Lisbon School of Economics & Management
Universidade de Lisboa

MASTER OF SCIENCE
Mathematical Finance

MASTER'S FINAL WORK
Internship Report

EU-WIDE STRESS TEST: ESTIMATION OF CREDIT RISK PARAMETERS AND IMPAIRMENTS

Eduardo Filipe da Silva Peso

October - 2023

Lisbon School of Economics & Management
Universidade de Lisboa

MASTER OF SCIENCE
Mathematical Finance

MASTER'S FINAL WORK
Internship Report

EU-WIDE STRESS TEST: ESTIMATION OF CREDIT RISK PARAMETERS AND IMPAIRMENTS

Eduardo Filipe da Silva Peso

SUPERVISION

José Cruz
Onofre Alves Simões

October - 2023

Abstract

Credit risk impairments pose significant challenges to various economic sectors by impacting their financial stability and overall performance. This study investigates the impact of credit risk impairments on various sectors of the economy, emphasizing the potential ramifications. Banks are obligated to incorporate potential losses stemming from credit defaults into their accounting practices, while considering various future economic scenarios, including both baseline and adverse conditions. The EU-wide Stress Test offers standardized methodologies for the computations regardless being individual or collective impairments. Estimations for the credit risk parameters are necessary for performing these computations. The 2023 Stress Test requires the computation of credit impairments under severe scenarios for various economic sectors, marking the first instance of such a requirement. The primary objective of this study is to identify and develop techniques for estimating credit risk parameters, specifically the probability of default (PD), loss given default (LGD), transition rates (TR), and loss rates (LR) to perform the impairment computation. The analysis and results revealed that certain variables exhibit a negative correlation with credit risk parameters, specifically the gross domestic product (GDP) and the harmonized index of consumer prices (HICP) while on the other side the Unemployment Rate has a positive relationship with credit risk. The utilization of stochastic models has proven to be effective in addressing challenges associated with limited historical data.

Keywords: stress test, credit risk, risk parameters, linear models, stochastic models

Resumo

As imparidades para riscos de crédito colocam desafios significativos a vários sectores económicos, afectando a sua estabilidade financeira e o seu desempenho global. Este estudo investiga o impacto das imparidades para riscos de crédito em vários sectores da economia, enfatizando as potenciais ramificações. Os bancos são obrigados a incorporar nas suas práticas contabilísticas as perdas esperadas resultantes de incumprimentos de crédito, considerando simultaneamente vários cenários económicos futuros, incluindo um cenário normal e um adverso. O EU-wide Stress Test disponibiliza metodologias padronizadas para os cálculos, no entanto as estimativas dos parâmetros de risco de crédito são necessárias para efetuar estes cálculos. O novo 2023 Eu-wide Stress Test exige o cálculo de imparidades de crédito para vários sectores económicos, marcando a primeira instância desse requisito. O principal objetivo deste estudo é identificar e desenvolver técnicas para estimar os parâmetros de risco de crédito, especificamente a probabilidade de "default"(PD), "Loss Given Default"(LGD), "Transition Rates"(TR) e "Loss Rates"(LR), para proceder ao cálculo da imparidade. A análise revelou que determinadas variáveis apresentam uma correlação negativa com os parâmetros de risco de crédito, nomeadamente o produto interno bruto (PIB), o índice harmonizado de preços no consumidor (IHPC) enquanto, por outro lado, a taxa de desemprego revelou ter uma correlação positiva com o risco de crédito. A utilização de modelos estocásticos provou ser eficaz na resolução de desafios associados à pouca existência de dados históricos.

Palavras-Chave: stress test, crédito de risco, parametros de risco, regressões lineares, modelos estocásticos

Acronyms

PD - Probability of Default

TR - Transition Rate

ECL - Expected Credit Losses

LGD - Loss Given Default

EAD - Exposure at Default

LR - Loss Rate

SSE - Sum of Squared Errors

IASB - International Accounting Standard Board

LR-LT - Lifetime expected Loss Rate

IFRS9 - International Financial Reporting Standards

IASB - International Accounting Standards Board

EBA - European Banking Authority

ECB - European Central Bank

GVA - Gross Value Added

OLS - Ordinary Least Squares

SDE - Stochastic Differential Equation

Acknowledgements

I wish to express my profound gratitude and appreciation to all those who have provided unwavering support during the journey of accomplishing this thesis.

Initially, I express my gratitude for my supervisor, Prof. Onofre Simões, for his guidance, advice, and highly helpful input. His profound expertise and commitment played a pivotal role in shaping this research and improving its quality.

I am indebted to Dr. José Cruz for his constant help. Without his ideas and advices throughout these last few months wouldn't be possible to finish this project.

I would also like to extend my gratitude to KPMG Portugal, in special to Dr. Pedro Loureiro for the opportunity of making this internship.

To the financial institution who provided the essential data for the project's realization.

I would like to express my deepest gratitude to my family. Their support and encouragement have been my pillar of strength throughout this academic journey.

I would want to express my gratitude to all of my friends, with a particular mention to my closest bachelor's friends, Mings, for consistently offering me encouragement, motivation, and relentless support over these years.

Lastly, I also extend my gratitude to all the master colleagues who have contributed to a stimulating academic environment.

Contents

List of Figures

List of Tables

1 Introduction

The current study was conducted as a 5-month curricular internship at KPMG-Advisory, serving as the culmination of the Master's degree program in Mathematical Finance at ISEG. In addition to the application and development of acquired concepts and methodologies, this experience enabled the acquiring of further knowledge, regarding the practical application of theoretical concepts in the financial system. Specifically, it provided an opportunity to study the implementation of credit risk impairment models and the application of the new EU-wide stress test in the context of a Portuguese bank.

Financial institutions are required to navigate through situations of uncertainty, with credit risk being recognized as one of the primary hazards that they must manage. Risk management in the banking sector plays a crucial role in maintaining financial stability. Consequently, there exists an ongoing imperative to enhance risk management procedures and laws. Credit risk is defined as the prospective financial loss that may be incurred by a lender or investment in the event that a borrower or debtor fails to fulfill their financial responsibilities, such as loan repayment or interest disbursement. This risk that a borrower will not make the requirement payments on a debt obligations is alternatively refer to as default risk or counterparty risk. In simpler terms, credit risk refers to the probability that a borrower will be unable to meet their contractual commitments [29]. In this context, the occurrence of credit losses can result in a decrease in the fair value of a company's assets, leading to a divergence between the fair value and the book value. The fair value represents the current market value of an asset or liability, assuming a willing buyer and seller in an open market, while the book value is the value of an asset as reported on the balance sheet, which is typically based on historical cost. The disparity between these two values is important when evaluating the borrower's financial strength and it is then recognized as an impairment credit loss.

Each financial institution must anticipate the possibility of incurring losses on its lending portfolio. In order to anticipate the potential credit risk, the bank assesses the projected loss on the loans and records a matching provision. A provision refers to an assessment made by a bank to anticipate probable losses resulting from credit risk. Financial institutions utilize their capital to offset these financial setbacks. This is achieved through the process of booking a provision, whereby the bank acknowledges a potential loss and subsequently decreases its capital by the corresponding amount that it is unable to recover from the client. Banks are not obligated to allocate provisions for the entire amount of a non-performing loan, as there remains the possibility of receiving partial repayments from the borrower.

The primary objective of the European Banking Authority is to uphold the systematic operation and ethical standards of financial markets, as well as to maintain the stability of the European Union's financial system. In pursuit of this objective, the European Banking Authority is entrusted with the responsibility of overseeing and evaluating market dynamics, while also identifying patterns, potential hazards, and susceptibilities originating from the micro-prudential domain. The EU-wide stress test exercise is considered a key supervisory instrument for conducting such an examination. The objective of these tests is to evaluate the ability of financial institutions to withstand very unfavorable market conditions, while also contributing to the comprehensive evaluation of systemic risk in the European Union's financial system. The current EU-wide stress test exercise in 2023 will contribute to this endeavor and to integrate the process into the Supervisory Review and Evaluation Process (SREP) cycle. The results will play a decisive role in establishing the minimum capital requirements for banks.

The test exercise evaluates the ability of European Union banks to withstand and recover from potential challenges within a shared macroeconomic framework. This evaluation encompasses both a baseline scenario and an unfavourable scenario for the period spanning from 2023 to 2025. The unfavourable scenario encompasses social and economic challenges that are anticipated to have a significant effect on both private consumption and investments. The presented methodology aims to offer a standardized strategy, framework, and scenarios for banks to evaluate their capital adequacy and financial resilience in the face of macroeconomic shocks.

The last implemented EU-wide stress test at the European Union level incorporates, for the first occasion, disturbances on the actual gross value added (GVA) across various economic sectors. The inclusion of climate risk into the capital assessment process is of utmost importance, particularly when examining significant sectoral concentrations. Nevertheless, although the technique is stated for the standard tests, the specific computational approach for the economic sectoral analysis is not provided by the European Banking Authority (EBA).

The main problem addressed by the banks is related with developing procedures capable of yielding consistent results with realistic outcomes. The goal of my internship was attempting to use methodologies for estimating the credit risk parameters in models to compute credit impairments across several industry sectors. This task proved challenging due to the recent emergence of this issue in 2023, resulting in a shortage of extensive research on this topic. The main research questions of this study are:

- What are the suitable methods to use that incorporate the macroeconomic impacts?
- What influence does this forward-looking information has in credit risk parameters?
- Do the methods applied provide accurate impairment results in agreement with the empirical information?

This report focuses on impairment computation regarding credit risk parameters estimations. In order to better analyze the mentioned topics, it is organized in 5 chapters. The second chapter "Stress Test and Regulation" provides an overview of the credit risk concepts and a concise explanation of the stress test implementation. In the subsequent chapter "Theory and Practical Approaches", a theoretical exposition is provided, supplemented by a comprehensive discussion of the models employed. The database and its implementation process are also thoroughly discussed in "Application". Finally, the concluding chapter carefully examines the major conclusions.

2 Stress Tests and Regulation

2.1 IFRS 9

The International Accounting Standards Board (IASB) has released a regulation known as IFRS 9, International Financial Reporting Standard 9. IFRS 9 has been effective since January 2018 and it focuses on financial instrument accounting. The three main areas encompassed in this study are hedge accounting, impairment of financial assets, and the categorization and evaluation of financial instruments. IFRS 9 is a replacement for the previous International Accounting Standard related to financial instruments, which was referred to as IAS 39. The new standard outlines the categorization and quantification of financial assets, liabilities, and specific agreements for the acquisition or disposal of non-financial products by an organization.

According to IFRS 9, when an organization becomes a party to a contractual provision of an instrument, it is required to acknowledge the presence of a financial asset or a financial liability in its condition report. During the initial recognition of financial assets or liabilities, entities deduct transaction costs that are specifically associated with the acquisition or issuance of said financial assets or liabilities. This action is undertaken irrespective of whether the financial asset or liability is valued at fair value for recognition in the income statement.

2.2 Credit Risk

Risk is a concept that refers to the presence of uncertainty, which has the potential to have adverse effects on an organisation. The predominant categories of risk that banks typically encounter encompass credit risk, market risk, liquidity risk, interest rate risk, currency risk, and operational risk. For further analysis, see "Risk Management and Financial Institutions" by Hull (2012) [19].

