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Non-performing loans and banks' profitability: Empirical evidence from Europe

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Summary

INTRODUCTION

The primary function of a commercial bank is to collect deposits and provide loans to individuals and entity. Consequently, their primary source of revenue relies heavily on their lending activities. When there is a shortage of cash flow and a substantial number of individuals or entities struggle to meet their financial commitments, loans can turn into default loans. If these default loans persist for more than 90 days, they are classified as non-performing loans (NPLs) because they no longer fulfil their intended function. Consequently, as loans represent a significant source of income for commercial banks, an increase in non-performing loans can negatively impact the bank's profitability, as it reduces the income generated from lending.

Following the financial crisis, the significant rise in non-performing loans has attracted the attention of researchers worldwide who seek to explain how NPLs can potentially affect the profitability of commercial banks. Several scholars, including Kingu, Macha, and Gwahula (2018), Messai and Jouini (2013), Anastasiou, Louri, and Tsionas (2016), Akter and Roy (2017), and Petkovski, Kjosevski, and Jovanovski (2018), have investigated the relationship between non-performing loans and bank profitability. They have revealed a noteworthy negative correlation between non-performing loans and profitability within their respective countries or regions. This study specifically focuses on examining the impact of non-performing loans on profitability among listed commercial banks in the European region.

The main reason that prompted me to address this topic is the significant relevance that this category of loans has gained in the last decade due to the notable increase in their percentage, which emerged following the financial crisis that began in 2007, and the importance this will also assume in the economic recovery phase in a post-Covid-19 era. Non-performing loans have been a problem that affected European banks, especially Italian ones, which, along with Greek banks, reported the highest increase in their balance sheets precisely during the period from 2007 to 2015. This is why the banking system, encouraged by European interventions, had undertaken numerous measures aimed at reducing this amount significantly between 2015 and 2019, successfully decreasing the presence of non-performing loans.

ORGANIZATION OF THE STUDY

The entire research is organized into three sections and the outline of each chapter is given as takes after.

CHAPTER-I CREDIT RISK AND BANKING SECTOR. The first chapter deals with the overview of the banking sector. It also includes the main aspects of banking regulation, then credit risk and its component are presented.

CHAPTER II NON-PERFORMING LOANS. In the second chapter, the chapter looked for the review of the previous studies related to this research subject to know the prevalent of the non-performing loan and its effect on profitability. This section deals with conceptual framework and with the review of related studies.

CHAPTER-III A STATISTICAL ANALYSIS ON THE EFFECT OF NPLs ON BANKING PERFORMANCE. This chapter deals with the research approach and method of doing research on which this study based upon. It also clears about the population sample taken and the research instrument taken to collect the data and to analysis tools. Results and discussions deal with the presentations and analysis of the data collected from various sources. It also deals with the different financial and statistical tools with findings and brief comment on them. This chapter includes conclusions and implication of the study. Finally, bibliography and webliography are also included at the end of the study.

CHAPTER 1: CREDIT RISK AND BANKING SECTOR

1.1 OVERVIEW BANKING SECTOR

The banking sector is crucial to the modern economy. A bank is a financial institution licensed to receive deposits and make loans. Banks may also provide financial services such as wealth management, currency exchange, and safe deposit boxes. The core services Banks traditionally provide are: deposit collection, accepting cash or money (deposits) from individuals and businesses (depositors) for safekeeping in a bank account, available for future use, payment services, the process of accepting and making payments on behalf of customers using their bank accounts and loan underwriting, evaluating, and deciding whether a customer (borrower) is eligible to receive credit and then extending a loan or credit to the customer. When a bank accepts deposits, the depositor, in effect, lends money to the bank. In exchange, the depositor receives interest payments on the deposit. The bank then uses the deposit to finance loans to borrowers and generates income by charging interest on the loans. The difference between the interest the bank receives from the borrowers and the interest it pays to the depositors is the bank's primary source of revenue and profit. When underwriting a loan, a bank evaluates the borrower's credit quality (the likelihood that the borrower will repay the loan). However, depositors, who lend money to the bank in the form of deposits, typically do not evaluate the bank's credit quality or ability to repay the demand deposits. Depositors assume their deposits with the bank are safe and will be returned in full by the bank "on demand." Banks occasionally fail and cannot repay deposits fully. To protect depositors against bank failures, governments have created safety nets such as deposit insurance. Through the core bank services mentioned, banks are critical facilitators of economic activity. Banks channel savings from depositors to borrowers, an activity known as financial intermediation. Banks create loans from deposits through asset transformation. Banks, through financial intermediation and asset transformation, engage in money creation. Money creation is the process of generating additional money by repeatedly lending.

Banks are required to hold on some reserve, in cash or in the form of liquid securities, and not lend out some portion of their deposits. The amount of those reserves depends both on the bank's assessment of its depositors' need for cash and on the requirements of bank regulators, typically the central bank—a government institution that is at the centre of a country's monetary and banking system. Banks keep those required reserves on deposit with central banks, such as the U.S. Federal Reserve, the Bank of Japan, and the European Central Bank. Banks create money when they lend the rest of the money depositors give them. This money can be used to purchase goods and services and can find its way back into the banking system as a deposit in another bank, which then can lend a fraction of it. The process of relending can repeat itself several times in a phenomenon called the multiplier effect. The size of the multiplier—the amount of money created from an initial deposit—depends on the amount of money banks must keep on reserve. Banks also lend and recycle excess money within the financial system and create, distribute, and trade securities. In general, banks, in addition to generating income by lending financial resources at a higher rate than they gather them, can also earn by trading securities and, furthermore, by providing various services to individuals and businesses for a fee. Banks earn on average between 1 and 2 percent of their assets (loans and securities). This is commonly referred to as a bank's return on assets.

As mentioned above, banks play a central role in the transmission of monetary policy, one of the government's most important tools for achieving economic growth. The central bank controls the money supply at the national level, while banks facilitate the flow of money in the markets within which they operate. At the national level, central banks can shrink or expand the money supply by raising or lowering banks' reserve requirements and by buying and selling securities on the open market with banks as key counterparties in the transactions. Banks can shrink the money supply by putting away more deposits as reserves at the central bank or by increasing their holdings of other forms of liquid assets—those that can be easily converted to cash with little impact on their price. A sharp increase in bank reserves or liquid assets—for any reason—can lead to a "credit crunch" by reducing the amount of money banks have to lend, which can lead to higher borrowing costs as customers pay more for scarcer bank funds. A credit crunch can hurt economic growth.

Banks can fail, just like other firms. But their failure can have broader ramifications—hurting customers, other banks, the community, and the market as a whole. Customer deposits can be frozen, loan relationships can break down, and lines of credit that businesses draw on to make payrolls or pay suppliers may not be renewed. In addition, one bank failure can lead to other bank failures.

When a bank is perceived—rightly or wrongly—to have problems, customers, fearing that they could lose their deposits, may withdraw their funds so fast that the small portion of liquid assets a bank holds becomes quickly exhausted. During such a "run on deposits" a bank may have to sell other longer-term and less liquid assets, often at a loss, to meet the withdrawal demands. If losses are sufficiently large, they may exceed the capital a bank maintains and drive it into insolvency.

Essentially, banking is about confidence or trust. Any crack in that confidence can trigger a run and potentially a bank failure, even bringing down solvent institutions. Many countries insure deposits in case of bank failure, and the recent crisis showed that banks' greater use of market sources of funding has made them more vulnerable to runs driven by investor sentiment than to depositor runs.

1.2 REGULATORY ENVIRONMENT

Bank safety and soundness are a major public policy concern, and government policies have been designed to limit bank failures and the panic they can ignite. In most countries, banks need a charter to carry out banking activities and to be eligible for government backstop facilities—such as emergency loans from the central bank and explicit guarantees to insure bank deposits up to a certain amount. Banks are regulated by the laws of their home country and are typically subject to regular supervision. If banks are active abroad, they may also be regulated by the host country. Regulators have broad powers to intervene in troubled banks to minimize disruptions.

Regulations are generally designed to limit banks' exposures to credit, market, and liquidity risks and to overall solvency risk. Banks are now required to hold more and higher-quality equity—for example, in the form of retained earnings and paid-in capital—to buffer losses than they were before the financial crisis. Large global banks must hold even more capital to account for the potential impact of their failure on the stability of the global financial system (also known as systemic risk). Regulations also stipulate minimum levels of liquid assets for banks and prescribe stable, longer-term funding sources.

Regulators are reviewing the growing importance of institutions that provide bank-like functions but that are not regulated in the same fashion as banks—so-called shadow banks—and looking at options for regulating them. The recent financial crisis exposed the systemic importance of these institutions, which include finance companies, investment banks, and money market mutual funds.

Banking regulation is a form of customer regulation that makes banks follow specific guidelines, requirements, and restrictions to create market transparency among banking institutions, corporations, and individuals with whom they conduct their business. However, banking regulation is more than just having rules in place, it is also about the ongoing oversight and enforcement of these rules (Supervision). The major objectives of banking regulations are: 1) Protect the depositor's money and reduce the level of risk to which banks creditors are exposed 2) Systematic risk reduction. Banks invest in the form of lending or investing, and there is, of course, a risk involved in causing multiple or major banks failures 3) Avoid bank malpractices. Risk of banks being used for criminal purposes like laundering the proceeds of crime, that is, money laundering or terrorist financing of banks which are acting like tax heavens 4) Protect bank's confidentiality 5) Proper credit allocation 6) Fair treatment of customers and practice in corporate social responsibility. Banking regulation in Europe is primarily governed by the European Union (EU) institutions and directives. The main regulatory body for financial services in the EU is the European Banking Authority (EBA), which plays a crucial role in promoting effective and consistent banking supervision and regulation across EU member states. The key regulatory framework for banks in the EU is established by:

Capital Requirements Regulation (CRR) and Capital Requirements Directive (CRD): This regulatory package, commonly referred to as CRD IV, sets out prudential rules for banks, including capital requirements, leverage ratios, and liquidity standards. The goal is to ensure that banks have sufficient capital to absorb losses and maintain financial stability.

Single Rulebook: The EU has established a "Single Rulebook" for banking regulation to harmonize rules and standards across member states. It aims to create a level playing field for banks and enhance financial stability within the EU.

Bank Recovery and Resolution Directive (BRRD): This directive establishes a framework for the recovery and resolution of failing banks. It aims to minimize the impact of bank failures on taxpayers and the broader financial system.

Deposit Guarantee Schemes Directive (DGSD): The DGSD ensures that depositors' funds are protected up to a specified amount in case of a bank's failure. It provides a minimum level of deposit protection across EU member states.

Market Abuse Regulation (MAR): This regulation addresses market abuse practices, such as insider dealing and market manipulation, to maintain market integrity and protect investors.

MiFID II/MiFIR: The Markets in Financial Instruments Directive (MiFID II) and the Markets in Financial Instruments Regulation (MiFIR) regulate financial markets and investment services. While they are not specific to banks, they impact banking activities related to securities and investment products.

The Basel Accords are a series of international banking supervision agreements that aim to ensure financial stability and strengthen the regulation, supervision, and risk management practices of banks worldwide. These accords are issued by the Basel Committee on Banking Supervision (BCBS), which is a global committee of banking supervisory authorities.

Here's a brief overview of each Basel Accord:

Basel I (1988): Basel I, also known as the Basel Capital Accord, was the first international regulatory framework for banking supervision. It primarily focused on credit risk and mandated banks to maintain a minimum capital requirement of 8% of risk-weighted assets. The assets were categorized into different risk buckets based on their perceived credit risk.

Basel II (2004): Basel II introduced a more comprehensive and risk-sensitive approach to bank regulation. It expanded the risk categories beyond credit risk to include operational risk and market risk. The framework also allowed banks to use internal models to calculate their capital requirements, known as the Internal Ratings-Based (IRB) approach. This Accord aimed to align capital requirements more closely with the actual risk exposure of banks.

Basel 2.5 (2009): Basel 2.5 was an interim revision between Basel II and Basel III to address the shortcomings in the treatment of trading book assets. It introduced additional capital requirements for specific risk exposures in the trading book.

Basel III (2010-2019): Basel III was developed in response to the 2008 global financial crisis to further strengthen the banking sector's resilience and risk management. It introduced several new measures, including: Higher capital requirements, including a Common Equity Tier 1 (CET1) capital requirement of at least 4.5% of risk-weighted assets and a capital conservation buffer. Liquidity requirements, including the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR) to ensure banks maintain sufficient liquidity during stress scenarios. Leverage ratio to limit excessive leverage in the banking system. Countercyclical capital buffer to address systemic risk. Additional capital requirements for global systemically important banks (G-SIBs).

Basel IV: Basel IV is not a formal accord like the previous ones but refers to the ongoing and proposed updates to the Basel III framework. These updates aim to further refine the regulatory framework and address any remaining shortcomings. Basel IV discussions have covered topics such as the standardization of the IRB approach, revised credit risk approaches, and the output floor to limit the variability of risk-weighted assets calculated by banks using their internal models.

1.3 OVERVIEW OF CREDIT RISK

Credit risk is most simply defined as the potential that a bank borrower will fail to meet its obligations in accordance with agreed terms. It represents the possibility of unexpected changes in the value of a credit position due to adverse movements in risk factors related to the creditworthiness of the counterparty. It is the primary risk that banks have concentrated on since the inception of the banking industry. It is explained by the fact that banks' activities mainly involve taking deposits and making loans. The loans made are predisposed to some level of default risk and hence some level of credit loss, credit risk.

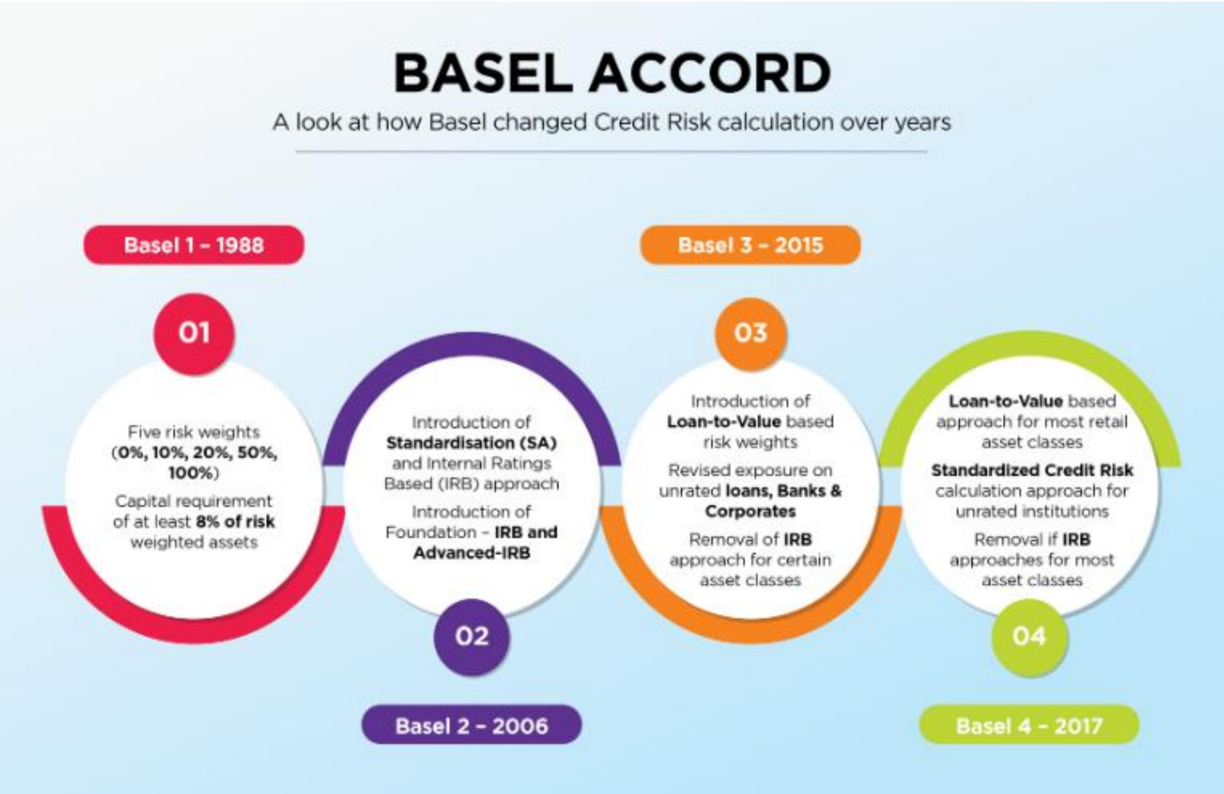
The risk is that of the lender and includes loss of principal and interest, that could be partial or complete. Losses can arise for several circumstances, for example: a consumer may fail to make a payment due on mortgage loan, credit card, or line of credit, a company is unable to repay asset-secured fixed or floating charge debt, a business or consumer does not pay a trade invoice when due, a business or government bond issuer not make a payment on a coupon or principal payment when due.

