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MASTER'S THESIS

METHODOLOGY AND THE USE OF CREDIT SPREAD RISK MEASUREMENT IN BANKING

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ABSTRACT

The thesis examines the measurement of Credit Spread Risk in the Banking Book (CSRBB) and analyses how methodological choice influences portfolio-level risk assessment. It compares simplified deterministic approaches with advanced stochastic Monte Carlo-based methods using a set of synthetic banking book portfolios with systematically varied structural characteristics. The results show that simplified approaches provide conservative baseline estimates but do not capture diversification and correlation effects, while advanced stochastic methods offer increased risk sensitivity through joint modelling of credit spread dynamics. The results of the study highlight the importance of aligning methodological complexity with portfolio structure, using simple approaches for simple portfolios and more detailed ones where needed.

KEY WORDS: CSRBB, portfolio, Monte Carlo simulation, Economic Value of Equity

SUSTAINABLE DEVELOPMENT GOALS

POVZETEK

Magistrsko delo obravnava merjenje kreditnega razmika v bančni knjigi (CSRBB) ter analizira, kako izbira metodologije vpliva na oceno portfeljskega tveganja. Primerjava poenostavljenih determinističnih pristopov in naprednih stohastičnih metod, temelječih na Monte Carlo simulacijah, je izvedena na naboru sintetičnih bančnih portfeljev z namensko raznoliko strukturo. Rezultati kažejo, da poenostavljeni pristopi zagotavljajo konservativne osnovne ocene, vendar ne zajemajo izrecno učinkov diverzifikacije in korelacij, medtem ko napredni stohastični pristopi omogočajo večjo občutljivost na portfeljsko strukturo in repna tveganja prek skupnega modeliranja gibanj kreditnih razmikov. Ugotovitve poudarjajo pomen sorazmerne izbire metodologije glede na strukturo portfelja in podpirajo večplastni pristop k merjenju CSRBB v bančnem upravljanju tveganj.

KLJUČNE BESEDE: CSRBB, portfelj, Monte Carlo simulacija, ekonomska vrednost kapitala

CILJI TRAJNOSTNEGA RAZVOJA

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LIST OF ABBREVIATIONS

ALCO – Asset and Liability Committee

CRD – Capital Requirements Directive

CSRBB - Credit Spread Risk in the Banking Book

EBA – European Banking Authority

EBF – European Banking Federation

ECB – European Central Bank

ES – Expected Shortfall

EVE – Economic Value of Equity

HHI – Herfindahl–Hirschman Index

ICAAP – Internal Capital Adequacy Assessment Process

ILAAP – Internal Liquidity Adequacy Assessment Process

IRRBB – Interest Rate Risk in Banking Book

LGD – Loss Given Default

NII – Net Interest Income

OAS – Option-Adjusted Spread

OIS – Overnight Indexed Swap

P&L – Profit and Loss

RWAs – Risk-Weighted Assets

SREP – Supervisory Review and Evaluation Process

VaR – Value-at-Risk

1 INTRODUCTION

Credit Spread Risk in the Banking Book (CSRBB) captures market-driven valuation effects arising from changes in credit risk premia and liquidity conditions, distinct from interest rate risk and default credit risk. CSRBB is forward-looking in nature and reflects changes in market perception rather than realized credit losses. In recent years, increased supervisory attention has elevated the importance of CSRBB as a distinct risk category within banks' internal risk management frameworks.

An important challenge in CSRBB measurement lies in the choice of methodology. Banks may apply simplified deterministic approaches, such as fixed spread shocks and sensitivity analyses, or more advanced stochastic approaches, such as Monte Carlo simulation. These methodological choices can lead to materially different assessments of CSRBB, particularly when portfolio characteristics such as diversification, concentration, maturity structure, and correlations among credit spreads are taken into account. The treatment of portfolio effects is therefore central to understanding how different CSRBB methodologies perform in practice.

The purpose of the thesis is to analyse and compare alternative methodologies for measuring CSRBB through the Economic Value of Equity (EVE) with a particular focus on the differences between simplified deterministic approaches and advanced stochastic approaches. The thesis investigates how methodological choice influences measured CSRBB and how portfolio structure affects risk outcomes under different methodologies. The main contribution of the thesis is an empirical, portfolio-based comparison of simplified and advanced CSRBB methodologies using a set of synthetic banking book portfolios with different, deliberately changed characteristics. By applying both approaches to the same portfolios, the thesis provides a controlled assessment of how diversification, concentration, credit quality, and maturity structure influence CSRBB measurement, which will provide a clear illustration of the extent to which advanced stochastic methods capture portfolio effects and tail risk that are not reflected in simplified deterministic approaches.

The research questions guiding the thesis are:

- How does portfolio structure influence the measurement of CSRBB under different methodological approaches?
- To what extent do advanced methods of Monte Carlo simulation capture portfolio effects (e.g., correlations, diversification, maturity structure) that are not reflected in simplified methods?
- How comparable are the results of different approaches when applied to the same banking book portfolios?

The thesis is structured as follows: the second chapter provides the theoretical and regulatory background to CSRBB by introducing the concept of credit spreads and their role in banking. It discusses the economic transmission channels through which credit spread movements affect bank profitability, solvency, and funding conditions, reviews evidence from past financial crises, and outlines the regulatory framework for Interest Rate Risk in Banking Book (IRRBB) and CSRBB under EBA and ECB guidelines. The chapter also presents key methodological concepts used in CSRBB measurement, including spread volatility, sensitivity-based valuation, and portfolio diversification effects. The third chapter presents the methodological framework applied in the thesis, describing the construction of synthetic banking book portfolios and detailing both simplified deterministic and advanced stochastic approaches. It explains the process of producing historical credit spread shocks, the valuation methodology for computing changes in economic value, the calculation of instrument-level effects at the portfolio level, and the Monte Carlo simulation framework, including multi-factor correlation structures, concentration-sensitive scaling, idiosyncratic risk treatment, and numerical stabilisation techniques. The fourth chapter applies these methodologies in an empirical case study, reporting and interpreting CSRBB estimates for five synthetic portfolios, examining differences in tail risk, diversification, and concentration effects, and providing a cross-method comparison to assess how methodological choices influence measured CSRBB across different portfolio structures. Finally, the fifth chapter evaluates and interprets the empirical results by comparing simplified and advanced CSRBB methodologies, discussing their strengths, weaknesses, and trade-offs, and assessing their alignment with academic literature and regulatory expectations, while also outlining practical implications for banks and supervisors.

2 THEORETICAL BACKGROUND

2.1 Credit Spread Risk and Its Role in Banking

A credit spread refers to the difference in yield between a default-risk-free benchmark bond (typically an AAA-rated government bond) and another bond of similar maturity that includes credit risk, such as a corporate, financial, or government bond. In terms of investing, it represents the additional return that investors demand to compensate for the possibility that the bond issuer might default. The additional yield compensates not only for default risk, but also for liquidity risk, tax considerations, and other market imperfections. In the context of banking, credit spread represents the additional risk that the bank calculates in order to compensate for the possibility that the bond issuer might default. Credit spread risk calculations are critically important because they influence funding costs, asset valuations, and risk management strategies (Hull, 2018).

To understand credit spreads in more depth, it is essential to disentangle their components. According to Schwarz (2019), credit spreads can be broadly decomposed into two main parts: credit component depends on the probability of default (PD) and loss given default (LGD), which represents the expected loss from the bond issuer’s potential failure to pay, liquidity component depends on market trading risks, reflecting the ease or difficulty of trading the bond. The mentioned decomposition is especially relevant in times of financial stress, when liquidity dries up and contributes to observed spread widening. Similarly, Du (2023) shows that credit spreads can be predictive of bank fragility, particularly in low capital (not enough cushion against losses) or high leverage (a lot of debt compared to their equity) situations. His studies indicate that rising spreads correlate with increased tail risk and decreased resilience of banks, providing further evidence that credit spreads are not just market indicators, but active transmitters of financial risk into the banking system.

Within the regulatory context, the concept of CSRBB has been formally defined under the European Banking Authority (EBA) guidelines as the risk that changes in credit spreads can adversely affect the economic value of banking book instruments. CSRBB is separate from IRRBB, which focuses on interest rate changes unrelated to credit perceptions. The introduction of CSRBB under the Basel Pillar 2 framework reflects a growing concern among regulators that market-driven volatility of spread represents a significant risk, particularly for hold-to-maturity assets. These bonds that banks intend to keep until repayment are not marked-to-market, but their economic value still changes when spreads change, because they still carry exposure to spread changes through discounting and valuation metrics. If spreads widen, the present value of those cash flows decreases, and the bank loses value even if it doesn’t sell the asset (EBA, 2022).

Finally, during periods of systemic stress (sudden loss of market confidence), credit spreads tend to widen, often reflecting more than just worsening fundamentals. As shown by He and Krishnamurthy (2019), these spikes can reflect market fear, liquidity shortages, and fire sales, which means that CSRBB is not only an issue that affects individual banks’ balance sheets but also a market concern. Financial stress could easily spread across banks and markets, amplifying systemic risk. Therefore, banks are expected to model CSRBB using scenario analysis, historical simulation, or other simulation methods, with a focus on capturing nonlinear behaviour in spread dynamics. Credit spreads matter in banking because they reflect risk, influence values, and tend to widen during periods of stress. Managing them properly requires understanding both theory and how they behave in practice (Longstaff et al., 2005).

2.1.1 Risk Shocks and Credit Spreads

At its most basic level, a risk shock can be understood as an unexpected event or shift in the financial environment that causes a sudden change in investors’ perception of risk and, as a consequence, leads to the credit spreads observed in financial markets. When a risk shock occurs, it alters these underlying risk perceptions, triggering a repricing of assets and a widening of credit spreads across the market (Schwarz, 2019).

Feldhütter and Schaefer (2023) integrate risk shocks into structural credit risk models, which shows that the dynamics of corporate leverage, volatility, and debt maturity play crucial roles in determining how sensitive credit spreads are to shocks when the three factors interact.

High leverage typically reflects a thinner safety cushion, meaning that even small shocks can significantly increase default risk (Merton, 1974). When combined with high volatility, which reflects uncertainty around a firm's asset value, it leads to increased spread sensitivity. Shorter debt maturities highlight this effect further, as the need for frequent refinancing exposes firms more directly to market-wide liquidity stress. The responsiveness of credit spreads to shocks depends not only on overall market conditions but also on each firm's specific financial structure and risk profile (Longstaff et al., 2005).

Structural models used to calculate credit risk – such as the Merton model - allow for a decomposition of spreads into expected loss (driven by default probability) and unexpected loss (driven by volatility or systematic risk) (Merton, 1974). The Merton model is central to modern quantitative finance and underpins many bank risk management practices. Furthermore, Anderson and Cesa-Bianchi (2024) show that the transmission of risk shocks through the "credit channel" is heterogeneous: firms with weaker balance sheets or shorter debt maturities experience sharper spread increases, which can propagate distress across portfolios and sectors. In the context of the CSRBB, this is particularly relevant because exposure to spread volatility depends not only on the average spread level but also on portfolio composition and credit quality (EBA, 2022).

The relationship between risk shocks, credit spreads, and banking stability is well-documented in both academic and regulatory literature. Empirical evidence shows that widening credit spreads are associated with higher fragility in bank balance sheets, as they increase funding costs and reduce asset values, thereby weakening profitability and capital buffers (Du, 2023). Changes in credit spreads also reflect not only firm-level credit risk but broader market conditions, including liquidity effects (Schwarz, 2019), and are closely linked to debt valuation and risk dynamics in the wider economy (Feldhütter & Schaefer, 2023). At the macro level, credit spreads capture more than individual borrower risk and act as indicators of financial stress that can affect economic activity (Gilchrist & Zakrajšek, 2012; He & Krishnamurthy, 2019). Periods of sharp spread widening are therefore typically associated with tighter credit conditions and weaker growth, as observed during the global financial crisis and the Eurozone sovereign debt crisis. These dynamics explain why the European Banking Authority treats CSRBB alongside IRRBB within the supervisory framework and requires banks to measure and manage their sensitivity to credit spread movements (EBA, 2022).

2.1.2 Role of Credit Spread Risk in Bank Profitability, Solvency, and Funding Structure

Banks are the largest holders of fixed-income assets and are influenced by the changes in credit spread, as those translate into changes in the economic value of assets, the cost of funding, and also banks' profitability. When credit spreads widen, the market value of fixed-income securities in the banking book typically declines, which is important for instruments held at amortized cost, where economic value losses may not be immediately reflected in accounting but can affect internal capital assessment. At the same time, wider spreads increase the cost of new funding and reduce the margins on existing interest-earning assets, compressing net interest income (NII) (Schwarz, 2019). As Du (2023) noted, sustained increases in credit spreads are empirically associated with lower bank profitability and greater fragility, particularly for banks with high leverage or a significant exposure to longer-maturity credit instruments. These spread-driven losses can deplete earnings buffers and inhibit the bank's ability to absorb shocks, ultimately threatening solvency.

Credit spread movements also affect bank solvency through their impact on asset valuation and capital adequacy. Structural models show that credit spreads are closely related to leverage, debt maturity, and refinancing conditions, which influence the valuation of risky debt (Feldhütter & Schaefer, 2023). In the banking context, spread increases reduce the economic value of assets and may weaken capital ratios used in internal capital assessments. Reflecting these risks, the EBA treats CSRBB as a Pillar 2 risk and requires banks to identify, measure, and manage the economic impact of spread movements even in the absence of default (EBA, 2022).

Credit spreads also influence banks' funding conditions. Widening spreads signal higher risk premia in financial markets and therefore increase the yields banks must offer to investors and lenders. Banks that rely on wholesale funding are particularly affected by that, as spread volatility may lead to higher funding costs and tighter liquidity conditions. Evidence suggests that rising credit spreads are associated with tighter financial conditions and higher borrowing costs across the economy (Gilchrist & Zakrajšek, 2012). Because spread shocks can simultaneously affect asset valuations, funding costs, and capital buffers, credit spread risk has become an important consideration in bank balance-sheet management and regulatory supervision (EBF, 2023).

2.1.3 Evidence from Past Crises

Historical crises illustrate how credit spread risk can transmit financial stress from markets to banks. During episodes of stress, risk shocks can cause spreads to widen sharply, amplifying valuation losses and liquidity pressures across intermediaries and markets. Empirical evidence suggests that such spread-driven stress is associated with tighter credit conditions and weaker financial stability (Gilchrist & Zakrajšek, 2012).

The Global Financial Crisis provides a clear example. Before the crisis, credit spreads on both investment-grade and high-yield bonds were unusually narrow, reflecting strong investor confidence and risk appetite in securitized credit markets (Gilchrist & Zakrajšek, 2012). When losses in the U.S. subprime mortgage sector emerged, and markets repriced risk and liquidity, credit spreads widened sharply as market participants reassessed both default and liquidity risk. The structural modelling framework developed by Feldhütter and Schaefer (2023) highlights how interactions between leverage, asset volatility, and debt valuation can lead to nonlinear and asymmetric widening of credit spreads under stress.

The Eurozone Sovereign Debt Crisis provided further evidence that credit spread risk can originate not only from private-sector credit risk but also from sovereign risk repricing. Widening sovereign spreads resulted in valuation losses on these holdings and revealed the limitations of treating sovereign bonds as risk-free in risk models and regulatory frameworks. The resulting stress had concerning macro-financial effects: financial conditions tightened, credit availability declined, and economic activity slowed — dynamics that are in line with theoretical models of financial amplification under stress (He & Krishnamurthy, 2019).

Evidence from financial crises shows that credit spread shocks are not merely reflections of issuer default risk but can amplify instability in the financial system. He and Krishnamurthy (2019) developed a theoretical framework in which stress in financial markets can lead to amplified responses of asset prices and risk measures under strain, complementing the empirical evidence on how widening risk premia can coincide with weaker credit availability and economic slowdowns. This shows why credit spreads are now considered important macrofinancial indicators, and why regulatory guidance such as the EBA (2022) guidelines requires banks to measure and manage CSRBB alongside IRRBB.

2.2 Regulatory Framework: IRRBB, CSRBB

The European regulatory framework for market risks in the banking book has been significantly strengthened in recent years, particularly through the explicit integration of CSRBB alongside IRRBB. While IRRBB has long been a core component of banks' internal risk management, regulators have increasingly recognised that not all valuation risk in the banking book is driven by changes in risk-free interest rates. Market-driven movements in credit spreads, even in the absence of changes in default risk, can materially affect the economic value of assets and liabilities and, in turn, banks' capital adequacy. Recognition of the importance of credit spreads led to the formalisation of CSRBB within the European supervisory framework, where it is treated as a distinct Basel Pillar 2 risk alongside IRRBB under the Supervisory Review and Evaluation Process (SREP) (EBA, 2022; ECB, 2024).

IRRBB refers to the risk to a bank's capital and earnings arising from adverse movements in interest rates that affect the present value and cash flows of assets and liabilities held outside the trading book. It has been a foundation of asset–liability management, especially for institutions with large portfolios of fixed-rate loans, deposits, and securities. However, CSRBB focuses on valuation changes driven by market-implied credit spread movements that are not attributable to changes in the credit quality of the issuer. In practical terms, this means that a bond may lose value because investors demand a higher spread, even if the issuer's fundamentals remain unchanged. The distinction between the two is important because IRRBB is often managed using interest rate derivatives and repricing strategies, while CSRBB typically requires more structural approaches, such as portfolio diversification, concentration limits, and scenario-based valuation techniques (EBF, 2023).

The shift from a framework focused primarily on IRRBB toward one that also incorporates CSRBB was driven by evidence from financial crises and periods of market stress. In particular, the global financial crisis and the Eurozone sovereign debt crisis highlighted that credit spread volatility can significantly erode the EVE and introduce procyclicality into banks' capital positions, even for instruments held at amortised cost. As banks increasingly held sovereign and corporate bonds for liquidity management and yield enhancement, supervisors observed that spread risk represented a material source of valuation risk that was not fully captured by traditional IRRBB frameworks. In response, the EBA updated its guidelines in 2022, and supervisory practice has since been further refined through the ECB's SREP methodology, placing CSRBB alongside IRRBB as a component of Basel Pillar 2 market risk supervision (EBA, 2022; ECB, 2024).

Under the current framework, banks are expected to assess the sensitivity of EVE and NII to interest rate and credit spread shocks. For IRRBB, the methodological approach includes standardised outlier tests, behavioural modelling of non-maturity deposits, and the evaluation of convexity, basis risk, and optionality, in line with Basel and EBA guidance. However, for CSRBB, the methodological landscape is less standardised, reflecting the inherent difficulty of isolating spread-related valuation effects from other risk drivers. The EBA defines CSRBB as the risk arising from changes in market-implied credit spreads, excluding those due to changes in credit quality, affecting instruments in the banking book, particularly bonds held at amortised cost. Consequently, institutions are required to develop internal frameworks capable of measuring spread sensitivity at both the instrument and portfolio level, using approaches such as historical simulation, scenario analysis, or stochastic modelling (EBA, 2022).

Supervisory evaluation of IRRBB and CSRBB is conducted through the SREP process, where the ECB assesses not only quantitative metrics but also the quality of governance, risk identification, measurement methodologies, monitoring processes, and internal controls. The 2024 ECB SREP Methodology Booklet emphasises consistency between internal models, ICAAP, and strategic planning, ensuring that market valuation effects are properly integrated into business and capital decisions (ECB, 2024). In the case of CSRBB in particular, supervisors place strong weight on qualitative assessments, examining whether banks have clear definitions, documented methodologies, appropriate ownership structures, and robust reporting lines for managing spread-sensitive exposures. Model assumptions, validation practices, and board-level oversight are also key elements of the supervisory review (EBF, 2023).

Despite the increased regulatory clarity on expectations, banks face significant interpretation and implementation issues, especially with respect to data availability, modelling choices, and the attribution of spread movements. A problem lies in the absence of a market-wide consensus on what constitutes "pure" credit spread risk, given that observed spreads reflect both credit risk and liquidity components, which makes it challenging to separate CSRBB from other valuation risks, such as liquidity risk or issuer-specific credit migration, a problem widely noted by industry participants. As a result, modelling practices vary across institutions, and supervisors often encourage a proportional approach that reflects portfolio materiality and modelling sophistication (EBF, 2023).

