Evaluating Credit Portfolios under IFRS 9 in the UK Economy

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Abstract

This research examines the effectiveness of IFRS 9 in credit risk management and capital reserve allocations for banks. It investigates the impact of major events like the COVID-19 pandemic and geopolitical instability on risk management strategies. The study utilizes the One-Factor Vasicek Model to simulate a mortgage portfolio's performance and incorporates the IFRS 9 provisions. Backtesting and forecasting exercises are conducted to evaluate the model's predictive performance. The findings highlight the stringent asset allocation requirements of IFRS 9 and the need for evidence-based parameter choices. The research acknowledges the potential shortfall in provision amounts during unforeseen economic shocks but emphasizes the potential buffer provided by excess capital accumulation.

Summary

Credit scoring models play a crucial role in evaluating credit risk, particularly in the aftermath of the Great Recession (2007-2009). To address the need for improved credit risk management, regulatory accords such as the International Financial Reporting Standard 9 (IFRS 9) have been implemented over the previous IAS39. Since its implementation in 2018, IFRS 9 has had a significant impact on banks' capital requirements, often resulting in more stringent reserve allocations. IFRS 9 introduced more forward-looking provisions for assessing credit risk, requiring banks to make timely provisions based on their credit exposure and potential losses.

This research provides insights into the effectiveness of IFRS 9 in addressing the challenges posed by major events like the COVID-19 pandemic and geopolitical instability, which can have a substantial impact on credit risk and the stability of financial institutions. By evaluating the performance of risk management strategies under these conditions, this study contributes to enhancing the understanding of the regulatory framework and its ability to ensure the resilience and soundness of the banking system.

This research aims to examine the effectiveness of IFRS 9 in credit risk management (models used to assess and mitigate the risks associated with lending and credit transactions) and capital reserve allocations (set aside some bank's capital as a buffer against potential losses, ensuring stability and compliance with regulatory standards outlined in accords) for banks. The key research question is whether the forward-looking provisions based on Expected Credit Losses(ECL) introduced by IFRS 9 adequately address the cumulative impact of significant events such as the COVID-19 pandemic and geopolitical instability. By evaluating the performance of banks' risk management strategies under these conditions, we aim to assess the effectiveness of IFRS 9 in ensuring compliance with regulatory standards. Specifically, we define the expected credit loss (ECL) as a quantitative measure of capital reserve allocation, which considers the probability of default, loss given default, and exposure at default to estimate the potential future credit losses for a specific asset or portfolio. These reserves act as safeguards to protect depositors, investors, and the overall stability of the banking system.

The objective of this project is to simulate a risk management strategy and evaluate its performance within the current macroeconomic landscape, especially in the Covid pandemic. By doing so, we also aim to assess the effectiveness of the strategy in navigating the future challenges posed by the economic problems.

In this study, we utilize the One-Factor Vasicek Model to simulate the performance of a portfolio consisting of 1000 mortgage loans, considering their credit ratings transition from 1989 to 2022. Additionally, we incorporate the IFRS9 provision into the portfolio by applying our self-defined impairment judgement. To assess the effective-

ness of our approach, we conduct a backtest spanning 2018-2022. Furthermore, we extend our analysis by employing the model to forecast the portfolio's performance during the period of 2023-2025.

The paper begins by discussing the background of the introduction of IFRS9 and its comparison with previous regulations, highlighting the challenges associated with its implementation and its broader impact. We then delve into the risk management practices at the financial institution level, focusing on the methods and techniques that enable the application of IFRS9. Specifically, we explore the One-Factor Vasicek model in detail, explaining how we estimate and calculate its various parameters. We proceed to simulate a synthetic mortgage portfolio and track its evolution using the Vasicek model, providing a comprehensive explanation of the assumptions and steps involved in the simulation. Additionally, we describe the implementation of the IFRS9 impairment for calculating the credit capital reserve. To evaluate the predictive performance of the model, we conduct a backtesting exercise that compares the predicted portfolio evolution with the actual portfolio evolution. We then proceed to present the forecasting section, which provides projections under different scenarios for the future allocation of the portfolio. Furthermore, we examine the model's performance by simulating the portfolio without the impact of the Covid era. Finally, we draw conclusions based on the discussions outlined above.

The research finds that the IFRS9 framework imposes stringent asset allocation requirements by introducing specific assumptions regarding portfolio migration and self-defined impairment judgments. However, these assumptions underscore the dynamic nature of credit risk management and the need for solid evidence to support parameter choices and modelling methodologies. Furthermore, it highlights the ability of banks to leverage the flexible definition of modelling rules under IFRS9 to align provision amounts with their goals. It is worth noting that in the face of unexpected and hard-to-predict economic shocks, the projected provision amount may occasionally fall short. Nonetheless, the accumulation of excess capital over preceding years can serve as a potential cushion during such times.

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Dictionary of Key Technical Terms

1. **Backtesting:** A process of assessing the accuracy and effectiveness of a predictive model by comparing its forecasts or estimates with actual historical data. It helps evaluate the model's performance and identify any potential shortcomings.

2. **Capital Reserve Allocations:** The allocation of funds within a bank's capital reserves to cover potential losses from credit and other risks. It ensures that banks have sufficient capital to absorb losses and maintain financial stability.

3. **COVID-19 Pandemic:** The global pandemic was caused by the outbreak of the novel coronavirus in late 2019. It resulted in widespread health, social, and economic impacts, including disruptions to financial markets and increased credit risk.

4. **Credit Risk Management:** The practice of identifying, assessing, and mitigating the potential losses associated with lending money or extending credit to borrowers. It involves analyzing the creditworthiness of borrowers, setting risk limits, and implementing strategies to minimize credit losses.

5. **Default Amount:** The amount of money that a borrower fails to repay according to the agreed terms and conditions of a loan or financial obligation. The default amount represents the principal, interest, or any other associated costs that remain unpaid.

6. **ECL:** Expected Credit Loss. It is the estimated amount of loss that a lender expects to incur on a financial asset over a specific period. ECL is calculated based on factors such as default probabilities, loss-given default, and exposure at default.

7. **Excess Capital Accumulation:** The accumulation of additional capital by a bank beyond regulatory requirements or minimum capital thresholds. Excess capital provides a buffer to absorb unexpected losses, enhance financial resilience, and support future growth.

8. **Geopolitical Instability:** Political and economic uncertainties arising from geopolitical factors such as conflicts, trade disputes, sanctions, or regime changes. Geopolitical instability can impact financial markets, credit risk, and overall economic stability.

9. **House Price Index:** A measurement of the average price changes of residential properties within a particular geographical area. The house price index provides insight into the trends and fluctuations in the housing market.

10. **IFRS 9:** International Financial Reporting Standard 9. It is an accounting standard that sets out the principles for financial instruments' classification, measurement, impairment, and hedge accounting.

11. **Inflation Rate:** The rate at which the general level of prices for goods and services is rising and, consequently, the purchasing power of currency is falling. The inflation rate is commonly measured using consumer price indices (CPI) or other price indexes.

12. **Mortgage Loans:** Loans secured by real estate property, typically used for purchasing or refinancing residential or commercial properties. Mortgage loans involve a borrower pledging the property as collateral for the loan, and failure to repay can result in foreclosure or repossession of the property.

13. **One-Factor Vasicek Model:** A mathematical model used to assess the credit risk of a portfolio by simulating the default probability of individual assets. The model incorporates a single factor to capture the systematic risk affecting the portfolio.

14. **PC1:** The first principal component is obtained through Principal Component Analysis (PCA). PC1 represents the linear combination of variables that explains the largest amount of variance in the dataset.

15. **PCA:** Principal Component Analysis. It is a statistical technique used to reduce the dimensionality of a dataset while preserving important information. PCA identifies the principal components that capture the maximum variance in the data.