There are mainly four different types of credit risk:

1. **credit default risk**: is the risk of loss arising from a debtor being unlikely to pay its loan obligations in full or in part or the debtor is more than 90 days past due on any material credit obligation, default risk may impact all credit-sensitive transaction;
2. **concentration risk**: is the risk with any single exposure or group of exposure with the potential to produce large enough losses to threaten a bank's core operations. It may arise in the form of single-name concentration or industry concentration;
3. **country risk**: is the risk of loss arising from a sovereign state freezing foreign currency payments in this circumstance transfer or conversion risk or when it defaults on its obligations, sovereign risk, this risk is prominently associated with the country macroeconomic performance and political stability;
4. **counterparty credit risk**: is the risk that the counterparty to a transaction could default before the final settlement of the transaction's cash flows, an economic loss would occur if the transactions or portfolio of transactions with the counterparty has a positive economic value at the time of default, unlike a firm's exposure to credit risk through a loan, where the exposure to credit risk is unilateral and only the lending bank faces the risk of loss, CCR creates a bilateral risk of loss: the market value of the transaction can be positive or negative to either counterparty to the transaction. The market value is uncertain and can vary over time with the movement of underlying market factors.

The goal of credit risk management is to maximise a bank's risk-adjusted rate of return by maintaining credit risk exposure within acceptable parameters. Banks need to manage the credit risk inherent in the entire portfolio as well as the risk in individual credits or transactions. Banks should also consider the relationships between credit risk and other risks. The effective management of credit risk is a critical component of a comprehensive approach to risk management and essential to the long-term success of any banking organisation. For what concern the regulation of credit risk the following graph explains how Basel Accords changed credit risk calculation over years.

Figure 1. How Basel Accords changed Credit Risk calculation over years



Source: *HCLTech.com*

It is worth mentioning that meeting regulatory capital requirements does not relieve a bank's board of directors and senior management of their responsibility to provide competent and prudent bank leadership and oversight. This includes the maintenance of adequate capital to support the bank's business activities beyond the scope of regulation. That is why, along with the calculation of Regulatory Capital and capital requirements, banks usually calculate also the amount of economic capital. For any bank or financial institution's effective capital management: the starting point is the regulatory capital, i.e., the capital computed by the Basel III capital adequacy framework; the next step is the development of an economic capital framework. Banks use the economic capital model as a tool primarily for two purposes: capital allocation and performance assessment. Within a bank, each business line is allocated economic capital to produce an optimum return in line with the strategy and risk appetite of the bank. Capital usage is regularly monitored, and mitigating measures are taken if capital usage exceeds the limit. Also, capital usage metrics are set, and the performance of business lines is evaluated against such metrics.

Figure 2. Economic capital, Regulatory capital, Equity capital, Debt capital

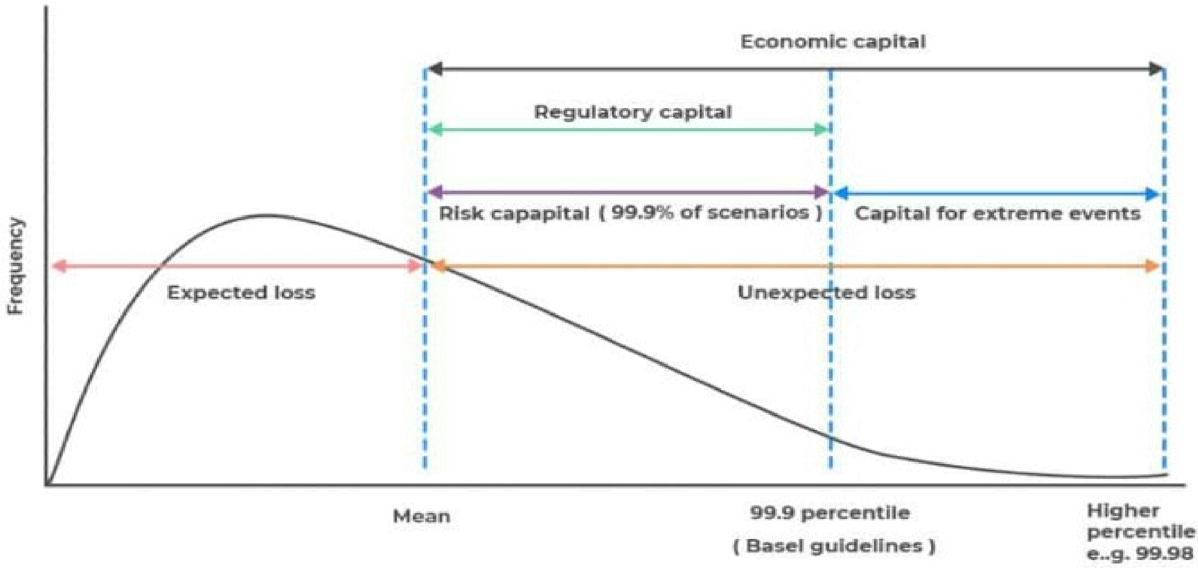
Economic Capital	The amount of capital that a bank needs in order *to remain solvent and maintain its day-to-day operations.* Also known as risk capital, it is the amount of capital required to absorb the impact of unexpected losses during a specified time horizon, at a given level of confidence.
Regulatory Capital	The amount of capital a bank is required to hold in accordance with laid down regulations, rules, and guidance. They are determined by BCBS, and supervisors implement the BCBS requirements in each country. For instance, according to Basel II, regulatory capital can be divided into three tiers: **Tier I capital** – core capital, **Tier II capital** – supplementary capital, e.g. general loan reserve, **Tier III capital**, e.g. short term subordinated debt.
Equity Capital	It represents the amount of money that would be returned to a company's shareholders if all of the assets were liquidated and all of the company's debt was paid off in the case of liquidation. In the case of acquisition, it is the value of company sales minus any liabilities owed by the company not transferred with the sale. The equity capital is described as "going concern capital" because the bank is solvent if its capital is positive.
Debt Capital	Banks also have what is called debt capital, funded by bondholders. In case the incurred losses deplete the equity capital, the debt holders should incur losses before the depositors. Debt capital is described as the "gone concern capital" because it acts as a cushion to the depositors when the bank becomes insolvent (no longer a going concern).

Source: Author's compilation.

1.4. CREDIT RISK COMPONENTS

To better understand and analyse credit risk, it is useful to divide it into its components. The first distinction is between expected loss and unexpected loss. Unexpected loss, because it cannot be known before an event occurs, is the principal risk the bank bears with respect to the exposure. Expected loss, on the other hand, is foreseeable and calculable in advance by the bank and does not constitute a risk.

Figure 3. Expected and Unexpected loss



Source: Author's compilation

1.4.1. THE EXPECTED LOSS

The expected loss is the average credit loss it could be expected from an exposure or a portfolio over a given period. It is the anticipated deterioration in the value of a risky asset. In Chapter 5, the Capital Requirements Regulation defines expected loss as "*the ratio of the amount expected to be lost on an exposure over a one-year horizon as a result of a potential default of a counterparty or dilution to the amount of the exposure at the time of default*"[1].

In mathematical terms,

$$EL = EAD\ x\ PD\ x\ LGD$$

Where:

- EAD = Exposure at Default;
- PD = Probability of Default;
- LGD= Loss Given Default (also known as loss rate).

Credit loss level are not constant but rather fluctuate from year to year. The expected loss represents the anticipated average loss that can be statistically determined. Businesses typically have a budget for the Expected Loss and try to bear the losses as part of the standard operating cash flows.

[1] European Banking Authority, Capital Requirement Regulation

The expected losses of a portfolio is equal to the summation of expected losses of individual losses.

In mathematical terms,

$$\boldsymbol{EL_p} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} \boldsymbol{EAD_i x PD_i x LGD_i}$$

1.4.2. EXPOSURE AT DEFAULT

EAD (exposure at default) is the predicted amount of loss a bank may be exposed to when a debtor defaults on a loan. It is a stochastic variable whose volatility depends on the type of facility granted to the borrower. In the case of a credit line, for example, the bank undertakes to lend a certain amount of funds to the customer, which chooses which portion to use and when. This means that the true size of the actual loan may vary over time due to decisions external to the bank.

The EAD is often deterministic and easily quantifiable. For example, many bank loans entail a non-stochastic exposure, following a pre-determined repayment plan of the capital and interest (so that the customer has no discretion as to the amount of the loan that he/she will be using in the future). The same applies to bonds, where cash flows are wholly defined at the time of issue.

Although the amount of the EAD should theoretically consider the value of the exposure at the expected time of the default itself, in the case of a 1-year time horizon, EAD is generally and cautiously assumed to be equal to the exposure at the time of the analysis.

The EAD varies according to the technical form of the exposure:

- For amortizing loans, it is usually equal to the sum of overdue and unpaid installments plus residual debt;
- For bullet loans, it is equal to the value to be repaid at maturity;
- For “committed” credit lines (i.e., non-revocable), the undrawn portion of the credit line margin is transformed into a “cash equivalent" by a conversion parameter (Credit Conversion Factor or CCF) which represents the portion of the undrawn line of credit that the obligor would likely utilize before defaulting;
- For "uncommitted" (or revocable) credit lines, the CCF is often assumed to be zero.

In mathematical terms,

$$EAD = DP + UP\ x\ CCF$$

Where:

- EAD = Exposure at Default;
- DP = Drawn portion;
- UP = Undrawn portion;
- CCF = Credit conversion factor

There are two methods to determine the exposure at default.

1. F-IRB: foundation internal rating-based approach, it is used by regulators;
2. A-IRB: advanced internal rating-based approach, it is used by financial intermediaries.

1.4.3. LOSS GIVEN DEFAULT

Loss given default (LGD) is the estimated amount of money a bank or other financial institution loses when a borrower defaults on a loan. LGD is depicted as a percentage of total exposure at the time of default or a single dollar value of potential loss. A financial institution's total LGD is calculated after a review of all outstanding loans using cumulative losses and exposure.

In mathematical terms,

$$LGD = 1 - RR$$

Where:

- RR = Recovery Rate

The LGD is never known when a new loan is issued, nor it is perfectly known when the default occurs, at least if there is no secondary market for the defaulted exposure.

In the late 90's, a survey by a Task Force appointed by the Basel Committee, concerning the rating systems of the major world banks, highlighted that only few of them carried out separate estimates for the LGDs of the exposures and the PDs of the borrowers. Many, in fact, used to estimate directly the expected loss rate (EL rate), given by the product of the two.

In 1999, the Task Force prompted the banks to adopt separate estimation models for PDs and recovery rates, as those two parameters mostly depend on different mechanisms and risk factors. Such an invitation was reiterated in 2004 by the new Basel accord on minimum bank capital, which required banks to adopt ad hoc rating systems for the LGD. Latterly, most banks have followed such suggestions.

There are several factors that affect LGD and they can be grouped in four main categories: the technical characteristics of the credit exposure, those of the borrower, the peculiarities of the bank managing the recovery process and, in conclusion, some external factors.

1. The technical characteristics of the exposure: these includes the presence of any collateral (financial asset, real estate, plants, inventories); the level of seniority of the exposure, senior or subordinated to other exposure; the presence of guarantees provided by third parties (banks, holding companies, public sector);
2. The characteristics of the borrower : these includes the industry in which the company operates (which can affect the liquidation process, that is, the ease with which the companies' asset can be sold and turned into cash for creditors; the country in which the obligors operates, which may affect the speed and effectiveness of the bankruptcy procedures; some financial ratios, like the leverage (the ratio between total assets and liabilities, which shows how many euros of assets are reported in the balance sheet for each euro of debt to be paid back) and the ratio of EBITDA (earnings before interest taxes depreciation and amortization) to total turnover (which indicates whether the defaulted company is still capable of generating an acceptable level of cash flow);
3. The characteristics of the bank managing the recovery process: such as the efficiency levels of the department which takes care of the recovery process (workout department) or the frequency with which out-of-Court settlements are reached with the borrowers, or non-performing loans are spun-off and sold to third parties;
4. External factors: such as the state of the economic cycle (if the economy is in recession, the value at which the companies' assets can be liquidated is likely to be lower) and the level of the interest rates (higher rates reduce the present value of recoveries); actually, the economic cycle, while driving the liquidation value of assets and LGD, is also likely to affect the default probability of the borrowers. A problem may therefore arise, due to the correlation between default risk and recovery risk; we will return to that in the last part of the Chapter.

Recovery rates on defaulted exposures can be computed based on different approach:

-**Market LGD**- The market approach is based on direct observation of prices of defaulted exposure as an estimate of the recovery rate and hence the loss rate. For example, if a debt instrument of an insolvent company is traded at 40 cents per euro of nominal capital, means that the market estimates a Recovery rate of 40% for exposure and a relative 60% loss rate. This measure essentially represents investors' expectations of the future discounted cash flows in relation to the debtor's repayment capacity but is calculatable for a type of debt not very common in the banking book of a bank traditional. Such an approach is usually employed by credit rating agencies and may be applied only to instruments traded in the secondary market and for which there is a price even after the default of the issuer. A variant of the classic LGD Market approach is the Emergence LGD5 proposed by Van de Castle and Keisman in 1999. This method is based on the estimation of the recovery rate on the basis of market for new financial instruments offered to investors to replace the old ones defaulted bonds. Such instruments are usually issued (and their market price becomes known) only when the restructuring process is over and the company emerges from default; their value must then be discounted back in time to the moment when the default took place, using an adequate discount rate. This is called the emergence LGD

-**Workout LGD**- Since most traditional banking loans are not traded, no market price can be observed. The Workout LGD has been introduced to overcame this issue. This approach is based on the measurement of the actual recoveries experienced by the banks in the months (or years) after a default took place. It requires that an historical database be compiled, where all defaulted exposures are filed and, for each of them, all information on recovered amounts, recovery lags and recovery procedures are recorded. Such data will then be segmented based on the type of exposure, on different types of borrowers, on the recovery procedure used, so that a finite number of clusters can be identified, made up of similar cases leading to similar LGDs. Such clusters will then be used as a reference for estimating the expected LGD on future defaults. The Workout LGD approach thus requires the computation of the present value of cash flows during the recovery process, i.e., between the onset of default and the closure of the process, net of recovery costs incurred by the bank. Once all cash flows have been discounted using a certain rate, the loss will be calculated as a percentage of the EAD. The final objective is to determine the LGD incurred on each exposure belonging to a given reference cluster and, using a backward-looking approach, estimate the loss given default for each cluster.

