks with the truer insight so it can result in the implementation of risk management system to ensure the due attention, since the loan quality deterioration represents the leading cause for the increase of NPL ratio.

Focusing on the consequences of the high NPL ratio, it is also important to take into consideration the impact of risk management as a direct tool for the identification, prevention, and resolution of NPL owing the fact that *"(…) non-performing loans are increasing due to lack of risk management which threatens the profitability of banks"*[5].

Over the many crises that Portugal has been through, the risk management matter increased in importance. The struggling of the banking system of the country led to strict supervision by regulatory entities that conducted acute analysis on the behavior of the country financial outlook and implemented NPL reduction strategies to improve loan credit quality.

By acknowledging the impact of the implementation of an RMS (risk management system), it was possible to revert the NPL ratio Portuguese situation, since it assessed the credit risk for the banking system and lead to the implementation of activities like monitorization and control, established in the bank procedures.

The recent uncertainty the global economy, along with the increase of unemployment rate and decrease of the GDP represent new challenges to the maintainance of the decreasing tendency of the non-performing loans in Portugal.

Considering the present events, the 2020 (induced by COVID-19) health crisis, when compared with the 2008 crisis, it is possible to observe that now banks have higher capital, there are more regulations on NPL, but the sovereign debt is considerably higher, banks are less profitable, and corporate balance sheets are weaker (Ratnovski, L. 2020).

By conducting the present study, the main objective is to provide an understanding on the factors with higher relevance for the increase of the NPL ratio in Portugal as well as the impact of the risk management modelling in the process, and furthermore assess the effect of unprecedent risks and challenges caused by COVID-19 crisis in the non-performing loans ratio.

[5] Haneef S. (2012): "Impact of Risk Management on Non-Performing Loans and Profitability of Banking Sector of Pakistan"

Banco de Portugal reveals that due to the COVID-19 crisis, the Portuguese banks have been taking loss prevention measures, in the context of the public health emergency, aiming to sustain their business and suppress the future financial losses caused by the ongoing pandemic. Moreover, have been applied several full liquidity conditions, in the longer and more advantageous terms, as Portugal is implementing one of the longest moratorium measures in Europe, which have already been applied to over 700.000 contracts by September 2020.

In December 2020 Economic Bulletin, Banco de Portugal (BdP) specified that even though there was a significant reduction of the GDP in Portugal in 2020, of almost 18% in the 1st quarter of the year, their forecasts estimate that the potential economy recovery for the 2021-2023 period, will be much efficient and faster than the 2011-2013 recovery, consequence of the continuous management of the pandemic, diminishing of uncertainty and effective monetary policy and crisis response measures.

Nevertheless, due to the 2020 4th quarter and 2021 1st quarter intensification of infections by COVID-19 across the world has led ECB to expect another decrease of activity in the Euro area, probably leading to an additional contraction in real GDP until the 1st quarter of 2021, that was verified in Portugal. The projection elaborated by the Euro system staff by December 2020 assumes that throughout 2021 the activity is forecasted to rebound but “even after the health crisis is largely resolved, the associated economic losses are assumed to persist.”

DATA AND METHODOLOGY

The research methodology of this paper consists in firstly, scientific research of the existing literature to identify the considerations from other authors on the results obtained for similar case studies, with the aim of providing relevant guidance for the definition of assumptions, followed by the extraction and analysis of the data to test various models and conduct result analysis and comparison with previous studies.

It was defined the period of analysis, from 2016 to 2021 and the periodicity, quarterly. This decision was based on the intention of comprising the most recent data as possible and, to comprehend the impact of the present COVID-19 pandemic and its potential challenges faced all over the world, especially the countries with the most fragile economies, such as Portugal.

The defining the variables to subject to analysis, took into consideration the extensive literature on the topic, which led to the choosing of the following variables: GDP growth, Unemployment Rate, and Government 10-year yield bond, ROA, ROE, Coverage of NPE, LCR, Credit Risk cost and NPL ratio of each bank.

Then, the data was compiled to build the dataset. To do so, the needed information was collected from several fonts, namely BPstat, INE, APB, AdvRatings, for the macro variables.

For the bank specific variables, it also required the definition of the restrict group banks that should be analyzed. This decision was made, taking into consideration the banks overall popularity in the county to better represent the banking sector of the country.

The selected sample is composed by the following banks: Caixa Geral de Depósitos, S.A., Novo Banco, S.A., Millennium - Banco Comercial Português, S.A., Banco BPI, S.A. and Caixa Económica Montepio Geral – caixa económica bancária, S.A.

The data collected for the bank specific variables was obtained from quarterly account reports, financial statements, and financial press releases, available on each bank's websites.

The dependent variable in this study is the Portuguese NPL ratio, as this is the variable chosen to be explained, using other macro and bank specific variables, to better understand if there is a correlation between them and this important credit risk indicator in Portugal.

NPL ratio is a primary indicator for bank failure and consequently for a potential country's financial crisis, therefore it is considered of great interest to study the impact of other indicators on this ratio, to not only reverse it but also to implementing more adequate preventing measures.

By analyzing the evolution of the NPL ratio in Portugal in the previous years it can be observed the overall impact of the implementation of credit risk management in the country's banking sector. Non-performing loans in Portugal have been progressively decreasing since 2016 first quarter peak, until this moment. These results show the solid efforts being made by the supervisory entities of the country that has already suffered two important crises in the 2000 century.