Within the particular context of credit risk, as already mentioned, it is imperative to acknowledge that credit losses possess the capacity to generate decreases in the fair value of an organization's assets, so establishing a discrepancy between the fair value and the book value. This discrepancy is then recognised as an impairment loss.

Financial institutions commonly bear the responsibility of loan losses associated with bad debts, however the precise estimation of these losses is constrained by their inherent unpredictability. However, it is possible to calculate the expected amount, which is often known as the Expected Loss (EL). The cost associated with the Expected Loss (EL) is a crucial factor in the operational costs of conducting business, as it has a direct influence on the pricing of credit and the allocation of provisions. The primary concerns revolve around significant losses that were not anticipated by the institutions, sometimes referred to as Unexpected Losses (UL). The term "UL" refers to significant losses that surpass anticipated losses and arise from occurrences that occur alone under several unforeseen circumstances. According to the Basel Committee on Banking Supervision (2005), these losses should ideally be covered by capital to a level of 99.9%.

Financial institutions must ensure that sufficient reserves are available to safeguard their viability and mitigate the impact of such losses. When it becomes unfeasible to mitigate all potential losses, including both anticipated and unanticipated ones, it becomes essential to strive for a state of balance. In essence, it is important to calculate a minimal capital reserve that guarantees conditions for keeping operating and having access to ECB funding facilities.

2.3 Stress Test

The European banking system assumes a pivotal role in fostering economic stability and prosperity within the European Union (EU). In order to fortify and uphold the integrity of this pivotal domain amidst financial upheavals, the European Union has implemented a stringent framework referred to as the EU-Wide Stress Test. The 2023 series of assessments seeks to appraise the capacity of European banks to endure adverse economic scenarios and shocks. This stress test is designed to evaluate the solvency of European Union banks by simulating a hypothetical adverse macroeconomic scenario spanning three years (2023-2025). Its purpose is to determine whether the capital levels of banks are adequate to support the economy during periods of stress.

The EU-Wide Stress Test has undergone significant evolution since its inception, establishing itself as a fundamental component of financial regulation within the European Union. It highlights the crucial role played by this tool in the identification of vulnerabilities, evaluation of capital adequacy, and strengthening of the fundamental pillars of the European banking sector. By subjecting financial institutions to hypothetical yet plausible scenarios, the stress test serves the dual purpose of assessing their capacity to withstand economic shocks and fostering transparency and investor confidence. The exercise is rooted in a common approach that is defined by internal consistency and the incorporation of relevant scenarios. Additionally, a collection of templates is utilized to capture initial data and stress test outcomes, enabling a thorough evaluation of the banks included in the sample.

The biennial stress test conducted by the European Banking Authority (EBA) in partnership with the European Central Bank (ECB), the European Systemic Risk Board (ESRB), and national supervisory authorities covers the whole European Union (EU). The exercise employs the methodology and templates established by the European Banking Authority, along with the scenarios presented by the European Systemic Risk Board [14]. The narrative depicts a hypothetical situation characterized by a significant deterioration in geopolitical circumstances, concomitant with a rise in commodity prices and a resurgence of COVID-19 transmission. The aforementioned scenario leads to a significant rise in inflation rates, thereby exerting detrimental impacts on both private consumption and investment activities. Moreover, this occurrence coincides with a global economic downturn, further exacerbating the overall situation. The deterioration of economic prospects is evident through a notable worldwide increase in long-term interest rates, a persistent decrease in GDP, and a rise in the unemployment rate.

The European Systemic Risk Board and the European Central Bank collaborate closely with competent authorities, the European Banking Authority and national central banks, to develop the unfavourable macroeconomic scenario and any shocks to risk types associated with the scenario. The European Central Bank provides the macroeconomic baseline scenario. The European Banking Authority is responsible for the coordination of the exercise, establishment of a standardized methodology, provision of guidance to the national authorities for the provision of minimum quality data, and maintenance of a central Q&A platform. The European Banking Authority also furnishes relevant authorities with standardized descriptive statistics to facilitate consistency checks, which are conducted using the data provided by banks.

The obligation for providing directions to banks regarding the execution of Stress Test and for receiving information straight from banks rests with national supervisor authorities. The responsibility for overseeing the quality assurance process lies with competent authorities. These authorities are responsible for many duties, including examining the data and stress test findings of banks, using computational analysis. Additionally, they analyze the models utilized by banks specifically for this purpose. If the national authorities think it is necessary, they have the option to carry out the EU-Wide Stress Test on additional samples, alongside the selected sample, and may also administer supplementary national stress tests, in accordance with their individual responsibilities.

Financial institutions are obligated to assess and communicate the potential influence of macroeconomic scenarios on their capital reserves, specifically in relation to impairments, as well as the risk exposure amount (REA) associated with positions that are susceptible to default risks from counterparties.

It is important to note that the impairment calculations are only one aspect of the Stress Test methodologies, which also involve a number of additional evaluations aimed at testing the banks' resilience.

The process of estimating credit impairments necessitates the utilization of statistical methodologies and its objectives are: to (i) determine initial values for the risk parameters through estimation, and (ii) assess the influence of the scenarios on the risk parameters. According to the EBA methodological note [14], banks are obligated to predict credit impairments that may arise from two distinct scenarios (baseline and adverse), following the principles outlined in IFRS 9.

2.4 The New Stress Test 2023-2025

The recently implemented stress test at the European Union level evaluates the ability of European Union banks to withstand economic pressures by subjecting them to a macroeconomic baseline scenario and an adverse scenario spanning the years 2023 to 2025. This experiment is conducted using the year-end 2022 data, and the scenarios are implemented from the end of 2023 through the end of 2025. The shocks regarding the adverse scenario are more severe than in previous tests, which could possibly imply more significant differences between both scenarios.

The new EU-wide Stress Test requires for the first time the need for computations regarding the sectors of economic activity, including a single template for these computations. The macroeconomic projections for the current year incorporate, for the first time, data regarding the variation of Gross Value Added (GVA) across 16 distinct sectors of economic activity. This segmentation will provide a more comprehensive evaluation of banks' performance based on their specific operational structure and sectoral exposures. In the previous stress tests the regulatory agencies provided some technical guidance to facilitate the implementation of these predicting models. However, for this new template, there are no appropriate guidelines on how to approach this problem giving some space to companies for exploring different methods. In spite of this, the regulation demanded that the models must include the GVA parameter variations to directly understand the impact of these shocks in the credit risk ratings.

The new template follows the logic of the previous template divided by scenarios and it is split by country of exposure, the scenario (baseline or adverse), year of provision and the sectors of economic activity, see Appendix A.1. The results should be consistent with the existing template divided by scenarios, mentioned before. The sectors are divided accordingly the NACE (Nomenclature of Economic Activities) sections, see Table I. It is the European statistical classification of economic activities and it is used to identify and group economic activities in order to facilitate statistical analysis.

2.5 Risk Parameters

The impairment models outlined in IFRS 9 adhere to a unified forward-looking projected credit loss framework that is uniformly applied to all financial instruments. In line with this standard, paragraph 5.5.17, "An entity shall measure expected

Table I: Industry sectors defined in EU-wide Stress Test template guidance

Economic Sectors (NACE)	
A Agriculture, forestry and fishing	**H** Transportation and storage
B Mining and quarrying	**I** Accommodation and food service activities
C-High Manufacturing related with high intensity activities	**J** Information and communication
C-Low Manufacturing related with low energy activities	**K** Financial and insurance activities
D Electricity, gas, steam and air conditioning supply	**L** Real estate activities
E Water supply, sewerage, waste management and remediation activities	**M-N** Professional, scientific and technical activities; administrative and support service activities
F Construction	**O-Q** Public administration and defence, compulsory social security; education; human health services and social work activities
G Wholesale and retail trade, incl. repair of motor vehicles and motorcycles	**R-U** Arts, entertainment and recreation; other service activities; activities of households; activities of extra-territorial organisations and bodies

Source: EBA's Template Guidance

credit losses of a financial instrument in a way that reflects: (a) an unbiased and probability-weighted amount that is determined by evaluating a range of possible outcomes; (b) the time value of money; and (c) reasonable and supportable information that is available without undue cost or effort at the reporting date about past events, current conditions and forecasts of future economic conditions" [20]. In order to calculate these expected Credit Losses, it is imperative to establish the initial level of quality at which the credits are positioned. Consequently, banks are obligated to supply information pertaining to the evaluation of their loans. The impairment models outlined in IFRS 9 and subsequently in the Stress Test provide three distinct rating stages to assess credit quality :

- Stage 1 (S1) – It refers to exposures whose credit risk has not undergone a considerable increase since their first recognition at the reporting date. For such exposures, the entities are required to measure the loss allowance at a value equivalent to the projected credit losses over a 12-month period.

- Stage 2 (S2) – When the credit risk of a loan has experienced a substantial increase since its initial recognition, but does not fall into the category of being regarded low, the recognition of lifetime Expected Credit Losses (ECLs) takes place. The computation of interest revenue is consistent with that of Stage 1.

- Stage 3 (S3) – In the case that the loan's credit risk escalates to a level where it is deemed credit-impaired, the interest revenue is determined by taking into account the loan's amortized cost, which refers to the gross carrying amount minus the loss allowance. ECLs are acknowledged, similar to the recognition in Stage 2.

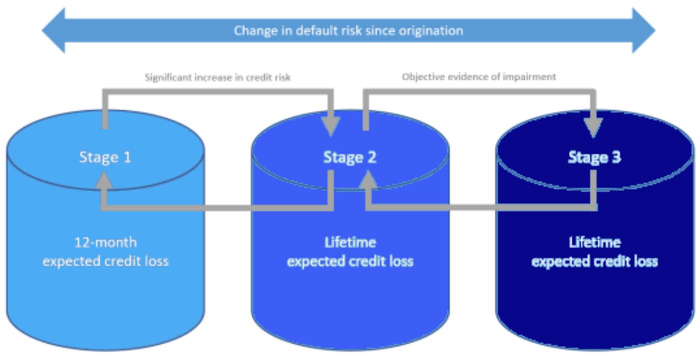


Figure 1: Stages of ECL model.

Source: Gross et.al (2020). Expected Credit Loss Modeling from a Top-Down Stressed Testing Perspective

The initial credit score can start in S1 or S2 and move to another stage with a corresponding probability and it might have an impact on the provisions calculated for the next years. If the credit goes to stage 3, the credit can not leave because it is equivalent to a credit default. Additionally, ECL must be recognised considering comprehensive credit risk information such as past and forward-looking macroeconomic information. Hence, a general approach to evaluate the credit losses is based on the following risk parameters:

- PD (Probability of default): probability of a default event occurring during a determined time period;

- EAD (Exposure at default): amount of money the client still owes to the banking institution when defaults;

- LGD (Loss Given Default): value that an institution really loses when a client goes to default;
- TR (Transition Rates): probability of a credit changing from one state of risk to another in one year;
- LR-LT (Lifetime Expected Loss Rate): applies to the anticipated loss rate during the lifespan of exposures that start in one stage at the beginning of the year and conclude in a different stage by the end of it.

A common method for ECL calculation based on these parameters is given by:

$$ECL = \sum_{i=1}^{N} PD \times LGD \times EAD \tag{2.5.1}$$

where N represents the total amount of assets inside the portfolio [12]. These liabilities represent the potential financial losses that the lender may incur as a result of providing a loan. The availability of information for model development may differ depending on the debtor's category.