16. **Provision Amounts:** Reserves set aside by banks to cover expected credit losses or impairments on loans and other financial assets. Provision amounts are determined based on risk assessments, historical data, and accounting standards such as IFRS 9.

17. **Real GDP:** Gross Domestic Product adjusted for inflation. Real GDP provides a measure of a country's economic output, accounting for changes in price levels over time.

18. **Unemployment Rate:** The percentage of the labour force that is jobless and actively seeking employment. The unemployment rate is an important economic indicator that reflects the health of the labour market and overall economic conditions.

19. **1992 Financial Crisis (Black Wednesday):** The UK's currency crisis was caused by overvalued pound sterling and withdrawal from the European Exchange Rate Mechanism. The crisis stemmed from Britain's decision to join the European Exchange Rate Mechanism (ERM) and peg the pound to the German mark. However, due to economic pressures, the pound became overvalued, leading to the Bank of England's inability to defend its target exchange rate. As a result, the government was forced to withdraw from the ERM, causing a significant devaluation of the pound. The crisis had a profound impact on the British economy, but it also revealed flaws in the ERM and prompted reforms in the European Union's monetary system.

20. **Dot-com Bubble (the late 1990s):** This bubble was fueled by the rapid rise of internet-related companies. Investors poured money into internet startups, many of which had no proven business models or earnings. The bubble burst in 2000, leading to a significant decline in the value of technology stocks.

21. **2008 Financial Crisis (Global Financial Crisis):** Triggered by the collapse of the subprime mortgage market in the US, leading to a global recession, financial institution failures, and extensive government interventions. It originated in the United States but had a profound impact on the global economy. The crisis was primarily triggered by the collapse of the subprime mortgage market, fueled by the widespread issuance of risky mortgage-backed securities. As housing prices declined, many borrowers defaulted on their mortgages, leading to significant losses for financial institutions worldwide. The crisis escalated when major financial institutions faced insolvency, triggering a credit freeze and a loss of confidence in the financial system. Governments intervened with massive bailouts and implemented unprecedented monetary and fiscal policies to stabilize the markets and prevent a total economic collapse. The crisis had far-reaching consequences, including a global recession, high unemployment rates, and long-lasting effects on financial regulations.

22. **2020 Financial Crisis (COVID-19 Pandemic):** Economic crisis caused by the pandemic, resulting in lockdowns, business closures, supply chain disruptions, and a worldwide recession. Governments implemented massive stimulus measures to mitigate the impact.

1 Introduction to IFRS9

1.1 Background on Causes of IFRS9 – Financial Crisis Overview

In June 2003, due to the internet bubble, the 9.11 event, and accounting scandals, the Federal fund rate was cut to 1% to make money available for consumers and businesses in the hope of boosting the economy. Consequently, there was increasing demand for houses at low mortgage rates, which thus increased housing prices. In particular, subprime borrowers qualified for larger loans with lower monthly payments, lax lending standards, and cheap credit risks. Banks sold loans to investment banks which packaged them into low-risk-financial instruments such as Mortgage-Backed Securities and Collateralized Debt Obligations, which soon established a big secondary market for originating and distributing subprime loans.

However, the Federal Reserve's decision to keep interest rates low for an extended period after the 2001 recession is often blamed for contributing to the financial crisis. Financial institutions struggled to earn satisfactory returns by maintaining low rates, leading them to take on riskier investments, according to [1]. Some argue that the Federal Reserve should have raised interest rates earlier or kept them higher to prevent the housing price bubble. Scholars like [44] suggest that monetary policy should be adjusted when clear signs of asset price bubbles emerge.

Moreover, according to [14], SEC lowered the net capital requirements for five investment banks that facilitated the growing housing market. In June 2004, homeownership reached 69.2%. Federal Reserve started to raise federal funds rate and maintained at 5.25% starting from June 2006. The increasing rates made the adjustable rate interest payments increase. Homes became worth less than what people paid for them. Subprime borrowers could not keep up with their mortgage payments once their rates reset. As a result, many defaulted on their loans. Banks had to foreclose on properties which caused home prices to plummet. The foreclosed property prices had less value than subprime lenders had lent to borrowers, causing massive losses for many banks and financial institutions. Meanwhile, other financial institutions were less hesitant to lend to subprime lenders, which made it more difficult for banks to continue lending to generate profits. Therefore, many banks filed for bankruptcy due to increased defaults and foreclosures. The Federal Reserve invested a staggering amount of money to save the banks, rescue the plummeting financial markets, and rescue the economy where millions lost their jobs and homes.

Summarized by [1], the problem during the financial crisis was that credit ratings from agencies were accepted without fully understanding the risks of mortgage portfolios. Additionally, there was insufficient stress testing of portfolios against market declines, and institutions did not have a comprehensive view of their risks. Instead, they considered different parts of their businesses separately rather than as part of more extensive companywide portfolios.

1.2 Introducing the IFRS9 – Financial Crisis Aftermath

During a crisis, traditional accounting standards may not provide an accurate picture of a company's financial health. IAS 39 was criticized for being too complex and challenging to apply, which resulted in inconsistent reporting of financial instruments [38]. It also relied heavily on historical cost accounting, which meant that assets and liabilities were valued based on their initial cost rather than their current market value. This approach did not always reflect the actual value of financial instruments during a crisis when market conditions could change rapidly. In the standard that preceded IFRS 9, the "incurred loss" framework required banks to recognise credit losses only when evidence of a loss was apparent.

The International Accounting Standards Board (IASB) recognized this. It aimed to address the weakness of the International Accounting Standard (IAS) 39, the international standard for determining financial assets and liabilities accounting in financial statements since 2001. By July 2014, the IASB finalized and published its new International Financial Reporting Standard (IFRS) 9 methodology, to be implemented by January 1, 2018. IFRS 9 covers financial organizations across Europe, the Middle East, Asia, Africa, Oceania, and the Americas (excluding the US) [34].

IFRS 9 applies a single impairment model to all financial instruments subject to impairment testing. At the same time, IAS 39 has different models for different financial instruments [31], which addresses the difficulty and complexity of complying with the risk management practice during the financial crisis. Under IFRS 9's Expected Credit Losses (ECLs) impairment framework, however, banks are required to recognise ECLs at all times, taking into account past events, current conditions and forecast information, and to update the number of ECLs recognised at each reporting date to reflect changes in an asset's credit risk. It is a more forward-looking approach than its predecessor and is intended to result in more timely recognition of credit losses [3].

IFRS 9 introduces a three-Stage approach to measuring ECLs for financial assets, such as loans. The Stages include performing (Stage 1), underperforming (Stage 2), and impaired (Stage 3) assets [42]. Performing assets require ECL estimation for the next 12 months while under-performing and impaired assets require ECL estimation for the entire credit lifetime. Moving an asset from one Stage to another is triggered by a "significant increase in credit risk" (SICR) after origination. The determination of a SICR is left to the bank's management. Assets with no significant increase in credit risk remain in Stage 1 with a 12-month ECL, while assets with a significant increase in credit risk are moved to Stage 2 with ECL based on the asset's estimated lifetime. For instance, a loan that is 30 days past due is presumed to have a SICR and should be moved to Stage 2.