In mathematical terms,

$$\boldsymbol{RR = \frac{DNR}{EAD} x \frac{FR - AC}{FR} x(1 + r)^{-T}}$$

Where:

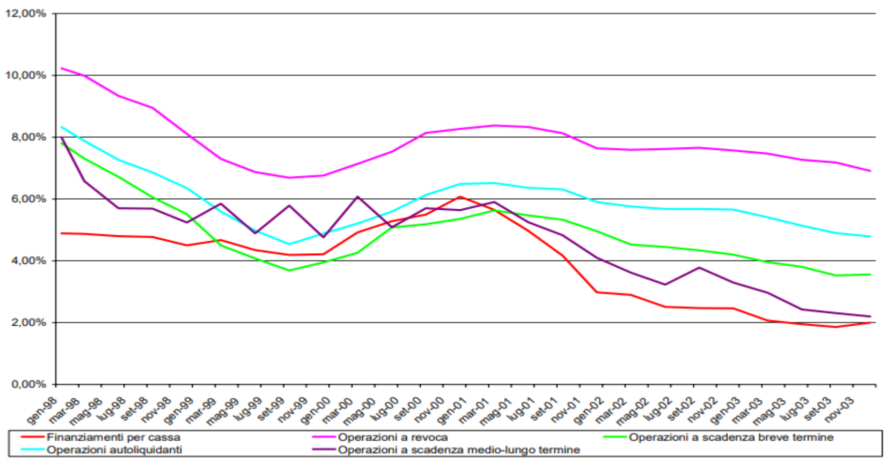
- RR = Recovery Rate;

- DNR = Discounted net value of the recovery, that is, the present value at the time of default of all recovered amounts, net of all cost;
- EAD = Exposure at Default;
- FR = Face Value of the recovered amount, as recorded in the bank's accounting data;
- AC = Administrative Costs connected with the workout procedure on the defaulted exposure;
- r = discount rate;
- T = duration of the recovery process.

In the calculation of ex-post LGD, a key role is taken by the choice of discounting factor (r in our case) through which flows are discounted. In this context, Gibilaro e Mattarocci (2006)[2] have attempted to give an answer to this question by proposing 3 solutions:

1. **the contractual rate applied to the customer**: This approach is based on the idea that the flows recovered by the intermediary after the event of insolvency, are discounted at the contractual rate defined at the beginning of the relationship or at the last contractual rate renegotiated with the customer. The adoption of such an approach can be considered reasonable only if the insolvency event does not change the risk profile of the transaction. Because of the large differences between contractual rates of different operations, this method requires the collection of comprehensive internal information sets segmented by exposure type;

Figure 4. Trends in contractual rate grouped by type of transaction



Source: Gibilaro L., Mattarocci G. (2006), "La selezione del tasso di attualizzazione nella stima del Loss Given Default: Un'applicazione del mercato italiano"

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[2] Gibilaro L., Mattarocci G. (2006), "La selezione del tasso di attualizzazione nella stima del Loss Given Default: Un'applicazione del mercato italiano"

2. **the risk-free rate**; The difficulty in finding all the information needed for a comprehensive database may make the solution of contractual rates impractical so, to simplify the procedure, one could opt to use the risk-free rate. In that case, the reference market and, of course, the proxy for the risk-free activity must be chosen;
3. **the risk-adjusted rate of return estimated by a multi-factor approach**: Taking into consideration that in a recovery procedure there is no certainty about flows and that intermediaries realize returns from lending in excess of risk-free rate, the choice to employ a risk-free rate could lead to an underestimation of the loss rate in the event of default. To overcome this problem, a specific and more appropriate rate could be computed through the CAPM model proposed by Sharpe (1964):

$$r = Rf + \beta(Rm - Rf)$$

Where r is the discount rate, Rf is the risk-free rate, Rm is the market return, and β is the index of change in r as rm changes. In this case, in addition to having to set a proxy for the risk-free asset, we need to decide which index can best represent the market return. The authors promote the use of an index that is an expression of defaulted corporate bonds or, alternatively, an index on general economic trends such as GDP. Once calculated, LGDs related to defaulted positions are filed together with all the technical specifications that marked the process of recovery, composing a database on past workout experiences useful for forecasting the loss rate on new exposures.

1.4.4. PROBABILITY OF DEFAULT

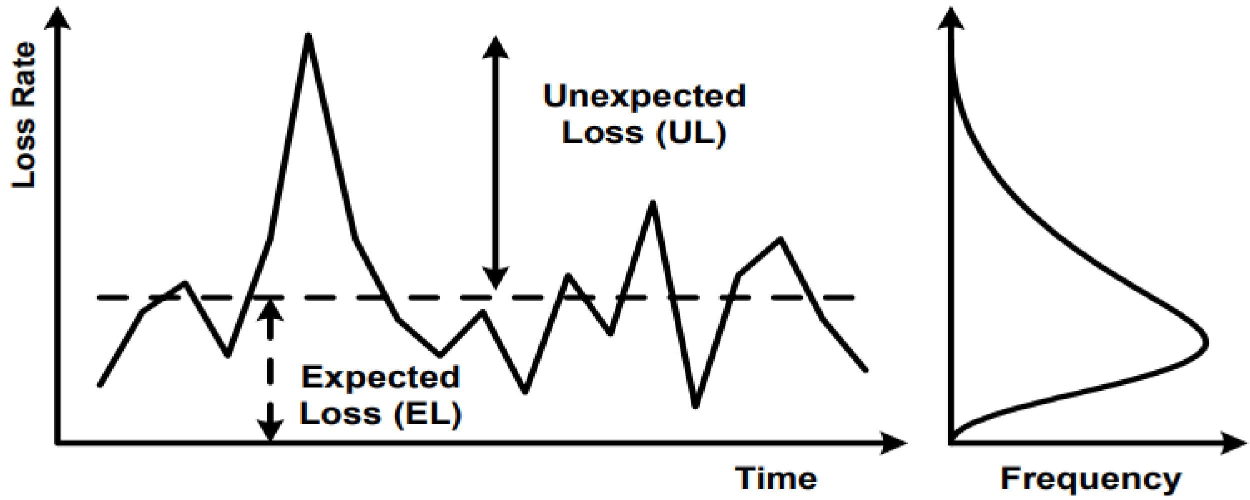
The probability of default (PD) measures the likelihood of a borrower defaulting on debt obligations within a specific timeframe. It is calculated using statistical models and historical data, considering financial health, credit history, and economic conditions. It does not predict future defaults but provides an estimate based on historical data. The probability of default is influenced by several variables such as the creditworthiness of the borrower, the time horizon, the definition of default.

There are many alternatives for estimating the probability of default. Default probabilities may be estimated from a historical data base of actual defaults using modern techniques like logistic regression. Default probabilities may also be estimated from the observable prices of credit default swaps, bonds, and options on common stock. The simplest approach, taken by many banks, is to use external ratings agencies such as Standard and Poor's, Fitch or Moody's Investors Service for estimating PDs from historical default experience.

1.4.5. UNEXPECTED LOSS

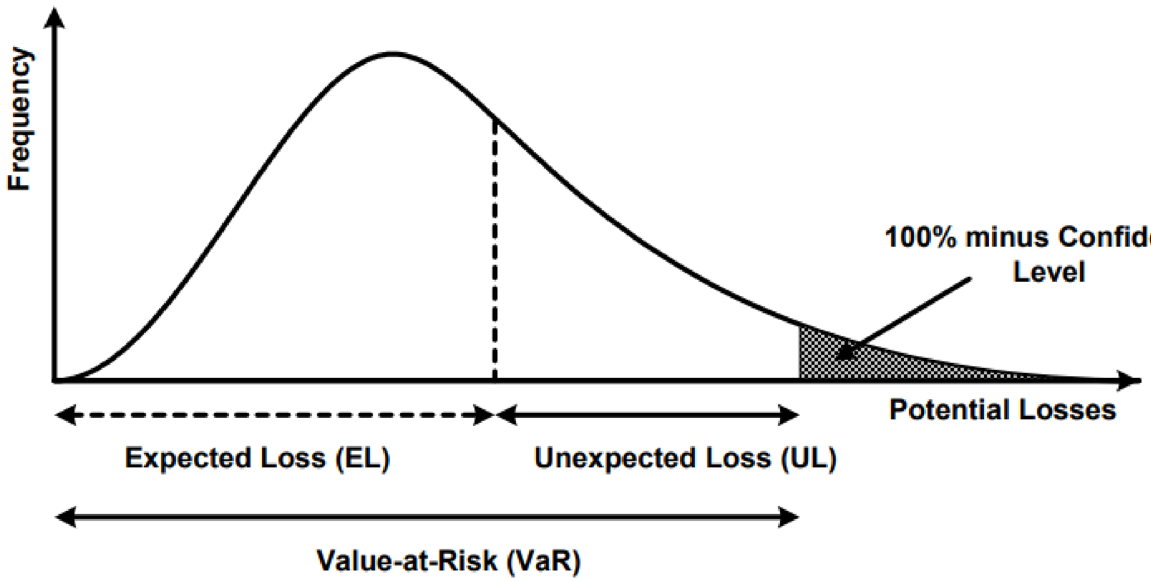
The Unexpected Loss (UL), represents the very essence of credit risk and is considered as the level of loss not expected by the intermediary at the time of loan origination. In other words, we can consider UL as the loss exceeding the expected level, i.e., EL. This type of eventuality must be covered by adequate provisions to regulatory capital.

Figure 5. Expected Loss and Unexpected Loss



Source: Bank for international Settlements (2005): An explanatory Note on Basel II IRB Risk Weight Functions

Figure 6. Probabilistic distribution of default losses



Source: Bank for international Settlements (2005): An explanatory Note on Basel II IRB Risk Weight Functions

Figure 6 shows the probability distribution function of default losses from credit risk. The area under the curve represents 100 percent probability, which in turn is divided into three areas representing the confidence levels of expected losses (covered with commissions and risk premiums on rates), unexpected losses (met with provisions to regulatory capital) and the actual losses (i.e., the eventuality of the bank being uncovered). The sum of EL + UL constitutes the Value at Risk (VAR), i.e., the maximum loss potential at a given confidence level. The area in white below the curve represents just the confidence level α of the VAR, while the black area represents the confidence level of actual losses, i.e., 1-α. In practice, if the regulatory capital conforms to the UL and the returns and commissions manage to cover the EL, then the probability that the bank remains solvent (for a defined time horizon) is equal to the confidence level of the VAR.

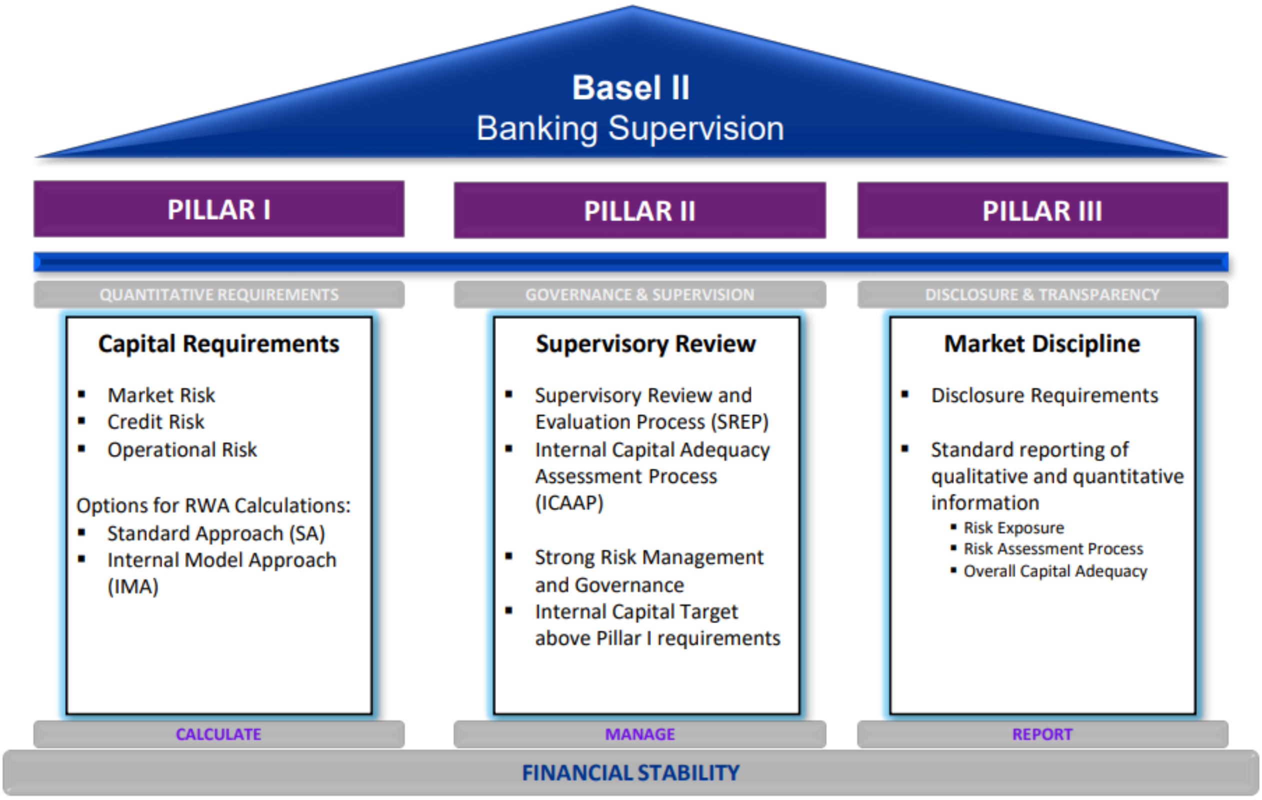
Unexpected loss for a single exposure can be expressed in mathematical terms as:

$$\boldsymbol{UL = EAD\ x \sqrt{PD\ x\ \sigma^2_{LGD} + LGD^2\ x\ \sigma^2_{PD}}\ where\ \sigma^2_{PD}\ =\ PD(1 - PD)}$$

1.5 CAPITAL REQUIREMENTS FOR CREDIT RISK

In 2004, after lengthy consultations, a new capital framework, Basel II, was introduced. The Basel II Accord defines a three-pillar framework to ensure banks adopt a consistent approach to their capital adequacy requirements.

Figure 7. Three-pillar framework, Basel II



Source: Author's compilation

Basel II – Pillar I sets the minimum capital requirements for market risk, credit risk and operational risk.

Under current regulations, a bank's regulatory capital should be at least equal to:

$$\mathbf{PV} \geq \mathbf{8\%\ RWA} + \mathbf{PVrm} + \mathbf{PVro}$$

Where:

- PV = regulatory capital

- RWA = risk weighted asset

- PVrm= capital required for market risk

-PVro = capital required for operation risk

For what concern the estimation of the Risk-weighted asset for Credit risk the regulator defines three main approach that can be implemented by the financial intermediary:

1. Standardized approach (SA-CR)
2. Foundation Internal Rating-Based (F-IRB)
3. Advanced Internal Rating-Based (A-IRB)

1.5.1 STANDARDIZED APPROACH

Under the Standardized Approach, the Risk Weights associated with a specific exposure are set by external credit assessment institutions such as rating agencies or other institutions recognized by the national supervisory authorities.