The supplementary information can be employed in order to build behavioral models. Potential risks can also include personality traits and behavior in addition to past loan history or financial transactions. Credit scores have historically been determined through the use of mathematical formulas that take into account the borrower's financial situation, demographics, and credit history. It is challenging to customize these credit scores, and they might not reflect the risk tolerance or decision-making approach that is best for a given person, situation, or business. Banks employ behavioral models to compute risk parameters and expected credit loss (ECL), hence determining the possibility of extending more loans to current customers [3].

2.6 Guidelines

At this point, it is fundamental to state some assumptions to better understand the stress test exercise [14] :

- The Stress Test is performed with the scenarios (baseline and adverse) provided by The European Banking Authority (EBA);

- It is necessary to forecast the transition rates between the three impairment stages, as well as all the credit risk metrics already stated, for each year of the exercise;

- The computation of Expected Credit Loss in stages 1 and 2 should incorporate forward-looking information. This implies that the estimation of risk factors employed in forecasting impairment computations should include trends associated with macroeconomic variables.

3 Theory and Practical Approaches

3.1 Literature Review

Numerous studies have been conducted pertaining to the estimate of risk parameters. In their respective studies, Witzany (2011) and Chabaane et al. (2004) employed a two-factor model to examine the link between probability of default and loss given default [33] [10]. Belkin et al. (1998) and Farinelli and Shkolnikov (2012) conducted research on a one-factor model for transition matrices and loss given default, where they inferred the distribution of the variables used in the factor from available data [2] [15].

A significant portion of the existing work pertains to the application of these methodologies to extensive credit portfolios and expansive databases including observed information. However, Shao et al. (2016) also address the macroeconomic-risk model using rating transition matrices models, although with certain assumptions that are less stringent compared to the work of Belkin et al. (1998) [27]. In essence, the transition rates can change from one stage to another, based on their risk assessment. The model provides an estimation of the likelihood of these transitions occurring. Belkin et al. (1998) proposes that the transition rates in question fit a normal distribution. Shao et al. (2016) do not make any assumptions regarding this matter, hence favoring techniques that rely less on historical data. The model proposed by Shao et al. (2016) incorporates the utilization of a latent variable, which is a variable that cannot be directly observed but is estimated based on a set of observable variables. This latent variable is influenced by a collection of macroeconomic factors that serve as indicators of the economic environment. This proposal entails the potential utilization of related methodologies, such as multiple linear regressions. Vanek and Hampel (2017) employs simple linear regression models to examine the relationship between economic growth and the rate of default [32]. Similarly, Simons and Rolwes (2018) utilizes a macroeconomic-based model to estimate risk parameters and identifies a strong association between certain explanatory variables and default rates [28].

Macroeconomic models are well-suited for the examination of stress situations, due to their capacity to facilitate cross-country comparative analysis through the utilization of extensive historical data series, which are often accessible for a majority of nations. Chan (2006) derives benefits by refraining from making assumptions regarding default rates based solely on historical observations [11]. However, it is important to note that these models necessitate a substantial dataset in order to accurately reflect the influence of the economic cycle on risk parameters. Without a sufficient amount of data, the model would be unable to effectively account for this impact. Furthermore, these models are susceptible to the Lucas critique, which posits that it is overly simplistic to attempt to forecast the consequences of a modification in economic policy solely based on historical data relationships [6]. This is due to the inherent difficulty in accurately capturing the intricate interplay between the economic state and the default rate.

The issue addressed in this work requires finding a delicate equilibrium between the need for a sophisticated methodology and the requirement for a substantial database. The primary obstacle in this scenario pertains to the limited availability of risk parameter data from the financial institution, which encompasses only two data points corresponding to the preceding two years (2022 and 2021). As previously stated, the European Central Bank (ECB) provides comprehensive templates for financial institutions to project risk factors for various asset classes. The implemented exercises incorporate complex multiple linear regression models that mix macroeconomic variables with certain parameters including "expert judgement." The feasibility of employing macroeconomic-based models for forecasting purposes is supported, with linear regressions being a prominent option.

3.2 Practical Approaches

Fot the sake of this being a self-contained text, the next subsections summarize the essential aspects of the most common approaches to the problem.

3.2.1 Linear Regression

The statistical method of multiple linear regression aims to establish a mathematical relationship among a number of independent variables and a dependent variable.

This objective is accomplished by using a linear equation to model the observed data. Various studies have explored the utility of this method in the context of our work, including Calderon et al. (2022) and Uyanik and Guler (2013) [8] [31]. To gain a more comprehensive understanding of linear regressions, it is suggested Wooldridge (2015) [35].

The formal representation of the multiple linear regression model, when considering n observations, where y is the dependent variable, $x_1, x_2, ..., x_p$ are the independent variables, $\beta_1, \beta_2, ..., \beta_p$ are the coefficients and ε is the errors, is as follows:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + ...\beta_p x_{ip} + \varepsilon_i, \text{for i= 1,2,...,}n. \tag{3.2.1}$$

The utilization of multiple linear regression enables the assessment of the overall adequacy of the model, as well as the evaluation of the individual predictors' respective contributions to the total variance explained. The coefficient of determination, symbolized as R^2, measures the fraction of the overall variability in a dependent variable that can be accounted for by the independent variables in a regression model. The measure in question can be interpreted as the ratio of the variation in the dependent variable, y, that can be explained by the independent variables, x. The formula can be defined as

$$R^2 = \frac{SSE}{SST} = 1 - \frac{\text{sum of squared residuals (SSR)}}{\text{total sum of squares (SST)}}. \tag{3.2.2}$$

The sum of squared residuals (SSR) quantifies the amount of variability in the dependent variable that remains unexplained by the selected regression model. The Total Sum of Squares (SST) is a statistical measure that assesses the overall extent of variability in the risk factors. Hence, this coefficient quantifies the extent to which the method employed in the analysis accounts for the variability observed in y. The SSE is always constrained within the interval [0,1] due to the inherent limitation that it cannot exceed the SST. If all the data points lie on the regression line, it indicates that the ordinary least squares (OLS) method yields a perfect fit to the data, resulting in a R^2 value of 1. A value of R^2 that approaches 0 suggests a fit model is not appropriate [22].

Moreover, the Variance Inflation Factor (VIF) is computed to assess the necessity of reducing the multicollinearity among the independent variables included in the adjustment. The Variance Inflation Factor is employed to assess collinearity, which involves identifying and removing variables that excessively increase the variance of other variables. This measure is defined in terms of the coefficient of determination, denoted as R_i^2, as follows:

$$VIF = \frac{1}{1 - R_i^2} \tag{3.2.3}$$

The denominator reflects the tolerance level. According to Daoud (2017), a Variance Inflation Factor value of 10 or above means the presence of multicollinearity, demanding the removal of the corresponding variables from the model [13].

The Durbin-Watson (DW) test is widely employed as a diagnostic tool to assess the presence of autocorrelation in the residuals of a regression model. This suggests that the presence of autocorrelation may lead to the erroneous identification of predictors as significant, even when they are not. The autocorrelation coefficient can exhibit either a positive or negative value, while the Durbin-Watson test statistic falls within the interval of [0,4]. When the Durbin-Watson statistic is equal to 2, it indicates the absence of autocorrelation. If the DW statistic is below 2, it indicates a positive correlation, whereas a number above 2 indicates a negative correlation. One significant constraint of the test is its limited ability to accurately analyze small samples, as highlighted by Yan et al. (2017) [36].

The p-values serve as indicators of the statistical significance of the link between the dependent variable and the predictor variables. According to Frost (2019), a low p-value suggests that the predictor variable is statistically significant, indicating a potential correlation between both variables [17].

3.2.2 Stochastic Differential Equations

Stochastic differential equations (SDEs) are mathematical models utilized to represent systems that are influenced by random fluctuations. SDEs are extensively employed to represent phenomena characterized by the presence of randomness, such as the fluctuations in stock values, random growth patterns or the motion of particles in a fluid. To see more detailed information about SDEs, it is suggested Bjork (2009) [4]. Forecasting with stochastic models plays a crucial role in situations when historical data is limited or when efforts are made to mitigate the absence of prior information. In contrast to ordinary differential equations (ODEs), stochastic differential equations incorporate both deterministic terms and stochastic components to capture unpredictable behavior, often modeled using Brownian Motion. The general form of a SDE is

$$dY(t) = a(t, Y(t))dt + b(t, Y(t))dW(t), Y(0) = Y_0, 0 \leq t \leq T. \tag{3.2.4}$$

The functions a and b are commonly known as the "drift" and "diffusion" coefficients, respectively. Additionally, W(t) represents a Brownian motion. It is important to acknowledge the presence of the "differential form," which should be distinguished from the "derivative" form commonly encountered in ordinary differential equations (ODEs). This distinction arises due to the fact that the majority of stochastic processes exhibit continuity but lack differentiability. The following equation is frequently expressed as the integral representation of equation 3.2.4

$$Y(t) = Y(0) + \int_0^T a(s, Y(s))ds + \int_0^T b(s, Y(s))dW(s), \tag{3.2.5}$$

given the initial condition Y(0) and considering the final integral as a "Itô integral". The aforementioned statement also provides an implicit definition of the solution Y(t). When a and b fullful certain conditions, it may be possible to analytically solve for Y(t) by evaluating the integrals. In the specific instance a Geometric Brownian Motion (GBM), where the function a is equal to μY and the function b is equal to σY , the Stochastic Differential Equation can be written as follows:

$$dY(t) = \mu Y(t)dt + \sigma Y(t)dW(t), \tag{3.2.6}$$

which is commonly used to model stock prices and random growth models.

The Brownian motion, alternatively referred to as a Brownian process or Wiener process, finds utility within the fields of economics and finance, namely in the domain of asset price and financial market modeling. In the areas of economics and finance, the Brownian motion model is used to explain the stochastic and uninterrupted fluctuations of financial variables, that involve stock prices, interest rates, and exchange rates. Hence, Brownian motion offers a mathematical framework for the representation and analysis of stochastic phenomena.

In the following subsections two methods to solve numerically SDEs, the Euler-Murayama method and the Milstein method, will be presented. These two methods are going to be applied in the next chapter.

3.2.3 The Euler-Maruyama Method

The integral form of Geometric Brownian Motion can be expressed in the following manner:

$$Y(t_{n+1}) - Y(t_n) = \mu \int_{t_n}^{t_{n+1}} Y(s)ds + \sigma \int_{t_n}^{t_{n+1}} Y(s)dW(s). \tag{3.2.7}$$

The Euler-Murayama technique, which is a stochastic extension of the normal Euler method for ordinary differential equations (ODEs) [18], represents the most straightforward approximation in this context. Notice that if $\sigma = 0$ then it is simply obtained. The explicit method takes the form of

$$X_{n+1} - X_n = \mu X_n \Delta t_n + \sigma X_n \Delta W_n. \tag{3.2.8}$$

This conclusion can be derived intuitively by considering the approximation of the first integral as $\mu X_n \Delta t$ and the second integral as $\sigma X_n \Delta W_n$. However, a formal derivation of this result relies on a Taylor expansion.