An additional concern is the alignment between accounting and economic perspectives. While many banking book instruments are measured at amortised cost under IFRS 9, CSRBB focuses on the sensitivity of economic value to market spread movements, which may not be immediately reflected in accounting profit and loss. Regulators, therefore, expect banks to reconcile these perspectives within their risk management and capital planning frameworks, meaning CSRBB has to be integrated into ICAAP, ILAAP, and ALCO processes, as well as into risk appetite frameworks and internal reporting. Recent supervisory guidance encourages closer cooperation between treasury, risk management, and finance functions to ensure that CSRBB frameworks are coherent, transparent, and operationally reflected (ECB, 2024).

2.3 Overview of Methodologies for CSRBB Measurement

2.3.1 Overview of Modelling Goals for CSRBB

The main objectives of CSRBB modelling include capturing: the volatility of credit spreads over time; EVE of spread shocks on portfolios; NII sensitivity, particularly for instruments where income may be fixed while market discount rates change; identifying concentration or diversification effects across bond holdings (EBA, 2022). According to EBF (2023), banks are expected to model CSRBB under both historical stress and forward-looking scenarios, using tools such as scenario analysis, historical simulation, and stochastic simulation depending on complexity and data availability.

For many institutions, particularly smaller or mid-sized banks, CSRBB modelling often begins with simple approaches, such as spreadsheet-based frameworks. Fixed credit spread shocks are then applied to the framework to calculate the sensitivities of a portfolio. Such sensitivity analyses are widely used in practice to assess the impact of spread movements on portfolio values, to derive spread-sensitivity measures, and to provide an initial view of the directional risk associated with spread widening or narrowing. These exercises are typically conducted on portfolios with varying maturity structures, rating classes, and concentration profiles in order to evaluate how portfolio composition affects exposure to spread risk (EBA, 2022).

As modelling sophistication increases, especially for institutions with larger or more complex portfolios, statistical approaches implemented in environments such as R or similar platforms become more relevant. A common advanced approach models credit spread changes as stochastic processes and applies simulations to generate large numbers of potential future spread paths, with the resulting distribution of portfolio value changes analysed using risk measures such as Value-at-Risk (VaR) or Expected Shortfall (ES) (Hull, 2018; EBF, 2023). Simulation-based frameworks are also in line with supervisory expectations that banks should assess CSRBB under both normal and stressed market conditions using scenario-based and model-driven approaches, rather than relying solely on static shocks (EBA, 2022).

A useful academic contribution in this area is the thesis by Pahne and Akerlund (2023), which applies a historical simulation approach to credit spread risk measurement. The model estimates spread shocks from historical market data and applies them to a bond portfolio in order to quantify the impact on the EVE and income-based measures. The approach by Pahne and Akerlund (2023) is in line with supervisory expectations that banks should base CSRBB assessments on both historical and stress-period spread movements, rather than relying solely on purely hypothetical shocks.

For advanced modelling, Monte Carlo simulation frameworks are often used to capture complex behaviours in credit spread dynamics, such as volatility clustering, nonlinear responses, and correlations across issuers — features that become particularly important in stress-testing environments (Hull, 2018). Such stochastic simulation approaches allow risk managers to generate large distributions of future spread paths and analyse joint tail behaviour, where simultaneous widening across sectors can substantially affect economic value and risk measures (ECB, 2024). One academic example of modelling spread dependencies is the copula-based Markov reward model proposed by D'Amico et al. (2019), which integrates transition dynamics and cross-sector dependencies into a unified framework for credit spread modelling. Although this and similar models are primarily theoretical, they illustrate how joint tail risks can be represented when multiple spread factors interact under stress.

Ultimately, the regulatory objective, as pointed out in the EBA Guidelines (2022) and the ECB's SREP expectations (ECB, 2024), is for banks to measure and manage both valuation and earnings sensitivity to credit spread movements, irrespective of accounting treatment, which includes instruments held at amortised cost, for which spread sensitivity may not be immediately visible in accounting profit and loss but can still materially affect economic value and strategic decision-making (EBA, 2018). A robust CSRBB framework, therefore, needs to integrate portfolio segmentation, curve construction, shock calibration, and appropriate reporting and governance processes in order to produce decision-useful information for internal management bodies and supervisors. The objective is not only regulatory compliance, but also to strengthen resilience to market shocks, improve risk-based pricing, and support informed strategic asset allocation under uncertainty (Basel Committee on Banking Supervision, 2016).

2.3.2 Methodologies from Simple Sensitivities to Advanced Simulations

The most basic methodology for calculating CSRBB is the sensitivity-based approach, which involves applying fixed credit spread shocks across various bonds in a banking book to estimate changes in present value. The shocks can be fixed across all bonds or can differ according to the type of bond or credit rating status (EBF, 2023). These calculations are typically run in spreadsheet-based frameworks and focus on the duration and credit spread of different instruments. While simplistic, this method is useful for illustrating fundamental dynamics and is encouraged by national regulators like the Bundesbank (2023) for low-materiality exposures.

A step up in complexity involves the use of historical simulation, as detailed in the academic benchmark paper by Pahne and Akerlund (2023). The method, a historical time series of market credit spreads, is used to derive realistic stress scenarios, which are then applied to current bond portfolios to estimate valuation losses and profit and loss impacts. The main advantage of the approach is that it captures actual market behaviours, including fat tails and asymmetric spread movements during crises. It also allows for non-parallel shocks across rating classes and sectors, reflecting real market dispersion. Methodology aligns closely with regulatory expectations under EBA Guidelines (2022), which recommend using actual market data to calibrate CSRBB scenarios. The Bank of England (2023) has also contributed to this modelling stream by developing a framework to decompose observed credit spreads into credit, liquidity, and risk premium components, allowing banks to isolate the "non-credit" portion of spread changes and avoid overlap with traditional credit risk capital charges.

For more granular and dynamic modelling, Monte Carlo simulation is increasingly used, particularly in institutions with large or complex bond portfolios. Stochastic models are built to simulate future spread paths using distributional assumptions derived from historical data or fitted models, such as GARCH or mean-reverting processes (Hull, 2018). Monte Carlo simulations allow for the generation of thousands of scenarios, capturing the probabilistic behaviour of spread changes and providing statistical risk measures like ES or VaR for CSRBB (Pahne & Akerlund, 2023), which is particularly useful in calculating tail-risk exposures and in assessing portfolio behaviour under extreme yet plausible market conditions. These simulations can be implemented using R programming or other tools, where spread volatility, sector correlations, and transition probabilities are encoded to reflect credit and liquidity stress simultaneously.

2.3.3 Key Portfolio Assumptions in CSRBB Modelling

Accurate modelling of CSRBB depends not only on the selection of appropriate methodologies, but also on the underlying assumptions about the structure and characteristics of the bond portfolio itself. Assumptions around bond characteristics, spread curve construction, and diversification behaviour significantly influence the sensitivity, volatility, and P&L outcomes produced by CSRBB models. To measure the risk meaningfully, banks must first define how individual instruments and the overall portfolio respond to spread movements, beginning with identifying key bond characteristics such as maturity, credit rating, and sector classification (ECB, 2024).

Maturity is particularly critical, as longer-dated instruments typically exhibit higher price sensitivity to spread shocks due to longer discounted cash flow horizons. In both simple spreadsheet-based frameworks and more sophisticated R implementations, maturity buckets are used to stratify synthetic portfolios and assess how spread shocks propagate through different tenors. Credit ratings serve as the primary driver of baseline spread levels and volatility assumptions: lower-rated bonds are generally more sensitive to credit spread shocks than investment-grade counterparts, particularly under stressed market conditions (Pahne & Akerlund, 2023). Sector segmentation is also essential; sovereign, financial, and corporate bonds have structurally different spread behaviours (Schwarz, 2019).

In addition to bond-level characteristics, modelling CSRBB requires careful construction of the spread curve, the set of credit spreads across different maturities and rating segments. Depending on data availability, institutions may use Z-spreads, I-spreads, or option-adjusted spreads (OAS), sourced from platforms like Bloomberg or constructed from market-traded benchmarks. Spread curves contain more than just default expectations; they preserve liquidity premiums and macro-financial risk sentiment, all of which must be disaggregated when applying spread shocks. Interpolation methods (e.g., linear, cubic spline, or Nelson-Siegel functions) are used to fill gaps between observable maturities, and the modelling approach must be consistent with the use of stress testing, historical simulation, or Monte Carlo path generation. In the advanced methodological framework, spread curves are modelled as stochastic processes with parameters calibrated to observed volatility and spread slope patterns over time (Hull, 2018).

Equally important are assumptions around diversification, correlation, and concentration effects, especially when measuring portfolio-wide CSRBB. Basic spreadsheet models often assume independent spread shocks per instrument or segment, which can underestimate tail risk. More robust frameworks introduce sector and rating correlations to reflect the empirical co-movement of spreads — particularly during crises (Schwarz, 2019). As demonstrated in D'Amico et al. (2019), a copula-based Markov reward model, capturing joint spread transitions across sectors, can reveal clustering of losses and compound effects that single-name shocks overlook. Similarly, a correlation matrix linking spread movements across rating and sector groups allows diversified portfolios to demonstrate resilience and concentrated portfolios to show amplified losses under spread stress. These effects are crucial to stress testing and capital planning.

Regulatory guidance (EBA, 2022; ECB, 2024) requires institutions to document and justify assumptions around bond maturity profiles, sectoral composition, rating distribution, and diversification levels. These assumptions impact not just valuation results but the credibility of ICAAP submissions and supervisory assessments. Therefore, a comprehensive CSRBB framework must combine methodological rigor with a detailed understanding of portfolio dynamics, spread curve construction, and systemic behaviour under market stress.

3 METHODOLOGICAL FRAMEWORK FOR CSRBB MEASUREMENT

This chapter presents the methodological framework applied for the measurement of CSRBB, with a focus on practical techniques used to quantify the impact of credit spread movements on the economic value of a bank's banking book. The framework is structured around two categories of methods: simplified, spreadsheet-based approaches and more advanced stochastic modelling techniques.

Across all methodologies, the central risk metric considered in the methodological chapter is the change in EVE attributable to credit spread movements, denoted as ΔEVE_CSRBB. The measure captures the change in the present value of future cash flows of banking book positions resulting solely from shifts in credit spreads, holding all other risk factors constant. Formally, ΔEVE_CSRBB represents the difference between the economic value of the banking book under a shocked credit spread scenario and its value under the base scenario.

In line with the EBA regulatory framework, institutions are required to assess both EVE and NII sensitivities when measuring interest rate and credit spread risks in the banking book. However, for purposes of this thesis, empirical analysis focuses exclusively on the EVE perspective. The NII dimension is intentionally excluded from the quantitative analysis in order to isolate valuation effects and to maintain methodological comparability between simplified and advanced approaches. Consequently, the results presented in the next chapter should be interpreted as reflecting long-term economic value sensitivity rather than short-term earnings volatility.

To ensure comparability across methods and to isolate methodological effects from institution-specific balance sheet characteristics, the analysis is conducted using five synthetic banking book portfolios. These portfolios are constructed to represent realistic compositions of credit-sensitive banking book exposures, differing in terms of maturity structure, credit quality, and sectoral or rating concentration. The use of synthetic portfolios provides a controlled setting in which differences in ΔEVE_CSRBB (between simplified and advanced methodology) can be directly attributed to methodological choices rather than to portfolio characteristics. Focusing on ΔEVE_CSRBB allows for a consistent and economically meaningful assessment of CSRBB, as it reflects the structural and long-term sensitivity of the banking book to changes in credit risk premia. Unlike short-term earnings measures, the valuation-based metric captures the full maturity profile of assets and liabilities and directly links credit spread movements to changes in the bank's underlying economic value. As such, ΔEVE_CSRBB is widely used in supervisory frameworks and internal risk management as a primary indicator of CSRBB exposure.

The methodological approaches differ in terms of modelling sophistication, data requirements, and ability to capture nonlinearities and uncertainty. Simplified approaches rely on deterministic spread shocks and sensitivity-based calculations to approximate ΔEVE_CSRBB in a transparent and computationally efficient manner. Advanced approaches extend this framework by modelling credit spreads as stochastic processes and using Monte Carlo simulation to generate distributions of ΔEVE_CSRBB, allowing for a more comprehensive assessment of tail risk and model dynamics. Despite these differences, all approaches are evaluated on their ability to provide a consistent and interpretable estimate of ΔEVE_CSRBB as a measure of CSRBB exposure.

3.1 Portfolio Construction

The portfolios used in the empirical case study are intentionally constructed to differ in their degree of diversification, sectoral composition, geographical exposure, credit quality, and maturity structure. Construction differences enable a controlled examination of how portfolio characteristics influence measured CSRBB under different methodological frameworks. The use of synthetic portfolios allows for full transparency and experimental control, and at the same time avoids confidentiality constraints associated with banks' data.

Each synthetic portfolio has a total market value of 100 million EUR and consists of fixed-income instruments across the government, financial, and corporate sectors. For all instruments, bond identifiers, issuer names, country of risk, credit ratings, market values, and maturities are constructed synthetically to reflect realistic banking book portfolios. Portfolio weights are calculated as the ratio of each bond's market value to the total portfolio market value.

Modified duration and convexity are approximated using stylized proxy formulas based on instrument maturity in order to reflect realistic price sensitivity characteristics, because of the absence of detailed coupon and yield curve information. Specifically, modified duration is approximated as a fixed 90% proportion of maturity, while convexity is approximated as the square of maturity, ensuring economically consistent scaling of price sensitivity with time to maturity.

$$MD_i = 0.9Ti \tag{1}$$

MDi denotes the modified duration of instrument i, approximated as a fixed proportion of its maturity Ti.

$$C_i = Ti^2 \tag{2}$$

Ci represents the convexity of instrument i, approximated as the square of its maturity Ti.

These approximated sensitivity measures are used directly in the valuation and shock calculations underlying ΔEVE_CSRBB in both the simplified and advanced methodological frameworks.

It must be acknowledged that these approximations are simplified. In practice, modified duration depends on maturity, coupon rate, and yield level, and may deviate materially from 90% of maturity depending on the bond's cash flow structure. For example, low-coupon or zero-coupon bonds may exhibit durations close to maturity, while high-coupon bonds typically have significantly shorter durations. The 90% scaling, therefore, represents a stylised average consistent with medium-coupon fixed-income instruments. Similarly, convexity is a function of maturity, coupon, and yield, and does not follow an exact quadratic relationship with maturity. Approximating convexity as maturity squared imposes a monotonic and accelerating sensitivity pattern but may overstate or understate second-order effects relative to market-calibrated values.

Because the objective of the analysis is comparative, as it evaluates methodological differences across portfolios under identical sensitivity assumptions, these stylised proxies affect all portfolios consistently. In a worst-case scenario, the duration approximation may misstate true modified duration by approximately 10–20%, depending on coupon and yield characteristics. Consequently, the calculation would translate into a proportional over- or underestimation of first-order valuation effects and, hence, of ΔEVE_CSRBB. Similarly, the quadratic convexity approximation may overstate or understate second-order sensitivity, particularly for long-maturity instruments, potentially affecting extreme tail outcomes (ES) more than central VaR estimates. However, because these approximations are applied uniformly across portfolios and methodological approaches, any bias is systematic rather than differential. The resulting ΔEVE_CSRBB values should still be interpreted as structurally consistent relative risk measures rather than precise market-consistent price sensitivities.

The five portfolios are constructed to exhibit systematically different structural properties. Key structural characteristics are presented in Table 1. The first portfolio is dominated by corporate and financial exposures, with a relatively high concentration in a small number of corporate issuers and a material share of lower investment-grade ratings. Portfolio 1 is intentionally designed to be less diversified and to exhibit elevated credit spread sensitivity. The second portfolio is broadly diversified across government, corporate, and financial sectors and includes a wide range of countries and issuers, resulting in a comparatively balanced exposure profile and higher diversification. The third portfolio is predominantly composed of high-quality government bonds, supplemented by selected financial and corporate exposures, and is therefore characterized by strong credit quality and relatively lower credit spread risk. The fourth portfolio emphasizes financial sector exposures, including both senior and subordinated instruments, and is constructed to reflect higher sensitivity to sector-specific and issuer-specific credit risk factors. The fifth portfolio is designed to highlight maturity and rating concentration effects, with a mixture of short and long-dated government and corporate bonds and a greater representation of lower-rated corporate exposures, thereby introducing structural features that are expected to amplify sensitivity to adverse credit spread movements. These systematic differences in diversification, sectoral allocation, and credit quality form the basis for evaluating how simplified and advanced methodologies respond to changes in portfolio structure.

Table 1: Key Structural Characteristics of Synthetic Portfolios

Portfolio	Avg Rating	Avg Maturity	Avg MD	Government Share	Corporate Share	Financial Share
1	BBB	7.19	6.47	0%	80%	20%
2	A	7.39	6.65	47%	41%	12%
3	AA	8.82	7.94	82%	9%	9%
4	A	6.67	6.00	17%	23%	60%
5	BBB	7.96	7.17	60%	40%	0%

Source: Own work.

The parameter choices and portfolio compositions are calibrated to be broadly representative of a banking book bond portfolios, while remaining stylized to support controlled methodological analysis. All five synthetic portfolios are held fixed across both methodological approaches, ensuring that differences in measured ΔEVE_CSRBB reflect methodological effects rather than changes in underlying portfolio composition. Portfolios are presented in the Appendix 1 Tables 4-8.

3.2 Simplified Approaches

Simplified approaches to the measurement of CSRBB are designed to provide a transparent and operationally feasible assessment of a bank's exposure to adverse credit spread movements. These approaches rely on deterministic stress calibration based on historical market data and sensitivity-based valuation techniques. The methodology is implemented in a spreadsheet-based environment using publicly available Bloomberg data and is applied under a static balance sheet assumption, whereby portfolio composition and volumes are held constant over the risk horizon.

The simplified framework focuses on estimating the change in economic value attributable to a severe but plausible widening of credit spreads, expressed as ΔEVE_CSRBB. The approach abstracts from dynamic balance sheet behaviour and stochastic risk factor interactions and instead provides a clear mapping from historical spread movements to valuation impacts at the portfolio level.

3.2.1 Heading Historical Credit Spread Construction

Credit spread shocks are calibrated using historical market data sourced from Bloomberg. For each relevant credit segment, representative market indices are selected based on issuer type and credit rating category. Government bond exposures are treated at the individual country level, such that each country represented in the synthetic portfolios is associated with a specific 5-year sovereign bond index: GTDEM5Y Govt (Germany), GTNLG5Y Govt (Netherlands), GTFIM5Y Govt (Finland), GTATS5Y Govt (Austria), GTFRF5Y Govt (France), GTBEF5Y Govt (Belgium), GTIEP5Y Govt (Ireland), GTSKK5YR Govt (Slovakia), GTSIT5Y Govt (Slovenia), GTESP5Y Govt (Spain), GTITL5Y Govt (Italy), and GTPTE5Y Govt (Portugal).

Corporate and financial bond exposures are associated with the following Bloomberg indices: H27962EU, I27963EU, I27964EU, I27965EU, I27404EU, BVSC0013, BVSC0014, BVSC0015, and BVSC0016, which represent euro-denominated credit segments differentiated by issuer type and rating bucket.

Historical credit spreads are defined as the difference between observed market yields on the selected credit indices and a corresponding risk-free benchmark yield. In this thesis, the risk-free rate is proxied by the YCSW0045 index, representing the EUR Interest Rate Swap curve (5-year maturity). For each observation date, the credit spread is calculated as the yield differential between the relevant credit index and the swap rate, thereby isolating the credit risk premium component reflected in market yields.

It must be acknowledged that EUR swap rates are not a pure risk-free benchmark in a strict theoretical sense, as they embed counterparty and interbank credit risk components. Alternative proxies, such as OIS rates or German Bund yields, could serve as closer approximations to a risk-free term structure. However, the EUR swap curve is widely used in market practice for spread decomposition and valuation, and its use ensures consistency across corporate, financial, and sovereign segments within the dataset. Given that the analysis focuses on relative spread volatility rather than absolute pricing levels, the choice of swap benchmark does not materially affect the comparative conclusions of the study.

The historical observation period begins on 30 June 2011 and extends through 31 December 2025, ensuring coverage of multiple market cycles and periods of financial stress. This fixed historical window is chosen to reflect information from past crisis episodes and to avoid potential underestimation of extreme but plausible spread movements that could arise from shorter rolling windows.

3.2.2 Risk Horizon and Spread Change Distribution

To align the measurement of CSRBB with realistic portfolio rebalancing and risk management considerations, a six-month risk horizon is adopted. Credit spread changes are therefore computed as six-month differences in the constructed daily credit spread time series. For each index, the spread change is calculated as the difference between the spread level at the end and the beginning of each six-month period.