Table 1. Risk Weights associated to different classes of borrowers and specific types of loans.

<table>
<tr><th></th><th>AAA</th><th>AAA−</th><th>AA+</th><th>AA</th><th>AA−</th><th>A+</th><th>A</th><th>A−</th><th>BBB+</th><th>BBB</th><th>BBB−</th><th>BB+</th><th>BB</th><th>BB−</th><th>B+</th><th>B</th><th>B−</th><th>Below B−</th><th>Unrated</th><th>Past-due</th></tr>
<tr><td>Corporates</td><td colspan="5">20%</td><td colspan="3">50%</td><td colspan="6">100%</td><td colspan="4">150%</td><td>100%</td><td>150%</td></tr>
<tr><td>Sovereign entities</td><td colspan="5">0%</td><td colspan="3">20%</td><td colspan="3">50 %</td><td colspan="6">100%</td><td>150%</td><td>100%</td><td></td></tr>
<tr><td>Banks</td><td colspan="5">20%</td><td colspan="6">50%</td><td colspan="6">100%</td><td>150%</td><td>50%</td><td></td></tr>
<tr><td>Banks, depending on the country of incorporation</td><td colspan="5">20%</td><td colspan="3">50%</td><td colspan="9">100%</td><td>150%</td><td>100%</td><td></td></tr>
<tr><td>Retail</td><td colspan="19">75%</td><td></td></tr>
<tr><td>Residential real estate mortganges</td><td colspan="19">35%</td><td>100%</td></tr>
<tr><td>Non-residential real estate mortgages</td><td colspan="19">From 100% to 50%, upon discretion of the national supervisory authorities</td><td>150%</td></tr>
</table>

Source: *Andrea Resti, Andrea Sironi, (2007), "*Risk management and shareholders' value in banking"

The table above shows the different classes of borrowers (e.g., Corporates, Sovereign Entities, Banks, Small Enterprise) and some specific types of loans, columns display how the different ratings that might be assigned to a counterpart.

From the combination of rows and columns, for instance, a loan of € 100 to a non-financial company with a A rating translates into € 50 of risk weighted assets, thus leading to a capital requirement of 50 × 8 % = €4 (or, in other words, 4 % of the non-weighted exposure).

1.5.2 INTERNAL RATING-BASED APPROACH

With the standard approach, the minimum capital associated with an exposure is simply 8 % of risk-weighted assets, where weighting is to be carried out subject to the system described in Table 1.

The IRB approach, on the other hand, relies on a more complex mechanism for transforming the characteristics of a loan (PD, LGD, EAD, maturity) and of its portfolio (granularity and correlation) into a capital requirement.

Banks applying for the internal ratings approach (whose risk measurement systems must be approved by the national supervisory authorities) are fully or partly responsible for assessing the degree of risk associated with each individual loan and to the credit portfolio.

The main difference between the *IRB foundation approach* and *IRB advanced approach* is that the first method mentioned allows only the estimation of the debtors' PD using internal models, while requiring to refer to pre-established values set by the Authorities for LGD, EAD, and maturity. On the other hand, the IRB advanced approach enables the measurement of all four risk profiles with the banks' internal models.

CHAPTER 2: NON-PERFORMING LOANS

2.1 NON-PERFORMING LOANS

According to the bank of Italy, non-performing loans are "*exposures to debtors who are no longer able to meet all or part of their contractual obligations because their economic and financial circumstances have deteriorated*"[3].

As of today, impaired loans can be classified as:

1. Bad loans: they are claims against persons who are in state insolvency or in substantially equivalent conditions; is the most serious case where the debtor is not more able to pay his debt;
2. Unlikely to Pay: are the claims for which the probability that the debtor can fully comply with the contractual conditions, or simply that he can pay the credit in full, is considered low by the creditor bank, even if the debtor is not yet insolvent. Banks often, rather than defaulting a position, prefer to restructure it to consider it "performing", so that it does not turn into a real loss for the bank itself;
3. Past Due: are the expired credits, for which the counterparty does not comply with the payment for at least 90 days.

The difference between Bad Loans and Past Due is based on the degree of risk of the individual credit. A credit is classified as a bad loan when the bank, because of a specific situation (e.g., the bankruptcy of a company or the non-payment for an extremely long period), considers that credit too risky. If, instead, a counterparty does not pay for at least three months, not because it is in a state of insolvency, but because of a particular situation, the credit is classified as Past Due, not resulting in suffering.

2.2 CREDIT VALUATION: IAS 39 and IFRS 9

The rules used to classify and assessing loans in banks' financial statement are established by international accounting standards (IAS-IFRS), a body of accounting standards approved by the International Accounting Standard Board. The accounting standard on which attention will be focused in this section is *International Accounting Standard 39 - Financial Instruments:*

[3] Bank of Italy, "Non- performing loans in Italy banking system"

Recognition and Measurement and the *International Financial Reporting Standard 9* which permanently replaced, from 1 January 2018, IAS 39.

According to IAS 39, loans may be included in one of the following portfolios:

1. *Financial Asset at fair value through profit or loss*: Includes purchased or originated financial assets held for the purpose of generating a profit from short-term fluctuations;
2. *Loans and receivables:* Includes receivables generated by the enterprise as a result of lending money to a person who qualifies as a debtor;
3. *Available for sale financial assets:* Includes all financial assets that do not fall under the previous categories.

On the classification of the loan depends the valuation methodology to be used, so the correct classification is not merely a matter of adequate representation of the post in the balance sheet, rather from the classification also descends the valuation model to be operated.

Table 2. Classification of Receivables according to IAS

Typology	Category	Valuation	Accounting treatment
Credits originated by the bank with the intention of holding them until maturity	Loans and Receivables	Historical amortised cost by calculation of effective interest rate and annual impairment test	Profit/Loss in the income statement on elimination of the asset following impairment test or amortisation
Credits originated by the bank with the intention of selling them before maturity	Fair value	Market values where available or DCF-type valuation methodologies	Profit/Loss in the income statement in the year in which it accrues
Credits not originated by the bank with the intention of holding them until maturity	(Held to maturity) Available for sale		
Credits not originated by the bank with the intention of selling them before maturity	Fair value	Market values where available or DCF-type valuation methodologies	Profit/Loss in the income statement on elimination of the asset following impairment test or amortisation

Source: Author's compilation

The initial recognition of a loan, regardless of the category to which it belongs, takes place according to the fair value criterion. The valuation process following the initial recognition, as shown in Table 2, is methodologically differentiated according to the portfolio to which it belongs.

Loan loss provisioning[4] under IAS 39 has two levels:

1. Analytical valuations of individual transactions;
2. Lump-sum portfolio valuations (portfolio approach).

In the first case, it is necessary to identify significant credits. These significance parameters are often articulated based on supervisory credit classification variables (performing, past-due, probable default, non-performing) and the absolute amount of credit used.

In the case of an assessment of a loan that is not significant and which, through the analysis of appropriate indicators, does not qualify for analytical assessment, it will be assessed on a collective basis only. IAS 39 defines the collective valuation process as interim: loans are first valued analytically, on an individual basis, and, if there is no evidence of impairment, aggregation into homogenous portfolios and portfolio impairment may be performed. When an individual loan shows evidence of impairment, it is removed from the reference portfolio and valued solely on an individual basis[5].

IAS 39 does not define a specific methodology for quantifying collective adjustments, but establishes reference principles. It is possible to use a statistical methodology or mathematical formula as long as it takes into account:

1. the monetary value of time;
2. of the entire time life of the loan and not just the first year;
3. Does not generate adjustments at the time the loan is disbursed;
4. Is consistent with the general principles of individual impairment models (IASB,2009, IAS 39 AG. 92).

With regard to point 4), the general principles of impairment involve discounting expected future cash flows at the original effective rate. This principle does not change since, if a market rate were used, one would fall back on the assumption of fair value and would take into account not only changes in the creditworthiness of customers, but also changes in the free risk rate and the price of market-defined risk in a given period. To neutralise these components and capture only

[4] A loan loss provision is an income statement expense set aside as an allowance for uncollected loans and loan payments. This provision is used to cover different kinds of loan losses such as non-performing loans, customer bankruptcy, and renegotiated loans that incur lower-than-previously-estimated payments. Loan loss provisions are then added to the loan loss reserves; a balance sheet item that represents the total amount of loan losses subtracted a company's loan.

[5] Cfr.IASB (2009), IAS 39, \AG 88: “Impairment losses recognised on a group basis represent an interim step pending the identification of impairment loss on individual asset in group of financial assets that are collectively assessed for impairment. As soon as information is available that specifically identifies losses on individually impaired assets in a group, those assets are removed from the group”.

the change in creditworthiness, *the original effective interest rate discounting of risk-adjusted cash flow* model is used, which fixes the interest rate at the denominator and makes the amount and dynamics of these vary over.

Since its introduction, IAS 39 has been particularly criticized by practitioners and academics for several reasons. First of all, its complexity, which often makes accounting measurement practices very distant from the operating practices used by banks. The principle of fair value, in particularly turbulent market situations, can lead to distorted valuations. Another criticism of IAS 39 is the delay in accounting for losses through the logic of incurred losses.

According to IFRS 9, financial assets and financial liabilities are classified according to two main parameters: a. the business model and; b. the contractual flow characteristics of the financial instrument. As for business models, those accepted by IFRS 9 are basically three: held to collect (HTC), held to collect and sales (HTCS) and fair value through profit and loss (FVTPL). In the first business model, the valuation of the asset is at amortised cost, which does not differ substantially from IAS 39, except for the operating methods by which the impairment of the accounting item is carried out. The assets classified in the other two portfolios (HTCS and FVTPL) are measured at fair value, but the accounting impacts of this valuation are different: in the first case, the changes in fair value are offset by a net capital buffer (Fair value through other comprehensive income, FVOCI) while, in the second case, the income statement will record any changes from fair value. The HTC category is the only one that allows valuation at amortised cost, reducing the volatility of economic results and giving greater stability to company margins. The HTC portfolio, in practice, should incorporate the Loans and Receivables and the assets held to maturity required by IAS 39.

The second characteristic to be used in order to correctly classify a financial asset is the type of cash flows provided by the contract. Financial assets may be covered by the "solely payment of principal and interest" - SPPI or, alternatively, non-SPPI compliant activities.

With respect to the Impairment model, IFRS 9 provides for an annual test for the following financial assets:

1. financial assets valued at amortised cost (in the HTC portfolio)
2. debt instruments measured at fair value against equity (F2 items in the HTCS portfolio)
3. leases
4. guarantees and credit commitments

The impairment model is compatible with the expected losses (expected losses) logic, but there are some differences between expected regulatory and accounting losses. Regarding the concept of expected loss, it is necessary to distinguish the expected loss at 12 months (12 month Expected Credit Losses) from the expected multi-periodical loss (Life Time Expected Credit Losses - LECL). The second definition is consistent with the notion of expected loss resulting from the accumulation of default events that may occur throughout the life of the credit. The expected loss at 12 months instead, can be understood as the portion of LECL resulting from default events that in the next 12 months the reporting date the bank expects.

A crucial step before quantifying prudential provisions on exposure lines is to divide existing loans into three classes. Stage 1 comprises exposures whose credit risk has not increased since the date of recognition. Stage 2 includes exposure whose credit risk increased significantly. Stage 3 comprises impaired loans (past due, unlikely to pay and non-performing loans).

The formula used to estimate the lifetime expected credit loss (LECL) is the following:

$$\boldsymbol{LECL = \left(\frac{\sum_{t=1}^{n} MPD_t \ x \ LGD_t \ x \ EAD}{(1+i)^t}\right)}$$

Where:

- MPD= Marginal Probability of default in year t
- LGD= Loss Given Default in year t
- EAD= Exposure at Default
- i= effective original rate
- LECL= Lifetime Expected Credit Losses

For exposures classified as stage 1, the probability of default and LGD for the first year must be considered. For stage 2 exposures, the entire life of the financial instrument including the effects of possible changes in the borrower's economic circumstances must be considered using an effective (risk-adjusted) discount rate. In particular, point in time (PIT) ratings are used to estimate PD.[6]

[6] ZHANG YU, GUAN YONGSHENG, YU GANG & LU HAIXIA, "Recognizing and Predicting the Non-Performing Loans of Commercial Banks", International Journal of Signal Processing, Vol.9, 2016

After briefly describing the main aspects of IAS 39 and IFRS 9, it can be argued that the main changes introduced by IFRS 9 concern three main aspects:

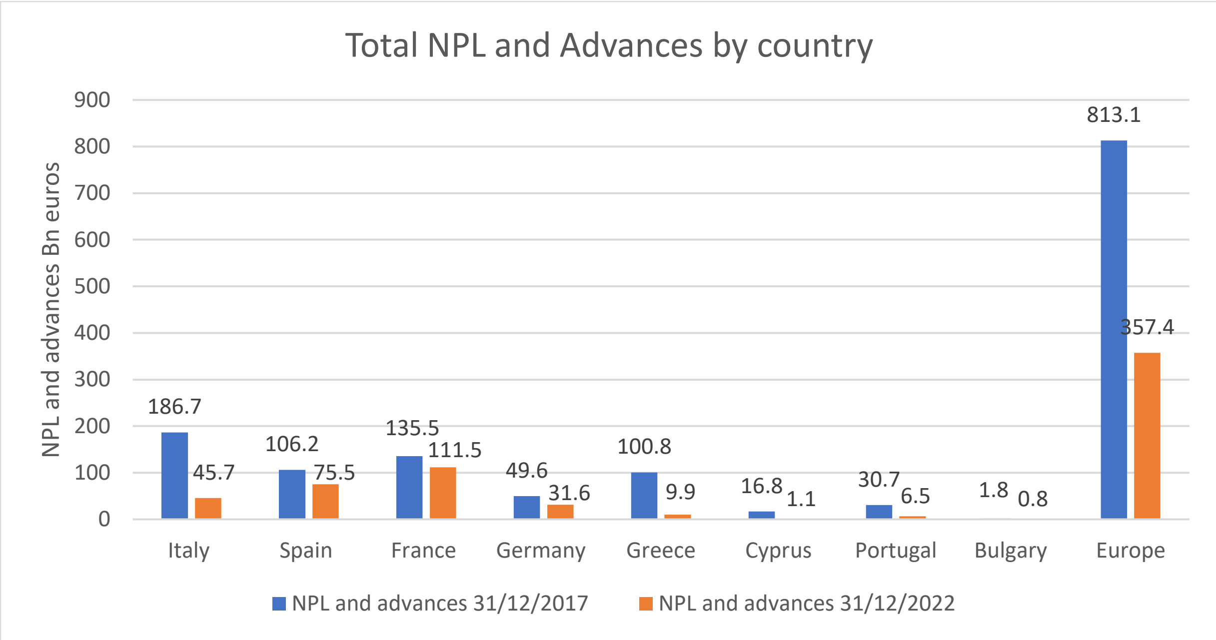
1. **The classification and valuation of financial instruments,** the number of categories into which instruments are classified has been reduced;
2. **A new and unique mode of impairment**, the goal is to reduce the number of methodologies for the calculation of provisions associated with financial instruments and use a single depreciation method based on a forward-looking logic. In this way, the new standard will enable the early detection of losses that will have to be calculated and attributed to the occurrence of the significant deterioration of the credit status compared to the origination of the credit;
3. **New hedge accounting policies**: in this section the IASB wanted to align hedge accounting to risk management activities especially when such activities have significant effects on the income statement and other comprehensive income.

