Finance Research Letters 82 (2025) 107501

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Modelling CSRBB under regulatory guidelines☆

Maxime Segal [a,b,*], Kristján Rúnar Kristjánsson [a], Björn Hrannar Björnsson [a]

[a] Íslandsbanki, Risk Modelling & Assessment Dpt., Hagasmári 3, Kópavogur, 201, Iceland
[b] Department of Science and Engineering, Reykjavik University, Menntavegur 1, Reykjavik, 102, Iceland

ARTICLE INFO

JEL classification:
G32
C51
G28
E43

Keywords:
CSRBB
IRRBB
EBA
Banking book
Credit spread
Risk management
Modelling

ABSTRACT

The European Banking Authority (EBA) provides limited standardization for Credit Spread Risk in the Banking Book (CSRBB), delegating its assessment to individual financial institutions. This has led to significant variation in how CSRBB guidelines are interpreted and applied across the banking sector. This study investigates how to model plausible but unlikely credit spread shocks using Principal Component Analysis (PCA), hypothesizing that systemic risk dominates fluctuations across government and corporate bonds. The model aligns with EBA requirements and provides insights to strengthen risk management frameworks.

1. Introduction

Banks face various risks that can affect their financial performance, including changes in interest rates and credit spreads, which are critical for maintaining stability and protecting stakeholders.

Interest Rate Risk in the Banking Book (IRRBB) refers to how changes in interest rates impact a bank's earnings or capital from non-trading activities. Credit Spread Risk in the Banking Book (CSRBB) relates to shifts in the premium required by investors for securities with credit risk compared to risk-free ones (Roncalli, 2020; Pahne and Åkerlund, 2023).

Institutions and regulatory bodies like the Basel Committee on Banking Supervision (BCBS) and the European Banking Authority (EBA) have issued guidelines to manage these risks (Basel Committee on Banking Supervision, 2016; European Banking Authority, 2018). In Europe, recent regulations such as CRD V and CRR2 require banks to assess both IRRBB and CSRBB, but due to a difference in mandate, the part on CSRBB is less standardized (European Banking Authority, 2022), leading to varied interpretations across the banking industry (Lubinska, 2022). In addition, the BCBS definition lacks a prescriptive measurement approach (Roncalli, 2020).

Per EBA, CSRBB consists of two components: (a) The market credit spread, i.e. the credit risk premium required by market participants for a given credit quality, and (b) The market liquidity spread, i.e. the liquidity premium that sparks market appetite for investments and presence of willing buyers and sellers.

In addition, the credit spread includes an idiosyncratic component, representing all the issuer-specific premiums that may arise from diverse factors, such as the issuer's financial health, industry or geographical location. This contrasts with systemic components,

☆ Preliminary findings from this research were presented at the 8th Marcus Evans Banking Book Risk Management Conference, held in Stockholm from September 23 to September 25, 2024, and have since been developed into this research letter. All authors approved the version of the manuscript to be published.

* Corresponding author at: Íslandsbanki, Risk Modelling & Assessment Dpt., Hagasmári 3, Kópavogur, 201, Iceland.
E-mail address: maximees@islandsbanki.is (M. Segal).

https://doi.org/10.1016/j.frl.2025.107501
Received 26 February 2025; Received in revised form 9 April 2025; Accepted 30 April 2025
Available online 15 May 2025

which are influenced by broader market conditions and affect all issuers alike. Importantly, EBA emphasizes that the idiosyncratic spread may be included only if it leads to more conservative results; otherwise, it is excluded. A common mistake is to include it in the measurement, without ensuring that it leads to a more conservative result.

In light of the regulatory requirements on CSRBB, it becomes essential to develop robust models that accurately capture the dynamics of credit spread fluctuations. This study seeks to address an open question highlighted by van den Oever and Ruwaard (2023): how should credit spread shocks be calibrated across different instrument types, particularly between government and corporate bonds? To answer this question, the remainder of the paper is structured as follows: Section 2 examines the interplay between interest rate and credit spread risk, focusing on how to address the research gap in CSRBB modelling. Section 3 introduces a methodology for the calibration of credit spread shocks. This is followed by a presentation of the results and conclusion, in Sections 4 and 5, respectively.