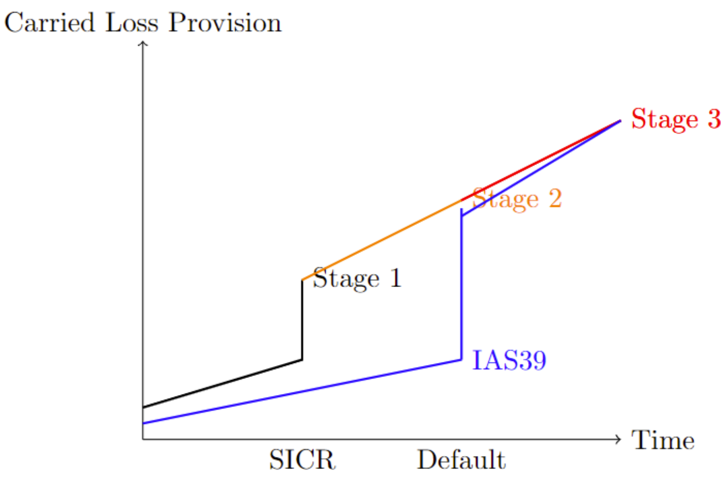

Figure 1: Provision under IAS39 vs IFRS9

Under IFRS 9, we can see from the graph above, there is a significant difference in provisions between Stage 1 and Stage 2, with Stage 2 provisions being higher due to a longer expected value horizon. This creates a cliff effect when assets move from Stage 1 to Stage 2, resulting in a sharp increase in carried loss provisions. This is a crucial distinction from the provisions recognized under IAS 39. The shift from Stage 2 to Stage 3 is triggered by a default event, aligning with the loss recognition approach in IAS 39.

1.3 Challenge of implementation in IFRS9

Implementing IFRS 9 requires banks to transition from an incurred loss model to an expected loss model, involving the forecasting of macroeconomic conditions and incorporating them into ECL models. This entails significant modelling efforts and management judgment to assess how macroeconomic conditions impact provisions [18].

Transparency is emphasized, with banks required to disclose their ECL modelling methods and management judgment on inputs and assumptions, providing valuable information on asset quality and credit risk. Furthermore, comparing provisions across different banks becomes more challenging. Additionally, IFRS 9 necessitates substantial enhancements to data, systems, quantitative models, and governance within financial institutions.

Nevertheless, banks can leverage this vague rule in SICR to define the bank's own risk management judgement to minimize the capital requirement.

1.4 Influence of IFRS9 on banks and economy

The impact of adopting IFRS 9 on loss allowances: In [28], European banks were examined and univariate analysis was conducted to test several hypotheses.

The findings indicate that the adoption of IFRS 9 over IAS39 did not lead to any significant differences in loan loss provisions and discretionary loan loss provisions. While multiple academic papers suggest an increase in loss allowances for credit losses during the transition to IFRS 9 [22][50][27], there are exceptions. One study observed a decrease in allowances during the transition, and at the end of the first year of IFRS 9 implementation, compared to the year prior [26]. Additionally, evidence based on Chinese entities adopting a converged standard, CAS 22, with IFRS 9 showed that the allowance for credit losses on financial assets did not change for most entities [41].

IFRS 9's impact on capital ratios is primarily influenced by increased provisions driven by Expected Credit Loss (ECL) requirements. Despite variations in sample sizes and bank coverage, studies suggest a transitional decrease of around 45-50 basis points (bps) in the CET1 ratio and a decrease of 31-35 bps in the total capital ratio, as reported by the European Banking Authority (EBA). [12] and [33], which studies a different number of banks in Europe, the Middle East, Africa, Asia Pacific, Americas, and [4] [15], which studies Europe all estimated a 50bps decrease in CET1 Ratio after adopting IFRS9.

Covid Amendments: Nevertheless, IFRS 9 application during the COVID-19 economic downturn may have led to a significant increase in credit loss provisions. To mitigate the impact on regulatory capital, the Basel Committee agreed on April 3, 2020, to allow more flexible transitional arrangements. In line with this, the European Commission published the CRR Quick Fix regulations [17], amendments to the EU prudential framework for banks, primarily the Capital Requirements Regulation (575/2013) (CRR)[16], to encourage lending by banks to mitigate the economic impact of the COVID-19 pandemic. One significant aspect of these regulations is the adjustment and extension of the IFRS 9 transitional rules. The CRR Quick Fix introduces a new transition period from 2020 to 2024 to facilitate a smoother implementation process and introduced a COVID-19 component (CC) to calculate provision differences. Institutions can add back a higher percentage of new ECL provisions to their CET1 capital in 2020 and 2021. These measures address the pandemic's impact on provisioning needs while maintaining existing transitional arrangements under IFRS 9. The CC will be phased out gradually, with no correction starting in 2025. The original static and dynamic components are not affected. The phase-out transition is summarized in the table below [35]. The impact of the IFRS 9 transitional rules on CET1 capital is thus not very high [35].

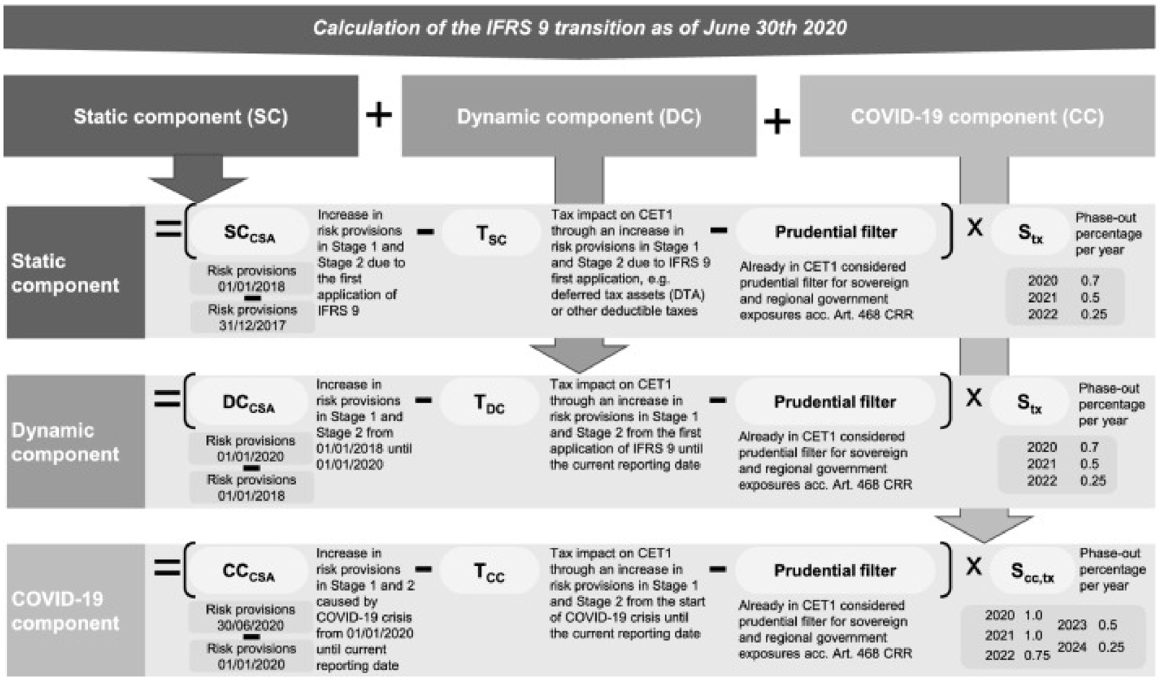

Figure 2: As of June 30, 2020, the transition rules for the standardised approach to credit risk (CSA) under IFRS 9, taken from [35].

Predictive ability of Expected Credit Losses (ECL) for credit and equity risk: IFRS 9's credit loss allowances provide more informative signals to participants in CDS markets compared to allowances under IAS 39 [13]. This results in a stronger positive relationship between CDS prices and credit loss allowances after implementing IFRS 9. The improved measurement and disclosure of credit losses under IFRS 9 increase market confidence and enable more informed decision-making in CDS markets. In another study, the information provided by the Expected Credit Loss (ECL) model under IFRS 9 was more predictive of future equity risk than credit losses under IAS 39, particularly in countries with deteriorating credit conditions [26]. This higher predictability was attributed to the banks' disclosures of ECL for loans in Stage 1 and Stage 2.