2.3 OVERVIEW NPLs EUROPE

According to Cotugno M. (2018) "*The subprime mortgage crises occurred in the years 2007-2009 and the subsequent one that characterized the sovereign debts of European countries in the years 2010-2011 have determined a deep contraction of the real economy, generating the deterioration of the solvency conditions of companies and households and, at the same time, the accumulation of significant volumes of non-performing loans (npls) in the banking system*"[7].

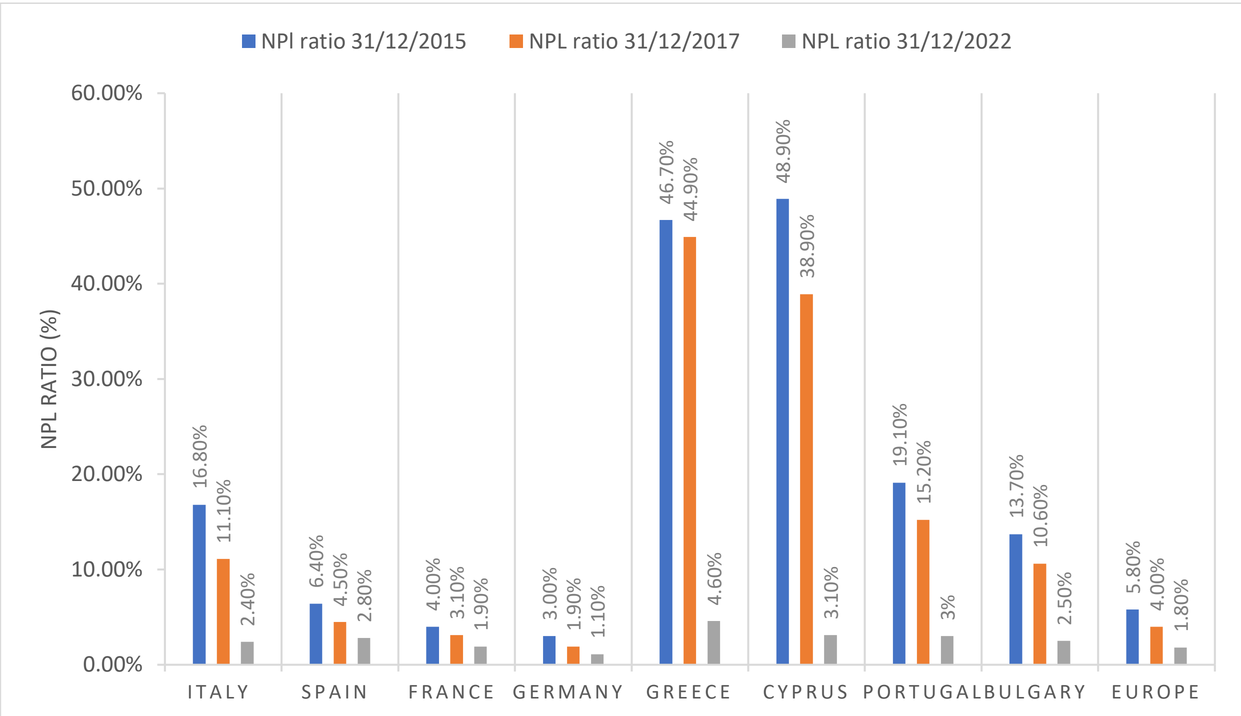
[7] COTUGNO M., "Gestione e Valutazione dei Non-Performing Loans", Agosto 2018

Graph 1. Total NPL and advances by country



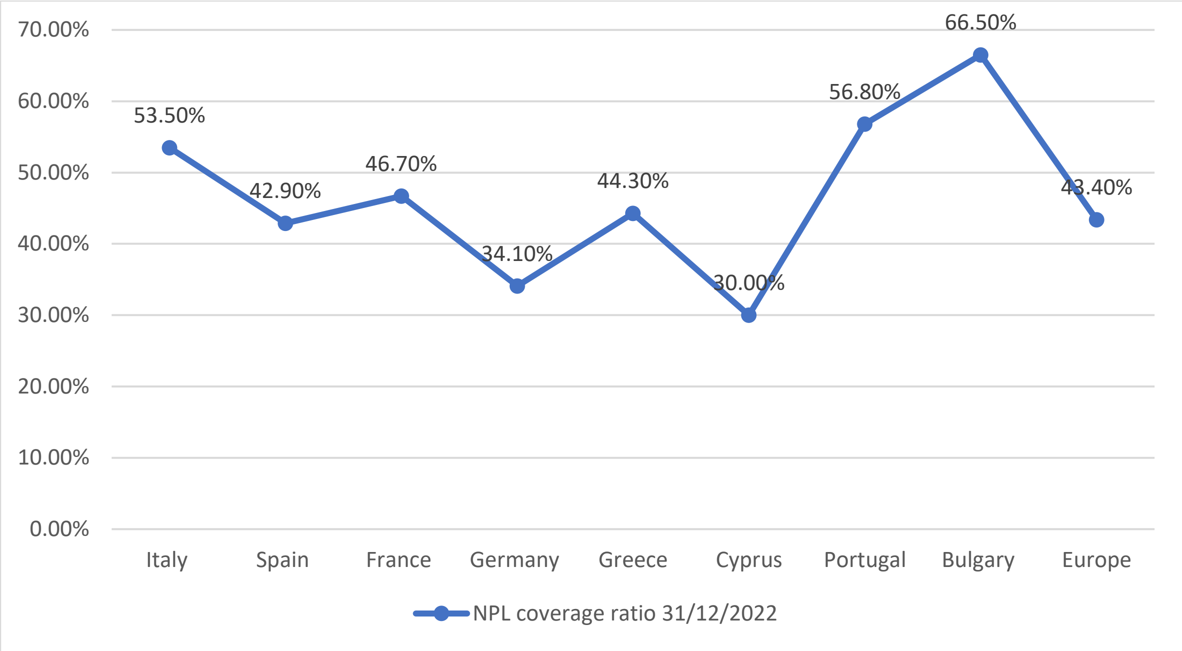
***Source:** Compiled from EBA data, Risk DashBoard, Q4 2017 and Q4 2022*

Graph 2. NPL Ratio among European countries



***Source:** Compiled from EBA data, Risk DashBoard, Q4 2015, Q4 2017, Q4 2022*

Graph 3. NPL coverage ratio among European countries



Source: *Compiled from EBA data, Risk DashBoard, Q4 2022*

The structural factors of the European economies have generated a considerable lack of homogeneity in terms of generation and accumulation of NPLS in different countries: the conditions of public finance, the structure of the industrial and banking system, the centrality of the role of credit intermediaries rather than financial markets, the efficiency of civil justice are only some variables that have affected the non-uniformity of the phenomenon.

As it can be seen from graph number 1, the total amount of NPL in Europe, in the year 2017, is equal to 813.1 billion euros. Italy is the country with the highest amount of net NPL in the European continent followed in order by France, Spain, and Greece.

Over the next five years, the total stock of NPL decreased to 357.4 billion euros in 2022, the percentage change was 56.7%. Looking at the data of 2022, we can see that the most virtuous country in a sense was Italy, the stock of NPL in 2022 is in fact, in Italy, equal to 45.7 billion euros, a percentage change of 75.5% compared to the values of 2017. The country with the highest amount of NPL in 2022 is France followed by Spain.

Let us now observe the evolution of the NPL ratio[8] and NPL over the years in the European continent. In trend terms, between 2015 and 2022, important progress is seen for all countries

[8] The NPL ratio indicator is calculated as the ratio between the total amount of net non-performing loans (Bad loans, unlikely to pay and past due) and the total gross loans and advances, while the Coverage

considered (Graph 2). The ratio between net non-performing loans and loans in Italy decrease from 16.8% in 2015 to 2.4% in the fourth quarter of 2022, thanks - among other things - to significant disposal operations. There are also signs of improvement in those countries with the highest level of NPL ratio, Greece NPL ratio went from 46.7% to 4.6% in 2022 and Cyprus NPL ratio from 48.9% to 3.1% in 2022.

2.4. BANKS' PROFITABILITY

In an ever-evolving dynamic environment within the financial sector, profitability could play a fundamental role according to which banks can determine and assess their level of performance and efficiency. A large body of empirical studies has investigated the role of different factors influencing bank performance. Based on these studies, determinants of bank profitability can be broadly categorised into three groups: (i) bank-specific factors, (ii) macroeconomic factors, and (iii) structural factors.

(i) bank-specific factors: Bank-specific determinants of profitability typically include factors controlled by bank management, such as bank size, efficiency, risk management, capital and diversification or business strategy. According to those who proposed the concept of size benefits, larger banks are likely to have a higher degree of product and loan diversification than smaller banks and should benefit from economies of scale, which in turn leads to higher profits[9]. Other studies suggest that the size/profitability relationship may be either non-linear or, even if large banks are more efficient than small ones, profitability benefits derive from emulating industry best practice in terms of technology and management structure, rather than from increasing the size of the bank[10]. Bank capitalisation (or capital management) is another important factor influencing profitability, according to several studies. Existing literature suggests that the impact of bank capital on profitability is ambiguous, although most studies find a positive relationship. On the

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ratio is calculated as the ratio between total provisions/allowances for loans and gross loans and advances. For further information please refer to Conca and Polita (2017). The data reported in the Risk dashboard are samples and refer to 189 European banks. Any discrepancies with the data reported are therefore attributable to the coverage sample that is totalitarian for data Bank of Italy.

[9] See, for instance, Shehzad, C.T., De Haan, J. and Scholtens, B., "The relationship between size, growth and profitability of commercial banks", Applied Economics, Vol. 45, 2013, pp. 1751-1765. See also Smirlock, M., "Evidence on the (non) relationship between concentration and profitability in banking", Journal of Money, Credit, and Banking, Vol. 17, No 1, 1985, pp.69-83.

[10] See Berger, A. and Humphrey, D., "Efficiency of financial institutions: International survey and directions for future research", European Journal of Operational Research, Vol. 98, 1997, pp. 175-212.

one hand, banks with higher capital ratios tend to face lower funding costs owing to lower prospective bankruptcy costs.[11] On the other hand, higher capitalisation can be associated with lower risk-taking, which in turn leads to lower (expected) returns.[12] Risk management and the level of risk are among the most important bank-specific factors determining performance. Empirical evidence suggests that higher credit risk – measured by non-performing loan or provisioning ratios – is associated with lower bank profitability.[13] These results reflect the fact that banks exposed to higher-risk loans incur higher loan losses, which translate into lower bank returns. Having researched financial statement of 114 EU banks Enrica Detragiache, Thierry Tressel, and Rima Turk-Aris (2018) found that asset growth is negatively associated with profitability, meaning that more rapid balance sheet expansions tend to be followed by declines in profits. The negative relationship between asset growth and decline in profits is particularly pronounced after the financial crisis. Moreover, they also concluded that better capitalization (measured by tangible capital ratio) was positively correlated with profitability. The previous study is broadly consistent with evidence about Italian banks in Bonaccorsi di Patti and Kashyap (2017)[14]. This study finds that banks which cut credit to problem borrowers early experienced a faster recovery in profitability than banks which continued to extend credit to such borrowers. Furthermore, some bank-level studies investigate the relationship between ownership type and bank performance, with results varying according to the geographical region and/or time period under investigation. More recent evidence for European banks suggests that mutual banks and government-owned banks exhibit lower profitability than privately-owned banks.[15]

(ii) macroeconomic factors: Several studies incorporate macroeconomic variables into the analysis in order to examine cyclical patterns in bank performance and behaviour. It is generally found that bank profitability tends to be pro-cyclical, driven in particular by the cyclical patterns in lending and other financial intermediation

[11] See Berger, A. N., "The profit-structure relationship in banking-tests of market-power and efficient structure hypotheses", Journal of Money, Credit and Banking, Vol. 27, 1995, pp. 404-431.
[12] See Goddard et al. (op. cit.) for evidence on a negative relationship.
[13] See Bikker, J.A. and Hu, H., "Cyclical patterns in profits, provisioning and lending of banks and procyclicality of the new Basel capital requirements", BNL Quarterly Review, 221, 2002, pp. 143-175
[14] Bonaccorsi di Patti E., Anil K. Kashyap, "Which Banks recover from Large Adverse Shocks?".
[15] See Iannotta, G., Nocera, G. and Sironi, A., "Ownership structure, risk and performance in the European banking industry", Journal of Banking and Finance, 31, 2007, pp. 2127-2149.

activities and loan loss provisions[16]. First, an increase in economic activity through higher demand for bank intermediation services (including lending and securities underwriting, advisory services and trading activities) will tend to increase banks' net interest income and income generated from fees and commissions. Second, weaker economic activity contributes to a worsening of bank asset quality and higher loan loss provisioning, thus exerting a negative influence on bank profits. IMF (2017b) and IMF (2017c) shows that NPLs, cost efficiency and cyclical factors impact the profitability of Spanish and Dutch banks as well as that of their European peers. Among other macroeconomic factors, inflation as well as the level and the term structure of interest rates are thought to have an impact on bank profitability. In particular, the slope of the yield curve is expected to positively influence bank profits via higher interest income (a wider margin) from maturity transformation activities[17]. The effects may, however, differ across banks depending on their interest rate sensitivity.

(iii) structural factors: Two alternative hypotheses exist on the relationship between market structure (market concentration) and bank profitability. The "structure-conduct-performance" hypothesis argues that more concentrated markets lead to collusive behaviour, giving banks the opportunity to earn monopolistic profits. By contrast, the "efficient structure" hypothesis states that the positive relationship between profitability and concentration can be driven by efficiency, in that more efficient banks gain market share and improve profitability.

2.5. NPLs: Key determinants

In the last two decades there has been a strong and articulated debate in the academic literature on the key determinants of NPLs.

[16] See Albertazzi, U. and Gambacorta, L., "Bank profitability and the business cycle", Journal of Financial Stability, Vol. 5, 2009, pp. 393-409.
[17] See, for example, Greenspan, A., "Risk and uncertainty in monetary policy", speech at the meeting of the American Economic Association, San Diego, California, 3 January 2004.

Beck R., Jakubik P., Piloiu A. (2015)[18] using a novel panel data set have estimated that the most significant factors affecting NPLs are real GDP growth, shares prices, the exchange rate, and the lending interest rate.

Allen N. Berger and Robert DeYoung (1997)[19] employed Granger-causality techniques to test four hypotheses regarding the relationships among loan quality, cost efficiency, and bank capital. They concluded that the bad management and moral hazard hypotheses were explaining a significant part of NPLs.

Espinoza and Prasad (2008)[20] introducing macro variables found that NPLs decline with growth and rise with interest rates and fiscal and external deficits.

Anastasiou Dimitros and Louri Helen (2016)[21] using a Generalized Method of Moments (GMM)[22] estimation examined for the very first time the roles of income tax and output gap as variables able to influence NPLs. They concluded that both the new variables introduced exerted a strong positive influence on NPLs.

It can be therefore argued that the variables influencing the level of NPLs are many, among academics there is a common tendency to identify two groups of variables: country specific variable and bank specific variable. Within the first set we find macroeconomic variables, such as real change in GDP, unemployment rate, exchange rate, inflation rate, sovereign debt as well as institutional determinants such as the efficiency of the judicial system, the quality of auditing activities and the role regulators play in the specific country. On the other hand, in the second set of variables we can find bank size, bank capitalization, bank performance, bank ownership concentration, bank operating inefficiency and internal governance.

2.6 NPLs and profitability

As will be further explained in chapter 3, the objective of this paper is to analyse the impact of NPLs on commercial bank's profitability, in particular their and ROA (Return on Asset), in Europe.