2. Literature review and research gap

EBA emphasizes that CSRBB should address risks distinct from those covered by existing prudential frameworks. For instance, in the case of a performing customer loan, the associated risk is generally covered by IRRBB, as long as the borrower remains solvent and regular payments are being received. However, when a loan becomes credit-impaired and provisions are made, it falls under the scope of credit risk, as there is now an IFRS 9 capital impact (Choudhry, 2023a). The EBA guidelines are actually stating that non-performing exposures should be excluded from the scope of CSRBB (European Banking Authority, 2022).

Defining the yield y as the sum of the pure risk-free rate r_f and credit spread s, such as $y = r_f + s$, fluctuations in credit spreads driven by interest rate shifts primarily affect the fair value of instruments rather than income, as fixed coupon payments remain constant (Choudhry, 2023b). Modelling the amplitude of significant but unlikely shock on the credit spread appears required for a comprehensive risk assessment of the banking book, justifying the need for separated guidelines on both IRRBB and CSRBB (Lubinska, 2022).

Given the requirement that no banking book instrument should be excluded from the scope *ex-ante*, and any exclusion must be documented and justified, the European Banking Federation recommends a decision tree for evaluating credit spread-sensitive positions (European Banking Federation, 2023). Nonetheless, if CSRBB originates from the combination of market credit spread and market liquidity spread that is not addressed by IRRBB (as defined in Section 1), the scope could be narrowed to the non-customer asset side of the banking book, which is most likely made of bond portfolios, held for liquidity.

In 2024, as part of their medium to long-term objectives listed in the IRRBB heatmap, EBA indicated its intent to monitor CSRBB exclusions and provide guidance where needed (European Banking Authority, 2024).

The previously discussed absence of a standardized approach further accentuates the diverse implementation methods observed across the industry, reflected in research papers and banks' Pillar 3 reports, where CSRBB discussions remained minimal despite the December 2023 application date (European Banking Authority, 2022). One notable exception is J.P. Morgan SE, which disclosed an allocation of €318m to cover structural credit spread risk (Morgan, 2024). From this disclosure, we derive a so-called CSRBB-to-IRRBB ratio, which turns to be 48%, underscoring the materiality of CSRBB in the overall interest rate risk profile.

Although CSRBB remains an underexplored research area, two research papers suggest the use of Principal Component Analysis (PCA) to model credit spread shocks, allowing for effectively isolating the idiosyncratic credit spread component and ensuring compliance to regulatory guidelines (van den Oever and Ruwaard, 2023; Boavida, 2022). However, its practical implementation presents challenges. Our paper seeks to address some of the open questions posed for future research in van den Oever and Ruwaard (2023), particularly by understanding how credit spread shocks may differ between instrument types, with a specific focus on government versus corporate bonds.

We hypothesize that the first principal component (PC1) captures the systemic component of credit spreads – common to all issuers – while subsequent components reflect idiosyncratic movements that the EBA excludes from the CSRBB scope. By testing this hypothesis, we aim to provide a more robust and EBA-compliant framework.

3. Data and methodology

Our analysis is based on the following steps:

Overnight Indexed Swaps (OIS) spread time series are fetched from Reuters. OIS represents the closest existing measure to risk-free rate and appears as a natural choice for the computation of credit spread. The data spans from January 2015 to March 2024.

In order to obtain stationary credit spread series, allowing to assess the size of a plausible but unlikely shock, the OIS spread is averaged for a given month and the month-on-month difference is computed. It results in the issuer-specific Month-on-Month (MoM) average credit spread difference.

PCA is a statistical technique used to reduce the dimensionality of a dataset while retaining trends and patterns. In our case, it transforms the original credit spread time series into a new set of variables, the Principal Components (PC), which are uncorrelated and ordered such that the first few retain most of the variance existing in the original credit spreads series.