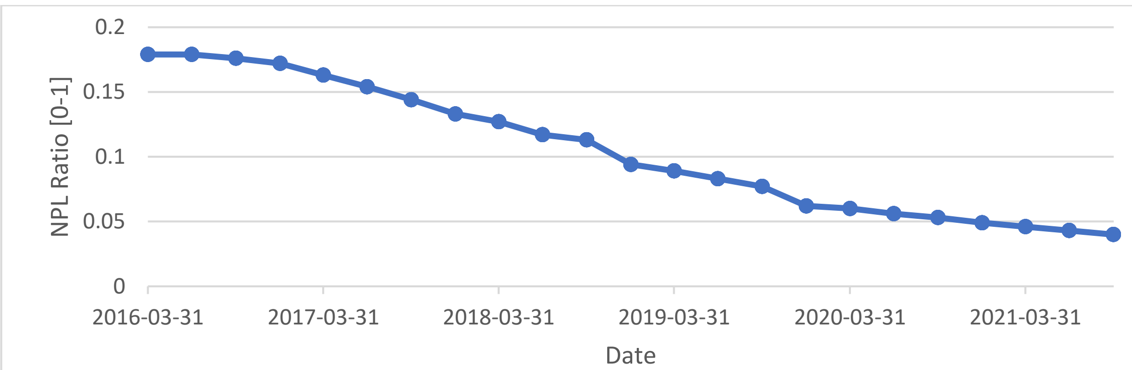

Figure 2 – Portugal's non-performing loans ratio evolution, 2016-2021

Source: Self elaboration

The independent variables chosen to explain NPL ratio of Portugal for the period of 2016 to 2021, was: GDP growth, Unemployment Rate, and Government 10-year yield bond, on the macro economical side, and ROA, ROE, Coverage of NPE, LCR, Credit Risk cost and NPL ratio of each bank on the Bank specific side (consult Annex I – Variables Glossary).

Table 1- Independent Variables description and expected correlation

Type of variables	Independent Variables	Measure unit	Expected behavior	Literature Review
Macro	Unemployment rate PT	%	(+)	Skarica (2013)
Macro	GDP (constant prices)	%	(-)	Messai e Jouini (2013);
Macro	Gov. Bond 10-year yield	%	(+)	Serrano, A. S. (2021)
Bank Specific	Total Loans	M€	(-)	Messai & Jouini, (2013)
Bank Specific	NPE Coverage	%	(-)	Alessi, L. et al (2021)
Bank Specific	Credit risk cost	%	(+)	Maggi and Guida, (2011)
Bank Specific	ROA	%	(-)/(+)	Louizis, et al (2012); Abiola, I., & Olausi, A. S. (2014)
Bank Specific	ROE	%	(-)/(+)	Makri et al. (2014); Abiola, I., & Olausi, A. S. (2014)
Bank Specific	Bank NPL ratio	%	(+)	Ozili (2019)
Bank Specific	LCR	%	(-)	Ozili (2019)

Source: Self-elaboration

The **Unemployment rate** is a topic of great concern in Portugal, given that recently the country has faced two financial crises in the time span of 2 decades, which has negatively affected the indicator.

Portugal most recent peak in the unemployment rate was reached in the third quarter of 2013, result of the continued crisis lived in the country, since then it has been declining, until 5,6% in the second trimester of 2020, the lowest value in recent years.

The likelihood of non-performing loans reacting to the rise of the Unemployment rate is often discussed, since the greater the number of people unemployed, lower the resources available, leading to a probable rise of incapacity of payment of the loans from the debtors. This correlation analysis has been recurrent in various papers, for different panel data sets in distinct locations and periods of time, such as Louzis, et al (2012) and Skarica (2013).

The **GDP growth** in Portugal, presented a solid growing tendency until late 2019, from where it registered robust growth around 3%, until the march 2020 Covid crisis. The past years have been showing a steady growth due to the country's increasing popularity, with the rise in private expenditure regarding the favorable climate and investment opportunities. ECB forecast that for 2020 the GDP growth was of -9,3%, but it only fell to - ,8%.

Considering the **long-term government bond yield**, the rates has been rapidly growing until the first quarter of 2012, reaching 13,22%, which was the turning point. Since then, the rates have been decreasing drastically, as in 2019 third quarter, interest rates have reached its recent lowest value of 0.27%. The tendency is for the long-term interest rates to maintain during the following periods.