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[18] Beck r., Jakubik P., Piloiu A. (2015), " Key Determinants of Non-performing Loans: New Evidence from Global Sample"

[19] Allen N. Berger, Robert DeYoung, (1997), "Problem loans and cost efficiency in commercial banks"

[20] Espinoza, R., Prasad, A., 2010. "Non-performing loans in the GCC banking system and their macroeconomic effects", IMF Working Paper 10/224.

[21] Anastasiou Dimitros, Louri Helen (2016), "Determinants of non-performing loans: Evidence from Euro-area countries".

[22] The Generalized Method of Moments (GMM) is a statistical method that combines observed economic data with the information in population moment conditions to produce estimates of the unknown parameters of this economic model.

We intend to determine whether the change in the level of NPLs is positively or negatively correlated with ROA of the concerned banks.

Over the years numerous studies have been carried out to examine the impact of NPLs on bank's profitability, however the results obtained are in some cases ambiguous.

Dramani Angsoyiri (2021) sampled 9 listed commercial banks in Ghana employing a Multivariate Linear Regression Model concluded that NPLs have a positive and statistically insignificant influence on ROA.

Catur Rahayu Martiningtiyas and Dewi Tirtarini Nitinegeri (2020) using a sample of 26 banks listed on the Indonesia Stock Exchange, employing a linear regression model, demonstrated that non-performing loans had a significant negative impact on bank's profitability.

John N. N. Ugoani (2015) collected data from the 20 Deposit Money Banks in Nigeria, then selected 3 Banks and using a descriptive and regressive statistical method concluded that NPLs have a negative effect on bank profitability.

According to Lata (2014) nonperforming loans in Bangladesh has become a problem that has significant negative impact on bank profitability. He posits that nonperforming loans is a topic of great concern in Bangladesh. He states that for the last eight years, loan default as a percentage of outstanding loans in state owned commercial banks were 50 percent or above where private commercial banks and foreign commercial banks hold maximum 5 – 10 percent of the total.

As regards the literature on European banks, a major study was carried out by Ayrton Psalia, Jonathan Spiteri, and Simon Grima (2019) using a descriptive statistic and four regression model (the Pooled OLS regression model, Fixed Effects (FE), Random Effects (RE) and the Arellano-Bond (AB)). Their findings showed that there is a negative impact of NPLs on ROA, indicating that problematic loans negatively impact listed commercial bank's profitability in the Euro-Mediterranean region.

In this context it makes sense to consider a research carried out by the IMF by Enrica Detragiache, Thierry Tressel, and Rima Turk-Aris and published in April 2018[23]. The paper analyses EU banks' profitability through the recent financial cycle using bank level balance sheet and income statement data. The study shows how asset growth is negatively associated with better profit

[23] Enrica Detragiache, Thierry Tressel, and Rima Turk-Aris (2018)," Where Have All the Profits Gone? European Bank Profitability over the financial Cycle".

performance and an increase in the NPL ratio of 5 percentage points produced an additional decline in profitability (measured by ROA) by more than 30 basis points.

CHAPTER 3: A STATISTICAL ANALYSIS ON THE EFFECTS OF NPLs ON BANKING PERFORMANCE

3.1 STATEMENT OF THE PROBLEM

The maintenance of asset quality, efficiency and profitability is a vital requirement for the survival and development of banks. Loans are the main asset class from which banks generate their major portion of income and signify the greatest risk to banks. Due to the detrimental effect that these loans have on a bank's revenue, it is essential to examine and investigate the effects that NPLs have on banking performance.

3.2 RESEARCH QUESTIONS

The main objective of this thesis is to investigates and analyse the relationship between NPL and banks profitability . Five main hypotheses and alternate hypothesis relating to the connection between ROA and NPLs are constructed:

i. H_1: There is no significant impact of Non-Performing Loans (NPLs) on the Profitability (ROA) of listed commercial banks in the European region.

   H_{a1}: There is a significant impact of Non-Performing Loans (NPLs) on the Profitability (ROA) of listed commercial banks in the European region.

ii. H_2: The Liquidity ratio (LQDT) cannot significantly explain the variances with Non-Performing Loans (NPLs) and Profitability (ROA) of listed commercial banks in the European region.

   H_{a2}: The Liquidity ratio (LQDT) can significantly explain the variances with Non-Performing Loans (NPLs) and Profitability (ROA) of listed commercial banks in the European region.

iii. H_3: The Solvency ratio (SLVT) cannot significantly explain the variances with Non-Performing Loans (NPLs) and Profitability (ROA) of listed commercial banks in the European region.

   H_{a3}: The Solvency ratio (SLVT) can significantly explain the variances with Non-Performing Loans (NPLs) and Profitability (ROA) of listed commercial banks in the European region.

iv. H_4: The Real Gross Domestic Product Growth Rate (GDPGR) cannot significantly explain the variances with Non-Performing Loans (NPLs) and Profitability (ROA) of listed commercial banks in the European region.

H_{a4}: The Real Gross Domestic Product Growth Rate (GDPGR) can significantly explain the variances with Non-Performing Loans (NPLs) and Profitability (ROA) of listed commercial banks in the European region.

v. H_5: The bank's Size (SIZE) cannot significantly explain the variances with Non-Performing Loans (NPLs) and Profitability (ROA) of listed commercial banks in the European region.

H_{a5}: The bank's Size (SIZE) can significantly explain the variances with Non-Performing Loans (NPLs) and Profitability (ROA) of listed commercial banks in the European region.

3.3 PURPOSE OF THE THESIS

This research uses hypothesis testing to see the effect of non-performing loans on bank profitability. Based on the type of data, this study is included in the panel data because it examines several conventional banks in Europe with several periods of research. For the purpose of this study 10 listed European commercial banks were chosen. Kingu, Macha, and Gwahula (2018) and Ayrton Psaila, Jonathan Spiteri and Simon Grima (2019) attempted to conduct a similar study about such relationship using a similar econometric model but applying respectively the case to listed commercial banks in Tanzania and Euro-Mediterranean region. Throughout this study, a similar econometric model was used but, with particular focus on listed commercial banks in the European region. Additionally, two more independent variable have been included in this research: bank size, measured as natural logarithm of total asset and real GDP growth rate. The econometric model explaining the aforesaid relationship is defined in the equation below:

$$\boldsymbol{ROA_{it}} = \alpha + \beta_1 \boldsymbol{NPL_{it}} + \gamma_2 \boldsymbol{LQDT_{it}} + \gamma_3 \boldsymbol{SLVT_{it}} + \gamma_4 \boldsymbol{GDPGR_{it}} + \gamma_5 \boldsymbol{SIZE_{it}} + \varepsilon$$

Where:

- ROA_{it} = Return on Assets of bank "ì" at time period "t"

- α = constant parameter (intercept)
- β_1 = Coeff of Non-performing Loans (independent variable)
- γ_2 = Coeff of Liquidity Ratio (control variable)
- γ_3 = Coeff of Capital Adequacy ratio (control variable)
- γ_4 = Coeff of Gross Domestic Product (control variable)
- γ_5 = Coeff of Bank Size (control variable)
- NPL_{it} = Non-performing Loans of bank "i" at time period "t"
- $LQDT_{it}$ = Loan to Deposit Ratio of bank "I" at time period "t"
- $SLVT_{it}$ = Capital Adequacy Ratio, Equity/Total Assets of bank "i" at time period "t"
- $GDPGR_{it}$ = Gross Domestic Product Growth Rate of country "i" at time period "t"
- $SIZE_{it}$ = Size of country "i" at time period "t"
- e = Random error term

In the econometric model, we use the bank's level of Return on Assets as the dependent variable, the level of the bank's Non-Performing Loans as of the core explanatory variable, together with four control variables being, a liquidity ratio, a solvency ratio, a real Gross Domestic Product growth rate and bank size. The control variables selected will enhance the internal validity of our study by limiting the influence of confounding and other extraneous variables.

Return on Assets: can be defined as a proxy of profitability and as such it is used broadly by various authors as a dependent variable in order to evaluate the overall bank's profitability affected by some explanatory variables (Căpraru and Ihnatov, 2014) (Petria, Căpraru, and Ihnatov, 2015) (Athanasoglou, Brissimis and Delis, 2005) (Anbar and Alper, 2011).

Non-Performing Loans: is the core indicator affecting profitability in this model and therefore changes in this figure will intrude a change in the dependent variable i.e. ROA. Messai and Jouini (2013) used NPL as an explanatory variable to find the effect on profitability.

Liquidity ratio: in the context of this study, the liquidity ratio deemed as the most representable is the loan-to-deposit ratio. This ratio is used as a control variable throughout this model, as it will show that the higher the loan ratio relative to that of the deposits, the lower the liquidity level of the bank would be. (Kingu, Macha and Gwahula, 2018).

Solvency ratio: in the setting of this study, the equity to total assets ratio was used. This ratio together with the liquidity ratio will be acting as a control variable in the econometric model of this study. Moreover, as Kingu, Macha, and Gwahula (2018) illustrated this can be a representative variable of a financial risk indicator in this model and concurrently as a capital adequacy ratio for banks.

Real GDP growth rate: this ratio together with liquidity ratio, solvency ratio, and the size of the banks will be used as a control variable in the econometric model of this research. We expect real GDP growth rate to exert a positive impact on the amount of assets and bank profits as it stimulates loan demand, facilitates funding, widens interest margins, and creates opportunities to intermediate the allocation of private financial wealth.

Size: in the context of this research, the bank size given by ln (TA) is used as a control variable. The Economic theory suggests that when larger banks have a greater control of the domestic market, and operate in a non-competitive environment, lending rates may remain high while deposit rates for larger institutions remain lower because they are perceived to be safer. Thus, larger banks may enjoy higher profits. The empirical evidence however remains inconclusive.

3.4 *DATA CLEANING AND PRE-PROCESSING*

For the purpose of this study 10 listed commercial banks were chosen. The criteria behind the selection of the sample of 10 banks are as follows:

1. Size of the banking group measured by the amount of total assets and their respective market share in a specific country;
2. Geographical dispersion, the objective was to identify a sample of banks that could represent as much as possible the European banking environment;
3. Ease with which data collection could be obtained.

Table 3. Listed Commercial Banks selected to represent the sample

Banks	Country
UniCredit	Italy, Austria, Bulgary, Croatia, Bosnia and Herzegovina
Intesa San Paolo	Italy
Caixa Bank	Spain, Portugal
Deutsche Bank	Germany
ING	The Netherlands
Banco Santander	Spain
KBC Bank	Belgium
Erste Bank	Austria
BNP Paribas	France
Piraeus Bank SA	Greece

Source*: Author’s compilation*

Data for NPL, ROA, loan-to-deposit ratio, the equity-to-asset ratio and size were extracted manually from the annual reports of each respective bank. Data collected from annual reports include the ‘total gross loans receivables and advances’ figure and the ‘NPL’ figure, to compute the NPL ratio.

Below is the equation used to compute the aforesaid:

$$Bank\ NPLs\ (\%\ of\ total\ gross\ loans) = \frac{NPL\ figure\ (€\ millions)}{Total\ value\ loan\ portfolio\ (€\ millions)}$$

Where; the total value of the loan portfolio should include NPLs before any deductions of explicit loan-loss provisions and the NPL figure must be the gross value of the loan as recognized on the balance sheet and not as the amount recorded to be overdue (The World Bank Group, 2018).

Despite all banks represented in the sample adhere to the same non-performing loan conventions and accounting standards i.e. IAS 39 and IFRS 9, different methodologies are still present across different countries. Therefore, heightened responsiveness to check which figures to include in the non-performing loan (% of total gross loans) calculation was raised. In fact, some banks did not include the NPL figure or ratio specifically. Instead, they referred to these loans as either ‘non-performing exposures’ or ‘impaired loans and advances’. Particular attention to focus on bank figures rather than group figures were also given, especially when group consolidated annual reports were also provided.

The selected time frame is from 2012 to 2022.Data for all banks were collected annually based on the financial year of each respective bank. The decision to focus on this specific timeframe was dictated by the desire to understand the hypothetical correlation between NPLs and profitability over the last decade, a period that has been characterised by two economic crises, the sovereign debt crisis in 2009-2012 and the one caused by the Covid-19 pandemic.

In this study, we used PYTHON software to estimate panel-specific regression models, namely the Pooled OLS regression model. Consequently, one post-estimation test was conducted, the Shapiro-Wilk test was conducted to assess the normality of residuals.

3.5 EMPIRICAL RESULT AND INTERPRETATION

The descriptive statistics of the variables used to test a hypothesis (return on asset ratio, non-performing loan ratio, liquidity ratio, solvency ratio, size, and GDPGR) are presented in Table 4.

Through the describe () function in Python I have obtained the following result:

Table 4. Descriptive statistics of the variable used

	Year	NPL	LQDT	SLVT	GDPGR	SIZE
count	110.00000	110.000000	110.000000	110.000000	110.000000	110.000000
mean	2017.00000	0.065727	0.979552	0.064885	0.009364	27.109923
std	3.17675	0.089744	0.187217	0.018993	0.036024	0.993831
min	2012.00000	0.010000	0.461201	0.006640	-0.110000	24.837919
25%	2014.00000	0.020000	0.851701	0.051842	0.000000	26.354940
50%	2017.00000	0.035000	0.976338	0.063539	0.010000	27.458295
75%	2020.00000	0.060000	1.078533	0.073482	0.020000	27.912390
max	2022.00000	0.400000	1.571887	0.141567	0.080000	28.611741

	ROA
count	110.000000
mean	0.002795
std	0.007671
min	-0.037687
25%	0.001390
50%	0.003806
75%	0.005799
max	0.029754

Source: Author's compilation

The data spans from 2012-2022, the average NPl ratio is approximately 6,6% with a minimum of 1% and a maximum of 40%. Based on the result of Table 4 the average of LQDT ratio is equal to 98% with a minimum of 46% and a maximum of 157%. For what concern the SLVT ratio and the GDPGR ratio they have mean respectively equal to 6,48% and 1%. The size, expressed as a ln(total asset) average 27,10 over the period considered, meaning average total asset is equal to €5,9 billion. And the last, ROA has an average of 0,28% with a peak equal to 2,97% and a low equal to -3,8%.

3.5.1 CORRELATION RESULTS

After the description analyses of the indicators presented in the section above, we employ the correlation matrix for the variables included in our study.