The transformation converts level-based spread series into empirical distributions of realised six-month spread changes, capturing both benign and adverse market movements over the selected horizon. The focus on spread changes directly targets the risk-relevant variable for valuation purposes, namely the potential widening of credit spreads over the assumed holding period.

3.2.3 Shock Calibration using Historical VaR

Based on the empirical distribution of six-month credit spread changes, a VaR measure at the 99th percentile is used to calibrate adverse credit spread shocks. The 99% confidence level is selected to represent a severe but plausible stress scenario in line with economic value-based risk measurement practices.

For each representative credit index, the 99th percentile of the historical distribution of six-month spread changes is computed. The upper tail of the distribution is used, reflecting the fact that CSRBB materialises primarily through widening rather than tightening of credit spreads. These 99th percentile spread increases are interpreted as deterministic adverse credit spread shocks and serve as stress inputs for portfolio valuation.

The historical simulation-based calibration avoids strong parametric assumptions regarding the distribution of spread changes while remaining transparent and computationally simple.

3.2.4 Instrument-level Shock Assignment

Each bond in the synthetic portfolios is assigned a credit spread shock based on its issuer type and credit rating category. Government bonds are mapped to country-specific sovereign shocks, while corporate and financial instruments are mapped to the corresponding sector- and rating-based shocks. This bucket-based mapping approach ensures consistency between instrument characteristics and historical stress calibration, while allowing the simplified framework to differentiate stress intensity across credit quality and issuer types in a transparent and operationally feasible manner.

3.2.5 Valuation Methodology

The valuation impact of the adverse credit spread shocks is computed using a sensitivity-based approximation incorporating both modified duration and convexity effects. In the absence of full coupon and yield curve information, modified duration and convexity are approximated using stylised proxy formulas based on instrument maturity. These proxies reflect the economically meaningful relationship between maturity and spread sensitivity and are sufficient for comparative and methodological analysis. Spread shocks expressed in basis points in Appendix 1 (Tables 4-8) are converted into decimal form prior to valuation.

For each instrument, the change in fair value resulting from the assigned credit spread shock is calculated using a second-order Taylor approximation of bond price sensitivity:

$$\Delta Fair\ Value = Market\ Value \times (-Modified\ Duration \times \Delta Spread + Convexity \times (\Delta Spread)^2 / 2) \quad (3)$$

The formulation captures both the linear duration effect and the non-linear convexity adjustment and provides a sufficiently accurate approximation for moderate-to-large spread shocks.

All calculations are implemented in an Excel-based environment and applied under a static balance sheet assumption.

3.2.6 Aggregation and ΔEVE_CSRBB

Instrument-level valuation changes are aggregated across all bonds within each synthetic portfolio to obtain the total change in economic value attributable to credit spread risk. The resulting measure is reported as ΔEVE_CSRBB at the 99% confidence level and represents the estimated loss in economic value under a severe credit spread widening scenario over the six-month horizon.

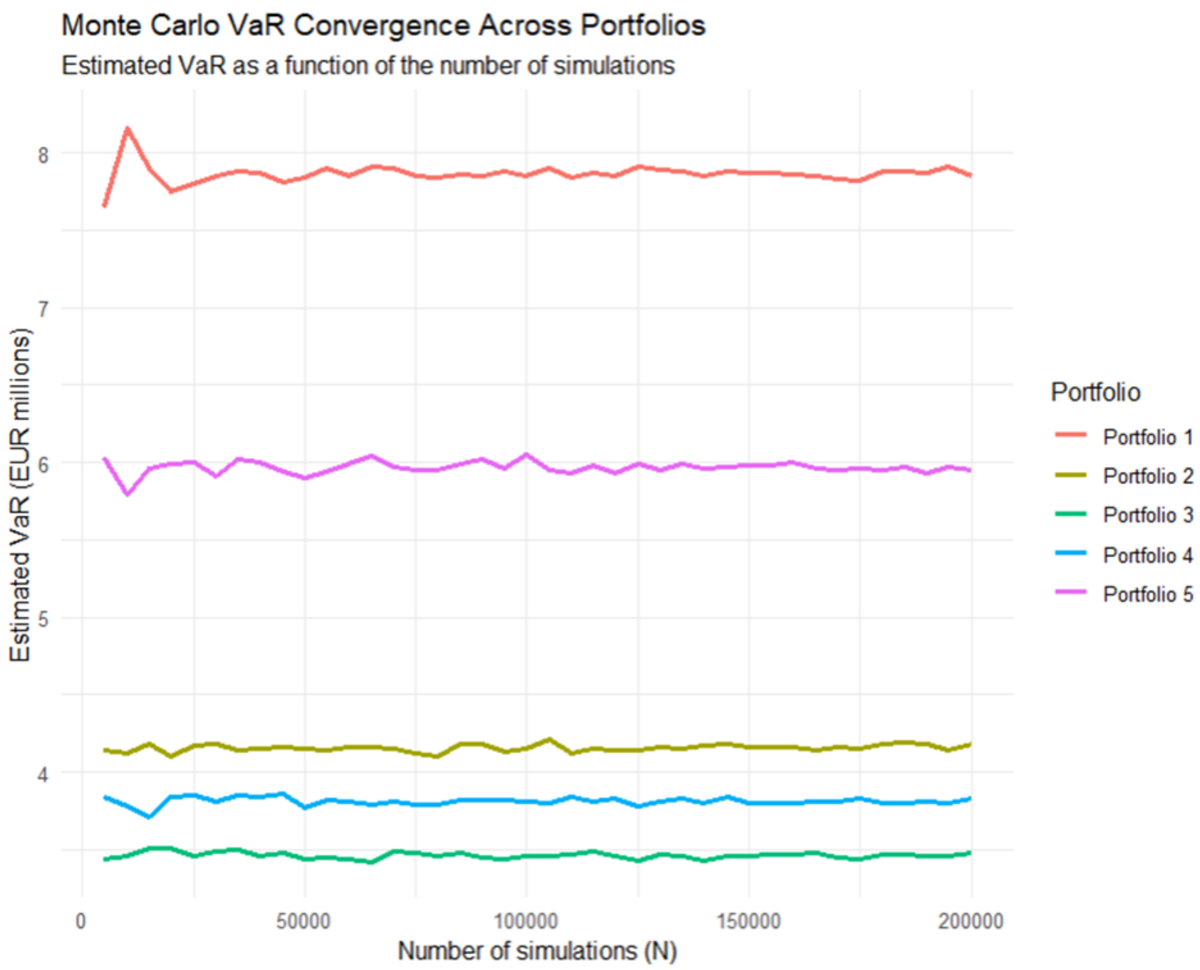
Within the simplified framework, ΔEVE_CSRBB provides a concise and interpretable metric of structural CSRBB exposure and serves as the deterministic benchmark for subsequent comparison with advanced stochastic modelling approaches presented in the following section.

3.3 Advanced Approaches

Advanced approaches to CSRBB measurement extend the simplified deterministic framework by modelling credit spread changes as stochastic risk factors and by explicitly capturing correlation, concentration, and non-linear portfolio effects through Monte Carlo simulation. Instead of producing a single stressed valuation outcome, the advanced methodology generates a full empirical distribution of portfolio-level valuation changes and derives tail risk measures of ΔEVE_CSRBB that reflect both systematic and idiosyncratic drivers of credit spread risk. The framework is implemented in RStudio using a "purpose-built" Monte Carlo simulation, which is presented in Appendix 3. The same simulation is applied to the five synthetic portfolios, which ensures that differences in measured ΔEVE_CSRBB arise from methodological choices rather than changes in portfolio composition. All simulations are conducted under a static balance sheet assumption, in line with the simplified framework, which ensures a comparison between methodologies later on.

The simulation function takes as inputs instrument-level market values, modified durations, convexities, and credit spread volatilities, together with categorical information on sector, country, rating, and issuer. The number of simulation paths is set to N=200,000, which represents a compromise between numerical stability of tail estimates and computational feasibility. As presented in Figure 1, the estimated VaR values stabilize as the number of simulations increases, with only minor fluctuations beyond 100,000 scenarios. The convergence supports the use of N = 200,000 simulation paths in the final model specification. A high number of simulations is required to obtain reliable estimates of the 99th percentile VaR and the associated ES.

Figure 1: MC VaR Convergence Across Portfolios



Source: Own work (n. d.).

3.3.1 Stochastic Modelling Framework

In the advanced framework, the six-month credit spread change of each instrument *i* is modelled as a random variable of the form:

$$\Delta si = \sigma i \cdot Zi \tag{4}$$

where σ_i denotes the instrument-specific credit spread volatility, and *Zi* is a standard normal random variable. The vector $Z = (Z_1, \ldots, Z_n)$ is assumed to follow a multivariate normal distribution with zero mean and a portfolio-specific correlation matrix.

Instrument-level spread volatilities σ_i are specified exogenously based on historical data from Bloomberg. For each relevant index, six-month spread changes are computed, and their standard deviation is used as the volatility input. Sovereign bonds use country-specific indices, while corporate and financial bonds are differentiated by issuer type and rating category. These volatilities are held fixed across simulation paths and serve to scale the simulated standardized shocks into economically meaningful spread movements.

Before simulation, the model performs a series of consistency checks and harmonisation steps. The portfolio is required to contain market value, modified duration, convexity, spread volatility, sector, country, rating, and issuer identifiers. Ratings are mapped into a reduced set of buckets (AAA, AA, A, BBB, BB) to ensure consistency between portfolio data and the factor structure of the model. In particular, rating notches (e.g., BBB+ and BBB-) are collapsed into their respective broad rating categories (e.g., BBB).

Credit rating simplification is necessary to maintain coherence with the construction of the Bloomberg corporate and financial indices, which are defined at the rating-bucket level rather than at individual notch granularity. It also ensures comparability across the five synthetic portfolios, including government bond portfolios, which are structured primarily by country rather than by rating notch. Both the factor structure and volatility inputs operate consistently at the same aggregation level. While collapsing rating notches implies that instruments with slightly different credit quality (e.g., BBB+ versus BBB−) are treated identically within the model, this is consistent with the data granularity available and with the objective of modelling systematic spread risk. Market values are used to compute portfolio weights, which in turn form the basis for concentration measures. Concentration is quantified using Herfindahl–Hirschman Indices (HHI) at the portfolio, sector, country, and issuer levels.

$$HHI_k = \sum_{g=1}^{G_k} s_{g,k}^2 \tag{5}$$

$s_{g,k}$ represents the share of exposure belonging to group g within dimension k (sector, country, issuer).

These measures play an important role later in the model by influencing factor loadings and correlation scaling, thereby linking portfolio structure directly to dependence assumptions.

3.3.2 Multi-factor Correlation Structure

The joint behaviour of credit spread changes is modelled using a multi-factor structure designed to reflect economically plausible sources of co-movement in credit markets. Five systematic factors are specified:

- a global market factor, capturing broad credit market conditions;
- a sector factor, reflecting common dynamics within government, corporate, and financial bonds;
- a country factor, capturing sovereign and macroeconomic influences;
- a credit rating factor, reflecting systematic differences across credit quality buckets;
- an issuer factor, capturing name-specific concentration effects for repeated issuers.

Each instrument is assigned factor loadings based on its sector, country, rating, and issuer identity. Baseline loadings are chosen to increase with credit risk and with exposure to market-sensitive sectors. For example, government bonds receive lower sector loadings than corporate or financial bonds, while lower-rated instruments receive higher rating factor loadings. The numerical values (e.g., 0.20 for government sector exposure, up to 0.40 for financials; 0.05 for AAA ratings up to 0.40 for BB ratings) are not intended to represent calibrated market estimates but rather to impose an economically intuitive ordering of systematic risk sensitivity across instruments.

Given the absence of direct empirical calibration, the robustness of results is assessed through a structured sensitivity analysis. Key structural parameters, including factor standard deviations, sector and rating loadings, and structural correlation bumps, are varied by ±50%, and the concentration amplification mechanism is independently toggled, which allows an explicit evaluation of how portfolio VaR, ES, and diversification metrics respond to alternative parameterizations. The results in Appendix 5 demonstrate that while absolute risk levels vary with systematic intensity, portfolio risk rankings and qualitative conclusions remain stable across specifications, confirming the structural robustness of the framework.

A common market loading of 0.30 is applied to all instruments to ensure a shared baseline dependence across the portfolio. Issuer loadings are applied only where multiple bonds from the same issuer are present, with a fixed value of 0.25 to introduce name concentration effects in a transparent and controlled manner. All loadings are bounded between zero and one to avoid implausible or unstable dependence structures.

3.3.3 Concentration-sensitive Scaling

To reflect the empirical observation that more concentrated portfolios tend to exhibit stronger effective dependence and reduced diversification benefits, the model incorporates concentration-sensitive scaling of factor loadings and correlations. Portfolio, sector, country, and issuer HHIs are used to scale the baseline loadings upward when concentration is high.

Specifically, sector and country loadings are increased as sectoral or geographical concentration rises, rating loadings are increased with overall portfolio concentration, and issuer loadings are amplified when issuer concentration is present. The scaling functions are capped using piecewise linear transformations to prevent excessive amplification. The numerical coefficients (e.g., scaling intensities of 1.0 for sectors, 0.8 for countries, and 1.5 for issuers) are not empirically calibrated but are selected to generate economically meaningful amplification of dependence while preserving numerical stability and positive definiteness of the correlation structure. Given the absence of direct empirical calibration, the robustness of results is assessed through a structured sensitivity analysis. Scaling parameters are varied by ±50%, and the concentration mechanism is independently deactivated to isolate its impact. The analysis results in Appendix 5 show that while absolute VaR levels respond to changes in systematic intensity, qualitative conclusions and portfolio risk rankings remain stable, confirming that the concentration mechanism introduces economically intuitive behaviour without rendering results parameter-fragile.

In addition, the correlation matrix of the systematic factors themselves is specified beforehand, with moderate positive correlations between market, sector, country, and rating factors. When concentration sensitivity is applied, correlations are increased for more concentrated portfolios, but they are capped at 0.99 to ensure the correlation matrix remains stable and well-defined.

3.3.4 Construction of the Covariance and Correlation Matrix

Given the matrix of factor loadings L, the factor covariance matrix is constructed using factor standard deviations (1.00 for market, 0.80 for sector, 0.70 for country, 0.60 for rating, and 0.50 for issuer). These values impose a declining hierarchy of systematic risk importance, in line with the notion that market-wide effects dominate, followed by sectoral and geographical influences, while issuer-specific effects are more localized.

The specific numerical values are not derived from direct empirical calibration but are selected to enforce a clear and economically intuitive ranking of factor influence within the model structure. The monotonic decline ensures that no lower-level factor mechanically dominates broader systematic drivers, thereby preserving coherence of the multi-factor hierarchy. To evaluate robustness with respect to this structural specification, factor standard deviations are varied by ±50% within the sensitivity analysis framework. The results indicate that while absolute VaR and ES levels adjust proportionally to changes in systematic intensity, portfolio risk rankings and qualitative conclusions remain stable. Confirming the model's conclusions are not dependent on the exact choice of standard deviation parameters but rather on the overall factor architecture.

The preliminary covariance matrix is obtained as

$$\Sigma_{sys} = LF_{cov}L^T \tag{6}$$

where F_{cov} denotes the covariance matrix of the systematic factors.

3.3.5 Idiosyncratic Risk and Residual Variance

To ensure that each instrument retains a meaningful idiosyncratic risk component, an additional diagonal variance matrix is added. The idiosyncratic variance is calibrated as the residual needed to bring total variance close to unity, subject to a minimum floor. The base floor is set to 0.30, ensuring that no instrument becomes almost perfectly correlated with the systematic factors.

When concentration sensitivity is enabled, the floor is allowed to decrease modestly for highly concentrated portfolios, reflecting the reduced relative importance of idiosyncratic risk when exposures are strongly clustered. However, a lower bound of 0.10 is imposed to reflect numerical stability and avoid unrealistically high correlations. The resulting total covariance matrix is then converted into a correlation matrix through standard normalization.

$$\psi_i = \max\left(\psi_{min}, 1 - \Sigma_{ii}^{sys}\right) \tag{7}$$

ψ_i represents the idiosyncratic variance of instrument i. psi sub min represents the minimum idiosyncratic variance floor imposed to ensure numerical stability and to prevent unrealistically high correlations. Σ_{ii}^{sys} represents the systematic variance contribution of instrument i, corresponding to the diagonal element of the covariance matrix generated by the systematic factor structure. Operator max ensures that the idiosyncratic variance is set to the larger of the residual variance $1 - \Sigma_{ii}^{sys}$ or the minimum variance floor ψ_{min}.

3.3.6 Structural Similarity Adjustments

Beyond the factor-based structure, the model introduces additional "structural bumps" to correlations between instruments that share key characteristics. Pairwise correlation increments are applied if two instruments belong to the same sector, country, rating category, or issuer. The relative magnitudes of these bumps (e.g. 0.06 for sector, 0.04 for country, 0.03 for rating, and 0.10 for issuer) are selected to impose a clear economic hierarchy of clustering strength.

The highest increment is assigned to common issuer identity, reflecting the empirical observation that bonds issued by the same entity tend to exhibit the strongest co-movement due to shared balance sheet risk and liquidity conditions. Sectoral similarity is assigned the next largest increment, capturing exposure to common industry-specific shocks. Country-level similarity is assigned a slightly lower increment, reflecting macroeconomic and sovereign influences that are generally broader and less granular than sector shocks. Rating similarity receives the smallest increment, as instruments within the same rating bucket may still differ substantially in sectoral and geographical exposure. These values are not empirically calibrated but are chosen to create economically intuitive clustering behaviour while maintaining numerical stability of the correlation matrix. To ensure that conclusions are not dependent on the exact magnitude of these increments, structural bump parameters are included in the ±50% sensitivity analysis. The results show that although absolute risk levels vary with the strength of clustering, portfolio risk ordering and qualitative findings remain stable.

Structural bump mechanism captures economically meaningful dependence effects without rendering results parameter-fragile. These bumps are further scaled by overall portfolio concentration and are capped at a maximum total increment per pair (0.25) to avoid excessive clustering. The mechanism allows the model to capture clustering effects observed in real credit portfolios, where similar instruments tend to move together more strongly in stressed conditions.

3.3.7 Positive Definiteness and Numerical Stabilisation

Because the combination of factor structure, concentration scaling, and structural bumps can lead to near-singular or indefinite matrices, the resulting correlation matrix is projected to the nearest positive definite matrix using numerical techniques. An eigenvalue floor (set to 10^{-4}) is applied to prevent extremely small or negative eigenvalues, after which the matrix is renormalized to ensure unit diagonal elements. An eigenvalue floor guarantees that the multivariate normal simulation can be performed reliably while preserving the intended dependence structure as closely as possible.

3.3.8 Monte Carlo Simulation and Valuation

Using the final stabilized correlation matrix, N=200,000 correlated standard normal vectors are generated. These are scaled by instrument-specific spread volatilities to obtain simulated credit spread changes in basis points, which are then converted to decimal form. For each simulation path and each instrument, the valuation impact is computed using the same duration and convexity-based approximation as in the simplified framework:

$$\Delta Fair\ Value = Market\ Value \times (-Modified\ Duration \times \Delta Spread + Convexity \times (\Delta Spread)^2 / 2) \tag{8}$$

Valuation changes are aggregated across the portfolio to obtain a simulated distribution of portfolio-level changes in economic value attributable to credit spread risk.

3.3.9 Risk Metrics and ΔEVE_CSRBB

From the simulated loss distribution, the primary CSRBB metric under the advanced framework is defined as the 99th percentile VaR:

$$\Delta EVE_{CSRBB}^{MC} = VaR_{99\%} \tag{9}$$

where $\mathrm{VaR}_{99\%}$ denotes the 99th percentile of the simulated loss distribution. In addition, the ES at the 99% level is computed to capture the average loss beyond the VaR threshold and to provide a more informative measure of tail risk. Additional diagnostics are also produced, including standalone instrument-level VaR measures, diversification ratios, and incremental risk contributions. While these outputs are not the primary focus of the methodological framework, they support the interpretation of diversification effects and concentration-driven risk.