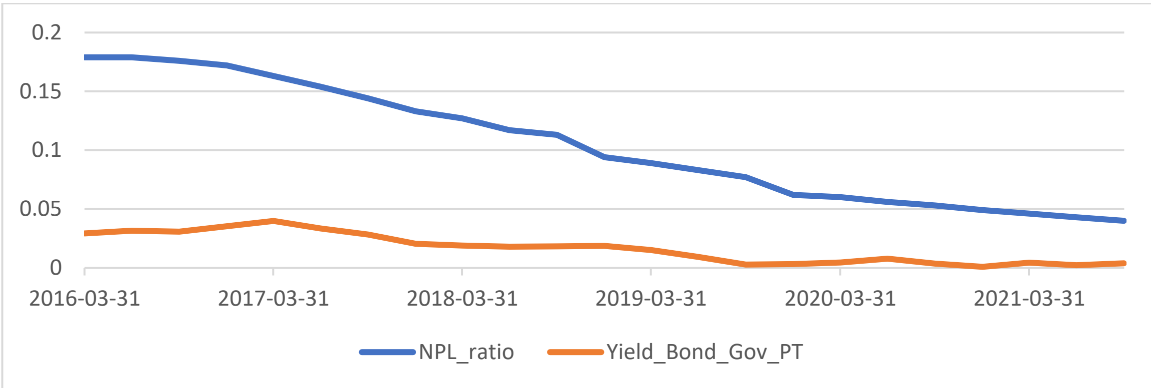

Figure 3 – Long-term yield and NPL Ratio evolution, 2016-2021

Source: Self-elaboration

The **total loans** of the most popular banks in the country, have been following a decreasing tendency in many of the banks in analysis. This variable can affect either negatively or positively the NPL ratio, because if there are more loans, the more spread out the "bad" loans will be, leading to a smaller NPL ratio, but an rise in the amount of loans can be associated with less restrictive credit policy, which is usually linked with an increase in risk for the banks and tends lead to less coverage of the risk exposure, leading to a more problematic scenario in case of a higher rate of defaults and tendentially a rise of overdue loans.

This variable can be deceiving, covering the reality of the credit quality, therefore this value should only be taken into consideration with additional variables, to guarantee a truthful perception of the overall quality of credit of the country.

The **coverage of non-performing exposure** is the ratio of on-balance sheet provisions for potential credit impairment losses. This consists of a buffer to absorb expected loan losses, so it is considered a good indicator of the banks' ability to face the adversities in case of an increase of problematic loans with overdue payments. The higher the provisions the bank possesses, the more prepared it will be for the rise of non-performing loans, which will facilitate the resolution of the problem, without putting at risk its business.

As NPLs affect banks' lending behavior, the analysis of performance ratios, such as **Return on Assets and Return on Equity is essential**. Since these variables indicate the banks efficiency, it can help them avoid "dangerous loans". These are impactful tools on the anticipation of the NPL ratio, and there are different approaches on the topic, but overall, the authors state that the increase in the bank's efficiency is expected to lead to the reduction of non-performing loans.

The **cost of credit risk** represents the provisions recognized by an entity to the average volume of the loan portfolio during the given period. This indicator identifies expected losses and measures the effort an entity makes, over a given period, to protect itself against estimated future losses in its loan portfolio, so it is expected to correlate positively with the rise of the NPL ratio. The latest economic crises produced many negative outcomes, especially the deterioration of credit, with an increase in non-performing debt. The increase in non-performing exposure impacts the cost of the risk which keeps growing due to the need of the banks to increase provisions and impairment losses on loans (Avantage Reply, 2014).

The **Liquidity coverage ratio** is one of most used liquidity indicators of a bank, implemented on Basel III reforms and applicable since 2015, to promote short-term resilience to liquidity shocks by requiring banks to hold a minimum quantity of high-quality liquid assets (HQLA), to survive a critical stress scenario lasting for one month (Behn, M., Corrias, R., & Rola-Janicka, M., 2019).

Banks' adaptation to global regulatory reforms seems to have affected credit industry, although various studies suggest that the introduction of the LCR has had only a limited impact on lending to the non-financial sector, as banks adjusted by reducing interbank lending and increasing HQLA holdings. There is also evidence specifically for the United Kingdom that tighter liquidity regulation had no detrimental effect on lending.

The analysis of the data occurred in three steps: exploratory analysis, correlation matrix and the analysis of the linear regressions of the dependent variable with each variable.

This methodology had the purpose of understanding the relationship between the dependent variable and each of the ten (10) independent variables, consisting of three (3) macroeconomic and seven (7) bank specific variables, to disclose the impact of each in the rise of the NPL ratio, and follows the subsequent flow.

Figure 4 – Data and methodology flow

Source: Self-elaboration

After gathering all the necessary information, the data was imported to SAS Guide. Subsequently, it was created a new project in SAS Miner, and applied the Statexplore function to the imported dataset, which consists in a brief preliminary exploratory data analysis.

In parallel, the descriptive statistics of the variables were also performed in Excel, using the Data Analysis Toolkit, in which were calculated for each variable (minimum, average, median, maximum, and standard deviation) to summarize the behavior of the data.

The exploratory analysis of the model (consult Annex II - Descriptive Statistics) revealed a negative asymmetric distribution, where the mean is lower than the median, for GDP growth, Total loans and ROE variables. On the other hand, Yield Bond, ROA and Credit Risk variables presented a symmetrical distribution, where the mean is equal to the median.

The following step consisted in the elaboration of the Pearson's Correlation Matrix (consult Annex III – Correlation Matrix), to find the highly correlated variables. The cut-off level considered was of coefficient equal or superior of |0,8|. If the correlation is situated between [-1, -0,8] or [0,8; 1] the variables will be excluded of the model.

The correlation matrix also eases the identification of multicollinearity between the independent variables. Multicollinearity consists in high intercorrelations among two or more independent variables in a multiple regression model. This leads to larger confidence intervals, consisting of less reliable probabilities in terms of the effect of independent variables in the regression model. If there are variables under this condition, they should be rejected from the model, so it doesn't contaminate the results.