Table.5 Correlation Matrix

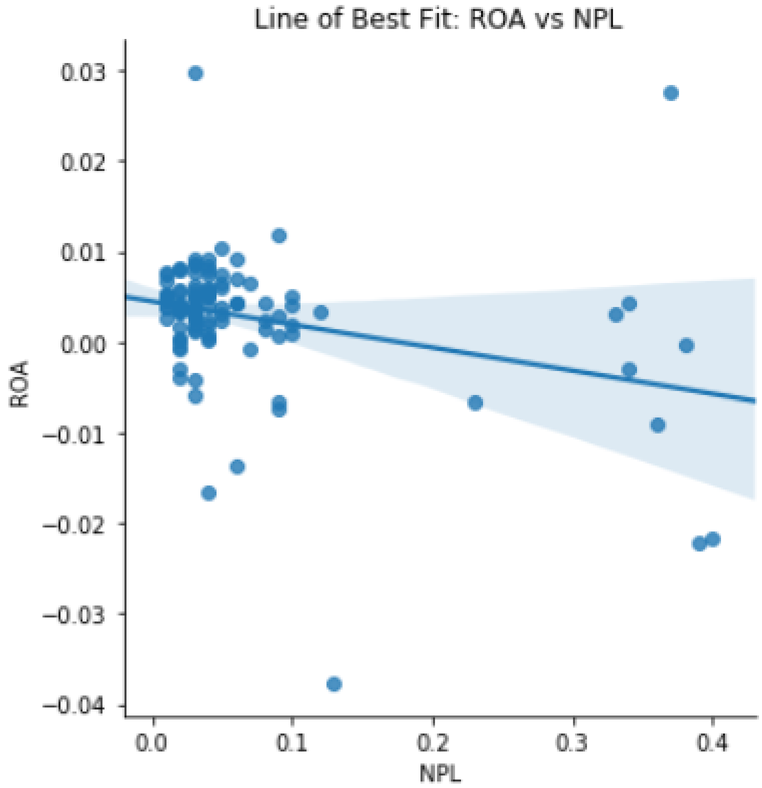
Correlation Matrix:

	ROA	NPL	LQDT	SLVT	GDPGR	SIZE
ROA	1	-0.29859	-0.069544	-0.07327	0.141175	0.148885
NPL	-0.29859	1	0.492392	0.734135	-0.192395	-0.697062
LQDT	-0.069544	0.492392	1	0.399924	-0.221273	-0.146022
SLVT	-0.07327	0.734135	0.399924	1	-0.036186	-0.731845
GDPGR	0.141175	-0.192395	-0.221273	-0.036186	1	0.058298
SIZE	0.148885	-0.697062	-0.146022	-0.731845	0.058298	1

Source: Author's compilation

Based on the correlation matrix (Table 5), we observed that the bank's profitability (ROA) and non-performing loans (NPL) had negative significant correlations. When (NPL) ratio increased by 1 unit, (ROA) decreased by 0.29. The correlation between ROA and LQDT (Liquidity) is around -0.070, suggesting a weak negative relationship. Higher liquidity seems to be associated with slightly lower ROA. The correlation between ROA and SLVT (Solvency) is approximately -0.073, indicating a weak negative relationship. Higher solvency appears to be linked to slightly lower ROA. The correlation between ROA and GDPGR (GDP Growth Rate) is about 0.141, indicating a weak positive relationship. As GDP growth rate increases, ROA also tends to increase. The correlation between ROA and SIZE (Bank Size) is around 0.149, showing a weak positive relationship. Larger banks tend to have slightly higher ROA.

Graph 4. Line of best fit showing the relationship between ROA and NPL



Source: Author's own compilation

Graph 4 shows the relationship between the "NPL" (Non-Performing Loans) independent variable and the "ROA" (Return on Assets) dependent variable. The scatter points represent the data points for each bank, while the line of best fit represents the linear regression model's prediction of the relationship between the two variables. The slope and intercept of the line of best fit provide insights into how changes in the "NPL" variable are associated with changes in the "ROA" variable.

3.5.2 OLS RESULTS

Ordinary least squares (OLS) is a linear regression technique used to find the best-fitting line for a set of data points by minimizing the residuals (the differences between the observed and predicted values). It does so by estimating the coefficients of a linear regression model by minimizing the sum of the squared differences.

The OLS method relies on several assumptions to be valid. The following is the list of key assumptions:

1. Linearity: There must be linear relationship between the dependent variable and the independent variables.
2. Independence: The observations must be independent of each other.
3. Homoscedasticity: The variance of the residuals should be constant across all levels of the independent variables.
4. Normality: The residuals / errors should be normally distributed.
5. No multicollinearity: The independent variables should not be highly correlated with each other.

After analysing the descriptive statistics and the correlation relationship between variables, I did some pre-tests to decide which model is more appropriate for my time-series data.

I imported pandas and statmodels on Python, the first software used for data manipulation the second for statistical modelling and analysis. I uploaded my data and specified the dependent and independent variables. I added a constant term intercept to the independent variables using the 'add_costant' function, then I created an Ordinary Least Squares (OLS) model using specified dependent and independent variables. Subsequently I fitted the model with Cluster-Robust Standard Errors. The main idea behind using cluster-robust standard errors is to account for potential clustering or heteroscedasticity in the data, which can affect the accuracy of the estimated standard errors and p-values in the regression analysis. Clustering is specified by using the groups parameter, which is a key concept in cluster-robust standard errors estimation. It indicates that observations within the same group (cluster) are potentially correlated and should be treated as such when calculating the standard errors.

```python
import pandas as pd
import statsmodels.api as sm

# Load data
df_panel = pd.read_csv('C:/Users/huawei/Downloads/Banksdata2.csv')

# Specify the dependent and independent variables
dependent_var = 'ROA'
independent_vars = ['NPL','LQDT','SLVT', 'GDPGR','SIZE']

# Create a model
X = sm.add_constant(df_panel[independent_vars])
y = df_panel[dependent_var]

model = sm.OLS(y, X)

# Use the index as groups for clustering
cluster_robust_results = model.fit(cov_type='cluster', cov_kwds={'groups': df_panel.index})

# Print the results
print(cluster_robust_results.summary())
```

Figure 8. OLS First result

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    ROA   R-squared:                       0.145
Model:                            OLS   Adj. R-squared:                  0.104
Method:                 Least Squares   F-statistic:                     3.793
Date:                Thu, 17 Aug 2023   Prob (F-statistic):            0.00332
Time:                        16:32:02   Log-Likelihood:                 388.79
No. Observations:                 110   AIC:                            -765.6
Df Residuals:                     104   BIC:                            -749.4
Df Model:                           5
Covariance Type:              cluster
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0003      0.041     -0.007      0.995      -0.081       0.080
NPL           -0.0480      0.021     -2.246      0.025      -0.090      -0.006
LQDT           0.0044      0.005      0.898      0.369      -0.005       0.014
SLVT           0.1129      0.080      1.417      0.156      -0.043       0.269
GDPGR          0.0146      0.024      0.616      0.538      -0.032       0.061
SIZE          -0.0002      0.001     -0.150      0.881      -0.003       0.002
==============================================================================
Omnibus:                       39.467   Durbin-Watson:                   1.829
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              825.663
Skew:                          -0.337   Prob(JB):                    5.12e-180
Kurtosis:                      16.405   Cond. No.                     2.61e+03
==============================================================================

Warnings:
[1] Standard Errors are robust to cluster correlation (cluster)
[2] The condition number is large, 2.61e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Source: Author’s computation

Based on the output of OLS (Figure 8), it seems there might be strong multicollinearity between the independent variables. Multicollinearity is a statistical phenomenon that occurs when two or more independent variables in a regression model are highly correlated with each other. In other words, multicollinearity indicates a strong linear relationship among the predictor variables. This can create challenges in the regression analysis because it becomes difficult to determine the individual effects of each independent variable on the dependent variable accurately. It is essential to detect and address multicollinearity to ensure the validity and robustness of regression models.

To ensure the validity and robustness of regression models it is necessary to detect and address multicollinearity. For this purpose, I used the Variance Inflation Factor (VIF), it is used to determine the strength of the correlation between the independent variables. It is predicted by taking a variable and regressing it against every other variable.

In mathematical terms:

$$\boldsymbol{VIF = \frac{1}{1 - R^2}}$$

Where:

R^2 = R-squared

Table 6. Variance Inflation Factor results

	VIF	***R-squared***
NPL	3,120559	0,6795445
LQDT	1,59688	0,3737787
SLVT	2,987612	0,6652845
GDPGR	1,090152	0,0826964
SIZE	2,862346	0,6506362

Source: Author's compilation

The VIF test shows that our variables are lower than 3 with the only exception of NPL, so I conclude that our model has no multicollinearity.

At this stage I decided to run the model again. The control variable "SIZE" with a coefficient equals to -0,0002 and p-value substantially higher than 0,05 can be considered non statistically significant with respect to the dependent variable. To improve the stability and reliability of the regression results while maintaining the interpretability of the model I opted to exclude the control variable "SIZE" from the model.