Evaluating the timeliness of Expected Credit Loss (ECL) recognition under IFRS 9: The academic literature on the timeliness of recognizing Expected Credit Losses (ECL) under IFRS 9 suggests that the implementation of IFRS 9 resulted in more timely recognition of ECL. Banks recognized more significant and timely loss allowances after adopting IFRS 9, especially for riskier banks with smaller loss allowances before [23][36]. In the case of Chinese banks, the impact of IFRS 9 on ECL allowances varied depending on the bank's ownership and political influence [32]. However, a case study on Greek government bonds found that estimated loss allowances under IFRS 9 appeared delayed and low compared to fair value losses [20].

2 Modelling Credit Risk

As indicated in the last section, the earlier regulation IAS39 only used historical data when evidence of default occurred, which led to the late estimation of credit losses. We thus need updated models to develop **quantitative estimates** of the amount of capital needed to support financial institutions' risk-taking activities. The **goal** of credit risk models was to develop quantitative estimates of the amount of economic capital needed to sustain a bank's risk-taking activities. Minimum capital requirements have been coordinated internationally since Basel I in 1998. In Basel I, four broad categories classify the bank's assets and allocate them to four weights. For instance, retail mortgages received a risk weighting of 50% [10]. Then $Bank's\ Total\ Minimum\ Capital\ Requirement\ =\ 8\% * \sum risk\ weighted\ assets$. However, this method has the problem of ignoring the cross-sectional distribution of risk. For example, all mortgage loans received the same capital requirement without regard to the underlying risk profile of the borrower, which might have caused banks to undertake excessive risks, typically associated with higher returns.

Basel II thus had a more granular approach for risk weighting. Under Basel II, credit risk management techniques can be classified under 3 approaches: standardized approach, foundational Internal ratings-based (FIRB) approach, and advanced IRB (AIRB) approach. The difference is summarized in the below figure [29].

Table 1: Credit Risk Capital Approaches

Approach	**Credit Risk Capital (Bolded Parameters Estimated By Institutions)**
SA	Capital requirement = constant × exposure × risk weight
FIRB	Capital requirement = constant × EAD × **PD** × LGD × M
AIRB	Capital requirement = constant × **EAD** × **PD** × **LGD** × **M**

In short, the Standardised approach involves a simple categorization of obligors, without considering their actual credit risks. It includes reliance on external credit ratings, for instance, claims secured by residential property have a Risk weight of 35%.

Table 2: Claim Types and Risk Weights

Claim Type	**Risk Weight**
Claims on retail products (e.g., credit card, overdraft, auto loans)	75%
Claims secured by residential property	35%
Claims secured by commercial real estate	100%

In the FIRB and AIRB approach, banks build internal models to calculate their regulatory capital requirement for credit risk.

BASEL III seeks to improve the standardized approach for credit risk in several ways, including strengthening the link between the standardized approach and the IRB approach and setting a 4.5% minimum CET1 requirement. It also increased capital levels by introducing usable capital buffers rather than capital minima [5].

Under Basel II/III, banks following the IRB approach compute capital requirements based on a formula approximating the Vasicek model of portfolio credit risk [10]. Discussed in the [19], Basel II proposal for an internal ratings-based approach to credit risk capital requirements utilizes a one-factor model, which allows for realistic correlated default behaviour while maintaining analytical tractability. This model is widely used in credit risk modelling. While banks face challenges in estimating some risk factors, they can generally provide reliable estimations of default risk. The one-factor model measures capital requirements based on the probability density function (PDF) of future losses in a bank's credit exposure portfolio over a specific period. This model provides an analytical expression for the PDF, using inputs such as PDF, Loss Given Default, and Maturity.

The Vasicek framework is described in the later section. Basel II has specified the asset correlation values for different asset classes [2], and so does Basel III [6].

The ECL formula in IFRS9 is as follows:

$$ECL = \sum_{i=1}^{n} PD_i^{FL} \cdot LGD_i^{FL} \cdot Exposure\ Amount. \tag{1}$$

In this equation, PD_i^{FL} represents the forward-looking probability of default for a given counterparty. LGD_i^{FL} represents the forward-looking loss given default for that counterparty type. Finally, the *Exposure Amount* represents the amount of exposure to that counterparty. The equation calculates the Expected Credit Loss (ECL) based on the product of the probability of default, the loss given default, and the exposure amount. Here the forward-looking probability of default would either be 12 months of lifetime, corresponding to 12-month ECL for Stage 1 obligors and lifetime ECL for Stage 2 and 3 obligors. Our proposed classification of each loan will be proposed later.

To calculate ECL, there are linear regression methods and migration matrix methods. However, the lack of default data for mortgages made it difficult for us to estimate. Magnou [29] proposed to use a one-factor model to compute the ECL, which incorporates a forward-looking scenario method.

Under the new IFRS9, we estimate the Expected Credit Loss (ECL) or minimum capital requirements to see if the forward-looking method that considers both the credit history of borrowers and the bank's predicted economic scenario would provide enough cushion in historical years [37]. In this study, we backtest using the predicted economic scenario during 2018-2022 and compare the provision result with the provision for the portfolio in the actual economy. We will then analyze and estimate the bank's ECL with different predicting scenarios in today's context of Brexit, inflation, and the shock of covid for the projection of 2023-2025.

2.1 Literature Review- Methods to Model Credit Risk Other Than One Factor Model

Machine learning: One paper demonstrates the application of ML in credit risk management [8]. In summary, it performed data analysis and preprocessing and trained and evaluated three models (KNN, logistic regression, and XGBoost) for predicting loan defaults and their probability. It used precision, recall, F1 score, and ROCAUC as evaluation metrics, focusing on the imbalanced dataset and discarding accuracy. Calibration of the models was assessed using a reliability plot and Brier score. XGBoost outperformed the other models in all metrics, and we identified important features using information gain.

The analysis from *S&P* compares different machine learning algorithms used in credit risk modelling for predicting the likelihood of default [49]. The study focuses on private companies and uses financial ratios, country risk scores, and industry risk scores as variables. The tested algorithms include Altman Z-score, logistic regression, support vector machine, naïve Bayes, and decision tree. The results show that logistic regression and support vector machine perform consistently well, and logistic regression is favoured for its interpretability. *S&P* Global Market Intelligence has also developed a PD Model Fundamentals (PDFN) - Private Corporates model based on logistic regression for transparent and interpretable predictions for global private companies.

Another paper presents an explainable AI model for credit risk management in peer-to-peer lending [9]. Using correlation networks and Shapley values, the model groups AI predictions based on similar explanations. Analyzing 15,000 small and medium companies seeking credit, the study shows that borrowers, whether risky or not, can be categorized based on similar financial characteristics. These characteristics help explain credit scores and predict future behaviour.

ML models have the advantage of uncovering subtle relationships and processing unstructured data without pre-defining a theoretical model. However, there are challenges in analyzing noisy financial data and imposing constraints on ML models mentioned in the paper.

Deep Learning: This paper provides a systematic review of research on credit risk assessment using statistical, machine learning, and deep learning techniques [40]. It introduces a novel classification methodology for ML-driven credit risk algorithms and ranks their performance using public datasets. The review highlights that deep learning models generally outperform traditional machine learning and statistical algorithms in credit risk estimation, and ensemble methods offer higher accuracy than single models.

Two-Factor Vasicek Model: This paper compares the one-factor and two-factor models used in the BIS II proposal for credit risk capital requirements [19]. The one-factor model has advantages such as analytical tractability and capital additivity. However, it tends to overestimate capital and can create incorrect incentives. The authors suggest that while the one-factor model is a valuable tool, future advancements should be made towards multi-factor or portfolio models. They also emphasize the importance of considering diversification and adjusting for the penalizing effects on SMEs and emerging markets.