3.2.4 The Milstein Method

The Milstein method, alternatively referred to as the Milstein scheme, is a robust numerical approach employed for the estimation of solutions to stochastic differential equations (SDEs). The development of this method can be attributed to Grigoriy Milstein, a prominent Russian mathematician, during the latter part of the 1970s. Since its inception, this technique has gained significant popularity and has found applications in diverse domains such as economics, physics, and biology.

The Milstein technique offers a numerical approach for approximating the solutions of stochastic differential equations (SDEs) by discretizing both the temporal and stochastic components. The method described is a variation of the Euler-Maruyama method. This particular extension involves the utilization of a forward Euler scheme to estimate the stochastic integral component. The Milstein's method incorporates Itô's lemma by integrating the second order term into the Euler-Maruyama scheme [7].

Nevertheless, the Euler-Maruyama technique exhibits a notable decrease in its order of convergence, particularly in cases when the stochastic differential equation possesses a significant level of nonlinearity. The primary concept underlying the Milstein approach is to enhance the convergence characteristics of the Euler-Maruyama technique by integrating higher-order corrections into the approximation. The Milstein scheme involves the expansion of the stochastic integral term up to the second order in a Taylor series expansion, resulting in an improved approximation of the solution. The process of expansion entails the computation of derivatives for the drift and diffusion functions of the SDE. This computation can be performed analytically for a variety of frequently encountered SDEs.

The inclusion of the second-order correction in the Milstein technique results in a greater level of convergence compared to the Euler-Maruyama method. This enhanced convergence is commonly observed as second order in the strong sense and 1.5 order in the weak sense. This implies that the Milstein technique yields more precise approximations for a given step size and has the capability to capture more intricate aspects of the solution. Moreover, the Milstein technique effectively maintains significant characteristics of stochastic differential equations, including the mean and variance, which holds immense significance in numerous practical contexts.

Nevertheless, it is crucial to acknowledge that the Milstein approach, akin to other numerical methods, possesses inherent limits. One potential drawback of this approach is its susceptibility to stability concerns when confronted with stiff stochastic differential equations or systems exhibiting strong nonlinearity. In addition, the computational expense associated with the evaluation of higher-order derivatives can be substantial, particularly in the case of complicated stochastic differential equations that involve multiple dimensions (Rosa, 2016) [25].

To provide an illustration of the Milstein approach, let us assume the stochastic differential equation represented by equation 3.2.4.

The Milstein technique is applied through an iterative process, whereby the system is constructed in a step-by-step manner, following the explicit form

$$Y(t+\Delta t) = Y(t)+a(t,Y)\Delta t+b(t,Y)\Delta W+0.5b'(t,Y)b(t,Y)((\Delta W)^2-\Delta t). \quad (3.2.9)$$

The inclusion of the term $0.5b'(t,Y)b(t,Y)((dW)^2 - dt)$ serves to rectify the discrepancy arising from the utilization of the Euler-Maruyama approach. The inclusion of the partial derivative of $b(t,Y)$ with regard to Y aids in capturing the nonlinearity present in the stochastic differential equation. This process is characterized by its continuity and the property that its increments over any given time interval are independently and identically distributed according to a normal distribution defined as

$$dW = \sqrt{dt} \times v_n \quad (3.2.10)$$

where $\{v_n : n \in \mathbb{N}\}$ is a sequence of standard Normal random numbers.

3.2.5 Calculations of Impairments

In this subsection, it is described the necessary formulas for the provisions, as defined in EBA's methodology note [14]. The stock of provisions depends on the current exposures in each phase and the additional exposures that have transitioned between stages.

For Stage 1,

$$\text{Prov S1} = \text{Prov for new S1 exposures} + \text{Prov for current S1 exposures}$$

$$\text{Prov Stock S1 (t+1)} = \text{Prov S2-S1 (t+1)} + \text{Prov S1-S1 (t+1)}$$

The provisions for new S1 exposures are established in the following manner:

$$\text{Prov S2-S1 (t+1)} = \text{S2-S1 flow} \times TR^{1-3} \text{ (t+2)} \times LGD^{1-3} \text{ (t+2)}$$

$$\text{S2-S1 flow} = \text{Exp } S2^{BoY} \text{ (t+1)} \times TR^{2-1} \text{ (t+1)}$$

The provisions for the current S1 exposures are determined as follows:

$$\text{Prov S1-S1 (t+1)} = \text{Exp } S1^{BoY}\text{(t+1)} \times \text{(1-}TR^{1-2}\text{(t+1) - }TR^{1-3}\text{(t+1))} \times TR^{1-3}\text{(t+2)} \times LGD^{1-3}\text{(t+2)}$$

For Stage 2,

$$\text{Provisions S2} = \text{Provisions for new S2 exposures} + \text{Provisions for current S2 exposures}$$

$$\text{Prov Stock S2 (t+1)} = \text{Prov S1-S2 (t+1)} + \text{Prov S2-S2 (t+1)}$$

The provisions for exposures transitioning from S1 to S2 are determined as follows:

$$\text{Prov S1-S2 (t+1)} = \text{S1-S2 flow} \times LRLT^{1-2} \text{ (t+1)}$$

$$\text{S1-S2 flow} = \text{Exp } S1^{BoY} \text{ (t+1)} \times TR^{1-2} \text{ (t+1)}$$

The provisions for S2 exposures that were also classified as S2 at the start of the year are determined as follows:

$$\text{Prov S2-S2 (t+1)} = \text{Exp } S2^{BoY} \text{ (t+1)} \times \text{(1-}TR^{2-1} \text{ (t+1) - } TR^{2-3} \text{ (t+1))} \times LRLT^{2-2} \text{ (t+1)}$$

For Stage 3,

$$\text{Provisions S3} = \text{Provisions for new S3 exposures} + \text{Provisions for existing S3 exposures}$$

$$\text{Prov Stock S3 (t+1)} = \text{Prov Cumul S1-S3 (t+1)} + \text{Prov Cumul S2-S3 (t+1)} + \text{Prov Old S3 (t+1)}$$

The provisions for new S3 exposures at time t is provided by:

$$\text{Prov S1-S3 (t+1)} = \text{Exp } S1^{BoY} \text{ (t+1)} \times TR^{1-3} \text{ (t+1)} \times LGD^{1-3} \text{ (t+1)}$$

$$\text{Prov S2-S3 (t+1)} = \text{Exp } S2^{BoY} \text{ (t+1)} \times TR^{2-3} \text{ (t+1)} \times LGD^{2-3} \text{ (t+1)}$$

The provisions for current S3 exposures are described by:

$$\text{Prov Old S3 (t+1)} = \text{Max}\{\text{Old Exp } S3^{BoY} \text{ (2023)} \times LRLT^{3-3} \text{ (t+1); Prov Old } S3^{BoY} \text{ (t+1)}\}$$

where:

- Old Exp $S3^{BoY}$ (2023) is the S3 exposures at the start of the exercise.
- Prov Old $S3^{BoY}$ (t+1) represents the stock of provisions at the start of t+1 allocated to S3 exposures existing at the start of the exercise.
- Exp $S1^{BoY}$ depicts the S1 exposures at the beginning of year t+1.
- Exp $S2^{BoY}$ denotes the S2 exposures at the start of year t+1.

4 Application

4.1 Data set

The application of the models involves utilizing a risk parameters database that consists of two annual observations (2022 and 2021), derived from a financial institution's credit contract portfolio. Table II provides a comprehensive overview of the key parameters utilized in the calculations of impairments. The sole available data collected consisted of the range of observations, as the practice of segmenting the data into industry sectors was only introduced in 2023, rendering these calculations unnecessary in prior periods.

The identification of the data difference for the year 2021, in relation to a "standard" year, was attributed to the company's proficiency in effectively managing specific risk factors. The observed results displayed a significant disparity when compared to the previous years. The primary focus of this study revolves around the consequences stemming from the COVID-19 pandemic, which have exerted a substantial influence on the global economy.

Table II: Parameters provided by the financial institutions

Credit Risk Parameters	
Transition Rate 1→2 (TR_{1-2})	Transition Rate 1→3 (TR_{1-3})
Transition Rate 2→1 (TR_{2-1})	Transition Rate 2→3 (TR_{2-3})
Loss Given Default 1→3 (LGD_{1-3})	Loss Given Default 2→3 (LGD_{2-3})
Loss Rate 1→2 (LR_{1-2})	Loss Rate 2→2 (LR_{2-2})
Loss Rate 3→3 (LR_{3-3})	

Source: Own elaboration

The European Banking Authority offers forecasts for macroeconomic indicators under both baseline and adverse scenarios, as detailed in Appendix A.V A.VI. Additionally, the European Central Bank, in collaboration with national authorities, provides estimates for the gross value added (GVA) in several industry sectors for the upcoming years (2023-2025). The provision of projections for certain macroeconomic variables is justified by their perceived relevance and substantial influence on the assessment of credit risk. The historical data pertaining to these macroeconomic indicators were acquired from statistical sources, as outlined in Table III.

Table III: The macroeconomic variables, the range of years and sources of the data set

Variables	**Years**	**Source**
Gross Domestic Product (GDP)	1995-2025	Pordata
Harmonized Index of Consumer Price (HICP)	1995-2025	Pordata
Unemployment Rate	1995-2025	Pordata
Residential Real Estate Prices (RRE)	2010-2025	INE
Commercial Real Estate Prices (CRE)	2010-2025	INE
Long-term Interest Rates	1995-2025	ECB
SWAP rates (1year)	1999-2025	Investing.com
Stock Prices	2021-2025	ECB
Foreign Demand	2021-2025	ECB
Itraxx	2021-2025	ECB
Exchange Rates (EUR/USD)	1999-2025	Investing.com

Source: Own elaboration

The Growth Value Added percentage changes were derived from reliable statistical sources, including the European Central Bank (ECB), Trading Economics, the National Institute of Statistics (INE), and PORDATA. Nevertheless, a few of these values were not expressed as percentages and hence required transformation from their absolute values.

The projections provided by EBA were limited to these variables, indicating their significant relevance in the evaluation of credit risk. Moreover, numerous research have been conducted to specifically analyze the effects of these variables. This is the reason why the following paragraphs are not in the Literature Review section. Lawrence (1995) and Aver (2008) have demonstrated the significant influence of GDP, real interest rate, and unemployment rate on the evolution of credit risk [21] [1]. Furthermore, the analysis unveiled that there exists a negative association between GDP and risk variables. Conversely, there exists a positive correlation between unemployment and interest rates in relation to credit risk.

Lindgren et al. (1996) examines the impact of exchange rates on credit risk performance, highlighting the significant relationship between exchange rates and credit risk. Indeed, it adversely affects the levels of economic stability within a nation and plays a substantial role in precipitating banking crises [23].

Boss (2002) conducted a study that revealed a strong relationship between several economic factors and the default rates of enterprises. Specifically, the study found that short-term interest rates, inflation rates, stock price indices, and oil prices all had a notable impact on default rates [5]. According to Wong (2008), there exists a correlation between interest rates, property values, and default rates of bank loans. This finding supports the notion that fluctuations in interest rates and property prices can impact the likelihood of loan defaults [34]. Lu (2012) examines the influence of changes in evolution on real estate values, specifically focusing on home prices and their association with loan default rates [24]. See Appendix A.I for the expected correlation between the variables and the credit risk.