3.3.10 Sensitivity Testing

To assess the robustness of the Monte Carlo framework with respect to stylised parameter choices, a structured sensitivity testing module is implemented directly within the simulation engine. Individual groups of structural parameters are varied separately while keeping the remaining parameters fixed at their baseline level. Factor standard deviations are scaled by ±50% relative to their baseline calibration in order to examine the sensitivity of the model to the assumed magnitude of credit spread shocks. In a separate set of scenarios, the correlation structure of the model is adjusted through proportional scaling of the correlation matrix. Additionally, the concentration-sensitive adjustment mechanism can be independently deactivated to isolate the contribution of concentration effects to overall portfolio risk.

All sensitivity scenarios are executed using the same Monte Carlo simulation architecture, identical random seeds, and unchanged portfolio compositions to ensure comparability across runs. The objective of the calculation is to evaluate the stability of VaR, ES, and diversification metrics under alternative structural calibrations, without altering the fundamental factor structure of the model.

3.4 Comparative Evaluation of Methodologies

Both methodological approaches share a common economic valuation basis and apply consistent duration and convexity-based pricing approximations to translate credit spread movements into changes in economic value. In both frameworks, CSRBB is measured as the change in EVE, attributable to adverse credit spread movements under a static balance sheet assumption, which ensures differences shown in comparison of both ΔEVE_CSRBB methodologies arise primarily from the treatment of credit spread dynamics and dependence structures, rather than from differences in valuation methodology.

The simplified approach relies on a single deterministic adverse credit spread shock calibrated from historical data using a 99th percentile VaR measure for each credit segment. The simplified framework produces a point estimate of ΔEVE_CSRBB and provides a transparent and easily interpretable measure of exposure. By construction, the simplified methodology does not explicitly model correlation across instruments and does not generate a distribution of portfolio outcomes. Diversification effects are therefore only reflected indirectly through portfolio composition and sensitivity aggregation, rather than through an explicit dependence structure.

In contrast, the advanced Monte Carlo framework models credit spread changes as correlated stochastic variables and generates a full empirical distribution of portfolio valuation outcomes, which enables the explicit modelling of cross-instrument dependence, diversification benefits, and non-linear aggregation effects. Portfolio concentration, sectoral and geographical clustering, and issuer overlap are incorporated directly into the correlation structure, allowing the effective dependence to vary endogenously with portfolio composition. As a result, the advanced approach captures structural features of the portfolio that are not reflected in deterministic shock-based methods.

From a risk measurement perspective, the simplified approach provides a conservative, stress-based estimate of ΔEVE_CSRBB under a severe but plausible scenario, while the advanced approach provides distribution-based tail risk measures derived from simulated outcomes. Although both approaches report a 99% confidence-level metric, the interpretation differs. In the simplified framework, ΔEVE_CSRBB represents the valuation impact of a calibrated historical shock, whereas in the advanced framework, it represents the 99th percentile of a simulated loss distribution. Distinguishing between the two is important when comparing results across methodologies. The two approaches also differ significantly in data, modelling, and computational requirements. The simplified framework can be implemented using standard spreadsheet tools through instrument-level inputs and historical spread series, making it suitable for institutions with constrained modelling resources or less complex portfolios. The advanced framework also requires instrument-level inputs, but additionally also explicit correlation modelling and Monte Carlo simulation, which leads to higher implementation and governance complexity but also greater risk sensitivity and analytical flexibility.

The simplified and advanced methodologies represent two complementary perspectives on CSRBB measurement. The simplified approach provides a transparent benchmark and supports proportional application, while the advanced approach offers a more comprehensive representation of portfolio risk by capturing correlation, concentration, and tail effects. The comparative application of both frameworks to the same synthetic portfolios in subsequent chapters allows for a controlled assessment of how methodological complexity and portfolio structure influence measured ΔEVE_CSRBB.

4 CASE STUDY APPLICATION

4.1 Application of Simplified Approaches

This section presents the empirical application of the simplified CSRBB measurement framework to the five synthetic portfolios. Using the deterministic shock-based methodology described in Chapter 3, credit spread shocks calibrated from historical data are applied to each portfolio and translated into changes in economic value using duration and convexity-based valuation. The resulting ΔEVE_CSRBB figures represent the estimated loss in economic value under a severe but plausible adverse credit spread widening scenario.

Tables from 4 to 8 in Appendix 1 report the portfolio-level data parameters and ΔEVE_CSRBB results for each synthetic portfolio. The red totals shown in the portfolio output tables represent the aggregate economic value impact for each case. The simplified framework produces materially different outcomes across portfolios, reflecting intentional variation in credit quality, sectoral composition, maturity structure, and diversification.

4.1.1 Simplified CSRBB Results Across Portfolios

The first portfolio exhibits the largest estimated loss in economic value under the simplified framework, with a ΔEVE_CSRBB of approximately –9.38 million EUR. Portfolio 1 is dominated by corporate and financial exposures and contains a significant share of BBB and BB-rated instruments. The large impact is primarily driven by the combination of elevated credit spread shocks applied to lower-rated exposures and moderate-to-long maturities, which increase valuation sensitivity through higher modified duration and convexity. In addition, concentration in a limited number of issuers amplifies the portfolio-level effect, resulting in the highest simplified CSRBB among the five portfolios.

The second portfolio, which is broadly diversified across government, corporate, and financial sectors and across multiple countries, records a substantially lower ΔEVE_CSRBB of approximately –5.09 million EUR. The presence of a large share of high-quality sovereign bonds moderates the overall impact of adverse credit spread shocks, despite the inclusion of corporate and financial exposures. Compared to Portfolio 1, the lower average credit risk and higher diversification lead to a materially smaller economic value loss, illustrating the stabilizing role of high-quality government exposures within the simplified framework.

The third portfolio, which is primarily composed of high-quality government bonds, exhibits the lowest sensitivity to credit spread risk, with a ΔEVE_CSRBB of approximately –3.97 million EUR. Although several sovereign positions have long maturities and therefore elevated duration and convexity, the relatively small credit spread shocks associated with high investment-grade government issuers limit the overall valuation impact. As a result, Portfolio 3 displays the most resilient profile under the simplified CSRBB methodology, highlighting the dominant role of issuer type and credit quality in determining deterministic stress outcomes.

The fourth portfolio, which emphasizes financial sector exposures, produces a ΔEVE_CSRBB of approximately –5.02 million EUR. The result reflects the higher sensitivity of financial institutions to adverse credit spread movements relative to sovereign issuers, particularly for BBB and BB-rated instruments. While the portfolio retains some diversification across issuers and includes selected government and corporate exposures, the concentration in financial sector risk results in a higher estimated loss than in more government-heavy portfolios.

The fifth portfolio, which is constructed to emphasize maturity and rating concentration, records a ΔEVE_CSRBB of approximately –7.81 million EUR, making it the second most sensitive portfolio under the simplified approach. The elevated impact is driven by the combination of long-dated corporate exposures and a high proportion of lower-rated bonds.

Extended maturities significantly increase modified duration and convexity, while lower credit quality leads to large deterministic spread shocks. Together, these structural features amplify valuation sensitivity and result in a substantial economic value loss under the simplified framework.

4.1.2 Cross-Portfolio Comparison

Across all five portfolios, the simplified CSRBB results exhibit economically intuitive patterns. Portfolios with higher exposure to lower-rated corporate and financial instruments, longer average maturities, and greater concentration consistently produce larger estimated losses in economic value. In contrast, portfolios dominated by high-quality sovereign exposures and broader diversification exhibit materially lower sensitivity to adverse credit spread shocks.

The deterministic framework, therefore, generates a clear ranking of portfolio risk that is primarily driven by credit quality, sectoral composition, and maturity structure. However, diversification effects are only reflected indirectly through portfolio composition and are not explicitly modelled through correlations. As a result, portfolios with similar aggregate sensitivities but different internal dependence structures may appear more similar under the simplified approach than under a stochastic framework.

4.2 Application of Advanced Approaches

This section presents the empirical results obtained from applying the advanced methodology of the CSRBB framework to the five synthetic portfolios. The stochastic approach of the simulation generates a full distribution of portfolio-level valuation outcomes, from which tail risk measures are derived. In contrast to the simplified framework, the advanced results explicitly reflect correlation, concentration, and diversification effects through the simulated joint dynamics of credit spread changes.

The key Monte Carlo simulation outputs for each portfolio are summarized in Appendix 4. The output values include:

- the number of exposures (n);
- index measuring concentration of market value weights, providing an insight into diversification across positions (HHI);
- index measuring concentration in the sector, providing an insight into sector diversification (sector_HHI);
- index measuring concentration in the origin country, providing an insight into clustering by geography (country_HHI);
- index measuring concentration in issuer, providing an insight into issuer diversification (sector_HHI);

– numerical stability check (min_eig), must be a positive definite;
– average correlation between two different bonds' spread shocks (avg_pair_corr);
– the maximum expected loss over the chosen time horizon that will not be exceeded with 99% confidence (Var 99%);
– the average loss in the worst 1% of scenarios (ES 99%);
– ratio between the sum of standalone (individual) VaRs and the portfolio VaR (how much risk reduction is achieved through diversification) (Diversification ratio).

4.2.1 Advanced CSRBB Results Across Portfolios

The first portfolio exhibits the highest tail risk under the advanced framework, with a 99% VaR of approximately 7.86 million EUR and a corresponding ES of approximately 8.93 million EUR. Portfolio 1 is characterized by high concentration in corporate and financial exposures and repeated issuers, which is reflected in a very high average pairwise correlation of approximately 0.90. It must be acknowledged that an average correlation of this magnitude is considered elevated relative to typical empirical estimates observed in diversified credit markets. The diversification ratio of 1.05 indicates only limited diversification benefits. Portfolio 1 consistently exhibits the highest dependence and tail risk across specifications. The results should be interpreted as illustrating the structural impact of concentration within the modelling framework; the high correlation reflects the model's deliberate amplification of co-movement under concentrated exposure profiles rather than a direct calibration to observed market correlations.

The second portfolio, which is broadly diversified across sectors, countries, and issuers, exhibits a substantially lower tail risk profile, with a 99% VaR of approximately 4.18 million EUR and an ES of approximately 4.73 million EUR. The average pairwise correlation is materially lower, at approximately 0.63, and the diversification ratio of 1.22 indicates meaningful diversification benefits relative to the sum of standalone risks. These results demonstrate the ability of a simulation to explicitly recognise and quantify diversification effects that are not directly captured under deterministic shock-based methods.

The third portfolio records the lowest tail risk among all portfolios, with a 99% VaR of approximately 3.42 million EUR and an ES of approximately 3.90 million EUR. Portfolio 3 is dominated by high-quality government bonds and exhibits strong diversification across countries. The relatively low average pairwise correlation of approximately 0.58 and the highest diversification ratio of 1.27 among all portfolios indicate substantial diversification benefits under the stochastic framework. The presence of long-dated sovereign exposures, high credit quality, and geographical diversification results in the most resilient tail risk profile.

The fourth portfolio, which emphasises financial sector exposures, exhibits a 99% VaR of approximately 3.81 million EUR and an ES of approximately 4.34 million EUR. The average pairwise correlation of approximately 0.76 reflects elevated common sectoral risk within the financial segment. The diversification ratio of 1.12 indicates moderate but limited diversification benefits. Compared to the second and third portfolios, the stronger sectoral concentration leads to higher effective dependence and a more pronounced tail risk profile, even though issuer and country diversification are present.

The fifth portfolio, which is constructed to highlight maturity and rating concentration effects, exhibits a relatively high tail risk, with a 99% VaR of approximately 5.94 million EUR and an ES of approximately 6.69 million EUR. The average pairwise correlation of approximately 0.58 suggests moderate overall dependence, while the diversification ratio of 1.18 indicates that diversification benefits are present but partially offset by the concentration in lower-rated and long-dated corporate exposures. The elevated tail risk reflects the combined effect of high spread volatility for lower-rated instruments and increased valuation sensitivity associated with extended maturities.

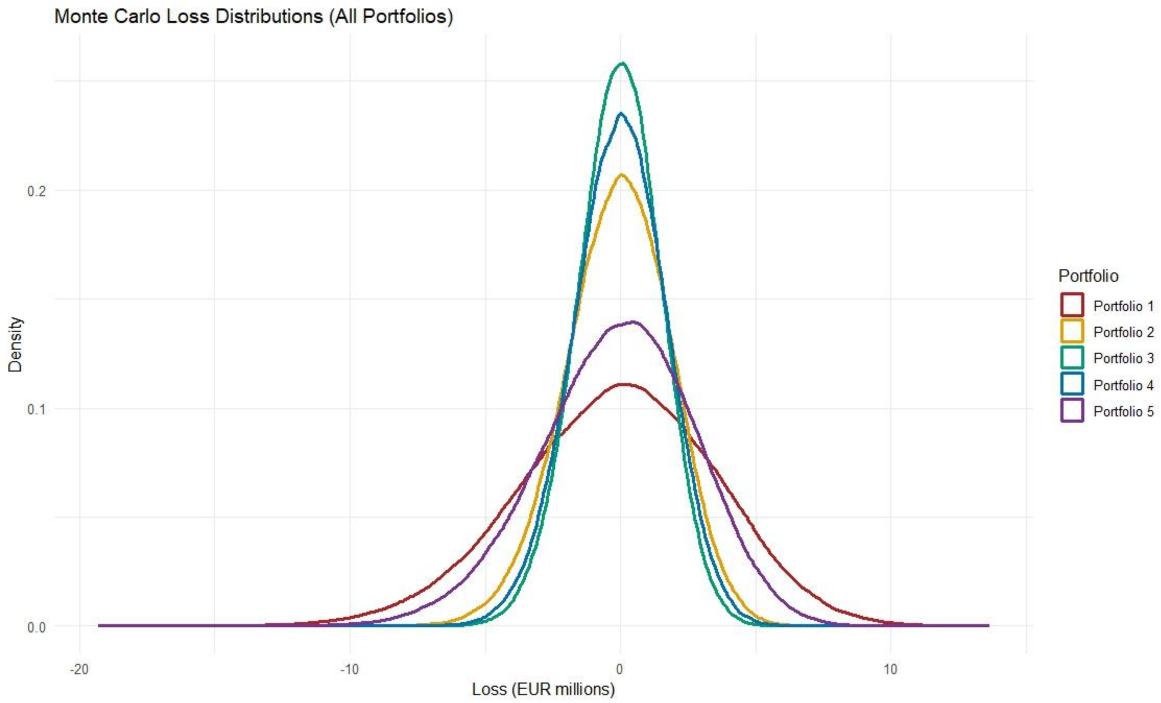
Across all five portfolios, the advanced CSRBB framework demonstrates internally consistent behaviour: higher concentration leads to stronger effective correlation, weaker diversification, and elevated tail risk, while diversified structures exhibit resilience through reduced co-movement. These patterns remain stable across sensitivity specifications, reinforcing the structural coherence of the modelling approach.

An important observation to note is that the ES/VaR ratio remains remarkably stable, ranging between approximately 1.12 and 1.13. Near-constant ratio reflects the properties of the multivariate normal distribution used in the Monte Carlo simulation. Under Gaussian assumptions, tail thickness is fixed, and the relationship between ES and VaR at a given confidence level is largely determined by the distributional form rather than by portfolio composition. As a result, changes in concentration and correlation primarily affect the scale of losses but not the relative thickness of the tail.

If credit spread shocks were instead modelled using a heavy-tailed distribution, such as a multivariate Student-t specification, the ES/VaR ratio would be expected to increase, particularly for lower degrees of freedom. In that case, extreme tail losses would become more pronounced relative to the 99% quantile, and portfolios with high systematic exposure could exhibit disproportionately larger ES values. The relatively stable ES/VaR ratio observed here therefore confirms that tail behaviour is primarily driven by the Gaussian assumption rather than by structural portfolio differences.

Loss distribution and tail ends are illustrated in Figure 2. Portfolio 1 exhibits the widest loss distribution and the most pronounced right tail due to high concentration and correlation. In contrast, Portfolio 3 shows the narrowest distribution, reflecting strong diversification and high credit quality.

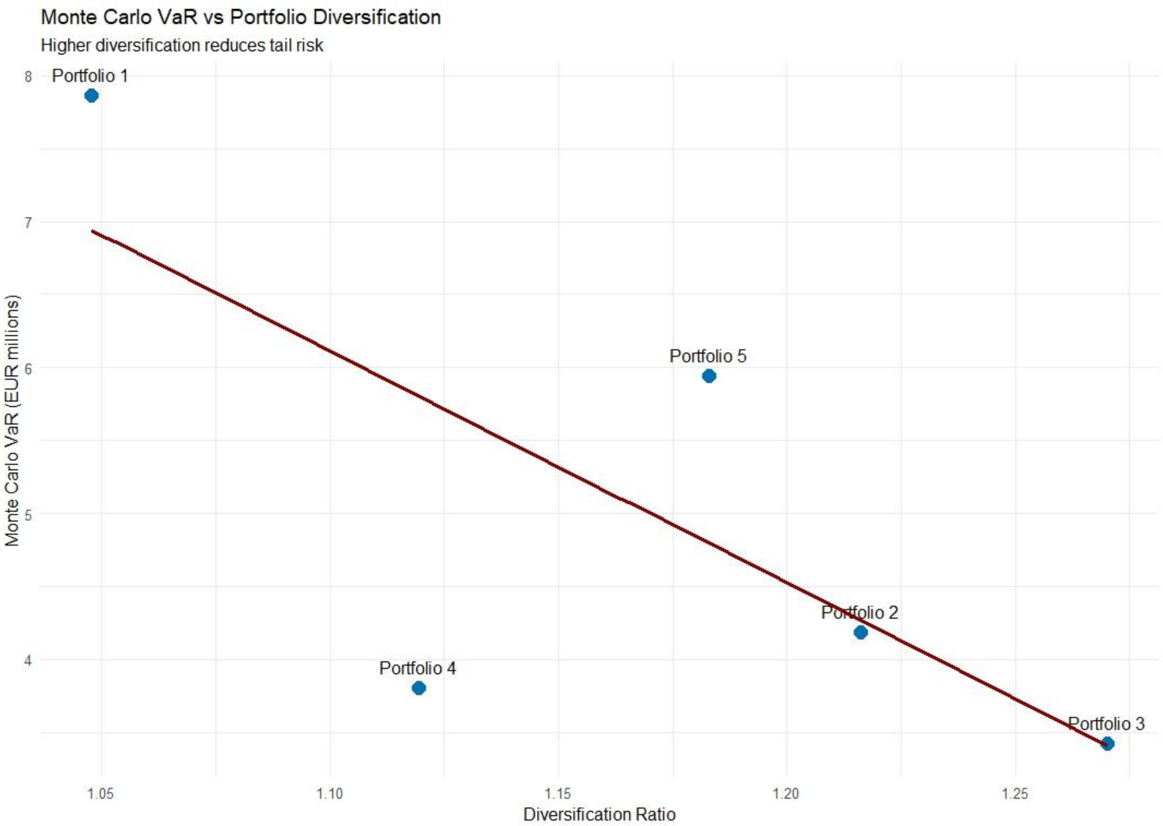
Figure 2: Loss Distributions



Source: Own work (n. d.).

The analysis presented in Figure 3 illustrates the relationship between portfolio diversification and tail risk. It is expected that portfolios with higher diversification ratios will exhibit lower VaR estimates, confirming that diversification reduces effective portfolio-level credit spread risk through lower dependence between exposures. Highly diversified portfolios benefit from partial offsetting effects across sectors, countries, and issuers, which reduces the magnitude of extreme losses. It is clearly seen in Figure 3 that Portfolios 4 and 5 slightly deviate from the trend, and their comparison is explained in Table 2 in more detail.

Figure 3: MC VaR vs Portfolio Diversification



Source: Own work (n. d.).

The difference in VaR between Portfolios 4 and 5 is drastic because portfolio VaR reflects both the aggregate standalone exposure of the instruments and the diversification effects arising from the dependence structure of credit spread shocks. Portfolio 4 has a sum of standalone VaR that amounts to 4.28 million EUR, which, after diversification, results in a portfolio VaR of 3.81 million EUR and a diversification benefit of approximately 0.47 million EUR. Although Portfolio 5 exhibits a higher diversification ratio (1.183 compared to 1.119 for Portfolio 4) and therefore a larger diversification benefit of roughly 1.13 million EUR, its aggregate standalone risk is substantially higher, reaching 7.08 million EUR. As a result, the diversification effect of Portfolio 5 is not sufficient to offset the higher underlying exposure, leading to a higher final portfolio VaR compared to Portfolio 4, which is consistent with the structural composition of Portfolio 5, which contains a greater share of lower-rated instruments and longer maturities, increasing spread volatility and valuation sensitivity.