Subsequently, it was performed various simple linear regressions between the dependent variable and all the remaining independent variables. This process aims to find which variables produce a relevant impact on the NPL ratio and it is expected to present relevant results to evaluate the significance of each factor in the for the rise of the NPL ratio and the correlation between the group of variables, disclosing the best variables to integrate in the multi regression model.

Lastly, several multi linear regression models were tested, each comprising a different combination of the independent variables, to compare the different results and the levels of significance of each variable to estimate the NPL ratio. The results were evaluated and compared, with the purpose of choosing the best model.

After obtaining the outputs of the models it is important to evaluate the estimates of coefficients of the regression models, to better understand the impact of each variable in the NPL ratio of Portugal.

The method used was the significance test, which is an efficient indicator of the model fit, by identifying if the variables used in the model are significantly associated with the dependent variable. First it is necessary to define the significance level, in this case it was defined as 10%. Thus, we reject hypothesis at a significance level of 10%, meaning that, individually, these variables are relevant to the model at least 90% confidence level.

Other relevant indicator of the model fit is the R-Squared of the model, that measures how much variance of the Dependent variable can be explained by the independent variables. Ranging from 0 to 1, this is a very common analysis of the goodness-of-fit measure for linear regression models.

To further evaluate the quality of the models, it was also analysed the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) usually used to compare different alternative models and determine which one is the best fit for the data.

These statistics are used for the comparison of models on the same sample and penalizes models that use more parameters. If two models explain the same amount of variation, the one with fewer parameters will have a lower AIC score and will be the better-fit model. The model with the smallest AIC is considered the best, although the AIC value itself is not meaningful.

The BIC is a well-known general approach to model selection that favours more parsimonious models over more complex models (Schwarz, 1978 and Raftery, 1995) and it also commonly used to evaluate the quality of the model.

Results analysis

After gathering all the required data, it was then performed the methodology defined earlier and conducted a careful analysis to the results:

The first step after analyzing the literature review on the topic and compilation of the assumptions for given variables, was the Pearson's Correlation Matrix (consult Annex III), where it was observed correlations higher than|0,8|, namely between:

- NPL_ratio and Unemployment_rate (0,86)
- NPL_ratio and Yield_Bond_Gov_PT (0,96)
- Unemployment_rate and Yield_Bond_Gov_PT (0,81)
- ROA and ROE (0,86)

After finding the highly correlated variables, it was decided to reject Unemployment_Rate and Yield_Bond_Gov_PT, since these 2 variables present high correlation, of 0,81, which represents multicollinearity and can undermine the statistical significance of the estimates.

The correlation matrix also revealed the high correlation between ROA and ROE, so it was tested 2 models, one using every variable except Unemployment_Rate and Yield_Bond_Gov_PT and ROE, and other excluding Unemployment_Rate and Yield_Bond_Gov_PT and ROA, to compare results.

Then, the performing of simple linear regressions between NPL_ratio and the remaining independent variables has served as a starting point for the investigation of the result of each variable on the increase in the non-performing loans ratio for Portugal (Consult Annex IV - Simple linear regression results).

The simple linear regressions presented as highly correlated variables (over 0,74) the Unemployment_rate, Yield_Bond_Gov_PT and T_loans, which led me to reject these variables from the next step, to assure a reliable result from the model. Considering the level of significance, all the independent variables level of significance was equal or greater than 1% except for ROA, CNPE and C_risk. ROA and C_risk presented not statistically relevant, and CNPE with level of significance of only 10%.

Lastly, were constructed four models with slight changes between them, identified as following:

Model 1 had as independent variables: GDP_growth, NPL_ratio_b, CNPE, ROA, LCR and C_risk. (Consult Annex V – model results).

The results of this model demonstrated significance level of 1% on NPL_ratio_b, ROA and LCR and significance of 5% on GDP_growth and C_Risk. CNPE was not statistically significant up to 10% in this model.

Model 2 tested GDP_growth, NPL_ratio_b CNPE, ROE, LCR and C_risk. (Consult Annex V – model results). The results also demonstrated CNPE as not statistically significant in this model, and all the remaining variables except GDP_growth obtained the same result. GDP_growth level of significance was of 10%, diverging from the 5% in the Model 1.

Model 3 was the same as the Model 1 but excluding the coverage of non-performing exposure of the banks (Consult Annex V – model results) since it was not statistically significant in the model 1.

Finally, model 4 was the same approach as model 3, by rejecting the CNPE variable, but keeping all the same variables from model 2 (Consult Annex V – model results), since the Coverage of non-performing exposures of the Portuguese banks was not statistically significant previously.

Table 2 – Model Significance level comparison

Comparison	*NPL_ratio*	*GDP_growth*	*Unemployment_rate*	*Yield_Bond_Gov_PT*	*NPL_ratio_b*	*CNPE*	*T_Loans*	*ROA*	*ROE*	*LCR*	*C_risk*
Model 1	Target	**	-	-	***	not statistically significant up to 10%	-	***	-	***	**
Model 2	Target	*	-	-	***	not statistically significant up to 10%	-	-	***	***	**
Model 3	Target	**	-	-	***	-	-	***	-	***	**
Model 4	Target	**	-	-	***	-	-	-	***	***	*

Significance levels: *10%, **5%, ***1%

Table 3 – Model Quality criteria comparison

Comparison	*R-Sq*	*AIC*	*BIC*
Model 1	38%	-886,6112	-883,8388
Model 2	36%	-883,1048	-880,3624
Model 3	38%	-888,2572	-885,7158
Model 4	36%	-886,4174	-881,8761

Table 2 presents the significance test analysis in a comparative table, comprising the results of the four models and table 3 has the comparison of the models, according with the results obtained for the r-square, AIC and BIC criteria. These tables were used to identify the most suitable model.