2.2 One-factor Vasicek model

We establish our probability space which comprises a sample space Ω, a σ-algebra $\mathcal{F}$, and a probability measure $\mathbb{P}$. Additionally, filtration is introduced, satisfying the standard conditions. A fixed time horizon T, typically set to one year, is specified within this framework. In the following context, $N(\cdot)$ and $\phi(\cdot)$ refer to standard normal cumulative distribution.

Merton's model in 1974 was one of the structural models that modelled the evolution of a firm's structural variables (assets) and determine the probabilities of default [30]. It assumes a firm's asset value evolves through a simple diffusion process. Default is triggered when the firm's asset value drops below the value of its debt. To determine a firm's probability of default under Merton's model, we need to know its assets and liabilities. In 1987, Vasicek expanded upon Merton's model to understand a portfolio probability of default once we know the firm's probability of default [47]. Furthermore, Vasicek assumed that a loan defaults when the value of the borrower assets A falls below the contractual value B of its obligations payable [48][46]. Let A_i be the value of the ith borrower's assets, described by the process

$$dA_i = \mu_i A_i dt + \sigma_i A_i dX_i, \tag{2}$$

where μ_i and σ_i are the drift and volatility of the value and X_i is a standard Brownian motion. Solving this equation, we obtain the representation of asset value at time T:

$$\log A_i(T) = \log A_i + \mu_i T - \frac{1}{2}\sigma_i^2 T + \sigma_i \sqrt{T} X_i. \tag{3}$$

The ith firm defaults if $A_i(T) < B_i$, so the probability of default of the ith loan is then:

$$p_i = P[A_i(T) < B_i] = P[X_i < c_i] = N(c_i), \tag{4}$$

where $c_i = \frac{\log(B_i/A_i) - (\mu_i - \frac{1}{2}\sigma_i^2)T}{\sigma_i \sqrt{T}}$ is the default threshold and N is the cumulative standard normal distribution function.

Vasicek also assumes that firms' asset returns are correlated, a concept at the heart of Markowitz's and modern portfolio theories [21]. For simplicity, Vasicek assumed that asset returns are equi-correlated, such that the creditworthy variables X_i can be represented as linear combinations of jointly standard normal random variables Z and Y_i. (Such derivation is because of the statistical properties of jointly equi-correlated standard normal variables, which stipulate that any two variables X_i and X_j are bivariate standard normal with correlation coefficient ρ if there are two independent standard normal variables Z and Y for which $X_i = Y\sqrt{\rho} + Z_i\sqrt{1-\rho}$.)

Therefore, the variables X_i in Equation (2) are jointly standard normal with equal pairwise correlations ρ, and can therefore be represented as

$$X_i = Z_t \sqrt{\rho} + \epsilon_i \sqrt{1-\rho}, \tag{5}$$

where Z, ϵ_1, ϵ_2, $\ldots$, ϵ_n are mutually independent standard normal variables. The variable Z can be interpreted as a portfolio common factor, such as an economic index, over the interval $(0, T)$. The asset correlation ρ, in short, shows how the asset value of one obligor depends on the asset value of another borrower. Then the term $Z\sqrt{\rho}$ is the company's exposure to the common factor and affects the creditworthiness of all obligors simultaneously. $\epsilon_i\sqrt{1-\rho}$ represents the company-specific risk and conditions inherent to each obligor. This is why they are assumed to be independent of each other.

When the systematic risk is known, the conditional probability of loss on any one loan is

$$\begin{aligned}
p_i(Z) &= Pr[D_i = 1|Z = z] \\
&= Pr[A_i(T) < B_i|Z = z] \\
&= Pr[X_i < c_i|Z = z] \\
&= Pr[\sqrt{\rho}Z + \sqrt{1-\rho}\epsilon_i < c_i|Z = z] \\
&= Pr\left[\epsilon_i < \left(c_i - \frac{Z\sqrt{\rho}}{\sqrt{1-\rho}}\right)\middle|Z = z\right] \\
&= \mathcal{N}\left(\frac{\mathcal{N}^{-1}(p_i) - Z\sqrt{\rho}}{\sqrt{1-\rho}}\right).
\end{aligned} \tag{6}$$

The quantity $p_i(Z) = PD_g|Z_t$ provides the loan default probability under the given scenario z. This is a Vasicek random variable.

Therefore, at time t, we denote the creditworthiness random variable $X_{o,t}$ for obligor o at time t of the portfolio evolution: $X_{o,t} = \sqrt{\rho} \cdot Z_t + \sqrt{1-\rho} \cdot \epsilon_{o,t}$. The conditional probability of default (PD_g), based on a specific default point (DP_g) for the obligor's grade g is: $PD_g|Z_t = \Pr(X_{o,t} \le DP_g|Z_t) = \mathcal{N}\left(\frac{DP_g - \sqrt{\rho}Z_t}{\sqrt{1-\rho}}\right)$. Thus, $PD_g|Z_t$ is a Vasicek random variable – with $\Phi^{-1}(\lambda) = DP_g$ and the second parameter being ρ itself.

Indeed, if $Y \equiv PD_g|Z_t$ is a Vasicek random variable, then

$$\begin{aligned}
\Pr(Y \le y) &= \Pr\left(\Phi\left(\frac{DP_g - \sqrt{\rho} \cdot Z_t}{\sqrt{1-\rho}}\right) \le y\right) \\
&= \Pr\left(DP_g - \sqrt{\rho} \cdot Z_t \le \sqrt{1-\rho} \cdot \Phi^{-1}(y)\right) \\
&= \Pr\left(-Z_t \le \frac{\sqrt{1-\rho} \cdot \Phi^{-1}(y) - DP_g}{\sqrt{\rho}}\right) \\
&= \Pr\left(Z_t \ge -\frac{\sqrt{1-\rho} \cdot \Phi^{-1}(y) - DP_g}{\sqrt{\rho}}\right) \\
&= \Pr\left(Z_t \le \frac{\sqrt{1-\rho} \cdot \Phi^{-1}(y) - DP_g}{\sqrt{\rho}}\right) \\
&= \Phi\left(\frac{\sqrt{1-\rho} \cdot \Phi^{-1}(y) - \Phi^{-1}(\lambda)}{\sqrt{\rho}}\right)
\end{aligned}$$

due to the symmetry of the systematic risk $Z_t \sim N(0, 1)$ and the assumption $\Phi^{-1}(\lambda) = DP_g$ made above.

Also, note that the unconditional probability of default is $PD_g \equiv \Pr(X_{o,t} \le DP_g) = \Phi(DP_g) = \lambda$. That is the long-run averaged conditional probabilities across all scenarios represented by the systematic variable Z_t.

There are three main approaches to estimating the parameters λ and ρ of a Vasicek-distributed random variable – direct moment matching, maximum likelihood estimation (indirect moment matching), and quantile-based estimating [43]. The same study compares these and concludes that λ is best estimated using the first two, while the MLE approach is most efficient in estimating ρ. Hence, we will calculate the parameters of the Vasicek-distributed $Y = PD_g|Z_t$ using the MLE (indirect moment matching) formulae.