Table 2: Additional Comparison of Portfolios 4 and 5

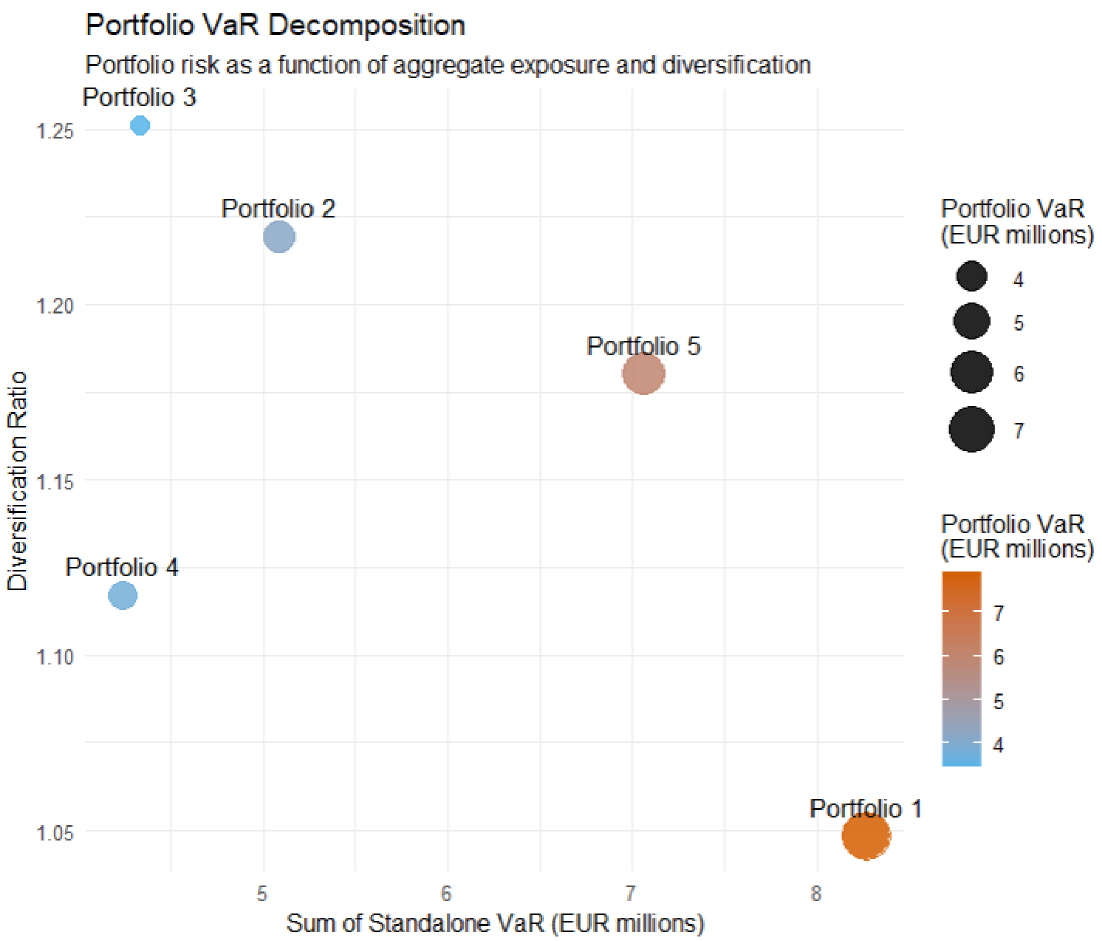
Portfolio	Standalone VaR Sum	Diversification Ratio	Portfolio VaR	Diversification Benefit
4	4.275.091	1.119	3.807.150	467.941

5	7.076.320	1.183	5.943.352	1.132.968

Source: Own work.

For a better understanding of the aggregate exposure and diversification effects, the following Figure 4 represents the decomposition of portfolio VaR in all five portfolios. The x-axis represents the sum of standalone VaR, the y-axis the diversification ratio, and point size and colour correspond to the resulting portfolio VaR.

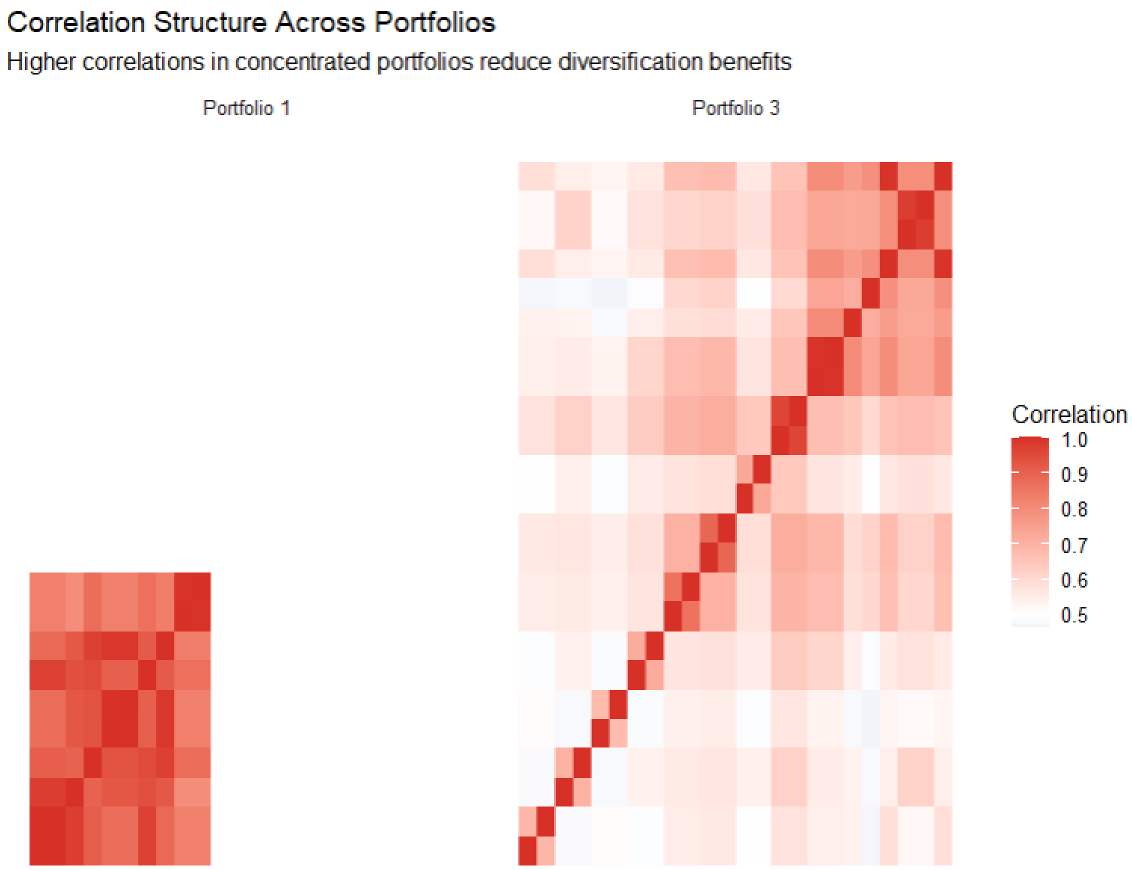
Figure 4: Portfolio VaR Decomposition



Source: Own work (n. d.).

Figure 4 also shows a large diversification ratio gap between Portfolio 1 and Portfolio 3. Portfolio 1 exhibits a highly correlated structure reflecting concentration, while Portfolio 3 shows lower correlations across instruments, enabling stronger diversification and lower portfolio VaR under the Monte Carlo framework. Correlation structure is clearly shown through the heatmap representation of the two contrasting correlation matrices in Figure 5. Portfolio 3 appears larger because of a higher number of instruments in the portfolio. Portfolio 1 has 10 bonds in total, while Portfolio 3 has a portfolio structure of 24 bonds.

Figure 5: Correlation Structure Across Portfolios



Source: Own work (n. d.).

4.2.2 Sensitivity Analysis Results

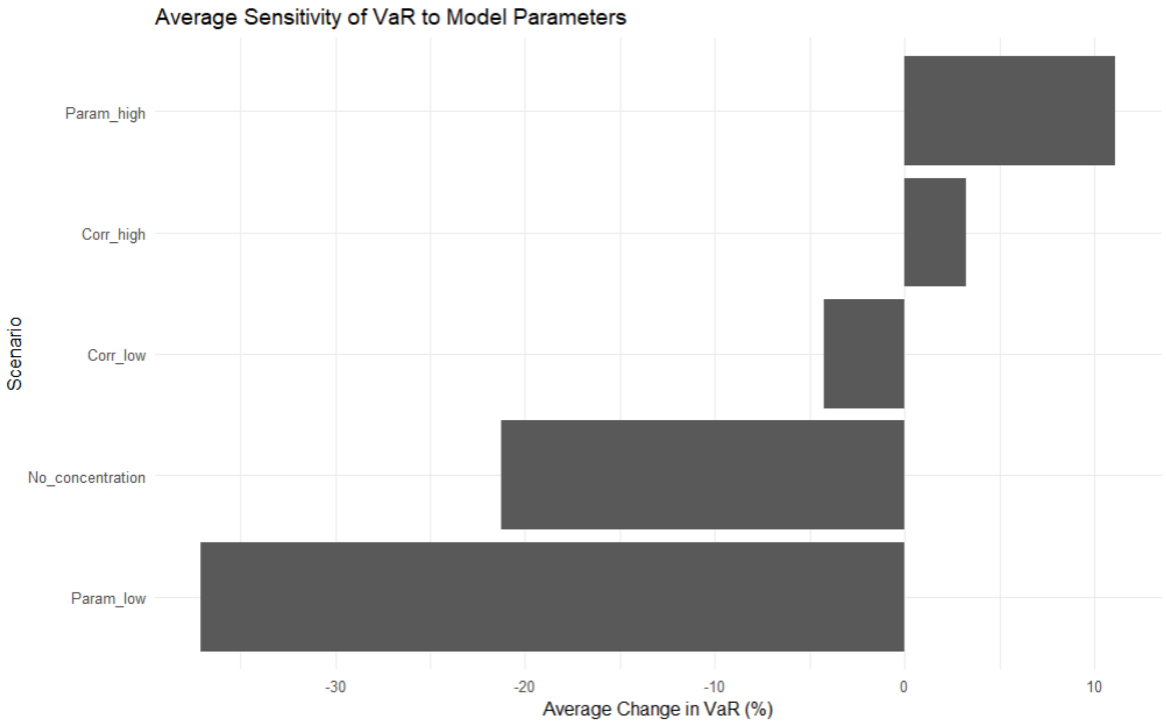
The sensitivity analysis confirms the robustness of the Monte Carlo CSRBB model across alternative parameter specifications. The results of sensitivity testing are provided in Appendix 5.

The sensitivity analysis shows that the model reacts most strongly to changes in factor standard deviations. Reducing these parameters by 50% leads to a substantial decline in VaR and ES across all portfolios. Increasing the parameters results in moderately higher risk estimates. In contrast, adjustments to the correlation structure have only a limited effect on the resulting risk measures. The importance of concentration effects shows through the removal of concentration-sensitive adjustment as VaR and ES decrease noticeably, and diversification ratios increase, particularly for portfolios with higher sectoral or issuer concentration.

Figure 6 presents the average change in VaR across all five portfolios relative to the baseline scenario. All five portfolios have a similar response to the sensitivity testing, all responding in the same direction, which can be seen through the sensitivity testing results in Appendix 5. The chart below aggregates portfolio-level results by computing the mean percentage change in VaR for each sensitivity scenario compared to the corresponding baseline values. The sensitivity testing approach allows the overall impact of individual model parameters to be assessed without focusing on a single portfolio. Variations in factor standard deviations have the largest effect on portfolio risk, followed by the concentration adjustment mechanism, while changes in the correlation structure have a comparatively smaller influence on VaR estimates.

The absolute level of CSRBB risk varies across scenarios, but the relative ranking of portfolios remains stable. Portfolios with higher concentration consistently exhibit higher tail risk, whereas more diversified portfolios maintain lower VaR and stronger diversification benefits. The results indicate that the model produces stable and economically consistent results under alternative parameter assumptions.

Figure 6: Average Sensitivity of VaR to Model Parameters



Source: Own work (n. d.).

4.3 Cross-Portfolio Comparison

Across the five portfolios, the advanced Monte Carlo simulation results reveal a clear relationship between portfolio concentration, correlation, and tail risk. Portfolios with higher issuer, sectoral, or rating concentration exhibit higher average correlations and reduced diversification benefits, leading to higher tail risk measures. In contrast, portfolios with broader diversification across countries, sectors, and issuers benefit from lower effective dependence and materially lower VaR and ES outcomes.

Relative to the simplified deterministic framework, the advanced results place greater emphasis on joint credit spread dynamics. While portfolios with lower credit quality and longer maturities continue to exhibit higher risk, the stochastic framework further differentiates portfolios based on their internal dependence structure. As a result, portfolios with similar aggregate sensitivities may display materially different tail risk once correlation and concentration effects are explicitly taken into account.

The results of the advanced approach demonstrate that CSRBB is driven not only by instrument-level credit quality and maturity, but also by the interaction of exposures through correlation and concentration. The advanced framework, therefore, provides a more granular and economically realistic representation of portfolio-level CSRBB, particularly in capturing diversification benefits and tail co-movement effects.

4.3.1 Comparative Results Across Methods

This section provides a direct comparison of CSRBB estimates obtained under the simplified deterministic framework and the advanced stochastic framework for the five synthetic portfolios. The objective is to assess how methodological choice influences measured CSRBB and to identify systematic differences in portfolio-level risk estimates.

Table 3 reports the absolute and relative differences between simplified deterministic CSRBB estimates and Monte Carlo VaR results. Positive gaps indicate that the simplified framework produces more conservative risk estimates due to its inability to account for diversification effects.

Table 3: Comparative Results Across Methods

Portfolio	Simplified VaR (EUR mio)	MC VaR (EUR mio)	MC ES (EUR mio)	ES/VaR	Diversification Ratio	Avg Pair Corr	Absolute Gap	Relative Gap (%)
1	9.38	7.86	8.92	1.13	1.048	0.899	1.52	19
2	5.09	4.18	4.73	1.13	1.216	0.612	0.91	22
3	3.97	3.42	3.90	1.14	1.270	0.575	0.55	16
4	5.02	3.81	4.34	1.14	1.119	0.759	1.21	32
5	7.81	5.94	6.69	1.13	1.183	0.581	1.87	31

Source: Own work.

The magnitude of the methodological gap also appears to be related to portfolio diversification. Portfolios exhibiting stronger diversification effects under the stochastic framework tend to display larger differences between the simplified and Monte Carlo estimates. For example, Portfolio 3, which is highly diversified and dominated by high-quality sovereign exposures, exhibits the smallest relative gap of approximately 16%. In contrast, Portfolios 4 and 5 display the largest relative differences of approximately 32% and 31%, respectively. These portfolios contain higher sector or rating concentration and longer maturity exposures, which increase the sensitivity of deterministic shock-based methods. The relationship suggests that the gap between simplified and advanced CSRBB measures is not unified across portfolios but depends on structural characteristics such as diversification, concentration, and credit quality.

Across all five portfolios, the simplified approach consistently produces larger absolute CSRBB estimates than the Monte Carlo-based 99% VaR measure. The absolute gaps range from 0.55 million EUR to 1.87 million EUR, while the relative differences range from 16% to 32%. The deterministic shock-based framework is therefore systematically more conservative than the stochastic tail risk estimates derived from the joint simulation of correlated credit spread movements.

The simplified methodology applies fixed adverse shocks at the instrument level and does not explicitly recognise diversification effects. As a result, portfolio-level losses reflect the full aggregation of stressed sensitivities without allowing for partial offsetting effects across exposures. In contrast, the advanced framework explicitly models cross-instrument dependence and incorporates diversification and concentration effects through the simulated correlation structure, leading to systematically lower VaR estimates for portfolios that benefit from broader diversification.

The magnitude of the methodological gap varies across portfolios and is closely related to portfolio structure. The largest relative differences are observed for Portfolios 4 and 5, where the simplified estimates exceed the Monte Carlo VaR by 32% and 31%, respectively. In absolute terms, Portfolio 5 shows the largest gap of 1.87 million EUR, reflecting the combined impact of long maturities, lower credit ratings, and concentration effects.

The degree of conservatism shown in the simplified approach varies across portfolios and is closely linked to portfolio structure. The largest relative differences are observed for portfolios with broader diversification across sectors, countries, and issuers. For example, Portfolio 2 exhibits a simplified ΔEVE_CSRBB of –5.09 million EUR compared to a Monte Carlo VaR of 4.18 million EUR (relative difference of 22%), reflecting the recognition of diversification benefits under the stochastic framework. Similarly, Portfolio 4 shows a materially lower Monte Carlo VaR relative to the simplified estimate, despite elevated sector concentration, indicating partial risk dispersion across issuers and countries.

For Portfolio 3, which is dominated by high-quality sovereign exposures, the difference between methodologies is comparatively small. The simplified and Monte Carlo estimates are 3.97 million EUR and 3.42 million EUR, corresponding to the smallest relative gap of

16%. Both are driven by relatively low spread volatility and high credit quality, limiting the scope for diversification effects to materially alter tail risk outcomes.

Portfolios 1 and 5, which exhibit higher credit risk, longer maturities, and greater concentration in lower-rated exposures, display elevated CSRBB under both methodologies. However, even for these high-risk portfolios, the simplified framework produces more conservative estimates, reflecting its inability to account for any diversification benefits, even where limited diversification is present.

The comparative results demonstrate that simplified deterministic CSRBB methodologies tend to systematically overstate tail risk relative to advanced stochastic approaches, particularly for diversified portfolios. The advanced Monte Carlo framework provides a more risk-sensitive and economically realistic representation of portfolio-level CSRBB by explicitly incorporating correlation, concentration, and diversification effects.

5 EVALUATION AND INTERPRETATION

The empirical findings confirm theoretical expectations regarding the behaviour of deterministic and stochastic risk measurement frameworks of measuring CSRBB. However, these differences are not specific to the particular synthetic portfolios analysed, but instead arise from fundamental conceptual distinctions between the two modelling frameworks.

A primary reason for the observed differences is the treatment of uncertainty and risk aggregation. Simplified approaches rely on the application of a single adverse credit spread shock calibrated from historical data and applied deterministically across instruments. The framework assumes that adverse credit spread movements occur simultaneously and uniformly within predefined risk buckets, without allowing for partial offsetting effects across instruments, countries, or sectors. As a result, simplified methodologies reflect a conservative aggregation of risk, as they do not recognize diversification benefits arising from imperfect correlation among credit spread movements. In contrast, advanced approaches explicitly model credit spread changes as stochastic variables and generate a full joint distribution of outcomes across instruments. This allows for the representation of partial co-movement and diversification effects, leading to systematically lower aggregate tail risk estimates for diversified portfolios and a more differentiated treatment of concentrated exposures.

From a regulatory perspective, the observed differences also align with supervisory expectations and the proportionality principle embedded in the EBA framework for IRRBB and CSRBB. Supervisory guidance recognizes that simplified methodologies may be appropriate for institutions with limited portfolio complexity. More advanced internal models are expected for banks with complex, concentrated, or exposed profiles. The conservative nature of simplified approaches, as observed in the empirical results, is consistent with their role as baseline supervisory tools designed to ensure prudent risk measurement and comparability across institutions. At the same time, the enhanced risk sensitivity and distributional insight provided by advanced stochastic approaches reflect the types of internal models that supervisors increasingly expect larger or more sophisticated institutions to develop for internal risk management and ICAAP purposes.

Conceptually, the two methodologies reflect different modelling objectives. Simplified approaches prioritise transparency, interpretability, and conservative aggregation, while advanced stochastic approaches prioritise risk sensitivity, distributional insight, and explicit modelling of portfolio interactions. These differences explain the systematic patterns observed in Chapter 4 and motivate the more detailed evaluation of strengths and weaknesses in the following section.