More precisely, it achieves the following operations: (1) Standardization of the data and construction of a covariance matrix. (2) Eigendecomposition of the covariance matrix to identify the PCs (i.e. the eigenvectors), capturing the direction of maximum variance in the data. The corresponding eigenvalues indicate the magnitude of variance that each PC captures. (3) Selection of the top principal component (i.e. with the highest eigenvalue), later used as a proxy for the systematic credit spread component

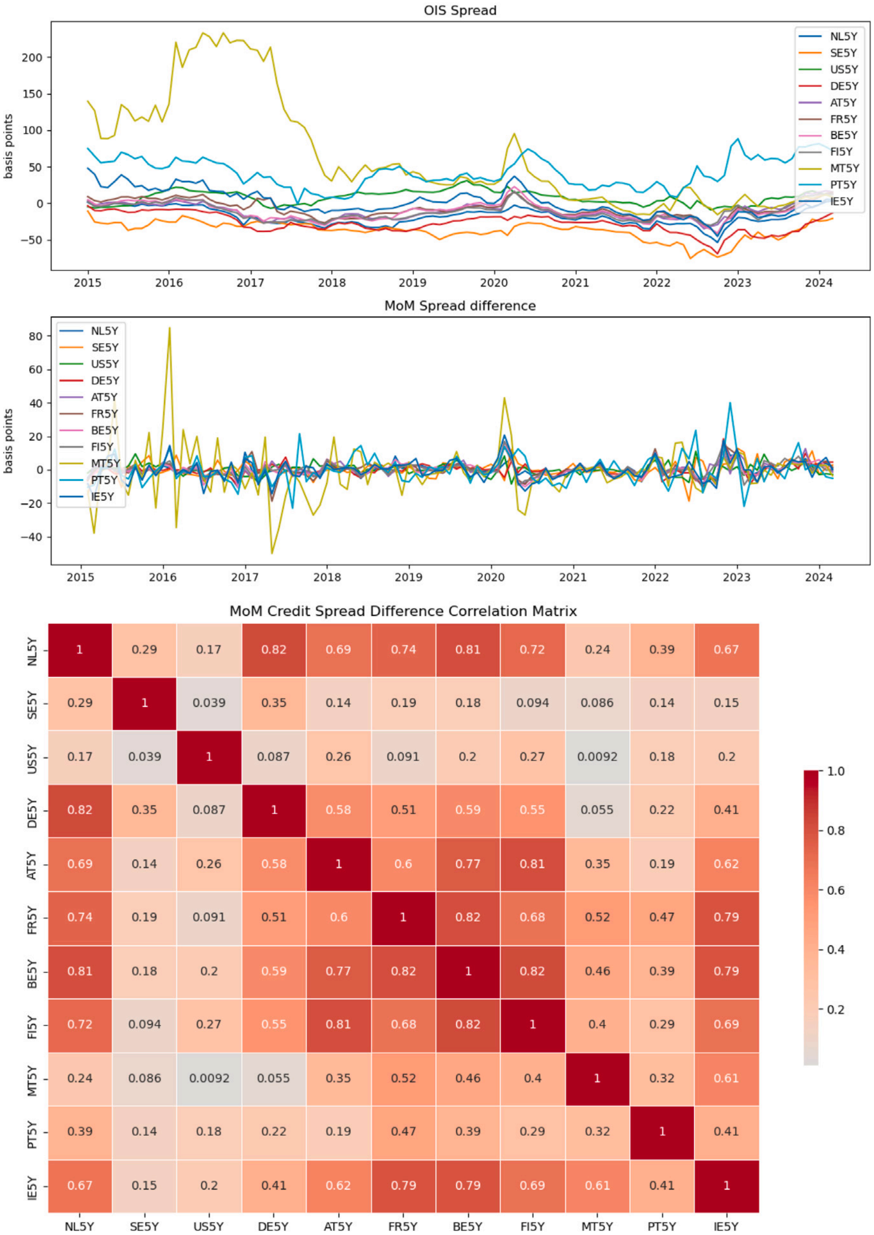

Fig. 1. Market data panel for Analysis 1, including historical OIS spread (top), MoM spread change (middle), and MoM credit spread difference correlation matrix (bottom).
Data: Reuters.

under the assumption that the idiosyncratic component is contributing to a lesser extent to the total variance in the credit spread movements, hence, captured in the 2nd, 3rd or nth PC.