4.2 Methodology

This section will provide a chronological description of the implemented techniques. The initial methodology employed was the implementation of linear regression models. Subsequently, attempts were made to employ SDEs.

The procedure began by attempting to fit linear regressions. Initially, it was necessary to determine the selection of macroeconomic factors, which was accomplished through the utilization of a correlation ranking matrix. This selection process was supported by economic evidence, indicating the significance of these variables, as well as the availability of sufficient data to contribute meaningfully to the case. The correlation matrix encompasses data and projections spanning a period of five years, specifically from 2021 to 2025, shown in Figure 2.

The multicollinearity of the independent variables is assessed by ranking them according to their absolute correlation with each other. When the degree of correlation between variables reaches a certain threshold, it can pose challenges in the interpretation of the results. The estimated coefficient is subject to change depending on the inclusion of other independent variables in the model, perhaps leading to an increase in the standard error of the coefficients [13]. The decrease in the accuracy of the calculated coefficients and the resulting decrease in the statistical power of the regression model are observable. This stage facilitates the identification of variables that may possess the highest degree of explanatory capability for the model.

	GDP	HICP	Unemployment rate	RRE prices	CRE prices	Long-term rates	SWAP rates 1y	Stock prices	ForeignDemandAll	Itraxx	Exchange rates
GDP	1.000000	0.083838	-0.429145	0.560892	0.523855	-0.155764	-0.059567	0.242849	0.387093	-0.922879	-0.232347
HICP	0.083838	1.000000	-0.251490	-0.466247	-0.637222	0.392695	0.642461	-0.031559	-0.148927	0.596187	-0.425363
Unemployment rate	-0.429145	-0.251490	1.000000	-0.473089	-0.251466	0.265714	-0.338772	0.380433	-0.845004	0.604436	0.515705
RRE prices	0.560892	-0.466247	-0.473089	1.000000	0.913878	-0.730972	-0.792704	0.326117	0.274832	-0.865590	-0.098738
CRE prices	0.523855	-0.637222	-0.251466	0.913878	1.000000	-0.667145	-0.867503	0.512307	0.077034	-0.963882	0.080072
Long-term rates	-0.155764	0.392695	0.265714	-0.730972	-0.667145	1.000000	0.466115	-0.234037	-0.342679	0.995519	0.188379
SWAP rates 1y	-0.059567	0.642461	-0.338772	-0.792704	-0.867503	0.466115	1.000000	-0.171964	-0.411665	0.988095	-0.188354
Stock prices	0.242849	-0.031559	0.380433	0.326117	0.512307	-0.234037	-0.171964	1.000000	-0.797992	-0.311451	-0.216007
ForeignDemandAll	0.387093	-0.148927	-0.845004	0.274832	0.077034	-0.342679	-0.411665	-0.797992	1.000000	-0.280205	0.505805
Itraxx	-0.922879	0.596187	0.604436	-0.865590	-0.963882	0.995519	0.988095	-0.311451	-0.280205	1.000000	-0.696269
Exchange rates	-0.232347	-0.425363	0.515705	-0.098738	0.080072	0.188379	-0.188354	-0.216007	0.505805	-0.696269	1.000000

Figure 2: Correlations between macroeconomic variables using adverse scenario

Source: Own elaboration with output from Python

Figure 2 illustrates the association between variables in the adverse scenario (a similar figure with respect to the baseline scenario is in Appendix A.2). For the regressions, it was removed an independent variable for each pair that had an absolute correlation above 75% due to their significantly high values, which would lead to a misrepresentation of the results [30]. Williams (2015) provides additional evidence regarding the issues related to autocorrelation. Moreover, upon conducting the F-test on larger samples such as GDP, HICP, or SWAP rates 1y, the resulting probability is found to be less than 0.05, indicating that the null hypothesis should be rejected.

As seen in Figure 2, when considering the quantity of data accessible for certain variables, the remaining variables are GDP, unemployment rate, HICP, Long-term interest rates, 1 year SWAP rates, and exchange rates. In addition to these variables, it is important to incorporate the GVA variation for the sector in order to fulfill the stipulated standards.

The results pertaining to the Variation Inflation Factors for the remaining variables are deemed acceptable, given the limited amount of data provided for the test, see Table IV. The observed values fell within a range of 1 to 5, suggesting a moderate correlation between the variables. However, this level of correlation is not deemed significant enough to result in substantial issues.

Once the variables for the model were determined, it became imperative to identify a methodology for incorporating historical data into the analysis. In order to do multiple linear regressions, it is important to utilize sample sizes that exceed a

Table IV: Variance Inflation Factor for the chosen variables

Variables	**Variance Inflation Factor (VIF)**
Gross Domestic Product (GDP)	1.682408
Harmonized Index of Consumer Price (HICP)	2.37546
Unemployment Rate	3.893246
Long-term Interest Rates	2.554674
SWAP rates (1year)	2.601322
Exchange Rates (EUR/USD)	2.10631

Source: Own elaboration output from Python

mere two observations. In a study conducted by Vanek (2017), an examination was undertaken to explore the correlation between select macroeconomic variables and the behavior of the Probability of Default. The findings of the study revealed that Gross Domestic Product exhibited a statistically significant link with credit risk [32]. According to Figlewski et al. (2012), it is crucial to include the fluctuations in GDP, unemployment rate, and interest rates when assessing credit risk [16]. The findings of Castren (2008) and Calderon (2022) indicate that there is a positive relationship between a decline in GDP and an increase in default probabilities within the corporate sector of the euro area across all industries. This conclusion is supported by the authors' analysis of GDP components in economic assessment [9] [8].

In cooperation with the company's mentor, it was discussed the option to extend the time series for further application of linear regressions. After this it was decided that the best work hypothesis was incorporating macroeconomic variables that have a significant influence on credit risk in order to provide a historical trend for the risk parameters. Hence, in order to mitigate the issue of limited time series data, a viable approach involved employing GDP as an instrument to estimate historical risk characteristics. For instance, in the event of a rise in the Gross Domestic Product within a specific year, there would be a subsequent fall in the Probability of Default owing to their negative association, as illustrated in Figure 3. The method was applied backwards to every single parameter until 1995 to get a wider data set to manage and to cover the whole timeline of the macroeconomic variables. The commencement of the study was set in the year 2022 due to the aforementioned issue pertaining to the distorted value of variables in 2021. This distortion posed a considerable deviation in the observed trend, which would compromise the integrity of the final outcomes.

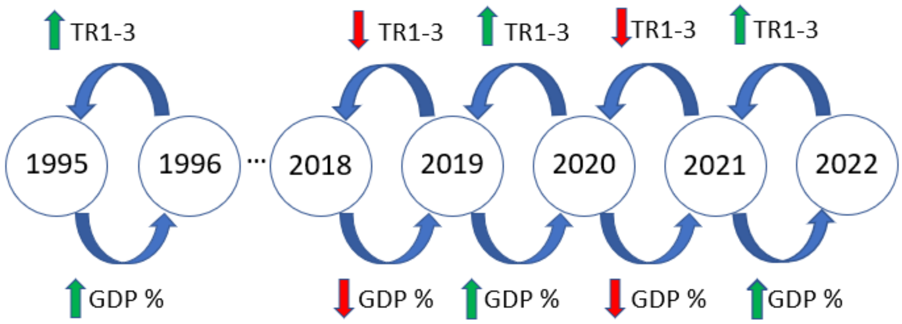
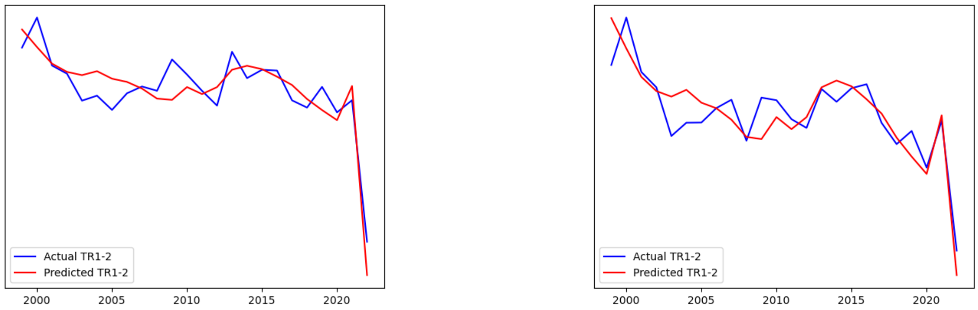


Figure 3: Representation of GDP shocks in risk parameters.

Source: Own elaboration.

However, it is important to note that there is a specific consideration while calculating TR_{2-1}. This parameter represents the likelihood of the credit transitioning from a higher risk scenario to a lower one, which distinguishes it from other estimated parameters. This indicates that there is a positive relationship between this parameter and GDP, suggesting that a positive change in GDP will correspondingly result in a rise in this transition rate. In the present study, a perfect negative (or positive) correlation, denoted by -1 (or +1), was employed to analyze the obtained results. For instance, if the GDP rate experiences a 5% increase from 2020 to 2021, it obviously means a decrease from 2021 to 2020. Subsequently, the credit risk parameters will increase from 2021 to 2020. Additionally, alternative scales, such as -0.8 (+0.8), were tested, along with a GDP growth rate that was 1.2 times bigger. However, these alternative approaches yielded poorer effects.

Subsequently, the linear regression analysis was conducted for each sector (16) and risk parameter (9), resulting in a total of 144 models for each method, in accordance with the preceding phases. The sm.OLS tool from the Python programming language was utilized in the estimation of the models. The obtained results pertaining to the coefficient of determination (R squared) were deemed satisfactory, indicating a reasonable fit of the regression model, see Appendix A.3. Consequently, the F-statistic also suggests that the regressions as a whole were statistically relevant. The Durbin-Watson test given the sample size, it is within the limits, according to [26]. Figure 4 presents comparison with the real estimated data. One noteworthy aspect to consider is the coefficients. The values, including the GVA, are considerably close to zero.



(a) Estimation of TR1-2 for sector A with $R^2 = 0.81$

(b) Estimation of LRLT2-2 for sector B with $R^2 = 0.79$

Figure 4: Estimations regarding sectors A and B using linear regressions with GDP.

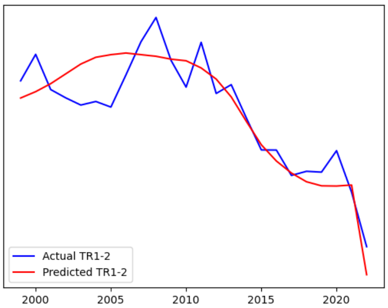
Source: Own elaboration with output from Python

Overall, the models for each sector and parameter were deemed satisfactory. The coefficients of determination suggest a decent fit of the data, see Appendix A.II. The Kurtosis values are near 3 and the Skewness values were close to 0, suggesting that the residuals are normally distributed. The F-statistic also indicates that the regressions were statistically significant.

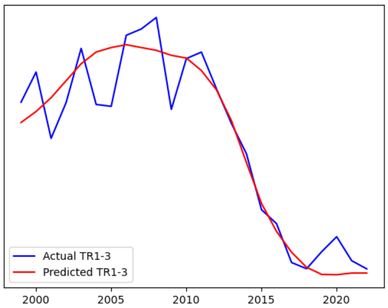
In a manner consistent with the preceding stage, a linear regression analysis was conducted, employing a backward approach with regard to the unemployment rate, Figure 5. The findings demonstrated a degree of similarity when comparing the results obtained through the utilization of GDP as a method. The coefficient of determination of the TR_{1-2} for sector A is considered reasonable. Furthermore, the Kurtosis, Skewness, and F-test align with the outcomes of the Backward GDP method, leading to identical conclusions, see Appendix A.4.