Note that $A \equiv \Phi^{-1}(Y) \sim N(\mu, \sigma^2)$, where

$$\mu = E[A] = \frac{\Phi^{-1}(\lambda)}{\sqrt{1-\rho}}$$

and

$$\sigma^2 = \text{var}[A] = \frac{\rho}{1-\rho}.$$

Then the MLE $(\tilde{\lambda}, \tilde{\rho})$ is estimated by:

$$\tilde{\lambda} = \Phi\left(\frac{\tilde{\mu}}{\sqrt{1+\tilde{\sigma}^2}}\right)$$

and

$$\tilde{\rho} = \frac{\tilde{\sigma}^2}{1+\tilde{\sigma}^2},$$

where $\tilde{\mu}$ and $\tilde{\sigma}^2$ are the estimators of equations:

$$\tilde{\mu} = \frac{1}{n}\sum_{i=1}^{n}\Phi^{-1}(y_i)$$

and

$$\tilde{\sigma}^2 = \frac{1}{n}\sum_{i=1}^{n}\Phi^{-1}(y_i)^2 - \tilde{\mu}^2.$$

Rating migration: We define the score random variable S for an obligor o at time t as

$$S_{o,t} = \sqrt{\gamma}\cdot Z_t + \sqrt{1-\gamma}\cdot\theta_{o,t},$$

where $\theta_{o,t}$ is correlated to $\epsilon_{o,t}$, the idiosyncratic risk variable when calculating creditworthiness. We define the covariance matrix of $\theta_{o,t}$ and $\epsilon_{o,t}$ as $\begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$. The probability that a borrower o's credit rating moves from score g to score is $\Pr(g \rightarrow$

$g \pm k) = \Pr(T_{g,k} < S_{o,t} \leq T_{g,k-1})$. Furthermore, given the systematic risk Z_t (CCI value), this relationship can be conditionally expressed as:

$$\begin{aligned}
\Pr(T_{g,k} < S_{o,t} \leq T_{g,k-1}|Z_t) &= \Pr(T_{g,k} < \sqrt{\gamma} \cdot Z_t + \sqrt{1-\gamma} \cdot \theta_{o,t} \leq T_{g,k-1}|Z_t) \\
&= \Pr\left(\theta_{o,t} \leq T_{g,k-1} - \frac{\sqrt{\gamma} \cdot Z_t}{\sqrt{1-\gamma}}\right) - \Pr\left(\theta_{o,t} < T_{g,k} - \frac{\sqrt{\gamma} \cdot Z_t}{\sqrt{1-\gamma}}\right) \\
&= \Phi\left(T_{g,k-1} - \frac{\sqrt{\gamma} \cdot Z_t}{\sqrt{1-\gamma}}\right) - \Phi\left(T_{g,k} - \frac{\sqrt{\gamma} \cdot Z_t}{\sqrt{1-\gamma}}\right).
\end{aligned}$$

To calculate the forward-looking probability of default (PD^{FL}) for obligors in Stages 2 and 3, three essential inputs are required: the PD data (PD), the correlation coefficient (ρ), and the standard normal random variable (Z). Under Basel II, residential morgtages has $Correlation(R) = 0.15$. Qualifying Revolving Retail Exposures has $R = 0.04$. Other Retail Exposures: $Correlation\ (R) = 0.03 \times (1 - e^{-35 \times PD})/(1 - e^{-35}) + 0.16 \times [1 - (1 - e^{-35 \times PD})/(1 - e^{-35})]$. Here, the asset correlations decrease with increasing PD and increase with firm size for different assets. Intuitively, the higher the PD, the higher the individual risk components of a borrower. The default risk depends less on the overall state of the economy and more on individual risk drivers. Also, the larger a firm, the higher its dependency on the overall economy. Here, we assumed the same asset correlation and chose $\rho = 0.06$ according to the Basel III [6].

The explanation for ρ: The parameter ρ measures the probability of the joint default of two obligors belonging to the same portfolio. In Vasicek, a portfolio with high correlations produces more significant default oscillations over the cycle S, compared with a portfolio with lower correlations. Consider a portfolio of borrowers where the default correlation is high. If one borrower defaults, it is more likely that other borrowers in the portfolio will also default around the same time. This means that the default rate of the portfolio will be more volatile and oscillate more over the cycle. Furthermore, correlations do not affect the default timing, so higher correlations do not imply that defaults are earlier or later than other portfolios. Thus, during good times a portfolio with high correlations will produce fewer defaults than a portfolio with low correlations, while in bad times, high correlations create more defaults.

PD used for the prediction is used from our simulation of the historical portfolio of 1000 mortgages ranging from 1989 to 2022. Each loan is classified using its historical credit migration into Stages 1-3 so that we calculate either 12-month PD^{FL} or lifetime PD^{FL}. The parameter Z, known as Credit Cycle Index, is used to incorporate forward-looking scenarios. There are different methods to predict Z that we discussed in the below section. Here, we reference predictive economic variables' changes to calculate CCI. Then after we found all 3 components to calculate the PD^{FL}, we estimated the expected loss using the above formula. We believe by using this methodology, banks can predict expected losses more accurately based on the macroeconomic scenario that banks choose. This methodology will make banks impair more on expected loss when the economy is not in a good condition, and the expected loss will be lessened during an excellent economic condition according to the PD^{FL} formula, just as the IFRS9 expects to see.

3 Credit Cycle Index(CCI) in One-Factor Vasicek Model

3.1 Various Methdologies to calculate the CCI

Explanation of CCI: Given a macroeconomic scenario, a Z_t can be computed, which can be used in the Vasicek framework to calculate the loss rate conditional on that specific situation. CCI is the aggregate macro-financial conditions extracted from observable economic data. Many macroeconomic and financial variables regularly collected contain relevant information on economic and financial conditions. Suppose we extract some information from each of these observable common parts of the information. In that case, we use this measure as the CCI in the Vasicek framework and compute the conditional loss rate. So through the estimated CCI, a specific macroeconomic scenario is considered in the default rate calculation. Therefore, CCI is the macro-to-micro default part of the framework whereby macroeconomic and credit conditions are translated into applicable default rates.

Impact of CCI: Two obligors are correlated because they are linked to the common factor CCI. So the Vasicek framework provides a relatively simple representation of the actual correlation structure but provides a straightforward calculation of the default risk of a portfolio. When we face good economic times, the aggregate credit risk characterised by the expected loss rate tends to be below the long-term average. In contrast, during bad times expected loss rate is expected to be above the long-term average.

We trial a proprietary Credit Cycle Indicator(CCI) at the macro geographical level in the United Kingdom. The Credit Cycle Index is a measure of the overall health of the credit market, reflecting the credit stress conditions that are present at a given point in time. It should consolidate information about indebtedness, asset prices, and financing conditions.

Literature review on various methods to compute CCI: [37] used Indonesia's GDP and standardized it to act as CCI. This method has the disadvantage of disregarding other aspects of the economy. According to [11], they developed a comprehensive Credit Cycle Index based on equity indices, property indices, and other customized indices. One critical difference is that we take CCI as the economic indicator, instead of pure credit cyclability. In that paper, the author takes the difference between the index and removes the drift or long-term trend and removes cycles in the time series that happen at periodicities of less than five quarters(noise and seasonality). However, in our setting, long-term trends, high-frequency noise, and seasonal patterns of the economic cycle are necessary for indicating the point-in-time economic condition. [7] minimized the weighted, mean-squared discrepancies between the model transition probabilities and the observed transition probabilities when determining the CCI. However, we lack the observed transition probabilities to conduct this method. Another paper [10] proposed using the Kalman filter to estimate the latent economic variable empirically. This method has the advantage of allowing the state variables to have unobservable magnitudes. Assumptions for the Kalman filter should be highlighted. The Kalman filter assumes that the process and measurement models are linear and can be expressed using matrices. It also assumes that the process and measurement noise are additive Gaussian. These assumptions must be satisfied for the Kalman filter to provide an optimal estimate [24].

In our study, we propose to use PCA (Principal Component Analysis) instead of other methods.

PCA Definition: PCA is a standard statistical technique to analyze and reduce the dimensions of large data sets and to identify patterns and trends in the data. PCA can be used to develop a Credit Cycle Index by identifying the most significant factors driving changes in the credit market. By reducing the dimensions of the data and identifying the key underlying factors, PCA can help to create a more accurate and reliable index that reflects the actual state of the credit market.