The time series are then simplified, without a substantial loss of information. The second part of the analysis consists in deriving the distribution of the principal component scores. By taking the 1st and 99th quantiles, one obtains the magnitude of shocks in credit spreads related to changes in the systematic spread in the transformed space.

Since the distribution of the PC is mostly symmetrical, and the transformation to the original space is linear, the shock is transformed back into the original credit spread space, allowing to obtain a single shock for each issuer.

Table 1
Credit spread shocks, derived from the PC1 for the Analysis 1.

Rating: AAA		Rating: AA– to AA+		Rating: A– to A+	
Country	CS shock (bp)	Country	CS shock (bp)	Country	CS shock (bp)
Sweden	4	USA	3	Malta	13
Germany	8	Austria	11	Portugal	25
The Netherlands	11	Finland	12		
		France	13		
		Belgium	13		
		Ireland	16		

4. Main results

4.1. Analysis 1 - Investment grade rated (IG) countries

The first analysis focuses on calibrating credit spread shocks for IG countries. A 5Y tenor is used to replicate a theoretical liquidity portfolio, and ensures credit spread sensitivity. The following countries are included in the scope of the analysis: Sweden, Germany, The Netherlands, Ireland, Belgium, France, Finland, Austria, USA, Portugal and Malta.

From the market data panel (Fig. 1), EUR time series for AA– to AAA rated countries exhibit increased inter-correlation. USD, SEK and A– to A+ time series exhibit lower correlation as they capture idiosyncratic movements that relate to country or region-specific events (e.g. Malta, USA, Sweden).

On the PCA panel (Fig. 3), the two first PC explain 63% of the total variance encompassed in the 11 time series (52% solely for PC1). The cloud representation shows that clustering is possible, with an acceptable number of outliers. PC1 is mostly symmetrical with increased right-tail density.

The bottom panel on Fig. 2 shows that the scaled MoM spread difference time series are well correlated to the PC1, confirming the initial hypothesis that PC1 captures the systemic credit spread component (affecting all issuers alike), whereas the remaining PC encompasses issuer-specific information.

Since the PC distribution is mostly symmetrical (Fig. 3) and transformation linear, shocks are converted back into credit spread space (Table 1), incorporating both credit spread and liquidity premiums. The idiosyncratic spread is effectively removed (as captured in the other PCs).

Table 1 demonstrates clear economic rationality, where the size of the calibrated credit spread shocks decreases as the credit rating improves, reflecting the lower risk associated with higher-rated instruments. There is one exception for the USA, although rated AA+, it behaves as a AAA rated country due to its unparallel economic resilience and the global confidence associated to its financial stability.

4.2. Analysis 2 - Financial corporations

The second analysis focuses on calibrating credit spread shocks for a pool of financial corporations with debt issued in Euros, and rated BBB, A and AA.[1] The 5-year tenor remains unchanged. It should be noted that, considering the aforementioned pool of corporate issuers, the idiosyncratic credit spread is expected to be partly removed.

From the market data panel (Fig. 4), the time series exhibit a very high correlation, with a clear and observable rating premium. Notably, this premium narrowed over time. Also, the MoM spread difference for the pool of BBB financial corporations is logically more volatile.

On the PCA panel (Fig. 6), the PC1 explains about 89% of the total variance. This is evaluated as very satisfying. It follows that the cloud representation shows that clustering is possible. The very few outliers represent the 2020 credit spread widening (in response to the COVID-19 crisis) and to a lesser extent the recent increase of uncertainty in response to "ongoing central bank rate hikes against a backdrop of persistent inflation, mounting recession fears, and intensifying instability in Europe" (Hinds and Greenleaf, 2022).

The bottom panel on Fig. 5 shows that the scaled MoM spread difference time series are almost perfectly correlated to the PC1. By taking the 1st and 99th quantile on the distribution of the principal component score, and transforming it back into the original credit spread space, we obtain the magnitude of shocks in credit spreads related to changes in the systematic spread (Table 2).