The model fit statistics of the four multi regressions was very identical, with the r-square ranging from 36% to 38% and both AIC and BIC quality criteria with low values, indicating good quality models.

It is noted that the R-squared result was only affected using return on assets (ROA) or return on equity (ROE), two bank-specific variables, calculated by five of the biggest banks in the Portuguese banking sector. The models that comprise ROA (model 1 and model 3) present an R-squared of 38% while the models that use the ROE variable instead (model 2 and model 4), present and R-squared of 36%.

The model selection phase is an especially crucial step in the investigation as it will affect the results presented. The methodology of this study required the creation of several models and therefore it was an exhaustive process until it reached the best possible model.

After testing various linear regressions between the dependent variable and the remaining independent variables, it was identified the best model according to the combination analysis of both hypothesis test and quality of the model criteria.

The Model 3 was the chosen since all the variables comprised in this model show confidence level of at least 95%, presented the lower AIC and BIC and had one of the highest R-square, despite the very close results obtained in the four models.

Table 4 - Final model: Analysis of Maximum Likelihood Estimates

Final Model	Estimate	Error	t Value	Pr>|t|	Significance level
Intercept	0.1263	0.0130	9.74	<.0001	***
C_risk	1.1250	0.5602	2.01	0.0467	**
GDP_Growth	0.1280	0.0588	2.18	0.0312	**
LCR	-0.0287	0.00514	-5.59	<.0001	***
NPL_ratio_b	0.2456	0.0679	3.62	0.0004	***
ROA	1.4194	0.4040	3.51	0.0006	***

Significance levels *10%, **5%, ***1%

Table 4 presents the analysis of the maximum likelihood estimates, classified between the regression coefficients, standard error, and the significance test for each variable in the selected model. The coefficient estimates allow us to quantify the effect of each of the explanatory variables on the non-performing loans ratio. The standard error of the estimators helps calculate the significance of the estimated coefficients.

Gross domestic product growth (GDP_growth), non-performing loans ratio (NPL_ratio_b) and return on assets (ROA) present positive correlation with the target while also being statistically significant at the 1% significance level. Cost of credit risk (C_risk) presents a positive correlation with a 5% significance level, and Liquidity Coverage ratio (LCR) shows a negative correlation with a 1% significance level.

The Significant coefficients represent the mean change in the dependent variable given a one-unit shift in the independent variable. Therefore, results presented in table 4 conclude that, keeping everything else constant:

- If the C_risk increases 1 basis point, NPL_ratio is estimated to increase 1.1250 b.p.
- If the GDP_growth increases 1 point, NPL_ratio is estimated to increase 0.1280 b.p.
- If the LCR increases 1 point, NPL_ratio is estimated to decrease 0.0287 b.p.,
- If the NPL_ratio_b increases 1 point, NPL_ratio is estimated to increase 0.2456 b.p.
- If the ROA increases 1 point, NPL_ratio is estimated to increase 1.4194 b.p

Table 5 - Final Model fit statistics

R-Square	0.3809
AIC	-888.2572
BIC	-885.7158
Number Observations	138

Finally, on table 5 it is present the outputs on fit and quality of the regression. The R-squared value of the model situates at 38%, a good value considering the nature of the study.

Based on AIC and BIC information results to evaluate the best model that can assess the impact on the non-performing loans ratio, Model 3 AIC and BIC presented negative values, that despite the AIC and BIC values themselves are not meaningful, the lower the value the better, therefore concluding a good quality of the model.

Analysing the model, it is possible to observe low AIC and BIC values, which is a good indicator of the quality of the model, but more importantly all the variables included in the model are statistically significant in the model (confidence level of 95%), consisting in the best option available.

The final model is composed of the following independent variables: Cost of credit risk, Liquidity Coverage Ratio (LCR), return on assets (ROA) and the non-performing loans ratio of the biggest 5 banks of Portugal, and GDP growth of the country, explain 38% of the dependent variable (non-performing loans ratio for Portugal).

In this multi linear regression, Cost of Credit Risk (C_risk) and ROA present the highest estimators coefficients, which means that these variables are the ones that create the bigger impact in the rise of the non-performing loans ratio, for the period between 2016 and 2021, in Portugal, but Liquidity Coverage ratio (LCR), non-performing loans ratio (NPL_ratio_b) and return on assets (ROA) of 5 biggest banks are the variables with an higher level of confidence, over 99%.

Discussion and Conclusions

The result of the final model presents noteworthy contribution to the state of the art on the impact of both macro and bank specific variables on the NPL ratio, for the Portuguese banking sector.

The results showed that GDP growth, Credit Risk Cost, ROA and NPL ratio of five of the most popular banks in the country impact positively the NPL ratio of Portugal, while Liquidity Coverage Ratio impacts negatively.