Figure 9. OLS Second result

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    ROA   R-squared:                       0.145
Model:                            OLS   Adj. R-squared:                  0.113
Method:                 Least Squares   F-statistic:                     4.644
Date:                Sun, 20 Aug 2023   Prob (F-statistic):            0.00169
Time:                        19:52:56   Log-Likelihood:                 388.78
No. Observations:                 110   AIC:                            -767.6
Df Residuals:                     105   BIC:                            -754.1
Df Model:                           4
Covariance Type:              cluster
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0059      0.005     -1.185      0.236      -0.016       0.004
NPL           -0.0469      0.023     -2.019      0.043      -0.092      -0.001
SLVT           0.1183      0.060      1.960      0.050   -2.57e-05       0.237
LQDT           0.0040      0.005      0.740      0.459      -0.007       0.015
GDPGR          0.0145      0.023      0.627      0.530      -0.031       0.060
==============================================================================
Omnibus:                       38.836   Durbin-Watson:                   1.828
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              806.574
Skew:                          -0.303   Prob(JB):                    7.16e-176
Kurtosis:                      16.252   Cond. No.                         113.
==============================================================================
```

Source: Author's compilation

The new result could be interpreted as follow:

Model Fit and Statistical Significance:

The model's goodness of fit is evaluated using the R-squared value, which indicates that approximately 14.5% of the variation in "ROA" is explained by the independent variables in the model. The adjusted R-squared value accounts for the number of predictors in the model, suggesting that the model's explanatory power decreases slightly after adjusting for the number of predictors.

The F-statistic tests the overall significance of the model and provides evidence that at least one of the independent variables is statistically significant in explaining the variation in the dependent variable. The p-value associated with the F-statistic (0.00169) indicates that the model's explanatory power is statistically significant.

Coefficients and Interpretation:

- "NPL" has a negative coefficient with a p-value below 0.05, suggesting it is statistically significant and negatively related to "ROA". As a result, an increase in non-performing loans is associated with a decrease in “ROA”.

-"SLVT" has a positive coefficient with a p-value close to 0.05, which suggests a potential positive relationship with "ROA".

-The coefficient for "LQDT" equals to 0.0040 suggests a positive but very small effect of liquidity on "ROA." However, the p-value is high (0.459), indicating that this variable might not be statistically significant.

-The coefficient for "GDPGR" (0.0145) suggests a small positive effect of GDP growth rate on "ROA," but the p-value is high (0.530), indicating no statistical significance.

Statistical Assumptions:

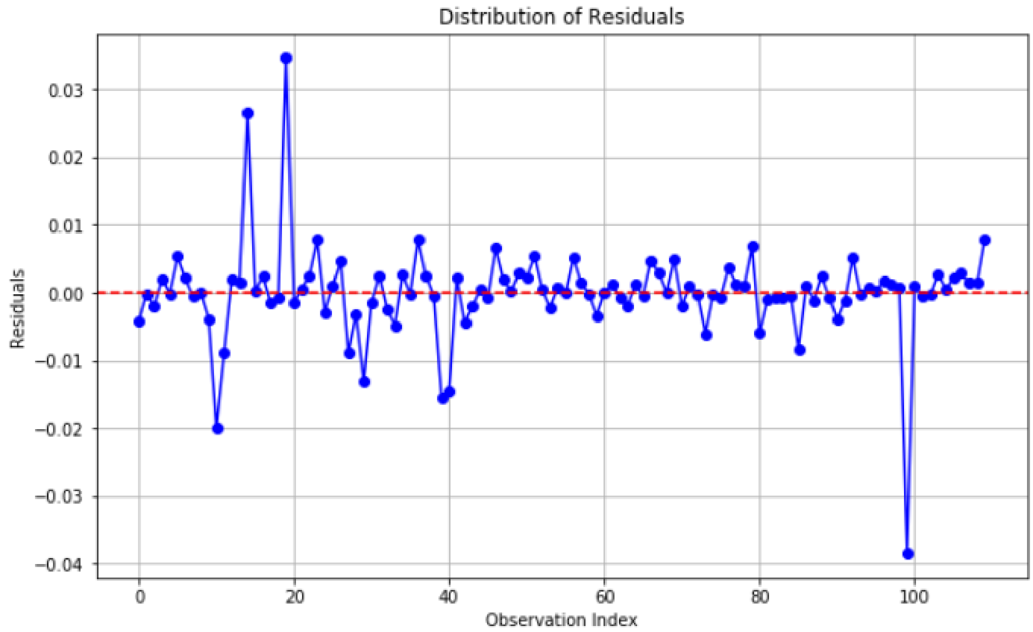
The Omnibus test and Jarque-Bera test are used to assess the normality of the residuals. A low p-value (close to zero) in the Omnibus test suggests that the residuals do not follow a normal distribution. The Jarque-Bera test provides further evidence of non-normality, as its p-value is also close to zero.

The Durbin-Watson statistic measures the presence of autocorrelation in the residuals. The obtained value (approximately 1.828) suggests that there is little autocorrelation.

3.5.3 RESIDUAL ANALYSIS

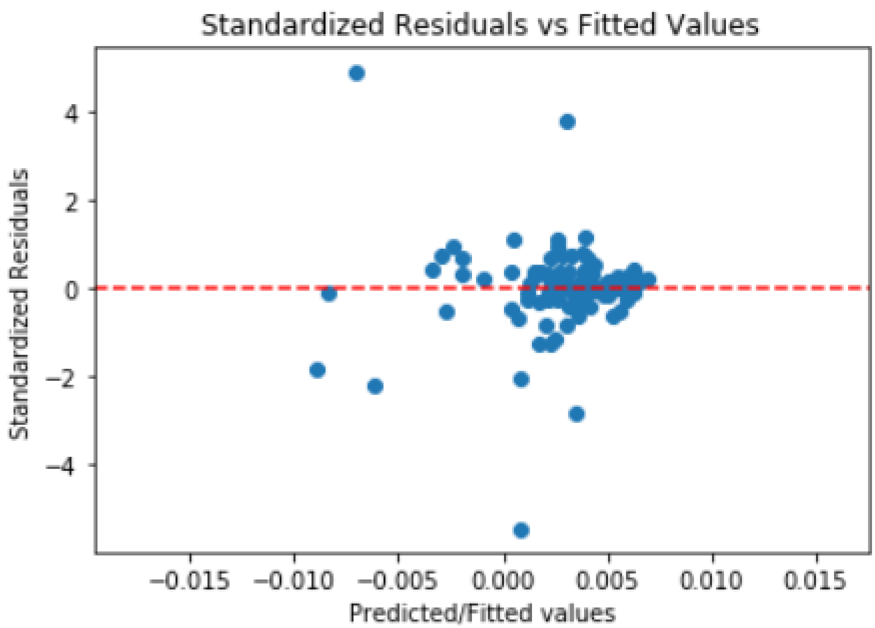
Once estimating the model, the analysis must take into consideration how residuals behave in order to test if there is presence of heteroscedasticity, autocorrelation and leverage points that can influence the inference estimates.

Figure 10. Line plot showing graphically the distribution of residuals along all observations



Source: Author’s compilation

Figure 11 Standardized Residual vs Fitted Values



Source: Author’s compilation

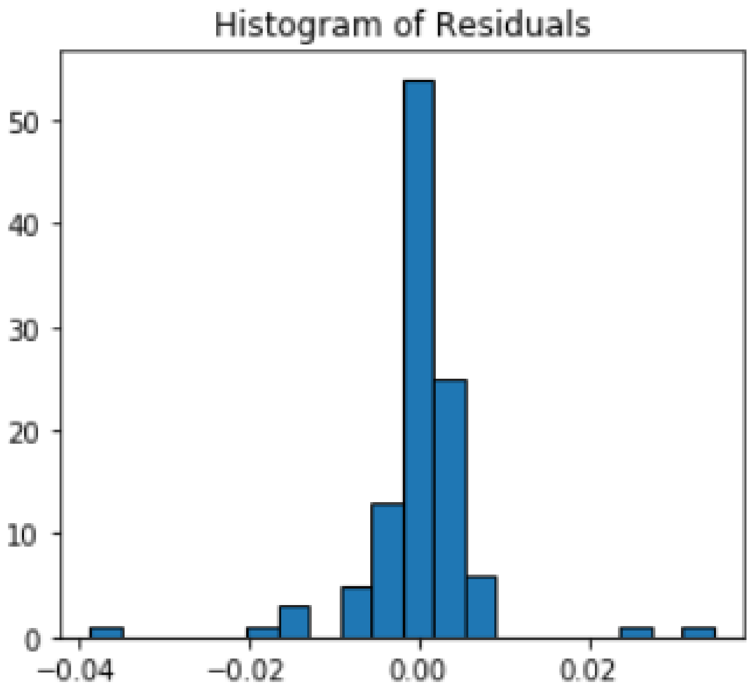
In Figure 10 above we can visually observe that serial correlation of the residuals is not persistent amongst all observations. It is evident that when the line graph spikes up it goes down again, and it continues doing the same movement up and down throughout all observations and does not remain constant in the same area for too long. It is possible to deduct the presence of heteroscedasticity. In statistics, a sequence (or a vector) of random variables is homoscedastic if all its random variables have the same finite variance; this is also known as homogeneity of variance. The complementary notion is called heteroscedasticity, also known as heterogeneity of variance. Assuming a variable is homoscedastic when in reality it is heteroscedastic results in unbiased but inefficient point estimates and in biased estimates of standard errors, and may result in overestimating the goodness of fit as measured by the Pearson coefficient.

In our case however, we have performed an OLS regression including Robust Standard Errors to correct for heteroscedasticity, this approach adjusts the standard errors of the coefficient estimates, ensuring reliable hypothesis tests and confidence intervals. I can conclude that standard errors reported in the output are adjusted for potential heteroscedasticity, making the inference reliable. It can be argued that in this specific case heteroscedasticity does not invalidate the statistical test.

3.6 NORMALITY OF RESIDUALS

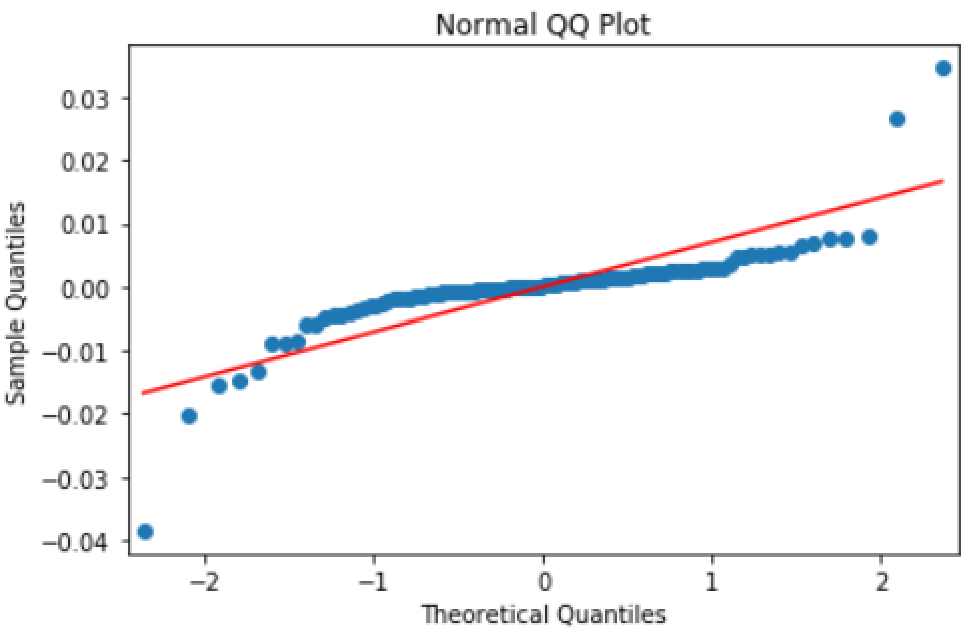
The normality assumption is important for the validity of inferential procedures and, for this purpose, it is useful to firstly analyse the Normal QQ-plot of the standardized residuals. As the plot QQ-plot shows, the standardized residuals approximate quite well the straight Normal QQ-plot line even though there is no evidence of points that are significantly far from the others.

Figure 11. Histogram of Residuals



Source: Author's compilation.

Figure 12 Normal QQ Plot



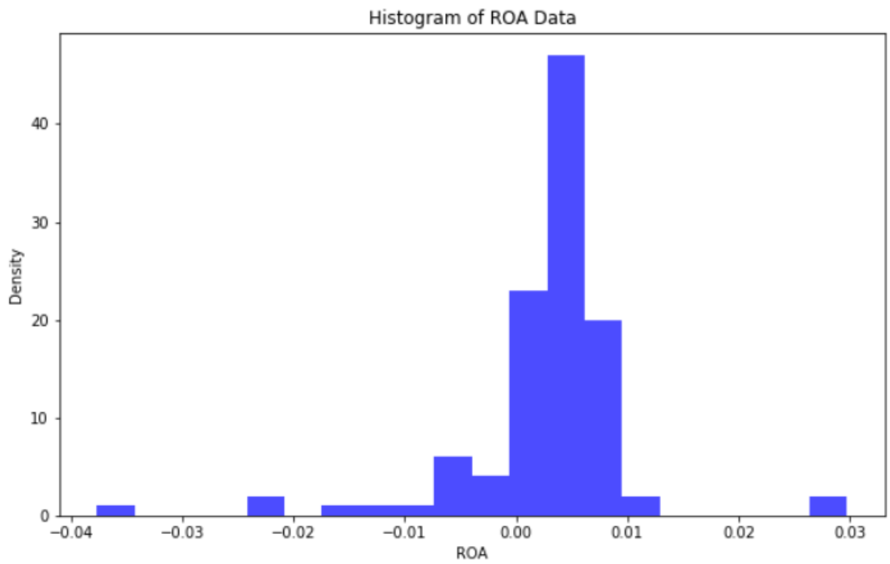
Source: Author's compilation.

However, a useful test to assess the normality of residuals is the Shapiro-Wilk test. In case of Normality the test statistic the p-value should be higher than 0.05. As we can see from the test results, we conclude that the residuals are not characterized by a normal distribution since p-value obtained is equal to 3,27e-13 < 0.05. As a result, I should reject the null hypothesis, the data does not follow a normal distribution. Even though the residuals do not follow a normal distribution, we have performed an OLS regression including Robust Standard Errors to account for non-normality in the residuals, this approach adjusts the standard errors of the coefficient estimates, ensuring reliable hypothesis tests and confidence intervals.

3.6.1 VISUAL INSPECTION

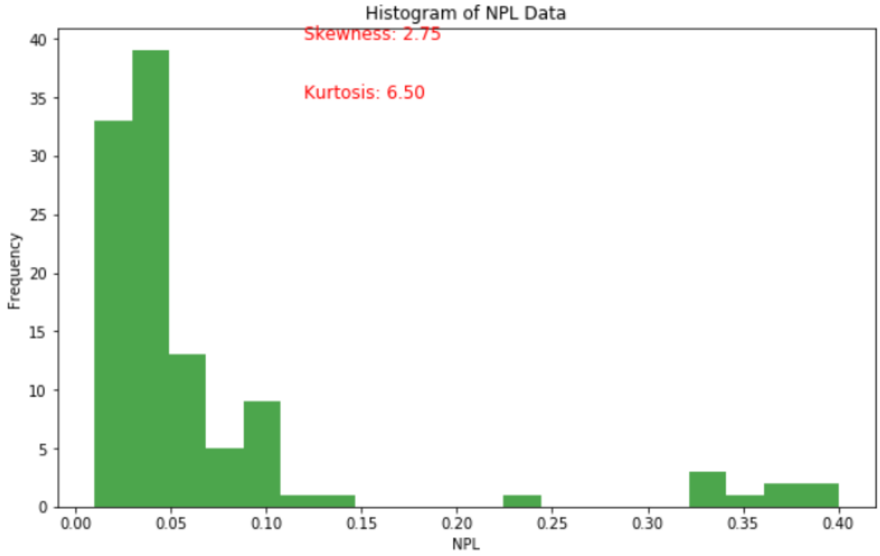
Testing for normality also involves a visual inspection of our data and hence histograms are used in this study to further validate our hypothesis that the data in our model is not normally distributed. In the below histograms, it is visually shown that the variables NPL, LQDT, and SLVT are not normally distributed and in fact, they are skewed to the left, whereas the variable ROA and GDPGR are skewed to the right-hand side. The histograms of the variables are shown in Figures 13, 14, 15, 16 and 17 respectively.

Figure 13. Histogram showing graphically the skewness and kurtosis of the ROA's data



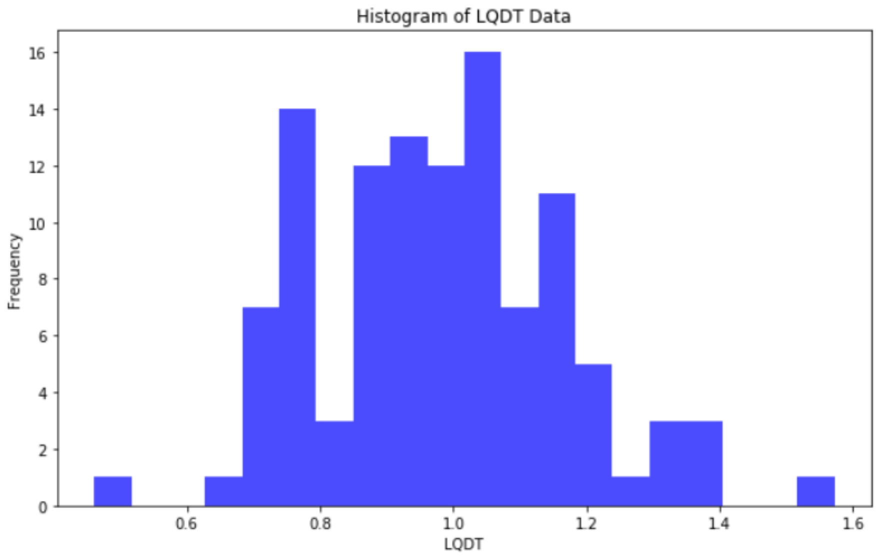
Source: Author's compilation.

Figure 14. Histogram showing graphically the skewness and kurtosis of the NPL'sdata



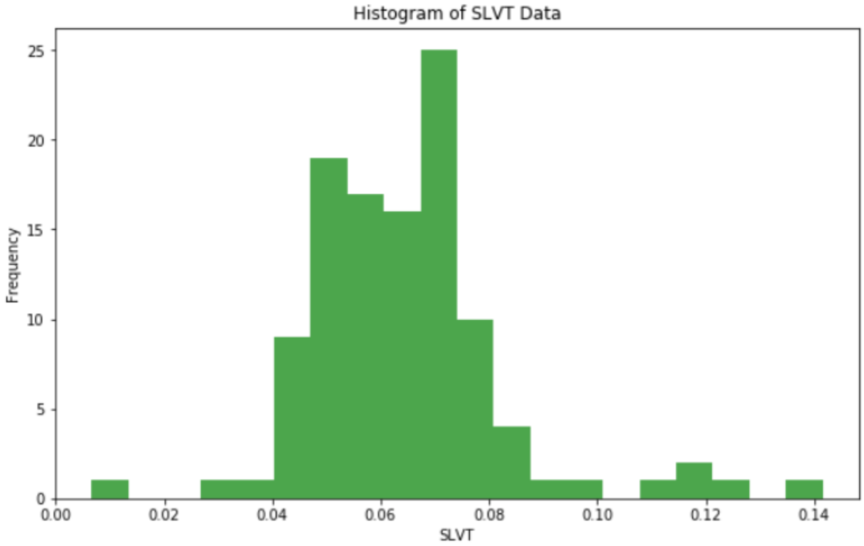
Source: Author’s compilation.

Figure 15. Histogram showing graphically the skewness and kurtosis of the LQDT's data



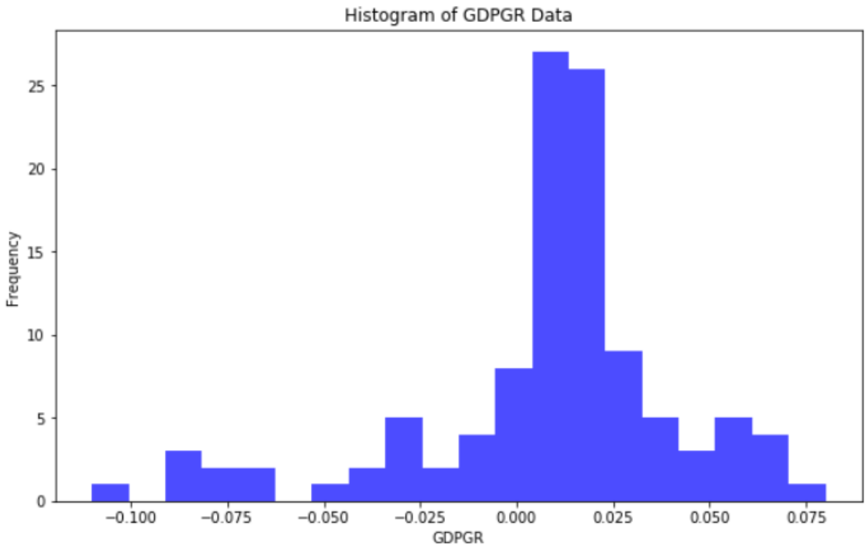
Source: Author’s compilation.

Figure 16. Histogram showing graphically the skewness and kurtosis of the LQDT's data



Source: Author’s compilation.

Figure 17. Histogram showing graphically the skewness and kurtosis of the LQDT's data



Source: Author’s compilation.

CONCLUSIONS

The findings from our research indicate that in the case of the European region, listed commercial bank's profitability is negatively impacted by NPLs. This negative correlation amongst returns on asset (ROA) and (NPL) is consistent with the findings of Akter and Roy (2017), Anastasiou, Louri and Tsionas (2016) Kingu, Macha and Gwahula (2018), wherein their study it was concluded that the liquidity ratio (LQDT) being the loan to deposit ratio as well, is negative and significant for commercial banks in Tanzania.

In our study however, the control variables represented as LQDT, SIZE, GDPGR were not considered to be adequate control variables for listed commercial banks in the European region since they were statistically insignificant according to the regression model executed. Thus, the appropriate control variable was deemed to be that representing the SLVT i.e., the equity-to-asset ratio.

The negative relationship between NPLs and ROA indicates that, in the European region the listed commercial bank's level of profitability is closely tied to the level of credit risk they are exposed to. Subsequently, this demonstrates that the lesser the amount of default risk, the greater the potential for enhanced profitability figures. Correspondingly, this negative relationship raises flags for the risk management teams of the said banks, to treat in a strict and orderly manner the shortlisting of prospective borrowers to mitigate the risk of elevated credit level problems and only accept debtors with good credit repute.

In turn, this can effectively decrease the level of NPLs and increase the level of ROA simultaneously. If loan quality from previous years is left unmanaged this may indicate that there could be hypothetically a poor bank risk management function and hence lower predictions for improved performance in the successive periods. For this to be effectively managed, commercial banks must also reduce the level of operating costs and implement further provisions for NPLs.

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