[1] RIC: BBBEURFIN5Y=, AEURFIN5Y= and AAEURFIN5Y=.

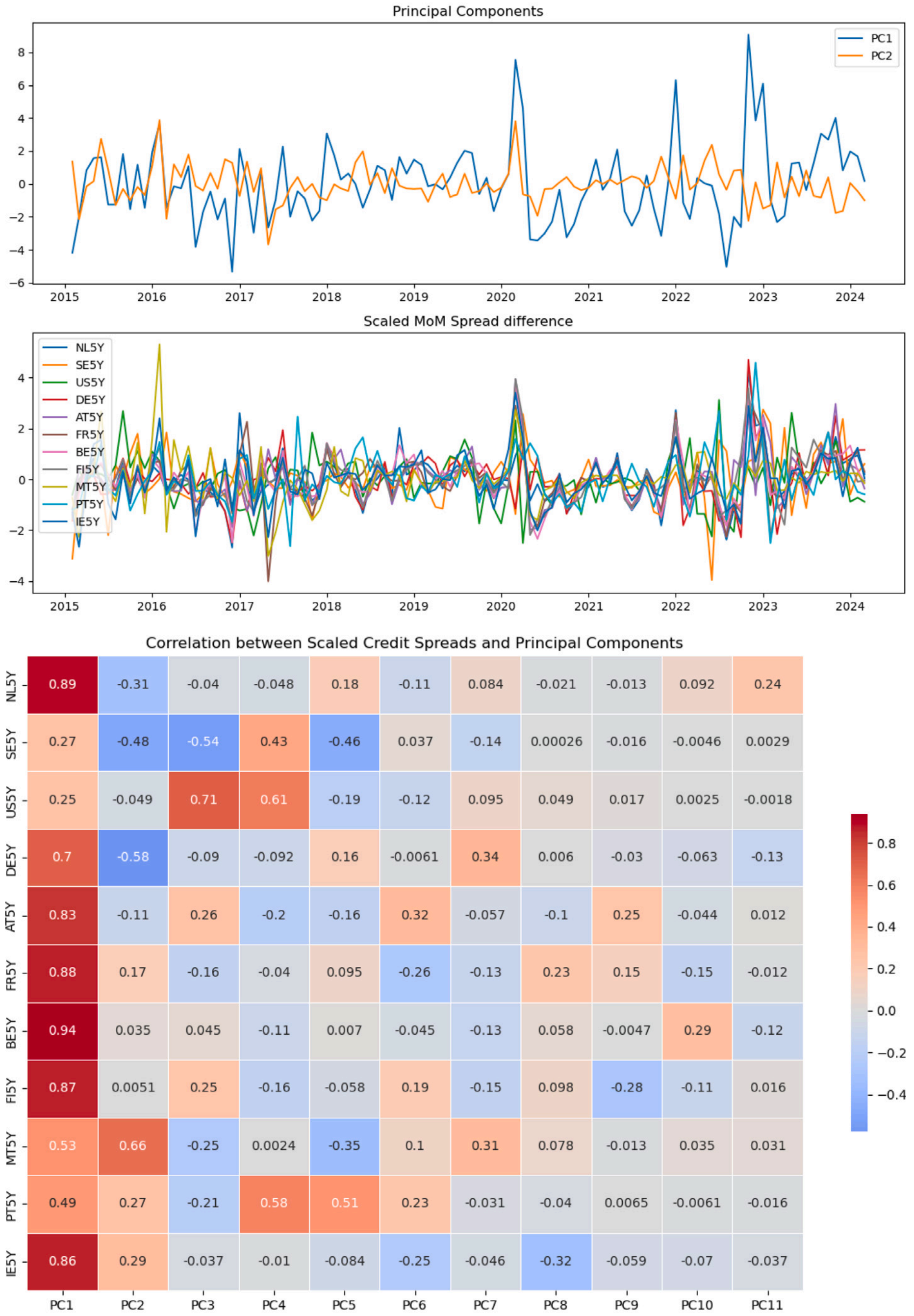

Fig. 2. Comparison of the first two PC (top panel) to the scaled MoM spread difference for Analysis 1 (middle panel), and correlation matrix (bottom panel).