When comparing the results of the present study model with the Literature review on the topic, some outcomes are identical with other authors' papers and other contradict them. This can be explained by the differences in the inputs, namely: different countries, different banks and different periods.

Results from Skarica (2013) suggest a strong inverse correlation between GDP and the NPL ratio, when analyzing European emerging markets from 2007 to 2012, as well as Radivojevic & Jovovic (2017) that concluded the same from a panel data approach between 2000 to 2011.

The results obtained in this study (positive correlation between GDP growth and NPL ratio), contradict the robust results from the literature review. The reason for this inconsistency remains on the unprecedent and peculiar effects of the covid-19 crisis.

During 2020 and 2021, moratorium and grace period has helped avoid the most likely abrupt rise of non-performing loans in Portugal, due to the inability of payment of the loans from the population, as a main effect of the rise of the unemployment rate. These incentives reduced the probability of default, therefore the NPL ratio continued the decreasing tendency despite the GDP growth fall. This produces very unexpected results, since GDP has proven to affect the credit quality, and therefore this unusual event should be taken into consideration when interpreting the results.

Louzis et al. (2012) and Anastasiou et al. (2016) are two examples of various authors that demonstrated that ROA presents a negative impact on NPLs, on the premise that a bank with higher profitability and better performance is most likely to have a lower NPL ratio. On the other hand, Godlewski (2004) states the inverse relation.

The results from this regression model, considering quarterly basis data from 2016 to 2021, in Portugal, validate the positive correlation between the NPL ratio and ROA.

Messai & Jouini (2013) analyzed the determinants of non-performing loans for a sample of 85 banks in three countries (Italy, Greece and Spain) for the period of 2004-2008. The results obtain indicate a strong positive correlation between NPL ratio and both unemployment rate and total loans.

Considering cost of credit, Maggi and Guida, (2011) results on the link between this bank-specific variable and the NPL ratio demonstrate a positive effect, as corroborated by the model.

The Liquidity coverage ratio of the panel data for 5 banks in Portugal proves a positive correlation with the NPL ratio of the country. Ozili P. (2019) contradicts these results, while analyzing a sample of 134 countries over the 2003 to 2014 period.

The impact of COVID-19 was more evident in the macro variables, than in the bank-specific ones, as expected and predicted from the most relevant banking authorities across the world, since this type of calamity, a health and social crisis instead of a non-financial one, is supposed to impact more rapidly the social economic variables rather than the bank specific indicators, despite the indirect impact observable across the financial system.

For example, GDP growth was highly affected, one of the most significantly impacted variables by the current pandemic, which was already expected, since this type of crisis affected severely the tourism sector, one of the most crucial activities that contributed to the GDP of Portugal. By suspending all the tourism activities, allied to the fact that due to the danger of spreading the disease, people were forced to remain indoor, which has damaged severely the catering business, or activities based essentially on exports, such as textiles and automobiles, which were penalized by the isolation period, that delayed the production in all the factories.

It was also anticipated a significative rise of the Unemployment rate right in 2020, but it didn't rise as much, mainly due to the Layoff measure, that helped both employers and employees, maintaining the jobs of thousands of people that would most likely would lose their jobs because of the pandemic, with a significant help form the Portuguese government, that supported part of the salaries of companies in activities that were more affected by the COVID and by the strict restrictions taken into place because of the pandemic.

Nevertheless, even with this measure, the COVID-19 pandemic came to last, therefore Portugal's unemployment rate has increased during this period, reaching 8% in the third quarter of 2020. However, Banco de Portugal had estimated that Portugal would reach its peak in 2021 with 8,8% of unemployment rate, but the highest rate in the pandemic era, so far was reached in 2020. The rate has been decreasing ever since, although at a slower pace reaching 6,1% in the third quarter of 2021, a great result considering the adverse conditions.

Focusing on latest financial crisis that Portugal went through, it was palpable the marks left, as it has put banks under close examination, creating a more conservative approach on lending from banks, making it more difficult to approve loans to customers, scared of returning to high levels of credit risk in the country.

By conducting this study, the main goals were to identify if the macro and bank specific variables form a data panel of 5 banks, that would be more likely of influencing the ratio, given its popularity, with the objective of explaining the effect of each of the indicators on the credit risk in Portugal and to further explain the effect of COVID-19 crisis in the overdue loan's ratio.

With this objective in mind, it was created a multi regression model that combined both macro and bank specific variables, and the results were subject to analysis.

Banks normally allocate capital to cover potential losses and write off bad debt in their P&L account, but as the number of non-performing loans increases, it is crucial to pay more attention for potential losses and possibly apply a constraint on the lending capacity of the bank. "Bad debt" affects not only the bank but also to the economy of the country and perhaps of the Eurozone, as it can be one of the most worrisome indicators of unhealthy financial management.

If the NPL ratio becomes too high, there are several critical consequences to the overall system, and since non-performing loans ratio is usually higher in Portugal than in the other European countries, it is considered urgent to apply preventive measures to avoid more drastic interventions.

Some examples of suitable preventive measures can be the implementation of minimum impairment provisions and good risk scoring models for the Portuguese banks, to counteract default and invert the country tendency. Risk management must be a key department in the banks organigram and should be responsible for indicating the best path to avoid excessive exposure.