The coefficients of determination for the risk parameter TR_{1-2} are deemed appropriate, see Appendix A.III. In general, the models yield satisfactory results for every parameter, however they exhibit a slightly lower performance compared to the backward GDP method.

The preceding methodologies have demonstrated that the utilization of backward techniques produced few estimations that were slightly out of the interval [0,1],



(a) Estimation of TR1-2 for sector A with $R^2 = 0.82$



(b) Estimation of TR1-3 for sector E with $R^2 = 0.91$

Figure 5: Estimations regarding sectors A and E using linear regressions with unemployment rate.

Source: Own elaboration with output from Python

influenced by the fluctuations in GDP or the Unemployment Rate. Hence, given that the credit risk factors are indicative of probability, it becomes evident that the stated proposition is unattainable. In order to address this inquiry, it was used a restriction of 0 for minimum and 1 for the maximum value whenever the estimations reach out of the interval.

Furthermore, for the scope of testing new hypothesis of these backward methods, it was tested starting with the 2021 data point and also with the average between 2021 and 2022. The observed results indicate a substantial decrease in each specific credit risk metric compared to the previous trials. The procedure was to use the backward method in relation to both of the GDP and the unemployment rate variables. See Appendix A.IV for R^2 values for the GDP approach to 2021.

In addition, in order to explore alternative approaches and mitigate the reliance on biased data, SDEs are employed, as suggested by the company.

The underlying principle of this technique is utilizing the initial reference point of 2022 and projecting subsequent outcomes from that point onward. The term "drift" $a(Y_n)$ represents the rate of growth of Gross Value Added (GVA) and is a fundamental component in the model. On the other hand, the term "diffusion" $b(Y_n)$ coefficient pertains to volatility. The term $b(Y_n)$ is the standard deviation of the observations. Although it may not appear to be the optimal choice for accurately portraying the variability of a potential real-world dataset, it was determined to be the most appropriate method for implementing the model and introducing some level of stochasticity to the process. Since the SDEs produce unpredictable paths, 1000 Monte Carlo simulations were conducted for each estimation in order to provide more accurate results. The selected number of simulations found a good balance between the time required to simulate trajectories for the 9 credit risk parameters over 16 sectors, under both macroeconomic scenarios, and the standard error associated with employing the Monte Carlo approach in SDEs.

The GVA shock has an inverse relationship with fluctuations in risk parameters, indicating that a positive change in GVA corresponds to a drop in all parameters, with the exception of an increase in TR_{2-1}. The forecasting process relies solely on the data from the previous year, hence eliminating the need for a substantial database. Detailed results can not be shown due to confidentiality issues.

The SDEs approaches were also employed to compute the backward method, using identical methodologies of GDP and Unemployment Rate for linear regressions.

The calculations of all credit risk parameters (9), whether obtained from linear regressions or utilizing the SDEs, for each economic sector (16) yielded a total of 144 forecasts per scenario (baseline and adverse). So, the total number of estimations per method was 288.

4.3 Impairment Results

After establishing the methodology and implementing the credit risk prediction models, the calculations for impairment may be conducted. The calculations were executed with the software Microsoft Excel.

The calculations are performed using the template provided by the EBA, which includes pre-defined formulas, included in the previous chapter. The outcomes arising from the impairment cannot be divulged, thus necessitating a comparison of the actual projections with the estimated values in terms of percentage deviation, equation 4.3.1.The percentage values presented in the following tables are associated with the estimated impairment outcomes.

$$\textbf{Percentage Deviation} = \frac{Projected - Estimated}{Projected} \times 100 \tag{4.3.1}$$

Several inferences can be drawn from the computed results. Firstly, some models demonstrate a high level of accuracy in providing correct results, particularly in baseline scenario. When considering the Milstein and Euler-Murayama approaches, it is evident that they exhibit strong performance in terms of the overall impairment values in the baseline scenario. However, it is important to note that there are significant variations in values across certain sectors. Interestingly, the overall total amount remains about the same, suggesting that the larger differences in variation may correspond to relatively minor differences in absolute value.

Upon analyzing the Milstein approach, it becomes evident that it falls short in providing precise outcomes across some sectors. Nonetheless, the overall anticipated level of exposure aligns closely with the actual projected outcomes. It might be claimed the reliability of the results for stages 2 and 3 in terms of expected exposures is higher compared to stage 1. The higher amount of exposure anticipated in the later stages is the primary factor contributing to this contrast, as compared to Stage 1.

Sectors such as "M-N Professional, scientific and technical activities; administrative and support service activities", "O-Q Public administration and defence, compulsory social security; education; human health services and social work activities" and "D Electricity, gas, steam and air conditioning supply" have notable disparities in variability across all models. This suggests that the bank have low exposures on these sectors, and consequently low impairment values. It indicates that even minor quantitative changes between the projected and the estimated results might yield substantial % deviation in the outcomes, they are not significant when looking to the overall results. Moreover, the stage 1 has a lower weight compared to the other stages in the overall impairment results, quantitatively speaking. This is consistent with later findings, hence justifying the larger % deviations observed in stage 1.

Table V: Percentage deviation comparing the projected impairment results with the estimated values for the baseline scenario

% Deviation in Milstein Method

Economic	**2023**			**2024**			**2025**		
Sector	**S1**	**S2**	**S3**	**S1**	**S2**	**S3**	**S1**	**S2**	**S3**
A	-17	-261	7	-49	-550	8	-52	-513	10
B	-1257	84	-35	-1362	90	-54	-1286	93	-66
C-High	-53	52	3	-93	55	4	-95	54	4
C-Low	16	-21	5	3	-26	8	4	-34	9
D	100	-67	-11	100	-611	-24	100	-464	-31
E	100	95	27	100	98	46	100	98	58
F	100	-23	2	100	-4	4	100	9	6
G	55	66	9	38	67	15	37	65	20
H	100	91	-8	100	88	-7	100	84	-6
I	100	98	27	100	99	32	100	99	36
J	100	91	15	100	89	24	100	87	30
K	100	-4790	2	100	-8068	3	100	-8587	4
L	54	32	4	45	36	7	44	37	9
M-N	56	-3503	0	52	-2302	-1	52	-9000	-2
O-Q	-3320	-928	0	-3374	-1032	-1	-3387	-1267	-1
R-U	-660	-556	0	-720	-678	-1	-762	-912	-1
Total	**42**	**-3**	**4**	**28**	**-7**	**6**	**28**	**-13**	**8**

Source: Own elaboration output from Excel

After analyzing the results for both methodologies employed, in the adverse scenario (see Table VII) it can be seen that in the two cases the models show significant disparities between the actual impairment calculations and the estimated values. It is possible that these models do not capture the influence of GVA shocks on the risk parameters.

In relation to linear regression approaches, it can be demonstrated that they exhibit slightly larger disparities in variability compared to stochastic models, indicating their worse performance relative to the aforementioned methods. One potential explanation could be the limited impact of GVA shocks within the models. Upon analyzing the coefficients of nearly all linear regression models, it becomes evident that the GVA parameters consistently exhibit a high degree of insignificance, with values approaching zero.

A comparative analysis of the two backward approaches employed in linear regressions, namely GDP and Unemployment Rate, revealed that GDP yields superior

Table VI: Percentage Deviation between the projected impairment results and the estimated values for the baseline scenario

Baseline Scenario Total Expected Impairments

Method	2023			2024			2025		
	S1	**S2**	**S3**	**S1**	**S2**	**S3**	**S1**	**S2**	**S3**
Backward GDP	36	-16	3	38	-16	5	37	-8	7
Backward UR	30	-15	-2	-6	-30	-3	-2	-82	-5
Backward Milstein	-6	-10	2	9	-35	1	-9	-35	1
Forward Milstein	42	-3	4	28	-7	6	28	-13	8
Euler-Murayama	42	-3	4	28	-7	6	28	-13	8

Source: Own elaboration output from Excel

Table VII: Percentage Deviation between the projected impairment results and the estimated values for the adverse scenario

Adverse Scenario Total Expected Impairments

Method	2023			2024			2025		
	S1	**S2**	**S3**	**S1**	**S2**	**S3**	**S1**	**S2**	**S3**
Backward GDP	86	51	15	87	52	21	84	52	26
Backward UR	85	52	10	78	46	14	73	20	17
Backward Milstein	77	-54	14	81	44	18	76	40	22
Forward Milstein	86	52	15	85	53	21	81	49	26
Euler-Murayama	86	52	15	85	53	21	81	49	26

Source: Own elaboration output from Excel

outcomes in both baseline and unfavorable circumstances, especially when analysing the individual sector values.

In relation to the Euler-Murayama and the Milstein methodologies, it is worth reiterating that the SDEs approaches exhibit superior performance. The dissimilarities between these two models are barely perceptible, since they diverge in terms of convergence ratio. However, this aspect is not applicable in the present study due to the absence of defined significant grids and the estimation of only three data points.

In terms of overall performance, it may be asserted that SDEs models exhibit superior performance compared to linear regressions. Furthermore, it is important to show prudence when comparing the estimated values with the expected results from the bank due to the fact that, as previously said, it is a new framework without specific established procedures. These computations are still in their early stages as banks still strive to have a clearer understanding of how to approach.

5 Conclusions

The objective of the project was to investigate the utilization of linear regressions with macroeconomic predictors and SDEs models in order to calculate credit risk impairments. The absence of historical data on credit risk parameters posed a significant challenge, as many studies rely on statistical techniques to forecast risk factors. Obtaining a comprehensive understanding of the outcomes necessitates access to extensive databases.

The utilization of linear regressions facilitated the derivation of conclusions regarding macroeconomic variables. It was observed that certain variables exhibit correlation with the risk parameters. Therefore, it exists a negative correlation between certain variables, namely Gross Domestic Product (GDP), Harmonized Index of Consumer Price (HICP), and interest rates, and the risk factors associated with the deterioration of credit ratings. Conversely, there exists a positive linear correlation between the unemployment rate and these risk parameters, indicating that an increase in the unemployment rate implies a growth in those parameters. The findings in the linear models also indicated a presence of correlation among the predictor variables, a challenge that is difficult to overcome given the limited size of the databases. The situation was characterized by ambiguity in terms of the presence of a statistically significant model and the comprehension of the resulting outcomes.

The utilization of SDEs models yielded satisfactory outcomes across various economic sectors. The Gross Value Added growth for each sector served as a primary influence, with the inclusion of random variance. This statement illustrates the correlation between the fluctuation of GVA and the subsequent evolution of risk parameters in the coming years.

The analysis of credit risk impairment reveals that there are no substantial differences between the baseline and adverse scenarios. The EU-wide Stress Test has highlighted the disparities between these two scenarios, further exacerbating the severity of the latter. This outcome was not widely observed, suggesting that the models may not accurately capture the impact of GVA changes. The occurrence of small GVA coefficients in linear regression models is a contributing factor. The linear models reveal small coefficients for each macroeconomic variable, indicating that they are not responding completely to fluctuations in these variables.