4.3. Discussion and implications

The two previous analyses are aligned with the expected risk profile, manifested by a lowering credit spread shock for higher rated issuers. Also, the shocks for corporates are logically higher than for governmental issuers.

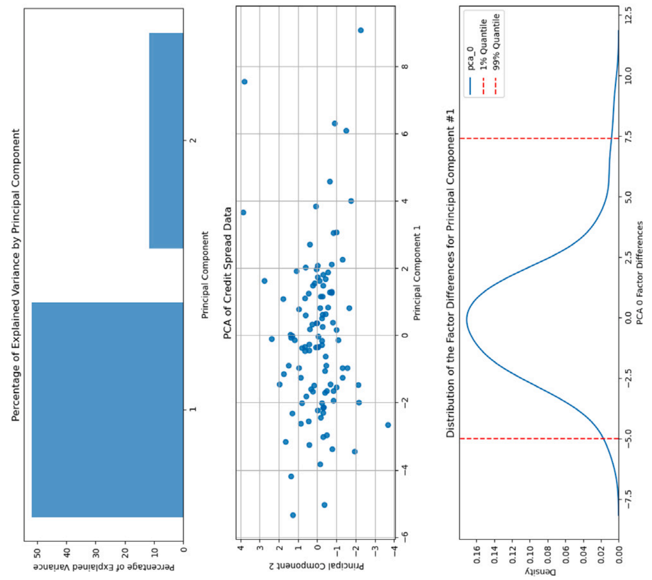

Fig. 3. PCA panel for Analysis 1, including percentage of explained variance (top), cloud representation of PC2 as a function of PC1 (middle) and distribution of the PC1 scores (bottom).

Table 2
Size of plausible but unlikely credit spread shocks, derived from the PC1 for the pool of financial corporates with debt issued in EUR.

EUR Fin. Corp. aggregate	
Rating	CS shock (bp)
AA	24
A	30
BBB	45

The findings also underline that systemic risk dominates the credit spread fluctuations, with the first principal component explaining most of the total variance and the PC1 highly correlated with all issuer time series. The remaining PCs show varying degrees of correlation with individual issuers but are not uniformly or strongly aligned with any one instrument, reflecting their role in capturing residual, idiosyncratic variation. Importantly, the principal components are orthogonal, meaning that each captures a distinct source of variation in the data.

The calibrated shocks falls in a similar order of magnitude as in van den Oever and Ruwaard (2023), although the analysis achieved in the present paper is more conservative (99% VaR instead of 95%) and for a different scope (mix of OIS curves).

The choice of OIS spread time series to be included in the PCA is critical, as it can influence the outcome of the calibrated shock. The diversity and quality of the time series used must be carefully considered to ensure that the resulting shocks are meaningful. Specifically, it is essential to pool time series that are sufficiently diverse to effectively isolate the idiosyncratic component of credit spread movements.

To illustrate the potential effects of changing inputs, Table 3 presents the adjusted CSRBB shocks for (a) a modified time horizon, now spanning from July 2022 to March 2024, and (b) the inclusion of Norway in the analysis.

This dataset captures the September 2022 credit spread widening due to the higher uncertainty in the market (Hinds and Greenleaf, 2022). Interestingly, the two first PC now explain 69% of the total variance encompassed in the 12 time series (with PC1 contributing up to 56%). For all countries except Portugal, calibrated shocks are constant or increasing. Portugal stands as an exception in light of their progressive rating improvement over the period 2015–2022.

A balance between time horizon and interpretability is crucial. Longer periods may capture credit rating migrations, which, while relevant for some risk assessments, are not part of EBA's CSRBB guidelines (European Banking Authority, 2022). Including these rating migrations introduces noise into the system, misrepresenting the true level of credit spread risk faced by the financial institution.

Fig. 4. Market data panel for Analysis 2, including historical OIS spread (top), MoM spread change (middle), and MoM credit spread difference correlation matrix (bottom).
Data: Reuters.