But the banks shouldn't be the only responsible for performing periodic risk analysis, the government must be proactive and employ relevant economic policy and credit risk protection measures composed of adequate plans to reduce NPL ratios when a certain level (i.e., 7% limit), and perform regular auditory to banks to ensure the application of corrective measures, until NPL ratio of the bank is back to values below the limit.

In conclusion, this study affirms that both macro and micro variables impact the NPL ratio, therefore banks and governments should work closely to ensure the mitigation of higher levels of credit risk.

This study contributes to the banking sector in Portugal, by investigating and analyzing some of the most relevant variables from the robust literature on the topic, applied to the Portuguese reality on the most recent data available.

It answers the main research question of the study:

What are the main drivers of a rise in the NPL ratio in Portugal?

According to the analysis of maximum likelihood of the chosen model, GDP growth (macro) and Credit risk cost, Liquidity coverage ratio, Return on Assets and NPL ratio of each bank (bank specific) are some of the most relevant drivers of the rise of the non-performing loans ratio in Portugal. Liquidity coverage ratio is the only variable that presented an inverse correlation, while the others were positively affected.

The answers for the sub-questions were also addressed on the dissertation are the following:

- **Which type of variables impact more severely the NPL ratio? Macro or bank specific?**

Both macro and bank specific variables produce a significative impact in the NPL ratio. Nevertheless, Macro variables present a higher correlation (consult annex III – correlation matrix) and more relevant significance level (consult annex IV – simple linear regressions results) when analyzing the impact in the dependent variable (NPL ratio for Portugal) in the 2016-2021 quarterly time frame.

- **How did the Coronavirus pandemic affect the NPL ratio and the other macro and bank specific variables in Portugal?**

The COVID-19 effects and implications are still being assessed and monitored. The long-term implications are still an issue to be addressed, as the focus of the countries all over the world, has been to stand and resolve in the more immediate and effective way the unprecedented challenges and risks that the world is facing.
The non-performing loans ratio in Portugal was not affected during the pandemic, maintaining its decreasing tendency, contrary to expected, but at a slower pace.

Unfortunately, some of the macro variables were substantially impacted, namely the GDP growth, with a fall of over 8%, and the unemployment rate, that had the most recently highest value in the 3rd trimester of 2020, but has already stabilized, returning to the 6,1% in the 3rd trimester of 2021.
On the bank specific variables, the impact was more discreet, product of the cooperation between banks and the government, that have worked together implementing preventive measures and avoiding more serious repercussions.

- **What type of credit risk management measures should be implemented to avoid a future rise of the non-performing loans ratio in Portugal?**

As pointed out earlier, the credit risk is a serious issue for banking systems, especially for the more fragile ones, such as Portugal, that due to the long history of recessions, has faced numerous times the shrinkage of resources to deal with the financial and economical distresses. Therefore, it is crucial do apply preventive measures to avoid future constrains.

It is recommended the application of clear and feasible actions at the bank level, such as the credit score modelling with accurate data that is continuously updated and improved, impairment targets that avoid exposure to default and requirements for collateral to be forfeited in the event of a default.

The Coverage against non-performing exposure ratio of the banks analyzed in the study presented an increasing tendency, which is a good indicator of the risk management of the banking sector.

On the government side, the measures that should be applied in order to avoid an increase of the non-performing loans, to mitigate the risk of a financial calamity in the entire banking system of the country, are the implementation of national policies, such as, banks can only lend 80% of the value of the total amount of the purchase, banks need at least 90% of provisions against the probability of default of their clients, or the increase of risk-awareness of the overall population by communicating the risk assessments that are periodically performed.

The present study has faced limitations, such as the fact that the model that comprises the explanation for the rise of non-performing loans ratio for Portugal, is of just 38%, composed of 5 explanatory variables, therefore there are 62% that could be explained by other variables.

As a recommendation for future work on the topic, would consider investigating more variables that can explain the rise of this important financial indicator, to present more risk management measures that can be taken into action soon by national banks and the government and ultimately avoid potential financial distress in the country would be of great interest.

In addition, would also recommend assessing the long-term impact of the COVID-19 on the NPL ratio and its determinants, as it was difficult to complete a extensive analysis of the topic due to the existence of moratorium, that could be hiding the actual impact of this specific crisis.

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APPENDIX INDEX

Annex I – Variables Glossary

Annex II – Descriptive Statistics

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Annex IV - Simple linear regression results

Annex V – Model Results

ANNEX I – VARIABLES GLOSSARY

NPL_ratio	Non-performing Loans Ratio for Portugal banking sector
GDP_growth	Gross Domestic Product growth at prices chained volume levels
Unemployment_rate	Quarterly unemployment rate for Portugal
Yield_Bond_Gov_PT	Yield for long-term (10 year) Portuguese Government Bond
NPL_ratio_b	Non-performing Loans Ratio for each bank of the panel data set
CNPE	Coverage of non-performing exposure for each bank of the data panel
T_Loans	Loans to Customers
ROA	Return on Assets
ROE	Return on Equity
LCR	Liquidity coverage Ratio
C_risk	Cost of credit risk