Why we choose PCA: PCA provides a clear interpretation of the principal components as directions in the feature space that capture the most variance. This can be useful for understanding the dominant patterns or features in the data. The Kalman filter, on the other hand, focuses on estimating the underlying state of a system and may not provide direct interpretability in terms of the original features. Furthermore, PCA does not involve parameter estimation. We need to provide initial estimates of parameters in the linear model in the Kalman Filter, which we also need to calibrate.

PCA is advantageous over a simple weighted average because it considers the correlations between data series and captures the maximum variation in the data. It identifies new components, called principal components, that explain the most variance in the original data. This reduces dimensionality while retaining important information and provides a more comprehensive understanding of complex relationships and patterns. PCA enables more accurate modelling and better insights than examining individual variables or their simple weighted averages.

The PCA leverages data mentioned in [11] and references this study's supervisors' suggestions. Our data include **Macroeconomic data** sourced from FRED and UK house price index: the unemployment rate, real Gross Domestic Product values, inflation rate, and house price index (HPI). All data are quarterly because, by the IFRS9, entities should recognise provisions quarterly. These data provide indicators of the overall labour market health, economic growth or contraction, changes in the general price level, and residential property prices, respectively. By incorporating these variables into the analysis, we aim to capture relevant economic conditions and their potential influence on credit risk.

3.2 CCI Calculation

1. Take the percentage change of these data so that data are in the same scale for PCA fit purposes. For instance, $\Delta\text{GDP1} = \frac{\text{GDP1}-\text{GDP0}}{\text{GDP0}}$. The data period is starting from 1989 Q3 to 2022 Q4. Here we take the negative of the delta unemployment rate since the unemployment rate has a negative relationship with the

economic cycle. All UE in the following analysis represents the unemployment data that has already been multiplied by -1.

2. Apply PCA using the logistics explained in **Application Steps of PCA** and the first principal component is our index.

3. Use insolvency rate to test the efficiency of the index through one-factor regression and paired t-test.

Application Steps of PCA:

1. Calculate the average values of each underlying data, known as $\bar{x}_1, \bar{x}_2, \bar{x}_3, \bar{x}_4$. Standardize the data. For instance, Standardized $\Delta\text{GDP} = \frac{\Delta\text{GDP} - \text{mean}(\Delta\text{GDP})}{\text{standard deviation}(\Delta\text{GDP})}$. The table below summarizes the mean value of the four variables. It is evident that the variables, in their current form, exhibit varying magnitudes, which can influence the calculation of variance in the Principal Component Analysis (PCA). To address this issue, it is necessary to standardize the variables, ensuring they are on a comparable scale. By standardizing the variables, we can remove the bias introduced by their disparate magnitudes and facilitate a more meaningful PCA analysis.

Table 3: Mean Values of Delta Variables

Delta Variable	**Mean Value**
GDP	0.004397
UE	0.004741
INF	0.028116
HPI	0.006582

2. Calculate the correlation matrix. From the figure, it is evident that all variables exhibit a positive linear association, indicating that they represent the economy in the same direction, and the PCA would characterize a piece of common information.

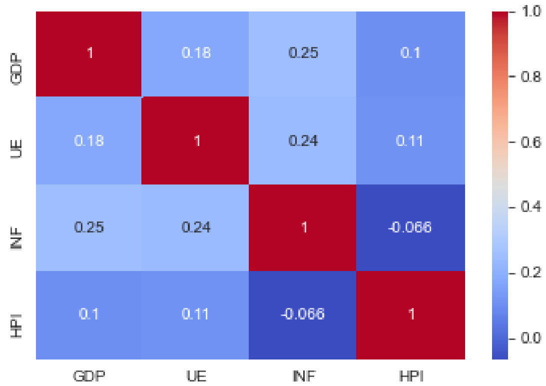

Figure 3: Correlation Matrix.

3. Calculate the eigenvalues $a_1, a_2, a_3, a_4 = [1.46476692\ 0.6647499\ 0.82007417\ 1.05040901]$ and eigenvectors of the correlation matrix =

$$\begin{bmatrix} 0.56800308 & 0.42886716 & -0.70091439 & 0.04652405 \\ 0.56160616 & 0.40846532 & 0.71195843 & 0.10425837 \\ 0.57325248 & -0.69549875 & 0.01024944 & -0.43307971 \\ 0.18262701 & -0.40682986 & -0.04158326 & 0.89409601 \end{bmatrix}.$$

4. Sort eigenvalues from large to small and choose corresponding eigenvectors for the largest eigenvalue as coefficients $b_1, b_2, b_3, b_4 =$

$$\begin{bmatrix} 0.56800308 & 0.42886716 & -0.70091439 & 0.04652405 \end{bmatrix}.$$

5. CCI $= a_i * Standardized\ Value_i$.

6. Standardize the CCI since we require CCI to be of standard normal distribution in the One Factor Vasicek model. The 4 figure below is the eventual Credit Cycle Index that we use in the afterwards computation. Upon careful examination of the data, it becomes apparent that the CCI exhibits a consistent pattern of negative values during significant historical financial crises. Notably, this trend is evident during 1992, 2002, and 2008, and the challenging period marred by the COVID-19 pandemic in 2020. These occurrences indicate that the CCI is a reliable indicator of the adverse economic impact experienced during financial turmoil and uncertainty. The significant drop and rise in 2020 are attributed to the rapid drop in GDP and the recovering GDP, leading to a significant negative value of ΔGDP and a significant positive value of ΔGDP, which then reflects in the PC1 result.

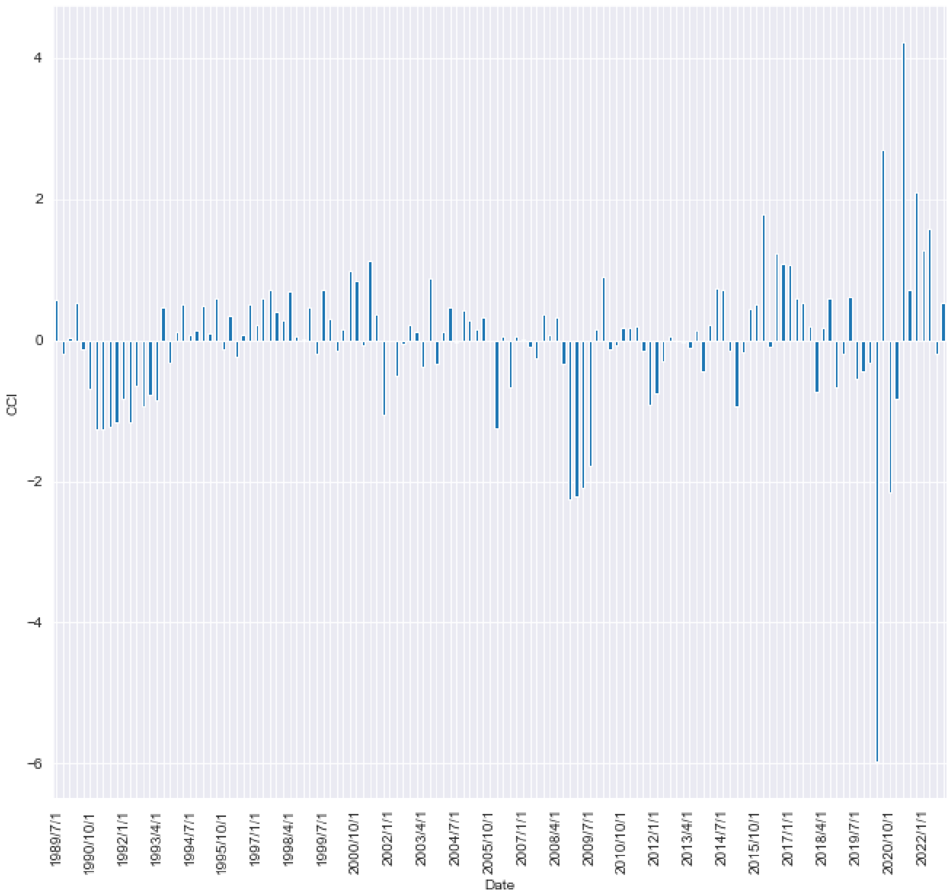

Figure 4: Credit Cycle Index

3.3 Efficiency Checks of CCI

We use simple linear regression between CCI and annual insolvency rate, which corresponds to our target asset (mortgages), to check whether CCI can represent the macroeconomy. If the CCI has a positive value, the general economy is good, generally correlating with a low insolvency rate.