Table 3
Adjusted shocks for Analysis 1 were obtained by restricting the data scope to the period from July 2022 to March 2024, and by including the Norwegian OIS spread. The numbers in brackets indicate the changes compared to Table 2.

Rating: AAA		Rating: AA− to AA+		Rating: A− to A+	
Country	CS shock	Country	CS shock	Country	CS shock
Norway	3	USA	3 (=)	Malta	16 (+3)
Sweden	6 (+2)	Austria	11 (=)	Portugal	11 (−14)
Germany	15 (+7)	Finland	12 (=)		
The Netherlands	15 (+4)	France	15 (+2)		
		Belgium	14 (+1)		
		Ireland	16 (=)		

Fig. 5. Comparison of the first two PC (top panel) to the scaled MoM spread difference for Analysis 2 (middle panel), and correlation matrix (bottom panel).

5. Conclusion

In this paper, we introduced a PCA-based approach to calibrate the size of plausible but unlikely credit spread shocks. The ability to separate the systemic component from the idiosyncratic spread is a major advantage offered by PCA, with direct implications for financial institutions seeking to comply with the EBA guidelines on CSRBB.

From a risk management perspective, the calibrated shocks, encompassing both market credit spreads and liquidity spreads, offer a practical basis for setting limits and defining stress-testing scenarios. Institutions can use the results of this study to enhance their risk appetite frameworks and better assess their portfolio exposures to credit spread risk.

The absence of a standardized CSRBB modelling framework across institutions highlights a gap in risk assessment and eventually results in an uneven playing field among financial institutions, which this study addresses by proposing a PCA-based approach to quantify systemic credit spread shocks. The variability in CSRBB practices suggests a need for regulatory convergence, which this research supports by offering an empirically validated method aligned with EBA guidelines.

As regulatory oversight evolves, financial institutions will need to continually adapt their methodologies to ensure compliance and maintain resilience in an ever-changing risk environment.

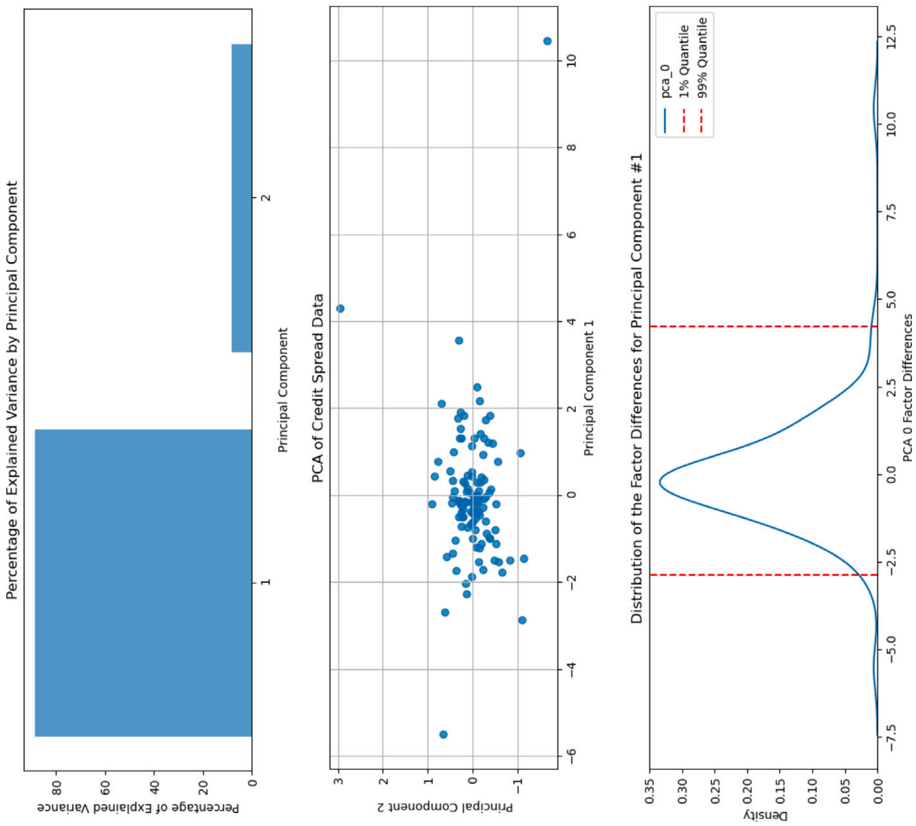

Fig. 6. PCA panel for Analysis 2, including percentage of explained variance (top), cloud representation of PC2 as a function of PC1 (middle) and distribution of the PC1 scores (bottom).