5.1 Strengths and Weaknesses of Different Methodologies

Simplified deterministic approaches offer important practical advantages in terms of transparency, ease of implementation, and governance. Their reliance on deterministic shocks and sensitivity-based valuation allows results to be easily traced to underlying assumptions, facilitating internal review and supervisory communication. These approaches also require relatively limited data and modelling infrastructure, making them suitable for institutions where CSRBB is not a dominant risk driver. From a prudential perspective, simplified methods tend to produce conservative estimates because diversification effects are not explicitly recognised. Conservatism of the simplified approach may be desirable in a supervisory context, as it reduces the risk of underestimating exposure to adverse credit spread movements. It is also important to point out that the absence of explicit modelling of correlations and joint spread dynamics limits the risk sensitivity of simplified frameworks. In particular, the methodology cannot capture diversification benefits across instruments, sectors, and countries, which can lead to systematic overestimation of risk in well-diversified portfolios. Furthermore, deterministic stress calculations provide only a single shocked valuation outcome rather than a full loss distribution. As a result, tail risk measures such as ES cannot be estimated, and the severity of extreme outcomes remains unobserved. These limitations reduce the usefulness of simplified approaches for portfolio optimisation and detailed risk attribution.

Advanced stochastic approaches address many of these limitations by modelling the joint dynamics of credit spreads through a simulation-based framework. By generating an empirical loss distribution, these models allow the estimation of tail risk measures such as VaR and ES and provide deeper insight into extreme loss scenarios. The explicit modelling of correlations enables recognition of diversification effects, resulting in a more economically realistic aggregation of portfolio risk. In addition, the incorporation of concentration-sensitive adjustments allows the model to reflect the amplification of tail risk in portfolios with clustered exposures, improving alignment with theoretical and empirical evidence on credit spread dynamics. Despite these advantages, stochastic methodologies introduce additional model risk and operational complexity. Risk estimates depend on assumptions regarding volatility calibration, factor structure, and correlation dynamics, and even moderate parameter changes can materially affect tail risk estimates. Consequently, these models require more extensive data, specialised quantitative expertise, and stronger validation and governance frameworks. Their probabilistic structure can also reduce transparency for non-technical stakeholders and supervisors.

There is a clear trade-off between transparency and risk sensitivity. Simplified approaches provide conservative and easily interpretable estimates but may overstate risk in diversified portfolios, while advanced stochastic frameworks deliver more economically realistic risk measurement at the cost of greater model complexity and governance requirements.

5.2 Alignment with Literature and Regulatory Expectations

The empirical results of this thesis can be aligned with both the academic literature on portfolio risk aggregation and the evolving regulatory expectations for the measurement of CSRBB under the EBA and ECB supervisory framework. As discussed in Chapter 2, regulatory developments have increasingly emphasized the importance of capturing valuation risk arising from non-default credit spread movements, particularly for institutions with material bond portfolios and long-duration exposures. The results obtained through analysis provide empirical support for regulatory focus and illustrate how methodological choice materially affects measured CSRBB.

The distinction between deterministic stress-based approaches and stochastic distribution-based risk measurement frameworks is emphasized in the theoretical foundation. Theoretical portfolio risk models show that aggregate risk is a function not only of individual position sensitivities and volatilities, but also of the correlation structure among risk factors. The simulation-based results, which model joint credit spread dynamics and concentration effects, are in line with the theoretical foundation. The finding that advanced stochastic methods generally produce lower tail risk estimates for diversified portfolios reflects principles of diversification and correlation-driven risk amplification. At the same time, stochastic methods highlight elevated tail risk for concentrated portfolios, which is also in line with the theoretical foundation.

From a regulatory perspective, the results align closely with the proportionality principle embedded in the EBA guidelines for IRRBB and CSRBB. As outlined in Chapter 2, supervisors explicitly recognize that the methodological sophistication required for CSRBB measurement should be commensurate with portfolio materiality, complexity, and risk profile. The empirical evidence also supports this supervisory opinion. Simplified deterministic approaches provide conservative and transparent baseline measures that are suitable for institutions with relatively simple, homogeneous, or immaterial CSRBB exposures. At the same time, the advanced simulation-based framework demonstrates important value for portfolios characterized by greater diversification, sectoral heterogeneity, and issuer concentration, where joint dynamics and tail dependence materially influence portfolio-level risk. The empirical differentiation shows supervisory guidance that encourages more advanced modelling for institutions with complex or material CSRBB exposures.

The results are also consistent with regulatory emphasis on economic value sensitivity and tail risk under Basel Pillar 2. The EBA and ECB frameworks place increasing weight on EVE measures and on the assessment of extreme but plausible scenarios, particularly for long-duration and lower-rated bond exposures. The stochastic framework produces full loss distributions and tail risk metrics such as VaR and ES, which are conceptually well aligned with supervisory expectations regarding severe but plausible stress outcomes. The deterministic simplified approach, by contrast, provides a single-point stress outcome that is easier to communicate and interpret, but does not fully capture distributional tail behaviour. The contrast reflects the regulatory distinction between baseline supervisory metrics and more advanced internal risk management tools.

Industry guidance and supervisory commentary further emphasize the challenges of isolating and modelling CSRBB, particularly due to the preserved liquidity and market risk components within observed credit spreads. As noted in Chapter 2, the EBF and several national supervisors highlight the lack of standardized shock calibration and modelling approaches for CSRBB, resulting in heterogeneity across institutions. The empirical framework also reflects this regulatory reality: both simplified historical shock calibration and advanced stochastic modelling rely on internal methodological choices and assumptions.

Importantly, the results also support the regulatory narrative that CSRBB is conceptually distinct from IRRBB and requires separate analytical treatment. While IRRBB methodologies benefit from standardized supervisory outlier tests and relatively well-established modelling practices, CSRBB remains less prescriptive and more principles-based. The empirical differences between simplified and advanced CSRBB estimates observed through analysis illustrate why regulators have refrained from imposing a single standardized approach for CSRBB. Instead, supervisory guidance emphasizes institution-specific modelling, materiality assessments, and proportional application of methodological complexity. The results provide empirical justification for the regulatory flexibility, as the appropriate level of modelling complexity clearly depends on portfolio characteristics.

The empirical evidence presented supports the regulatory view that simplified CSRBB methodologies play an important role as conservative baseline tools, while advanced stochastic frameworks offer enhanced risk sensitivity and analytical depth for institutions with more complex or material exposures. The alignment confirms the credibility of the methodological framework developed in this thesis and supports its relevance for the risk management practice.

5.3 Practical Implications for Banks and Supervisors

Even though the analysis is based on synthetic portfolios, the results illustrate general principles that are directly relevant for institutions managing material bond portfolios and for supervisors assessing the adequacy of CSRBB frameworks under the Basel Pillar 2 regime. For banks, the results highlight the importance of aligning methodological sophistication with portfolio complexity and risk materiality. Simplified CSRBB approaches provide transparent and conservative baseline measures that are well-suited for institutions with relatively simple, homogeneous, or immaterial CSRBB exposures. Such approaches can serve as effective first-line tools for identifying exposure to adverse credit spread movements and for meeting baseline supervisory expectations with limited operational burden. And advanced stochastic methodologies are beneficial for banks with diversified, concentrated, or structurally complex portfolios. For such institutions, advanced approaches can complement simplified measures by providing additional insight for internal risk management, portfolio construction, and capital planning, particularly in the context of ICAAP and stress testing processes.

From a supervisory perspective, the results confirm the proportionality principle embedded in the EBA and ECB frameworks. Simplified methodologies may be appropriate for benchmarking and comparability purposes, while advanced internal models can enhance risk sensitivity and analytical depth for more complex institutions. A multi-layered approach allows supervisors to balance the need for transparency and consistency with the recognition that portfolio heterogeneity and concentration materially influence CSRBB.

The results suggest that effective CSRBB management is best supported by a complementary use of simplified and advanced methodologies. Simplified approaches provide a transparent and conservative foundation, while advanced stochastic models offer incremental analytical value for institutions capable of supporting their operational and governance requirements. The framework confirms current regulatory expectations and supports both prudent supervision and sound internal risk management practice.

The empirical results also suggest that portfolio concentration indicators may provide useful practical signals for determining when more advanced modelling approaches become valuable. In particular, measures such as the HHI or the number of issuers can help identify portfolios where concentration effects materially influence CSRBB estimates. While the thesis does not aim to define strict thresholds, the results indicate that as portfolio concentration increases, stochastic modelling frameworks provide additional analytical value by capturing correlation-driven tail risk and issuer concentration effects. For highly diversified portfolios with low concentration levels, simplified deterministic approaches may provide sufficiently informative baseline risk estimates.

6 CONCLUSION

The thesis examined the measurement of Credit Spread Risk in the Banking Book (CSRBB) with a particular focus on the impact of methodological choice on portfolio-level risk assessment. CSRBB represents an important source of valuation risk for banks, as changes in credit spreads and market perceptions can materially affect the economic value of banking book positions even in the absence of borrower default.

The goal was to show how simplified deterministic approaches and advanced stochastic approaches differ in their treatment of portfolio effects, with the main focus of the thesis being a controlled empirical analysis that compares simplified and advanced CSRBB methodologies. Methodologies differ in their complexity and were applied to a set of five synthetic banking book portfolios with systematically varied structural characteristics, to show the methodological differences through five different scenarios.

By applying both simplified and advanced approaches to the same portfolios, the results show that methodological choice materially influences measured CSRBB and that portfolio structure plays an important role in shaping risk outcomes. Simplified approaches and advanced stochastic frameworks provide different perspectives on CSRBB, reflecting their distinct modelling objectives and assumptions. The results also support the view that no single CSRBB methodology is universally optimal. Simplified deterministic approaches provide transparent baseline sensitivity measures that are relatively easy to implement and interpret. In contrast, advanced stochastic approaches explicitly model correlation structures and portfolio interactions, enabling a more risk-sensitive representation of diversification and concentration effects.

The analysis is subject to several limitations. The empirical analysis is based on synthetic portfolios rather than real banking book data, which limits the ability to fully capture the complexity of actual bank balance sheets. The modelling framework assumes static balance sheet structures and does not incorporate dynamic portfolio management, behavioural responses, or NII sensitivity analysis. Several modelling parameters are necessarily simplified or arbitrarily calibrated for the purpose of the empirical exercise. In addition, the simulation framework relies on assumptions such as normally distributed credit spread changes and simplified correlation structures, which may differ from the heavier-tailed dynamics observed in real financial markets. The modelling approach collapses rating categories into simplified spread buckets, which may not fully reflect the heterogeneity of credit quality and rating migration dynamics observed in practice.

Future research could extend this work by applying similar methodologies to real banking book portfolios, incorporating dynamic balance sheet assumptions, or modelling rating transitions and regime-dependent correlation structures. Additional research could also examine the interaction between CSRBB and other balance sheet risks, such as IRRBB or liquidity risk, in order to better understand how these risks jointly affect bank valuation and capital sensitivity. Such extensions would further enhance understanding of CSRBB under stressed real-life market conditions and improve the practical relevance of advanced modelling approaches.

The thesis shows that the measurement of CSRBB is highly sensitive to both methodological choice and portfolio structure. A layered and proportional approach that combines simplified baseline measures with more advanced stochastic analysis and can therefore provide a balanced and practical framework for effective CSRBB measurement and management, consistent with both portfolio risk theory and current supervisory expectations.

LIST OF KEY LITERATURE

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APPENDICES

Appendix 1: Data and Calculation in Simplified Measurement Approach - Spreadsheet

Table 4: Synthetic Portfolio 1

Bond ID	Issuer	Sector	Country	Rating	Šifra	Market Value (EUR)	Weight	Maturity (yrs)	Modified Duration (proxy)	Convexity (proxy)	SpreadVol	CR shock	CR shock PnL
C1	CorpA	Corporate	DE	BBB	Corp_BBB	25.000.000	25%	5,2	4,68	27,04	35,60	97,04	- 1.103.557,24
C2	CorpA	Corporate	DE	BBB–	Corp_BBB	12.000.000	12%	8,4	7,56	70,56	35,60	97,04	- 840.493,44
C3	CorpA	Corporate	DE	BB+	Corp_BB	13.000.000	13%	10	9,00	100,00	95,58	254,71	- 2.558.390,12
C4	CorpB	Corporate	FR	BBB	Corp_BBB	8.000.000	8%	6,1	5,49	37,21	35,60	97,04	- 412.190,42
C5	CorpC	Corporate	IT	BB	Corp_BB	7.000.000	7%	7	6,30	49,00	95,58	254,71	- 1.012.000,33
C6	CorpD	Corporate	ES	BB	Corp_BB	6.000.000	6%	4,8	4,32	23,04	95,58	254,71	- 615.361,16
C7	CorpE	Corporate	DE	BBB–	Corp_BBB	5.000.000	5%	9,2	8,28	84,64	35,60	97,04	- 381.825,77
C8	CorpF	Corporate	FR	BB+	Corp_BB	4.000.000	4%	3,9	3,51	15,21	95,58	254,71	- 337.874,94
F1	FinZ	Financial	UK	BBB	Fin_BBB	8.000.000	8%	7,8	7,02	60,84	54,50	143,91	- 757.777,60
F2	FinY	Financial	UK	BBB–	Fin_BBB	12.000.000	12%	9,5	8,55	90,25	54,50	143,91	- 1.364.334,49
													- 9.383.805,51

Source: Own work

Table 5: Synthetic Portfolio 2

Bond ID	Issuer	Sector	Country	Rating	Šifra	Market Value (EUR)	Weight	Maturity (yrs)	Modified Duration (proxy)	Convexity (proxy)	SpreadVol	CR shock	CR shock PnL
G1	DE_Gov	Government	DE	AAA	Germany	5.769.231	5,77%	8,6	7,74	73,96	14,13	37,68	- 165.224,50
G2	DE_Gov	Government	DE	AAA	Germany	5.384.615	5,38%	7,4	6,66	54,76	14,13	37,68	- 133.031,33
G3	FR_Gov	Government	FR	A	France	5.000.000	5,00%	5	4,50	25,00	15,40	41,19	- 91.606,12
G4	FR_Gov	Government	FR	A	France	5.000.000	5,00%	5	4,50	25,00	15,40	41,19	- 91.606,12
G5	NL_Gov	Government	NL	AAA	Netherlands	4.615.385	4,62%	12	10,80	144,00	13,95	39,98	- 193.989,85
G6	AT_Gov	Government	AT	AA	Austria	4.230.769	4,23%	3,8	3,42	14,44	18,26	45,36	- 64.996,84

G7	SK_Gov	Government	SK	A	Slovakia	3.846.154	3,85%	8,7	7,83	75,69	36,09	73,15	-	212.505,37
G8	IT_Gov	Government	IT	BBB	Italy	3.846.154	3,85%	9,5	8,55	90,25	59,35	191,40	-	565.830,51
G9	BE_Gov	Government	BE	AA	Belgium	3.846.154	3,85%	15,1	13,59	228,01	25,13	31,89	-	162.206,33
G10	FI_Gov	Government	FI	AA	Finland	1.538.462	1,54%	4,5	4,05	20,25	12,34	36,75	-	22.689,54
G11	FI_Gov	Government	FI	AA	Finland	1.538.462	1,54%	4,5	4,05	20,25	12,34	36,75	-	22.689,54
G12	IE_Gov	Government	IE	AA	Ireland	2.692.308	2,69%	20	18,00	400,00	81,07	39,78	-	184.237,06
C1	CorpA	Corporate	DE	A	Corp_A	3.846.154	3,85%	3,7	3,33	13,69	21,38	60,50	-	76.520,17
C2	CorpB	Corporate	DE	A	Corp_A	3.846.154	3,85%	4,2	3,78	17,64	21,38	60,50	-	86.712,93
C3	CorpC	Corporate	DE	A	Corp_A	3.846.154	3,85%	6,9	6,21	47,61	21,38	60,50	-	141.145,69
C4	CorpD	Corporate	DE	AA	Corp_AA	3.461.538	3,46%	8,4	7,56	70,56	17,79	48,63	-	124.363,62
C5	CorpE	Corporate	DE	A	Corp_A	3.461.538	3,46%	4	3,60	16,00	21,38	60,50	-	74.376,03
C6	CorpF	Corporate	FR	BBB	Corp_BBB	3.076.923	3,08%	10,2	9,18	104,04	35,60	97,04	-	259.032,13
C7	CorpG	Corporate	NL	A	Corp_A	3.076.923	3,08%	6,2	5,58	38,44	21,38	60,50	-	101.705,62
C8	CorpH	Corporate	IT	BBB	Corp_BBB	3.076.923	3,08%	8,1	7,29	65,61	35,60	97,04	-	208.166,36
C9	CorpI	Corporate	ES	BB	Corp_BB	2.692.308	2,69%	3	2,70	9,00	95,58	254,71	-	177.293,27
C10	CorpJ	Corporate	FR	A	Corp_A	2.692.308	2,69%	4,8	4,32	23,04	21,38	60,50	-	69.228,45
C11	CorpK	Corporate	NL	BBB	Corp_BBB	2.692.308	2,69%	7,4	6,66	54,76	35,60	97,04	-	167.061,27
C12	CorpL	Corporate	ES	BB	Corp_BB	2.692.308	2,69%	12,6	11,34	158,76	95,58	254,71	-	638.993,22
F1	FinZ	Financial	FR	A	Corp_A	2.692.308	2,69%	3,6	3,24	12,96	21,38	60,50	-	52.134,18
F2	FinY	Financial	ES	BBB	Fin_BBB	2.307.692	2,31%	5,5	4,95	30,25	54,50	143,91	-	157.156,43
F3	FinX	Financial	IT	BB	Fin_BB	2.307.692	2,31%	6,1	5,49	37,21	70,13	192,77	-	228.271,37
F4	FinW	Financial	DE	BBB	Fin_BBB	2.307.692	2,31%	4,1	3,69	16,81	54,50	143,91	-	118.524,54
F5	FinV	Financial	NL	A	Fin_A	2.307.692	2,31%	9,3	8,37	86,49	26,32	84,67	-	156.393,35
F6	FinU	Financial	IT	BB	Fin_BB	2.307.692	2,31%	9,6	8,64	92,16	70,13	192,77	-	344.839,83
													-	**5.092.531,55**

Source: Own work

Table 6: Synthetic Portfolio 3

Bond ID	Issuer	Sector	Country	Rating	Šifra	Market Value (EUR)	Weight	Maturity (yrs)	Modified Duration (proxy)	Convexity (proxy)	SpreadVol	CR shock	CR shock PnL
G1	GovDE	Government	DE	AAA	Germany	10.256.410	10,26%	9,10	8,19	82,81	14,13	37,68	- 310.478,61
G2	GovDE	Government	DE	AAA	Germany	8.791.209	8,79%	3,70	3,33	13,69	14,13	37,68	- 109.451,36
G3	GovFR	Government	FR	AA	France	8.058.608	8,06%	14,10	12,69	198,81	15,40	41,19	- 407.585,48
G4	GovFR	Government	FR	AA	France	7.326.007	7,33%	5,30	4,77	28,09	15,40	41,19	- 142.175,91
G5	GovNL	Government	NL	AAA	Netherlands	6.593.406	6,59%	1,80	1,62	3,24	13,95	39,98	- 42.536,89
G6	GovNL	Government	NL	AAA	Netherlands	5.494.505	5,49%	11,60	10,44	134,56	13,95	39,98	- 223.446,03
G7	GovAT	Government	AT	AA	Austria	5.128.205	5,13%	6,90	6,21	47,61	18,26	45,36	- 141.927,01
G8	GovAT	Government	AT	AA	Austria	4.761.905	4,76%	19,80	17,82	392,04	18,26	45,36	- 365.668,25
G9	GovSI	Government	SI	A	Slovenia	4.395.604	4,40%	4,20	3,78	17,64	52,56	59,05	- 96.757,14
G10	GovSI	Government	SI	A	Slovenia	4.029.304	4,03%	10,00	9,00	100,00	52,56	59,05	- 207.102,30
G11	GovIT	Government	IT	A	Italy	3.663.004	3,66%	7,40	6,66	54,76	59,35	191,40	- 430.190,60
G12	GovIT	Government	IT	A	Italy	3.296.703	3,30%	2,40	2,16	5,76	59,35	191,40	- 132.815,40
G13	GovBE	Government	BE	AA	Belgium	2.930.403	2,93%	15,30	13,77	234,09	25,13	31,89	- 125.177,09
G14	GovBE	Government	BE	AA	Belgium	2.564.103	2,56%	8,60	7,74	73,96	25,13	31,89	- 62.316,92
G15	GovIE	Government	IE	AA	Ireland	2.564.103	2,56%	12,20	10,98	148,84	81,07	39,78	- 108.963,06
G16	GovIE	Government	IE	AA	Ireland	2.197.802	2,20%	4,90	4,41	24,01	81,07	39,78	- 38.133,73
F1	FinZ	Financial	AT	A	Fin_A	3.663.004	3,66%	17,60	15,84	309,76	26,32	84,67	- 450.612,58
F2	FinY	Financial	AT	A	Fin_A	2.930.403	2,93%	5,80	5,22	33,64	26,32	84,67	- 125.987,25
F3	FinX	Financial	DE	AA	Fin_AA	2.564.103	2,56%	3,10	2,79	9,61	20,50	50,44	- 35.770,55
C1	CorpA	Corporate	ES	A	Corp_A	2.197.802	2,20%	13,00	11,70	169,00	21,38	60,50	- 148.768,66
C2	CorpB	Corporate	DE	A	Corp_A	1.831.502	1,83%	6,20	5,58	38,44	21,38	60,50	- 60.539,06
C3	CorpC	Corporate	FR	AA	Corp_AA	1.831.502	1,83%	11,00	9,90	121,00	17,79	48,63	- 85.548,53
C4	CorpD	Corporate	FR	AA	Corp_AA	1.465.209	1,47%	9,70	8,73	94,09	17,79	48,63	- 60.569,34
C5	CorpE	Corporate	DE	A	Corp_A	1.465.194	1,47%	8,00	7,20	64,00	21,38	60,50	- 62.105,51
													- 3.974.627,28