Based on the findings of this study, it can be inferred that the SDEs models exhibited superior performance compared to the linear models, although with room for further enhancements in both approaches. In order to increase the performance of linear regressions in predicting credit risk estimators, it is imperative to obtain more precise data and larger sample sizes. Although the behaviour of the SDEs models was satisfactory, there are some concerns regarding the volatility employed in the process. In order to enhance the scope of future research, it may be deemed appropriate to consider the incorporation of stochastic volatility into the model.

There are various potential avenues for future research that could expand beyond the findings of this study. Initially, researchers may undertake an analysis of the influence exerted by additional macroeconomic factors on the performance of linear models. Furthermore, researchers can potentially employ several techniques in order to mitigate the issue of small sample sizes. In conclusion, future investigations may direct their attention towards different techniques for incorporating unpredictability inside SDEs models.

Overall, this project facilitated an exploration of financial modelling in the context of credit risk, thereby enhancing comprehension of the various challenges that may arise in this domain. The months dedicated to experimenting and tailoring the models, complying with the applicable regulations, provided a great introduction to the model techniques employed in the field, and the importance of the intersection between complex numerical methods and financial knowledge.

References

[1] Boštjan Aver et al. An empirical analysis of credit risk factors of the slovenian banking system. *Managing Global Transitions*, 6(3):317–334, 2008.

[2] Barry Belkin, Stephan Suchower, and Lawrence Forest. A one-parameter representation of credit risk and transition matrices. *CreditMetrics monitor*, 1(3):46–56, 1998.

[3] Enrique Benito, Silviu Glavan, and Peter Jacko. A comparison of credit risk models. *Risk Theory, Working Paper*, 2005.

[4] Tomas Björk. *Arbitrage theory in continuous time.* Oxford university press, 2009.

[5] Michael Boss. A macroeconomic credit risk model for stress testing the austrian credit portfolio. *Financial Stability Report*, 4:64–82, 2022.

[6] Karl Brunner, Alan Meltzer, et al. Econometric policy evaluation: A critique. In *Theory, Policy, Institutions: Papers from the Carnegie-Rochester Conferences on Public Policy*, volume 1, page 257. North Holland, 1983.

[7] David Cai. Stochastic taylor expansion. 2015. `https://math.nyu.edu/~cai/Courses/Derivatives/compfin_lecture_5.pdf`.

[8] Valent Calderon-Contreras, J Ostos, Wilmer Florez-Garcia, and H Angulo-Bustinza. Determinants of credit risk: A multiple linear regression analysis of peruvian municipal savings banks. *Decision Science Letters*, 11(3):203–210, 2022.

[9] Olli Castrén, Stéphane Dées, and Fadi Zaher. Global macro-financial shocks and expected default frequencies in the euro area. 2008.

[10] Ali Chabaane, Jean-Paul Laurent, and Julien Salomon. Double impact: credit risk assessment and collateral value. *Revue Finance*, 25(1):157–78, 2004.

[11] Jorge A Chan-Lau. Fundamentals-based estimation of default probabilities: a survey. 2006.

[12] Cristian Ciurea, Nora CHIRIȚĂ, and Ionuț NICA. A practical approach to development and validation of credit risk models based on data analysis. *Economic Computation & Economic Cybernetics Studies & Research*, 56(3), 2022.

[13] Jamal I Daoud. Multicollinearity and regression analysis. In *Journal of Physics: Conference Series*, volume 949, page 012009. IOP Publishing, 2017.

[14] EBA. 2023 eu-wide stress test - methodological note. 2023. https://www.eba.europa.eu/sites/default/documents/files/document_library/Risk%20Analysis%20and%20Data/EU-wide%20Stress%20Testing/2023/Scenarios/1051436/2023%20EU-wide%20stress%20test%20-%20Methodological%20Note.pdf.

[15] Simone Farinelli and Mykhaylo Shkolnikov. Two models of stochastic loss given default. *arXiv preprint arXiv:1205.5369*, 2012.

[16] Stephen Figlewski, Halina Frydman, and Weijian Liang. Modeling the effect of macroeconomic factors on corporate default and credit rating transitions. *International Review of Economics & Finance*, 21(1):87–105, 2012.

[17] Jim Frost. *Regression analysis: An intuitive guide for using and interpreting linear models*. Statisics By Jim Publishing, 2019.

[18] Desmond J Higham. An algorithmic introduction to numerical simulation of stochastic differential equations. *SIAM review*, 43(3):525–546, 2001.

[19] John Hull. *Risk management and financial institutions,+ Web Site*, volume 733. John Wiley & Sons, 2012.

[20] IFRS Foundation IASB. Ifrs 9 - financial instruments. 2020. https://www.ifrs.org/content/dam/ifrs/publications/pdf-standards/english/2022/issued/part-a/ifrs-9-financial-instruments.pdf?bypass=on.

[21] Emily C Lawrence. Consumer default and the life cycle model. *Journal of Money, Credit and Banking*, 27(4):939–954, 1995.

[22] Joseph Lee Rodgers and W Alan Nicewander. Thirteen ways to look at the correlation coefficient. *The American Statistician*, 42(1):59–66, 1988.

[23] Mr Carl-Johan Lindgren, Ms GG Garcia, and Mr Matthew I Saal. *Bank soundness and macroeconomic policy.* International Monetary Fund, 1996.

[24] Wei Lu and Zhiwei Yang. Stress testing of commercial banks' exposure to credit risk: A study based on write-off nonperforming loans. *Asian Social Science*, 8(10):16, 2012.

[25] Matilde Rosa. Numerical methods for stochastic differential equations. *Institute Superior Tecnico, Lisbon*, 2016.

[26] Nathan E Savin and Kenneth J White. The durbin-watson test for serial correlation with extreme sample sizes or many regressors. *Econometrica: Journal of the Econometric Society*, pages 1989–1996, 1977.

[27] Jinghai Shao, Siming Li, and Yong Li. Estimation and prediction of credit risk based on rating transition systems. *arXiv preprint arXiv:1607.00448*, 2016.

[28] Dietske Simons and Ferdinand Rolwes. Macroeconomic default modeling and stress testing. *Eighteenth issue (September 2009) of the International Journal of Central Banking*, 2018.

[29] Erika Spuchl'áková, Katarína Valašková, and Peter Adamko. The credit risk and its measurement, hedging and monitoring. *Procedia Economics and finance*, 24:675–681, 2015.

[30] Martina Udovičić, Ksenija Baždarić, Lidija Bilić-Zulle, Mladen Petrovečki, et al. What we need to know when calculating the coefficient of correlation? *Biochemia Medica*, 17(1):10–15, 2007.

[31] Gülden Kaya Uyanık and Neşe Güler. A study on multiple linear regression analysis. *Procedia-Social and Behavioral Sciences*, 106:234–240, 2013.

[32] Tomáš Vaněk and David Hampel. The probability of default under ifrs 9: multi-period estimation and macroeconomic forecast. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, 2017.

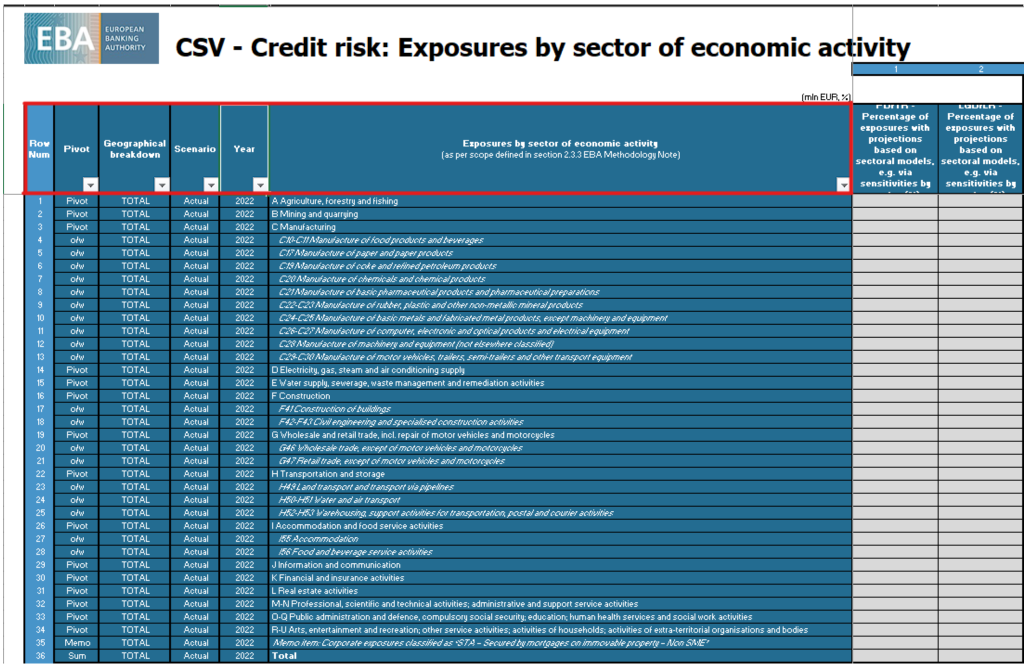
[33] Jirì Witzany. A two-factor model for pd and lgd correlation. *Available at SSRN 1476305*, 2011.

[34] Jim Wong, Ka-fai Choi, and Tom Fong. A framework for stress testing bank's credit risk. *Hong Kong Monetary Authority, Working Papers*, 2, 01 2006.

[35] Jeffrey M Wooldridge. *Introductory econometrics: A modern approach*. Cengage learning, 2015.

[36] Yuxing Yan. *Python for Finance*. Packt Publishing Ltd, 2017.