CRediT authorship contribution statement

Maxime Segal: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kristján Rúnar Kristjánsson:** Writing – review & editing, Validation, Resources, Project administration, Investigation, Conceptualization. **Björn Hrannar Björnsson:** Writing – review & editing, Validation, Investigation.

Disclaimer

The view and opinions expressed in this paper are solely those of the authors and do not reflect the official position or endorsement of Íslandsbanki.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Preliminary findings from this research were presented at the 8th Marcus Evans Banking Book Risk Management Conference, held in Stockholm from September 23 to September 25, 2024, and have since been developed into this research letter.

All authors approved the version of the manuscript to be published.

Data availability

Data will be made available on request.

References

Basel Committee on Banking Supervision, 2016. Standards – Interest Rate Risk in the Banking Book. BCBS 368, Bank for International Settlements.
Boavida, D., 2022. Credit Spread Risk in the Banking Book. Finalyse.
Choudhry, M., 2023a. Credit Spread Risk in the Banking Book. CSRBB, Finance Unlocked.
Choudhry, M., 2023b. The Principles of Banking, second ed. In: Wiley Finance Series.
European Banking Authority, 2018. Guidelines on the Management of Interest Rate Risk Arising from Non-Trading Book Activities. EBA/GL/2018/02.
European Banking Authority, 2022. Guidelines Issued on the Basis of Article 84 (6) of Directive 2013/36/EU Specifying Criteria for the Identification, Evaluation, Management and Mitigation of the Risks Arising from Potential Changes in Interest Rates and of the Assessment and Monitoring of Credit Spread Risk, of Institutions' Non-Trading Book Activities. EBA/GL/2022/14.
European Banking Authority, 2024. Heatmap Following the EBA Scrutiny on the IRRBB Standards Implementation in the EU. EBA/REP/2024/02.
European Banking Federation, 2023. Credit Spread Risk in the Banking Book: Banking Industry Common Understanding.
Hinds, B., Greenleaf, R., 2022. Monthly Market Snapshot: 2022. Wellington Management.
Lubinska, B., 2022. Interest Rate Risk in the Banking Book, a Best Practice Guide to Management and Hedging. In: Wiley Finance Series.
Morgan, J.P., 2024. Annual Report 2023 of J.P. Morgan SE.
Pahne, E., Åkerlund, L., 2023. Modelling Credit Spread Risk in the Banking Book. CSRBB (Master's Thesis). KTH.
Roncalli, T., 2020. Handbook of Financial Risk Management. In: Chapman & Hall/CRC Financial Mathematics Series.
van den Oever, M.X., Ruwaard, C., 2023. Quantifying CSRBB Shocks using PCA. Probability & Partners.

Maxime Segal Graduated with a Ph.D. from Reykjavik University (RU) in the field of Contingent Convertibles bonds, Maxime works as a senior specialist in the Risk Modelling department of Íslandsbanki while also serving as an Adjunct Professor at RU. His scope of work covers Market Risk and most notably IRRBB, CSRBB and behavioural modelling.

Kristján Rúnar Kristjánsson Graduated with a Ph.D. in Physics from the University of Iceland, Kristján is the deputy CRO of Íslandsbanki where he worked for the past 17 years, providing him with extensive expertise in risk management, quantitative analysis, and strategic decision-making within the financial sector.

Björn Hrannar Björnsson Graduated with a M.Sc. in Financial engineering and risk management from Imperial College Business School, Björn is a senior specialist in the Risk Modelling department of Íslandsbanki with a focus on market and liquidity risk.