Source: Own work

Table 7: Synthetic Portfolio 4

Bond ID	Issuer	Sector	Country	Rating	Šifra	Market Value (EUR)	Weight	Maturity (yrs)	Modified Duration (proxy)	Convexity (proxy)	SpreadVol	CR shock	CR shock PnL
F1	FinZ	Financial	DE	A	Fin_A	7.500.000	7,50%	3,5	3,15	12,25	26,32	84,67	- 196.745,32
F2	FinZ	Financial	DE	BBB	Fin_BBB	5.000.000	5,00%	6,2	5,58	38,44	54,50	143,91	- 381.595,82
F3	FinY	Financial	FR	A	Fin_A	6.250.000	6,25%	4	3,60	16,00	26,32	84,67	- 186.928,41
F4	FinY	Financial	FR	BBB	Fin_BBB	4.375.000	4,38%	6,8	6,12	46,24	54,50	143,91	- 364.360,63
F5	FinX	Financial	NL	AA	Fin_AA	6.875.000	6,88%	3,7	3,33	13,69	20,50	50,44	- 114.278,79
F6	FinX	Financial	NL	BB	Fin_BB	3.750.000	3,75%	6,7	6,03	44,89	70,13	192,77	- 404.626,04
F7	FinW	Financial	ES	BBB	Fin_BBB	5.625.000	5,63%	4,5	4,05	20,25	54,50	143,91	- 316.040,94
F8	FinW	Financial	ES	BB	Fin_BB	3.125.000	3,13%	7,2	6,48	51,84	70,13	192,77	- 360.261,39
F9	FinV	Financial	IT	BBB	Fin_BBB	5.625.000	5,63%	3,9	3,51	15,21	54,50	143,91	- 275.265,05
F10	FinV	Financial	IT	BB	Fin_BB	3.125.000	3,13%	7,8	7,02	60,84	70,13	192,77	- 387.565,79
F11	FinU	Financial	FR	A	Fin_A	5.000.000	5,00%	3,9	3,51	15,21	26,32	84,67	- 145.874,06
F12	FinU	Financial	FR	BBB	Fin_BBB	3.750.000	3,75%	7,6	6,84	57,76	54,50	143,91	- 346.690,55
C1	CorpA	Corporate	DE	A	Corp_A	5.625.000	5,63%	8	7,20	64,00	21,38	60,50	- 238.428,14
C2	CorpB	Corporate	DE	A	Corp_A	5.000.000	5,00%	6,6	5,94	43,56	21,38	60,50	- 175.692,76
C3	CorpC	Corporate	FR	AA	Corp_AA	4.375.000	4,38%	5,2	4,68	27,04	17,79	48,63	- 98.163,72
C4	CorpD	Corporate	NL	A	Corp_A	4.375.000	4,38%	9	8,10	81,00	21,38	60,50	- 207.904,06
C5	CorpE	Corporate	IT	BBB	Corp_BBB	3.750.000	3,75%	7,1	6,39	50,41	35,60	97,04	- 223.635,08
G1	DE_Gov	Government	DE	AAA	Germany	6.250.000	6,25%	10,6	9,54	112,36	14,13	37,68	- 219.678,94
G2	FR_Gov	Government	FR	AA	France	5.625.000	5,63%	8,4	7,56	70,56	15,40	41,19	- 171.773,10
G3	FI_Gov	Government	FI	A	Finland	5.000.000	5,00%	12,6	11,34	158,76	12,34	36,75	- 203.028,25
													- 5.018.536,84

Source: Own work

Table 8: Synthetic Portfolio 5

Bond ID	Issuer	Sector	Country	Rating	Šifra	Market Value (EUR)	Weight	Maturity (yrs)	Modified Duration (proxy)	Convexity (proxy)	SpreadVol	CR shock	CR shock PnL
G1	DE_Gov	Government	DE	AAA	Germany	8.000.000	10,60	8,00%	9,54	112,36	14,13	37,68	- 281.189,04
G2	FR_Gov	Government	FR	AA	France	1.200.000	2,10	1,20%	1,89	4,41	15,40	41,19	- 9.295,88
G3	NL_Gov	Government	NL	AAA	Netherlands	2.500.000	13,20	2,50%	11,88	174,24	13,95	39,98	- 115.269,07
G4	FI_Gov	Government	FI	AA	Finland	3.000.000	5,00	3,00%	4,50	25,00	12,34	36,75	- 49.110,01
G5	AT_Gov	Government	AT	AAA	Austria	3.800.000	7,90	3,80%	7,11	62,41	18,26	45,36	- 120.100,88
G6	DE_Gov	Government	DE	AAA	Germany	4.200.000	2,30	4,20%	2,07	5,29	14,13	37,68	- 32.600,84
G7	FR_Gov	Government	FR	AA	France	4.500.000	12,60	4,50%	11,34	158,76	15,40	41,19	- 204.108,04
G8	NL_Gov	Government	NL	AAA	Netherlands	4.800.000	1,20	4,80%	1,08	1,44	13,95	39,98	- 20.672,20
G9	SI_Gov	Government	SI	A	Slovenia	5.500.000	9,40	5,50%	8,46	88,36	52,56	59,05	- 266.273,73
G10	IT_Gov	Government	IT	A	Italy	6.000.000	15,10	6,00%	13,59	228,01	59,35	191,40	- 1.310.088,32
G11	DE_Gov	Government	DE	AAA	Germany	6.500.000	3,90	6,50%	3,51	15,21	14,13	37,68	- 85.263,96
G12	FR_Gov	Government	FR	AA	France	7.000.000	8,60	7,00%	7,74	73,96	15,40	41,19	- 218.749,54
G13	NL_Gov	Government	NL	AAA	Netherlands	3.200.000	2,50	3,20%	2,25	6,25	13,95	39,98	- 28.628,25
C1	CorpA	Corporate	DE	BB	Corp_BB	2.800.000	11,60	2,80%	10,44	134,56	95,58	254,71	- 622.346,48
C2	CorpB	Corporate	FR	BBB	Corp_BBB	1.500.000	4,80	1,50%	4,32	23,04	35,60	97,04	- 61.255,70
C3	CorpC	Corporate	IT	BB	Corp_BB	1.000.000	13,20	1,00%	11,88	174,24	95,58	254,71	- 246.073,13
C4	CorpD	Corporate	ES	BBB	Corp_BBB	5.000.000	9,10	5,00%	8,19	82,81	35,60	97,04	- 377.889,73
C5	CorpE	Corporate	BE	BB	Corp_BB	4.000.000	12,70	4,00%	11,43	161,29	95,58	254,71	- 955.248,00
C6	CorpF	Corporate	PL	BBB	Corp_BBB	3.500.000	5,50	3,50%	4,95	30,25	35,60	97,04	- 163.139,44
C7	CorpG	Corporate	PT	BB	Corp_BB	2.000.000	7,60	2,00%	6,84	57,76	95,58	254,71	- 310.968,27
C8	CorpH	Corporate	GR	BB	Corp_BB	3.500.000	2,30	3,50%	2,07	5,29	95,58	254,71	- 178.530,16
C9	CorpI	Corporate	IE	BBB	Corp_BBB	4.000.000	10,50	4,00%	9,45	110,25	35,60	97,04	- 346.052,67
C10	CorpJ	Corporate	SK	BB	Corp_BB	500.000	12,60	0,50%	11,34	158,76	95,58	254,71	- 118.670,16
C11	CorpK	Corporate	HU	BB	Corp_BB	6.000.000	1,60	6,00%	1,44	2,56	95,58	254,71	- 215.085,38
C12	CorpL	Corporate	EE	BB	Corp_BB	6.000.000	13,20	6,00%	11,88	174,24	95,58	254,71	- 1.476.438,78
													- 7.813.047,67

Source: Own work

Appendix 2: Data in Advanced Measurement Approach – R code

```
## THE DATA - 5 PORTFOLIOS

portfolio1 <- data.frame(
  BondID = paste0("B", 1:10),
  Issuer = c(
"IndusCo_A","IndusCo_A","IndusCo_A","IndusCo_B","IndusCo_C","IndusCo_D","IndusCo_E","IndusC
o_F","BankCo_X","BankCo_Y"
  ),
  Sector = c(
    rep("Corporate", 8),
    rep("Financial", 2)
  ),
  Country = c(
    "DE","DE","DE","FR","IT","ES","DE","FR","UK","UK"
  ),
  Rating = c(
    "BBB","BBB-","BB+","BBB","BB","BB","BBB-","BB+","BBB","BBB-"
  ),
  MV = c(
    25000000, 12000000, 13000000, 8000000,  7000000,  6000000, 5000000, 4000000, 8000000,
12000000
  ),
  Maturity = c(
    5.2,  8.4, 10.0, 6.1,  7.0,  4.8,  9.2,  3.9, 7.8,  9.5
  ),
  MD = c(
    4.68, 7.56, 9.00, 5.49, 6.30, 4.32, 8.28, 3.51, 7.02, 8.55
  ),
  Convexity = c(
    27.04, 70.56, 100.00, 37.21, 49.00, 23.04, 84.64, 15.21, 60.84, 90.25
  ),
  SpreadVol = c(
    35.60, 35.60, 95.58, 35.60, 95.58, 95.58, 35.60, 95.58, 54.50, 54.50
  )
)

portfolio2 <- data.frame(
  BondID = paste0("B", 1:30),
  Issuer = c(
"DE_Gov1","DE_Gov2","FR_Gov1","FR_Gov2","NL_Gov","AT_Gov","SK_Gov","IT_Gov","BE_Gov","FI_Go
v1","FI_Gov2","IE_Gov","Siemens","Volkswagen","BASF","Allianz","BMW","TotalEnergies","Shell
","Enel","Telefonica","Airbus","Philips","Iberdrola","BNP","Santander","Intesa","DeutscheBa
nk","ING","UniCredit"
  ),
  Sector = c(
    rep("Government", 12),
    rep("Corporate", 12),
    rep("Financial", 6)
  ),
  Country = c(

"DE","DE","FR","FR","NL","AT","SK","IT","BE","FI","FI","IE","DE","DE","DE","DE","DE","FR","
NL","IT","ES","FR","NL","ES","FR","ES","IT","DE","NL","IT"
  ),
  Rating = c(
    "AAA","AAA","AA","AA","AAA","AA","A","BBB","AA","AA","AAA","AA",
"A","A","A","AA","A","BBB","A","BBB","BB","A","BBB","BB","A","BBB","BB","BBB","A","BB"
  ),
  MV = c(
5769231, 5384615, 5000000, 5000000, 4615385, 4230769, 3846154, 3846154, 3846154, 1538461.5,
1538461.5, 2692308, 3846154, 3846154, 3846154, 3461538, 3461538, 3076923, 3076923, 3076923,
2692308, 2692308, 2692308, 2692308,2692308, 2307692, 2307692, 2307692, 2307692, 2307692
  ),
  Maturity = c(
    8.6, 7.4, 5, 5, 12, 3.8, 8.7, 9.5, 15.1, 4.5, 4.5, 20,3.7, 4.2, 6.9, 8.4, 4, 10.2, 6.2,
8.1, 3, 4.8, 7.4, 12.6, 3.6, 5.5, 6.1, 4.1, 9.3, 9.6
  ),
  MD = c(
```

```
    7.74, 6.66, 4.50, 4.50, 10.80, 3.42, 7.83, 8.55, 13.59, 4.05, 4.05, 18.00, 3.33, 3.78,
6.21, 7.56, 3.60, 9.18, 5.58, 7.29, 2.70, 4.32, 6.66, 11.34,
    3.24, 4.95, 5.49, 3.69, 8.37, 8.64
  ),

  Convexity = c(
    73.96, 54.76, 25.00, 25.00, 144.00, 14.44, 75.69, 90.25, 228.01, 20.25, 20.25, 400.00,
13.69, 17.64, 47.61, 70.56, 16.00, 104.04, 38.44,   65.61, 9.00, 23.04, 54.76, 158.76,
12.96, 30.25, 37.21, 16.81, 86.49, 92.16
  ),
  SpreadVol = c(
    14.13, 14.13, 15.40, 15.40, 13.95, 18.26, 36.09, 59.35, 25.13, 12.34, 12.34, 81.07,
21.38, 21.38, 21.38, 17.79, 21.38, 35.60, 21.38, 35.60, 95.58, 21.38, 35.60, 95.58, 21.38,
54.50, 70.13, 54.50, 26.32, 70.13
  )
)

portfolio3 <- data.frame(
  BondID = paste0("B", 1:24),
  Issuer = c(
"GovDE","GovDE","GovFR","GovFR","GovNL","GovNL","GovAT","GovAT","GovES","GovES","GovIT","Go
vIT","GovBE","GovBE","GovIE","GovIE", "FinAT","FinAT","FinDE",
"CorpES","CorpDE","CorpFR","CorpFR","CorpDE"
  ),
  Sector = c(
    rep("Government", 16),
    rep("Financial", 3),
    rep("Corporate", 5)
  ),
  Country = c(
"DE","DE","FR","FR","NL","NL","AT","AT","SI","SI","IT","IT","BE","BE","IR","IR",
"AT","AT","DE",
"ES","DE","FR","FR","DE"
  ),
  Rating = c(
"AAA","AAA","AA","AA","AAA","AAA","AA","AA","A","A","A","A","AA","AA","AA","AA",
"A","A","AA","A","A","AA","AA","A"
  ),
  MV = c(
    10256410, 8791209, 8058608, 7326007, 6593406, 5494505, 5128205, 4761905, 4395604,
4029304, 3663004, 3296703, 2930403, 2564103, 2564103, 2197802, 3663004, 2930403, 2564103,
2197802, 1831502, 1831502, 1465209, 1465194
  ),
  Maturity = c(
    9.10, 3.70, 14.10, 5.30, 1.80, 11.60, 6.90, 19.80, 4.20, 10.00, 7.40, 2.40, 15.30,
8.60, 12.20, 4.90, 17.60, 5.80, 3.10, 13.00, 6.20, 11.00, 9.70, 8.00
  ),
  MD = c(
    8.19, 3.33, 12.69, 4.77, 1.62, 10.44, 6.21, 17.82, 3.78, 9.00, 6.66, 2.16, 13.77, 7.74,
10.98, 4.41, 15.84, 5.22, 2.79, 11.70, 5.58, 9.90, 8.73, 7.20
  ),
  Convexity = c(
    82.81, 13.69, 198.81, 28.09, 3.24, 134.56, 47.61, 392.04, 17.64, 100.00, 54.76, 5.76,
234.09, 73.96, 148.84, 24.01, 309.76, 33.64, 9.61, 169.00, 38.44, 121.00, 94.09, 64.00
  ),
  SpreadVol = c(
    14.13, 14.13, 15.40, 15.40, 13.95, 13.95, 18.26, 18.26, 52.56, 52.56, 59.35, 59.35,
25.13, 25.13, 81.07, 81.07, 26.32, 26.32, 20.50,
    21.38, 21.38, 17.79, 17.79, 21.38
  )
)

portfolio4 <- data.frame(
  BondID = paste0("B", 1:20),
  Issuer = c(
    "DB_Senior", "DB_Sub", "BNP_Senior", "BNP_Sub", "ING_Senior", "ING_Sub", "SAN_Senior",
"SAN_Sub", "UCG_Senior", "UCG_Sub", "AXA_Senior", "AXA_Sub", "Siemens", "Volkswagen",
"TotalEnergies", "Shell", "Enel", "DE_Gov", "FR_Gov", "FI_Gov"
  ),
  Sector = c(
    rep("Financial", 12),
    rep("Corporate", 5),
    rep("Government", 3)
```

```
  ),
  Country = c(
    "DE","DE","FR","FR","NL","NL","ES","ES","IT","IT", "FR","FR","DE","DE","FR","NL","IT",
"DE","FR","FI"
  ),
  Rating = c(
    "A", "BBB", "A", "BBB", "AA", "BB", "BBB", "BB", "BBB", "BB", "A", "BBB", "A", "A",
"AA", "A", "BBB", "AAA", "AA", "A"
  ),
  MV = c(
    7500000, 5000000, 6250000, 4375000, 6875000, 3750000, 5625000, 3125000, 5625000,
3125000, 5000000, 3750000, 5625000, 5000000, 4375000, 4375000, 3750000, 6250000, 5625000,
5000000
  ),
  Maturity = c(
    3.5, 6.2, 4.0, 6.8, 3.7, 6.7, 4.5, 7.2, 3.9, 7.8, 3.9, 7.6, 8.0, 6.6, 5.2, 9.0, 7.1,
10.6, 8.4, 12.6
  ),
  MD = c(
    3.15, 5.58, 3.60, 6.12, 3.33, 6.03, 4.05, 6.48, 3.51, 7.02, 3.51, 6.84, 7.20, 5.94,
4.68, 8.10, 6.39, 9.54, 7.56, 11.34
  ),
  Convexity = c(
    12.25, 38.44, 16.00, 46.24, 13.69, 44.89, 20.25, 51.84, 15.21, 60.84, 15.21, 57.76,
64.00, 43.56, 27.04, 81.00, 50.41, 112.36, 70.56, 158.76
  ),
  SpreadVol = c(
    26.32, 54.50, 26.32, 54.50, 20.50, 70.13, 54.50, 70.13, 54.50, 70.13, 26.32, 54.50,
21.38, 21.38, 17.79, 21.38, 35.60, 14.13, 15.40, 12.34
  )
)

portfolio5 <- data.frame(
  BondID = paste0("B", 1:25),
  Issuer = c(
"DE_Gov_Short_1","FR_Gov_Short_1","NL_Gov_Short_1","FI_Gov_Short_1","AT_Gov_Short_1","Gov_M
ed_1","Gov_Med_2","Gov_Med_3","Gov_Med_4","Gov_Med_5","Gov_Short_Extra_1","Gov_Med_Extra_1"
,"Gov_Short_Extra_2","Corp_Long_1","Corp_Long_2","Corp_Long_3","Corp_Long_4","Corp_Long_5",
"Corp_Long_6","Corp_Long_7","Corp_Long_8","Corp_Long_9","Corp_Long_10","Corp_Long_Extra_1",
"Corp_Long_Extra_2"
  ),
  Sector = c(
    rep("Government", 13),
    rep("Corporate", 12)
  ),
  Country = c(
    "DE", "FR", "NL","FI", "AT", "DE", "FR", "NL", "SI", "IT", "DE", "FR", "NL", "DE",
"FR", "IT", "ES", "BE", "PL", "PT", "GR", "IE", "SK", "HU", "EE"
  ),
  Rating = c(
    "AAA", "AA", "AAA", "AA", "AAA", "AAA", "AA", "AAA", "A", "A", "AAA", "AA", "AAA",
"BB", "BBB", "BB", "BBB", "BB", "BBB", "BB", "BB", "BBB", "BB", "BB", "BB"
  ),
  MV = c(
    8000000, 1200000, 2500000, 3000000, 3800000, 4200000, 4500000, 4800000, 5500000,
6000000, 6500000, 7000000, 3200000,
    2800000, 1500000, 1000000, 5000000, 4000000, 3500000, 2000000, 3500000, 4000000,
500000, 6000000, 6000000
  ),
  Maturity = c(
    10.60, 2.10, 13.20, 5.00, 7.90, 2.30, 12.60, 1.20, 9.40, 15.10, 3.90, 8.60, 2.50,
11.60, 4.80, 13.20, 9.10, 12.70, 5.50, 7.60, 2.30, 10.50, 12.60, 1.60, 13.20
  ),
  MD = c(
    9.54, 1.89, 11.88, 4.50, 7.11, 2.07, 11.34, 1.08, 8.46, 13.59, 3.51, 7.74, 2.25, 10.44,
4.32, 11.88, 8.19, 11.43, 4.95, 6.84, 2.07, 9.45, 11.34, 1.44, 11.88
  ),
  Convexity = c(
    112.36, 4.41, 174.24, 25.00, 62.41, 5.29, 158.76, 1.44, 88.36, 228.01, 15.21, 73.96,
6.25, 134.56, 23.04, 174.24, 82.81, 161.29, 30.25, 57.76, 5.29, 110.25, 158.76, 2.56,
174.24
    ),
  SpreadVol = c(
```

```
    14.13, 15.40, 13.95, 12.34, 18.26, 14.13, 15.40, 13.95, 52.56, 59.35, 14.13, 15.40,
13.95, 95.58, 35.60, 95.58, 35.60, 95.58, 35.60, 95.58, 95.58, 35.60, 95.58, 95.58, 95.58
  )
)
```