A Appendix



CSV - Credit risk: Exposures by sector of economic activity

(mln EUR, %)

Row Num	Pivot	Geographical breakdown	Scenario	Year	Exposures by sector of economic activity (as per scope defined in section 2.3.3 EBA Methodology Note)	1 Percentage of exposures with projections based on sectoral models, e.g. via sensitivities by	2 Percentage of exposures with projections based on sectoral models, e.g. via sensitivities by
1	Pivot	TOTAL	Actual	2022	A Agriculture, forestry and fishing		
2	Pivot	TOTAL	Actual	2022	B Mining and quarrying		
3	Pivot	TOTAL	Actual	2022	C Manufacturing		
4	o/w	TOTAL	Actual	2022	*C10-C11 Manufacture of food products and beverages*		
5	o/w	TOTAL	Actual	2022	*C17 Manufacture of paper and paper products*		
6	o/w	TOTAL	Actual	2022	*C19 Manufacture of coke and refined petroleum products*		
7	o/w	TOTAL	Actual	2022	*C20 Manufacture of chemicals and chemical products*		
8	o/w	TOTAL	Actual	2022	*C21 Manufacture of basic pharmaceutical products and pharmaceutical preparations*		
9	o/w	TOTAL	Actual	2022	*C22-C23 Manufacture of rubber, plastic and other non-metallic mineral products*		
10	o/w	TOTAL	Actual	2022	*C24-C25 Manufacture of basic metals and fabricated metal products, except machinery and equipment*		
11	o/w	TOTAL	Actual	2022	*C26-C27 Manufacture of computer, electronic and optical products and electrical equipment*		
12	o/w	TOTAL	Actual	2022	*C28 Manufacture of machinery and equipment (not elsewhere classified)*		
13	o/w	TOTAL	Actual	2022	*C29-C30 Manufacture of motor vehicles, trailers, semi-trailers and other transport equipment*		
14	Pivot	TOTAL	Actual	2022	D Electricity, gas, steam and air conditioning supply		
15	Pivot	TOTAL	Actual	2022	E Water supply, sewerage, waste management and remediation activities		
16	Pivot	TOTAL	Actual	2022	F Construction		
17	o/w	TOTAL	Actual	2022	*F41 Construction of buildings*		
18	o/w	TOTAL	Actual	2022	*F42-F43 Civil engineering and specialised construction activities*		
19	Pivot	TOTAL	Actual	2022	G Wholesale and retail trade, incl. repair of motor vehicles and motorcycles		
20	o/w	TOTAL	Actual	2022	*G46 Wholesale trade, except of motor vehicles and motorcycles*		
21	o/w	TOTAL	Actual	2022	*G47 Retail trade, except of motor vehicles and motorcycles*		
22	Pivot	TOTAL	Actual	2022	H Transportation and storage		
23	o/w	TOTAL	Actual	2022	*H49 Land transport and transport via pipelines*		
24	o/w	TOTAL	Actual	2022	*H50-H51 Water and air transport*		
25	o/w	TOTAL	Actual	2022	*H52-H53 Warehousing, support activities for transportation, postal and courier activities*		
26	Pivot	TOTAL	Actual	2022	I Accommodation and food service activities		
27	o/w	TOTAL	Actual	2022	*I55 Accommodation*		
28	o/w	TOTAL	Actual	2022	*I56 Food and beverage service activities*		
29	Pivot	TOTAL	Actual	2022	J Information and communication		
30	Pivot	TOTAL	Actual	2022	K Financial and insurance activities		
31	Pivot	TOTAL	Actual	2022	L Real estate activities		
32	Pivot	TOTAL	Actual	2022	M-N Professional, scientific and technical activities; administrative and support service activities		
33	Pivot	TOTAL	Actual	2022	O-Q Public administration and defence, compulsory social security; education; human health services and social work activities		
34	Pivot	TOTAL	Actual	2022	R-U Arts, entertainment and recreation; other service activities; activities of households; activities of extra-territorial organisations and bodies		
35	Memo	TOTAL	Actual	2022	*Memo item: Corporate exposures classified as 'STA – Secured by mortgages on immovable property – Non SME'*		
36	Sum	TOTAL	Actual	2022	**Total**		

Figure A.1: Template's Header divided by group areas

Source: Template provided by EBA

	GDP	HICP	Unemployment rate	RRE prices	CRE prices	Long-term rates	SWAP rates 1y	Stock prices	ForeignDemandAll	Itraxx	Exchange rates
GDP	1.000000	0.352140	-0.426451	0.494433	0.533780	-0.110507	0.120198	0.263296	0.364044	-0.544825	-0.376683
HICP	0.352140	1.000000	-0.408517	-0.026951	-0.077098	0.283459	0.520043	-0.065772	0.218130	0.480258	-0.358208
Unemployment rate	-0.426451	-0.408517	1.000000	-0.688318	-0.681849	0.290450	-0.477727	-0.216007	0.505805	-0.988967	0.612752
RRE prices	0.494433	-0.026951	-0.688318	1.000000	0.888746	-0.824042	-0.450431	0.241768	0.382732	-0.504174	-0.618937
CRE prices	0.533780	-0.077098	-0.681849	0.888746	1.000000	-0.806851	-0.241451	0.029592	0.544781	-0.839338	-0.652792
Long-term rates	-0.110507	0.283459	0.290450	-0.824042	-0.806851	1.000000	0.340737	0.151792	-0.606960	0.973140	0.328257
SWAP rates 1y	0.120198	0.520043	-0.477727	-0.450431	-0.241451	0.340737	1.000000	-0.095157	-0.465455	0.869017	-0.115804
Stock prices	0.263296	-0.065772	-0.216007	0.241768	0.029592	0.151792	-0.095157	1.000000	-0.797992	0.255249	-0.216007
ForeignDemandAll	0.364044	0.218130	0.505805	0.382732	0.544781	-0.606960	-0.465455	-0.797992	1.000000	-0.599689	0.505805
Itraxx	-0.544825	0.480258	-0.988967	-0.504174	-0.839338	0.973140	0.869017	0.255249	-0.599689	1.000000	-0.988967
Exchange rates	-0.376683	-0.358208	0.612752	-0.618937	-0.652792	0.328257	-0.115804	-0.216007	0.505805	-0.988967	1.000000

Figure A.2: Correlations between macroeconomic variables using baseline shocks

Source: Own elaboration output from Python

Table A.I: Expected correlation with credit risk

Variables	Expected Sign
Gross Domestic Product (GDP)	-
Harmonized Index of Consumer Price (HICP)	-
Unemployment Rate	+
Residential Real Estate Prices (RRE)	+
Commercial Real Estate Prices (CRE)	+
Long-term Interest Rates	-
SWAP rates (1year)	+
Stock Prices	-
Foreign Demand	-
Itraxx	-
Exchange Rates (EUR/USD)	-

Source: Own elaboration

Table A.II: List of R^2 of the estimations regarding the Transition Rate 1-2 for every sector for the baseline scenario using linear regressions (Backward GDP method)

Economic Sector	R^2
A	0.810
B	0.812
C-High	0.808
C-Low	0.797
D	0.798
E	0.820
F	0.794
G	0.825
H	0.778
I	0.773
J	0.796
K	0.843
L	0.775
M-N	0.797
O-Q	0.795
R-U	0.797

Source: Own elaboration output from Python

Table A.III: List of R^2 of the estimations regarding the Transition Rate 1-2 for every sector for the baseline scenario using linear regressions (Backward Unemployment Rate method)

Economic Sector	R^2
A	0.810
B	0.812
C-High	0.808
C-Low	0.797
D	0.798
E	0.820
F	0.794
G	0.825
H	0.778
I	0.773
J	0.796
K	0.843
L	0.775
M-N	0.797
O-Q	0.795
R-U	0.797

Source: Own elaboration output from Python

Table A.IV: R^2 of the estimations regarding the Transition Rate 1-2 for every sector for the baseline scenario using linear regressions (Backward GDP 2021)

Economic Sector	R^2
A	0.586
B	0.595
C-High	0.605
C-Low	0.594
D	0.591
E	0.648
F	0.632
G	0.612
H	0.587
I	0.586
J	0.605
K	0.586
L	0.599
M-N	0.603
O-Q	0.609
R-U	0.587

Source: Own elaboration output from Python

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      A   R-squared:                       0.810
Model:                            OLS   Adj. R-squared:                  0.727
Method:                 Least Squares   F-statistic:                     9.743
Date:                Sat, 14 Oct 2023   Prob (F-statistic):           9.52e-05
Time:                        16:08:59   Log-Likelihood:                 81.143
No. Observations:                  24   AIC:                            -146.3
Df Residuals:                      16   BIC:                            -136.9
Df Model:                           7
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
const                 0.2352      0.021     11.331      0.000       0.191       0.279
GDP                   0.0004      0.001      0.504      0.621      -0.001       0.002
Unemployment rate     0.0002      0.001      0.172      0.865      -0.002       0.003
HICP                 -0.0101      0.002     -5.938      0.000      -0.014      -0.006
SWAP rates 1y         0.0067      0.002      3.432      0.003       0.003       0.011
Exchange rates       -0.0534      0.020     -2.709      0.015      -0.095      -0.012
Long-term rates       0.0034      0.001      2.704      0.016       0.001       0.006
gva                   0.0007      0.001      1.074      0.299      -0.001       0.002
==============================================================================
Omnibus:                        1.102   Durbin-Watson:                   1.623
Prob(Omnibus):                  0.576   Jarque-Bera (JB):                1.053
Skew:                          -0.412   Prob(JB):                        0.591
Kurtosis:                       2.388   Cond. No.                         147.
==============================================================================
```

Figure A.3: Estimation of Transition Rate 1 → 2 for sector A-"Agriculture, forestry and fishing" (Backward GDP method)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      A   R-squared:                       0.822
Model:                            OLS   Adj. R-squared:                  0.744
Method:                 Least Squares   F-statistic:                     10.57
Date:                Sat, 14 Oct 2023   Prob (F-statistic):           5.79e-05
Time:                        17:25:32   Log-Likelihood:                 56.356
No. Observations:                  24   AIC:                            -96.71
Df Residuals:                      16   BIC:                            -87.29
Df Model:                           7
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
const                 0.1354      0.058      2.323      0.034       0.012       0.259
GDP                  -0.0026      0.002     -1.100      0.287      -0.008       0.002
Unemployment rate    -0.0003      0.003     -0.082      0.936      -0.007       0.006
HICP                 -0.0111      0.005     -2.323      0.034      -0.021      -0.001
SWAP rates 1y         0.0242      0.005      4.449      0.000       0.013       0.036
Exchange rates        0.0575      0.055      1.038      0.315      -0.060       0.175
Long-term rates       0.0072      0.003      2.058      0.056      -0.000       0.015
gva                   0.0009      0.002      0.508      0.619      -0.003       0.005
==============================================================================
Omnibus:                        0.968   Durbin-Watson:                   1.147
Prob(Omnibus):                  0.616   Jarque-Bera (JB):                0.954
Skew:                           0.364   Prob(JB):                        0.621
Kurtosis:                       2.350   Cond. No.                         147.
==============================================================================
```

Figure A.4: Estimation of Transition Rate 1 → 2 for sector A-"Agriculture, forestry and fishing" (Backward Unemployment Rate Method)

Table A.V: Macroeconomic projections for the baseline scenario

Variables	**Baseline Growth (%)**		
	2023	**2024**	**2025**
Gross Domestic Product (GDP)	1.5	2	1.9
Harmonized Index Consumer Price (HICP)	5.8	3.3	2.1
Unemployment Rate	5.9	5.9	5.9
Residential Real Estate Price (RRE)	2.5	3	2.7
Commercial Real Estate Price (CRE)	2.1	2.1	2
Long-term Interest Rates	2.88	2.98	3.12
SWAP rates (1year)	3.67	3.47	3.23
Stock Prices	-55	-48	-43
Foreign Demand	-8.6	-14.4	-17.5
Itraxx	97	100	102
Exchange Rates (EUR/USD)	1.05	1.05	1.05

Source: Own elaboration output from ESRB

Table A.VI: Macroeconomic projections for the adverse scenario

Variables	**Adverse Growth (%)**		
	2023	**2024**	**2025**
Gross Domestic Product (GDP)	1.6	-3.1	-0.4
Harmonized Index Consumer Price (HICP)	8.3	6.3	5.6
Unemployment Rate	7.6	10.1	11.4
Residential Real Estate Price (RRE)	-9.1	-16.9	-1.3
Commercial Real Estate Price (CRE)	-17.2	-12.4	-4.7
Long-term Interest Rates	6.98	5.73	5.42
SWAP rates (1year)	5.19	4.68	4.26
Stock Prices	-55	-48	-43
Foreign Demand	-8.6	-14.4	-17.5
Itraxx	283	232	215
Exchange Rates (EUR/USD)	1.05	1.05	1.05

Source: Own elaboration output from ESRB