ANNEX II - DESCRIPTIVE STATISTICS

Descriptive Statistics	Mean	Median	Std. Deviation	Minimum	Maximum
NPL_ratio	0,10	0,09	0,05	0,04	0,18
GDP_growth	0,01	0,03	0,06	-0,18	0,16
Unemployment_rate	0,08	0,07	0,02	0,06	0,13
Yield_Bond_Gov_PT	0,02	0,02	0,01	0,00	0,04
NPL_ratio_b	0,08	0,06	0,06	0,02	0,32
CNPE	0,61	0,58	0,16	0,36	1,41
T_loans	31920,80	33616,50	11340,78	12239,00	52980,00
ROA	0,00	0,00	0,01	-0,03	0,07
ROE	0,02	0,04	0,11	-0,32	0,35
LCR	1,87	1,68	0,75	0,84	4,94
C_risk	0,01	0,01	0,01	0,00	0,04

ANNEX III – CORRELATION MATRIX

Correlation Matrix	*NPL ratio (target)*	*GDP growth (m)*	*Unemployment rate (m)*	*Yield Bond Gov PT (m)*	*NPLratiob (bs)*	*CNPE (bs)*	*T Loans (bs)*	*ROA (bs)*	*ROE (bs)*	*LCR (bs)*	*Crisk (bs)*
NPL_ratio	1										
GDP_growth	0,25	1									
Unemployment_rate	0,86	0,16	1								
Yield_Bond_Gov_PT	0,96	0,24	0,81	1							
NPL_ratio_b	0,40	0,13	0,25	0,38	1						
CNPE	-0,16	-0,11	0,08	-0,15	-0,12	1					
T_loans	0,06	0,02	0,06	0,06	0,03	0,03	1				
ROA	-0,12	0,08	-0,17	-0,11	-0,55	0,00	0,15	1			
ROE	-0,08	0,15	-0,17	-0,07	-0,57	0,02	0,11	0,86	1		
LCR	-0,49	-0,14	-0,40	-0,45	-0,40	0,14	0,26	0,44	0,25	1	
C_risk	0,21	-0,15	0,28	0,18	0,44	-0,01	-0,16	-0,65	-0,70	-0,32	1

ANNEX IV – SIMPLE LINEAR REGRESSIONS RESULTS

Simple linear regressions of IV with DV	R- Square	Pr > |t|	SL
C_risk	0.0462	0.0114	-
CNPE	0.0247	0.0659	*
GDP_growth	0.0689	0.0019	***
LCR	0.2431	<.0001	***
T_loans	0.9983	<.0001	***
Npl_ratio_b	0.1583	<.0001	***
ROA	0.0141	0.1659	-
ROE	0.0057	<.0001	***
Unemployment_rate	0.7406	<.0001	***
Yield_Bond_Gov_PT	0.9126	<.0001	***

ANNEX V – COMBINED MODELS RESULTS

Model 1

Model 1	Estimate	Error	t Value	Pr>|t|	Significance level
Intercept	0.1337	0.0182	7.34	<.0001	***
CNPE	-0.0126	0.0218	-0.58	0.5629	-
C_risk	1.1241	0.5616	2.00	0.0474	**
GDP_Growth	0.1258	0.0591	2.13	0.0351	**
LCR	-0.0284	-0.0284	-5.47	<.0001	***
NPL_ratio_b	0.2420	0.0684	3.54	0.0006	***
ROA	1.4005	0.4063	3.45	0.0008	***

Significance levels: *10%, **5%, ***1%

R-Square	0.3825
AIC	-886.6112
BIC	-883.8688
Number Observations	138

Model 2

Model 2	Estimate	Error	t Value	Pr>|t|	Significance level
Intercept	0.1254	0.0194	6.48	<.0001	***
CNPE	-0.0178	0.0220	-0.81	0.4201	-
C_risk	1.2141	0.6125	1.98	0.0496	**
GDP_Growth	0.1186	0.0603	1.97	0.0512	*
LCR	-0.0227	0.00510	-4.45	<.0001	***
NPL_ratio_b	0.2539	0.0724	3.51	0.0006	***
ROE	0.1329	0.0461	2.88	0.0046	***

Significance levels: *10%, **5%, ***1%

R-Square	0.3666
AIC	-883.1048
BIC	-880.3624
Number Observations	138

Model 3

Model 3	Estimate	Error	t Value	Pr>|t|	Significance level
Intercept	0.1263	0.0130	9.74	<.0001	***
C_risk	1.1250	0.5602	2.01	0.0467	**
GDP_Growth	0.1280	0.0588	2.18	0.0312	**
LCR	-0.0287	0.00514	-5.59	<.0001	***
NPL_ratio_b	0.2456	0.0679	3.62	0.0004	***
ROA	1.4194	0.4040	3.51	0.0006	***

Significance levels: *10%, **5%, ***1%

R-Square	0.3809
AIC	-888.2572
BIC	-885.7158
Number Observations	138

Model 4

Model 4	Estimate	Error	t Value	Pr>|t|	Significance level
Intercept	0.1151	0.0145	7.91	<.0001	***
C_risk	1.2013	0.6115	1.96	0.0516	*
GDP_Growth	0.1221	0.0600	2.03	0.0441	**
LCR	-0.0231	0.00507	-4.57	<.0001	***
NPL_ratio_b	0.2579	0.0721	3.57	0.0005	***
ROE	0.1334	0.0461	2.90	0.0044	***

Significance levels: *10%, **5%, ***1%

R-Square	0.3634
AIC	-884.4174
BIC	-881.8761
Number Observations	138