Appendix 3: Monte Carlo Simulation - R code

```
## THE SIMULATION
set.seed(12345) #to eliminate randomness

library(MASS)   # mvrnorm
library(Matrix) # nearPD

run_csrbb_mc <- function(portfolio,
                         N = 200000,
                         conf = 0.99,
                         concentration_sensitive = TRUE,
                         eigen_floor = 1e-4,
                         param_scale = 1,
                         corr_scale = 1,
                         verbose = TRUE) {

  stopifnot(is.data.frame(portfolio))
  req_cols <- c("MV","MD","Convexity","SpreadVol","Sector","Country","Rating","Issuer")
  missing_cols <- setdiff(req_cols, names(portfolio))
  if(length(missing_cols) > 0) stop("Portfolio missing columns: ", paste(missing_cols,
collapse = ", "))

  n <- nrow(portfolio)

  ## normalization
  portfolio$Sector  <- as.character(portfolio$Sector)
  portfolio$Country <- as.character(portfolio$Country)
  portfolio$Issuer  <- as.character(portfolio$Issuer)
  portfolio$Rating  <- toupper(as.character(portfolio$Rating))
  portfolio$Rating  <- gsub("\\+", "", portfolio$Rating)
  portfolio$Rating  <- gsub("-", "", portfolio$Rating)

  rating_map_names <- c("AAA","AA","A","BBB","BB")
  portfolio$Rating[!portfolio$Rating %in% rating_map_names] <- "BB"

  portfolio$MV <- as.numeric(portfolio$MV)
  portfolio$MD <- as.numeric(portfolio$MD)
  portfolio$Convexity <- as.numeric(portfolio$Convexity)
  portfolio$SpreadVol <- as.numeric(portfolio$SpreadVol)

  ##weights
  portfolio$Weight <- portfolio$MV / sum(portfolio$MV)

## metrics (concentration measures of the portfolio: overall, across sectors, countries,
issuers)
  HHI_portfolio <- sum((portfolio$Weight)^2)
  sec_share <- tapply(portfolio$Weight, portfolio$Sector, sum)
  sector_HHI <- sum((sec_share)^2)
  cty_share <- tapply(portfolio$Weight, portfolio$Country, sum)
  country_HHI <- sum((cty_share)^2)
  iss_share <- tapply(portfolio$Weight, portfolio$Issuer, sum)
  issuer_HHI <- sum((iss_share)^2)

  if(verbose){cat(sprintf("n=%d | HHI=%.4f | sector_HHI=%.4f | country_HHI=%.4f |
issuer_HHI=%.4f\n",
                n, HHI_portfolio, sector_HHI, country_HHI, issuer_HHI))}

## factor loadings//structure (construction of multi-factor correlation structure)
  market_loading <- rep(0.30, n) #(baseline exposure to overall market conditions)

  sector_baseline <- c("Government" = 0.20, "Corporate" = 0.35, "Financial" = 0.40)
#(different sensitivity per sector)
  sector_load <- sector_baseline[portfolio$Sector]
```

```
 # countries <- unique(portfolio$Country)
 # country_levels <- seq(0.15, 0.45, length.out = length(countries))
 # names(country_levels) <- countries
 # country_load <- country_levels[portfolio$Country]

  cty_risk <- tapply(portfolio$SpreadVol, portfolio$Country, mean, na.rm = TRUE) #(measures
average spread volatility per country)

  rescale01 <- function(x){
    if(length(unique(x)) == 1) return(rep(0.5, length(x)))
    (x - min(x)) / (max(x) - min(x))
  }  #(normalization between 0-1)

  cty_scaled <- rescale01(cty_risk) #(higher spread vol -> higher factor loadings)
  country_levels <- 0.15 + cty_scaled * (0.45 - 0.15)
  country_load <- country_levels[portfolio$Country]

  rating_map_vals <- c("AAA"=0.05,"AA"=0.10,"A"=0.18,"BBB"=0.28,"BB"=0.40) #(lower rating -
> higher risk loading)
  rating_load <- rating_map_vals[portfolio$Rating]

  issuer_load <- rep(0.0, n) # (issuer specific factor to capture concentration risk)
  dup_issuers <- names(which(table(portfolio$Issuer) > 1))
  if(length(dup_issuers) > 0) issuer_load[portfolio$Issuer %in% dup_issuers] <- 0.25

  # concentration-sensitive (increases loadings if portfolio is concentrated)
  if(concentration_sensitive){
    scale_sector  <- 1 + 1.0 * pmin(1, sector_HHI / 0.3)
    scale_country <- 1 + 0.8 * pmin(1, country_HHI / 0.3)
    scale_issuer  <- 1 + 1.5 * pmin(1, issuer_HHI / 0.15)
    sector_load  <- sector_load * scale_sector
    country_load <- country_load * scale_country
    rating_load  <- rating_load * (1 + 0.5 * pmin(1, HHI_portfolio / 0.12))
    issuer_load  <- issuer_load * scale_issuer
  }

  L <- cbind
    Market  = market_loading,
    Sector  = sector_load,
    Country = country_load,
    Rating  = rating_load,
    Issuer  = issuer_load
  ) #(matrix defines how each instrument is exposed to each risk factor)

  L[L < 0] <- 0
  L[L > 1] <- 1

  factor_sd <- param_scale * c(Market = 1.00, Sector = 0.80, Country = 0.70, Rating = 0.60,
Issuer = 0.50) #(hierarchy of risk drivers, market-wide effects dominate)

  factor_corr <- matrix(c(          #(defines how risk factors interacts with each other)
    1.00, 0.25, 0.20, 0.15, 0.00,
    0.25, 1.00, 0.20, 0.20, 0.00,
    0.20, 0.20, 1.00, 0.15, 0.00,
    0.15, 0.20, 0.15, 1.00, 0.00,
    0.00, 0.00, 0.00, 0.00, 1.00
  ), 5, 5, byrow = TRUE)

  if(concentration_sensitive){
    conc_mult <- 1 + 0.6 * pmin(1, HHI_portfolio / 0.20)
    factor_corr <- factor_corr * conc_mult
  }

  factor_corr <- factor_corr * corr_scale #(adding concentrations -> stronger correlation)

    factor_corr[factor_corr > 0.99] <- 0.99
    diag(factor_corr) <- 1
  }

  Fcov <- diag(factor_sd) %*% factor_corr %*% diag(factor_sd) # factor covariance matrix
  pre_cov <- L %*% Fcov %*% t(L)

  ## IDIOSYNCRATIC RISK
```

```
  diag_pre <- diag(pre_cov) #(exclude variance already explained by factors)
  idio_floor <- 0.30
  if(concentration_sensitive){
    idio_floor <- pmax(0.10, 0.30 - 0.15 * pmin(1, HHI_portfolio / 0.20))
  }
  idiosyn <- pmax(idio_floor, 1 - diag_pre) #(add remaining variance as idiosyncratic risk)
  psi <- diag(idiosyn, n) #(add idiosyncratic variance to covariance matrix)
  Sigma_model <- pre_cov + psi

  Dinv <- diag(1 / sqrt(pmax(1e-12, diag(Sigma_model)))) #(narmalization of covariance
matrix -> correlation matrix)
  corr_model <- Dinv %*% Sigma_model %*% Dinv

  ##"structure bumps"
  corr_struct <- corr_model
  bump_weights <- list(sector = 0.06 * param_scale, country = 0.04 * param_scale, rating =
0.03 * param_scale, issuer = 0.10 * param_scale)
  conc_mult2 <- 1 + 0.8 * pmin(1, HHI_portfolio / 0.20) #(more concentration -> stronger
correlation)

  max_pair_bump <- 0.25   # stress cap on total similarity bump

  for(i in 1:n){
    for(j in 1:n){
      if(i == j) next
      bump <- 0
      if(portfolio$Sector[i] == portfolio$Sector[j])  bump <- bump + bump_weights$sector
      if(portfolio$Country[i] == portfolio$Country[j]) bump <- bump + bump_weights$country
      if(portfolio$Rating[i] == portfolio$Rating[j])  bump <- bump + bump_weights$rating
      if(portfolio$Issuer[i] == portfolio$Issuer[j])  bump <- bump + bump_weights$issuer

      bump <- min(bump, max_pair_bump) # caps total bump per pair

      corr_struct[i,j] <- corr_struct[i,j] + bump * conc_mult2
    }
  } # (additional correlation between instruments that share structural characteristics:
sector, country, rating, issuer)

  corr_struct[corr_struct > 0.995] <- 0.995
  corr_struct[corr_struct < -0.995] <- -0.995 #(staying inside realistic boarders)

  ##to nearest PD (use corr=TRUE to enforce diag=1) (fix the matrix to be usable)
  pd_obj <- nearPD(corr_struct, corr = TRUE)
  corr_final <- as.matrix(pd_obj$mat)
  diag(corr_final) <- 1

##eigenvalues (decompose correlation matrix into eigenvalues)
  eig <- eigen(corr_final, symmetric = TRUE)
  if(min(eig$values) < eigen_floor){
    eig$values[eig$values < eigen_floor] <- eigen_floor
    corr_final <- eig$vectors %*% diag(eig$values) %*% t(eig$vectors)
    # rescale to correlation matrix
    Dinv2 <- diag(1 / sqrt(diag(corr_final)))
    corr_final <- Dinv2 %*% corr_final %*% Dinv2
    diag(corr_final) <- 1
    # final nearPD safety
    corr_final <- as.matrix(nearPD(corr_final, corr = TRUE)$mat)
    diag(corr_final) <- 1
  }

  if(verbose){
    min_eig <- min(eigen(corr_final, symmetric = TRUE)$values)
    avg_pair_corr <- mean(corr_final[upper.tri(corr_final)])
    cat(sprintf("corr_final: min_eig=%.6g | avg_pair_corr=%.4f\n", min_eig, avg_pair_corr))
  }

##MC simulation (simulate many correlated spread scanarios using final correlation matrix)
  Z <- mvrnorm(n = N, mu = rep(0, n), Sigma = corr_final)
  shocks_bps <- sweep(Z, 2, portfolio$SpreadVol, "*")
  shock_decimal <- shocks_bps / 10000

#PnL (translating spread changes into valuations changes: change in fairvalue)
  DeltaPV <- matrix(0, N, n)
```

```
  for(i in seq_len(n)){
    s <- shock_decimal[, i]
    DeltaPV[, i] <- portfolio$MV[i] * (-portfolio$MD[i] * s + 0.5 * portfolio$Convexity[i]
* (s^2))
  }
  PORTFOLIO_dPV <- rowSums(DeltaPV) #(sum all instruments -> portfolio loss)
  loss_vec <- -PORTFOLIO_dPV

##VaR & ES
  VaR_99 <- as.numeric(quantile(loss_vec, conf))
  ES_99  <- mean(loss_vec[loss_vec >= VaR_99])

 # standalone_VaR <- sapply(seq_len(n), function(i){
 #   s <- rnorm(N, 0, portfolio$SpreadVol[i]) / 10000
 #   d <- portfolio$MV[i] * (-portfolio$MD[i] * s + 0.5 * portfolio$Convexity[i] * s^2)
 #   as.numeric(quantile(-d, conf))
 # })

  standalone_VaR <- sapply(seq_len(n), function(i){ #))risk of each instrument separately)
    s <- shock_decimal[, i]
    d <- portfolio$MV[i] * (-portfolio$MD[i] * s + 0.5 * portfolio$Convexity[i] * s^2)
    as.numeric(quantile(-d, conf))
  })

  div_ratio <- sum(standalone_VaR) / VaR_99 #("how much risk reduction is achieved through
diversification")

  worst_idx <- which(loss_vec >= VaR_99)
  if(length(worst_idx) < max(10, round(0.01 * N))){
    worst_idx <- order(loss_vec, decreasing = TRUE)[1:max(10, round(0.01 * N))]
  }
  IRC <- -colMeans(DeltaPV[worst_idx, , drop = FALSE]) #(contribution of each instrument to
tail risk)
  IRC_pct <- IRC / sum(IRC)

## RETURN
  result <- list(
    VaR_99 = VaR_99,
    ES_99  = ES_99,
    Diversification_Ratio = div_ratio,
    Standalone_VaR = standalone_VaR,
    IRC = IRC,
    IRC_pct = IRC_pct,
    loss_vec = loss_vec,
    DeltaPV = DeltaPV,
    corr_final = corr_final,
    diagnostics = list(
      HHI = HHI_portfolio,
      sector_HHI = sector_HHI,
      country_HHI = country_HHI,
      issuer_HHI = issuer_HHI,
      avg_pair_corr = mean(corr_final[upper.tri(corr_final)]),
      min_eig = min(eigen(corr_final, symmetric = TRUE)$values)
    )
  )

  if(verbose){
    cat("VaR 99% =", round(result$VaR_99/1e6, 3), "million EUR\n")
    cat("ES  99% =", round(result$ES_99/1e6, 3), "million EUR\n")
    cat("Diversification Ratio =", round(result$Diversification_Ratio, 3), "\n\n")
  }

  return(result)
}


run_sensitivity <- function(portfolio, N = 200000) {

  scenarios <- list(

    Base = list(param_scale = 1, corr_scale = 1, conc = TRUE),

    Param_low = list(param_scale = 0.5, corr_scale = 1, conc = TRUE),
```

```
    Param_high = list(param_scale = 1.5, corr_scale = 1, conc = TRUE),

    Corr_low = list(param_scale = 1, corr_scale = 0.5, conc = TRUE),
    Corr_high = list(param_scale = 1, corr_scale = 1.5, conc = TRUE),

    No_concentration = list(param_scale = 1, corr_scale = 1, conc = FALSE)
  )

  results <- lapply(names(scenarios), function(name){

    sc <- scenarios[[name]]

    res <- run_csrbb_mc(
      portfolio,
      N = N,
      param_scale = sc$param_scale,
      corr_scale = sc$corr_scale,
      concentration_sensitive = sc$conc,
      verbose = FALSE
    )

    data.frame(
      Scenario = name,
      VaR = res$VaR_99,
      ES = res$ES_99,
      Div_Ratio = res$Diversification_Ratio
    )
  })

  table <- do.call(rbind, results)
  rownames(table) <- NULL

  return(table)
}

## RESULTS
res1 <- run_csrbb_mc(portfolio1)
res2 <- run_csrbb_mc(portfolio2)
res3 <- run_csrbb_mc(portfolio3)
res4 <- run_csrbb_mc(portfolio4)
res5 <- run_csrbb_mc(portfolio5)

table_p1 <- run_sensitivity(portfolio1)
table_p2 <- run_sensitivity(portfolio2)
table_p3 <- run_sensitivity(portfolio3)
table_p4 <- run_sensitivity(portfolio4)
table_p5 <- run_sensitivity(portfolio5)

format_table <- function(tab){
  tab$VaR <- round(tab$VaR / 1e6, 2)
  tab$ES  <- round(tab$ES  / 1e6, 2)
  tab$Div_Ratio <- round(tab$Div_Ratio, 3)
  return(tab)
}

format_table(table_p1)
format_table(table_p2)
format_table(table_p3)
format_table(table_p4)
format_table(table_p5)
```

Appendix 4: Monte Carlo Simulation – R code Results

```
> res1 <- run_csrbb_mc(portfolio1)
n=10 | HHI=0.1336 | sector_HHI=0.6800 | country_HHI=0.3654 | issuer_HHI=0.2898
corr_final: min_eig=9.99935e-05 | avg_pair_corr=0.8987
VaR 99% = 7.863 million EUR
ES  99% = 8.925 million EUR
Diversification Ratio = 1.048

> res2 <- run_csrbb_mc(portfolio2)
```

```
n=30 | HHI=0.0367 | sector_HHI=0.3920 | country_HHI=0.1778 | issuer_HHI=0.0484
corr_final: min_eig=0.0485883 | avg_pair_corr=0.6124
VaR 99% = 4.182 million EUR
ES  99% = 4.726 million EUR
Diversification Ratio = 1.216

> res3 <- run_csrbb_mc(portfolio3)
n=24 | HHI=0.0555 | sector_HHI=0.6894 | country_HHI=0.1564 | issuer_HHI=0.1060
corr_final: min_eig=0.040102 | avg_pair_corr=0.5753
VaR 99% = 3.421 million EUR
ES  99% = 3.895 million EUR
Diversification Ratio = 1.27

> res4 <- run_csrbb_mc(portfolio4)
n=20 | HHI=0.0527 | sector_HHI=0.4420 | country_HHI=0.2209 | issuer_HHI=0.0816
corr_final: min_eig=9.99965e-05 | avg_pair_corr=0.7590
VaR 99% = 3.807 million EUR
ES  99% = 4.34 million EUR
Diversification Ratio = 1.119

> res5 <- run_csrbb_mc(portfolio5)
n=25 | HHI=0.0493 | sector_HHI=0.5208 | country_HHI=0.1035 | issuer_HHI=0.0880
corr_final: min_eig=0.0928781 | avg_pair_corr=0.5813
VaR 99% = 5.943 million EUR
ES  99% = 6.691 million EUR
Diversification Ratio = 1.183


Portfolio  VaR_99   ES_99 DivRatio   AvgCorr        HHI
1        P1 7862786 8924831 1.047795 0.8987281 0.13360000
2        P2 4181860 4726357 1.216280 0.6124251 0.03674556
3        P3 3420872 3894768 1.270153 0.5753185 0.05545492
4        P4 3806935 4340068 1.119486 0.7590281 0.05273438
5        P5 5943221 6691450 1.182844 0.5813003 0.04926400
```

Appendix 5: Monte Carlo Sensitivity Analysis – R code Results

```
> format_table(table_p1)
         Scenario  VaR   ES Div_Ratio
1            Base 7.86 8.89     1.048
2       Param_low 5.38 6.10     1.536
3      Param_high 8.10 9.14     1.017
4        Corr_low 7.72 8.73     1.069
5       Corr_high 7.96 9.04     1.038
6 No_concentration 6.22 7.05     1.324
> format_table(table_p2)
         Scenario  VaR   ES Div_Ratio
1            Base 4.14 4.71     1.225
2       Param_low 2.51 2.85     2.022
3      Param_high 4.75 5.36     1.068
4        Corr_low 3.93 4.44     1.293
5       Corr_high 4.35 4.92     1.169
6 No_concentration 3.26 3.71     1.556
> format_table(table_p3)
         Scenario  VaR   ES Div_Ratio
1            Base 3.44 3.92     1.270
2       Param_low 2.07 2.37     2.103
3      Param_high 4.13 4.70     1.055
4        Corr_low 3.26 3.72     1.336
5       Corr_high 3.65 4.17     1.195
6 No_concentration 2.65 3.02     1.644
> format_table(table_p4)
         Scenario  VaR   ES Div_Ratio
1            Base 3.83 4.37     1.116
2       Param_low 2.39 2.72     1.786
3      Param_high 4.14 4.71     1.037
4        Corr_low 3.70 4.20     1.151
5       Corr_high 3.89 4.44     1.095
6 No_concentration 2.98 3.39     1.433
> format_table(table_p5)
         Scenario  VaR   ES Div_Ratio
1            Base 6.00 6.76     1.178
2       Param_low 3.81 4.31     1.843
```

```
3        Param_high 6.65 7.45      1.057
4          Corr_low 5.71 6.43      1.235
5         Corr_high 6.18 6.96      1.141
6 No_concentration 4.90 5.54      1.437
```