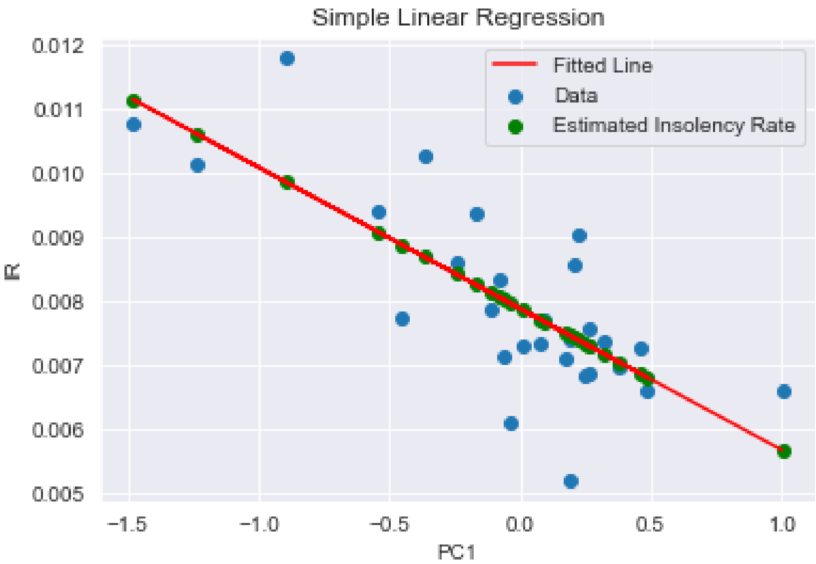

Figure 5: One-factor regression between CCI and IR

Since the insolvency rate is on an annual basis, we calculate the average mean of quarterly CCI as the annual data. The regression result is: $Insolvency = -0.0022 * CCI + 0.0079$, with both parameters having a 0.000 p-value, indicating their significant difference from zero. The $R - squared$ value is 0.586, meaning that the CCI variation can explain 58.6% of the insolvency rate variation. This suggests that CCI is a reasonably good predictor of the insolvency rate. Figure 6 compares the estimated and actual insolvency rates, showing a similar shape. Therefore, CCI can be used as an indicator of the macroeconomy regarding the insolvency rate, with higher CCI values associated with lower insolvency rates.

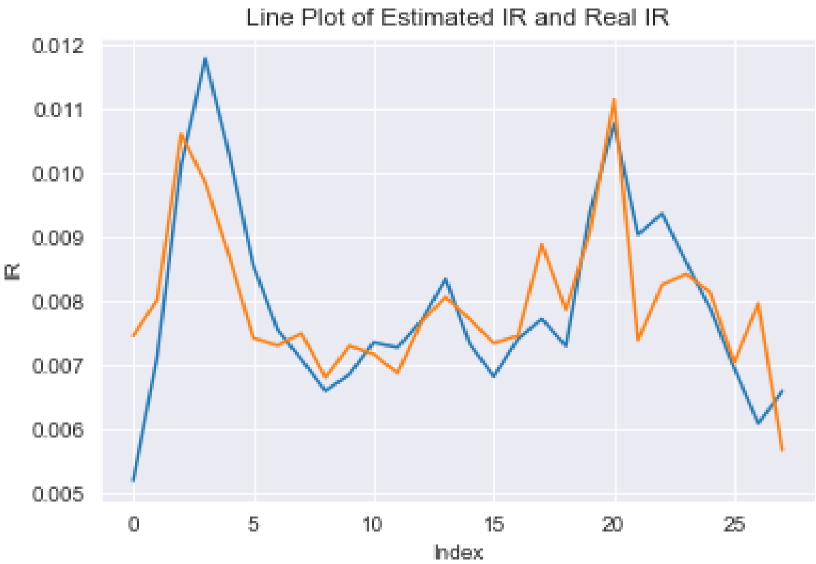

Figure 6: Estimated IR vs Real IR

Potential Research Area: We use the Explained Variance Ratio to assess the usefulness of principal components. This metric represents the percentage of variance explained by each selected component. The first principal component, or the CCI, does not have a variance ratio of over 80%. This signals the relatively low variance representative ability of the principal component in the underlying data. If we only use three underlying components which characterize fewer aspects of the economic market, the variance ratio improves due to better co-movement and a more straightforward structure.

We have also trialled developing indexes including Financial data: real average housing market values of all types, interbank lending rate, and FTSE 100 index. However, the relationship between the financial data and economic performance has not been rigorously researched, we do not include them in PCA analysis in pursuit of better explainability. Future researchers could research other kinds of data to establish a more rigorous index.

In the One-Factor Vasicek Model, the Credit Cycle Index is assumed to have a standard normal distribution. Nevertheless, our PC1, or the CCI, does not have a standard normal distribution. After we have standardized it, the Credit Cycle Index still does not pass the standard normal distribution test. If we remove all outliers, setting all data below $mean - 1.5 * IQR$ by $mean - 1.5 * IQR$ and above $mean + 1.5 * IQR$ by $mean + 1.5 * IQR$, the PC1 we eventually get from the above procedure passes the standard normal test. Nevertheless, since the outliers lie in the Covid era, we do not remove the outliers so that we can gauge the influence of Covid on the model prediction under IFRS9.

4 Portfolio Simulation

To conduct our study within the given time constraints and research focus, we have chosen to simulate a synthetic mortgage portfolio instead of using real-world mortgage loan data. To keep the calculations straightforward and manageable, we have made certain simplified assumptions. It is important to note that these assumptions do not fully reflect the complexity of an actual portfolio, which would include factors such as discounted future cash flows, varying monthly payments, flexible or fixed-rate mortgages, and payment rates based on individual obligor profiles. Incorporating these realistic financial figures would require significant time and resources, which is not feasible for this study. Therefore, we have opted for a simplified approach that aligns with our research objectives and allows us to proceed efficiently.

4.1 Portfolio Simulation Assumptions

1. **Loans Duration:** Regarding the business operation of Sopra Steria Financial Services Group, We assumed a mortgage length between 3 and 7 periods. Each loan's length is uniformly selected from the interval [3,7] and then rounded to the nearest integer. This is flexible to change subject to real concerns. In reality, we may have mortgage loans ranging from 3 to 7 years.

2. **Borrower's loan amount:** Each loan amount is randomly selected from the normal distribution with 10^6 *and* 10^7 amounts. Using the $68 - 95 - 99.7$ rule, we wish the 99.7% of data to fall within the three standard deviations from the mean. Therefore, the standard deviation is $0.5 \times \frac{(10^7 - 10^6)}{3}$. Researchers can also set the loan amount to be three to five times the income. For instance, the Median household disposable income in the UK in 2022 is $32,300$, according to Office for National Statistics, so we can adopt loan amounts to be randomly selected from a normal distribution with this mean.

3. The **time horizon** aligns with the CCI value. The portfolio has a quarterly migration record each year from 1989 Q3 to 2022 Q4.

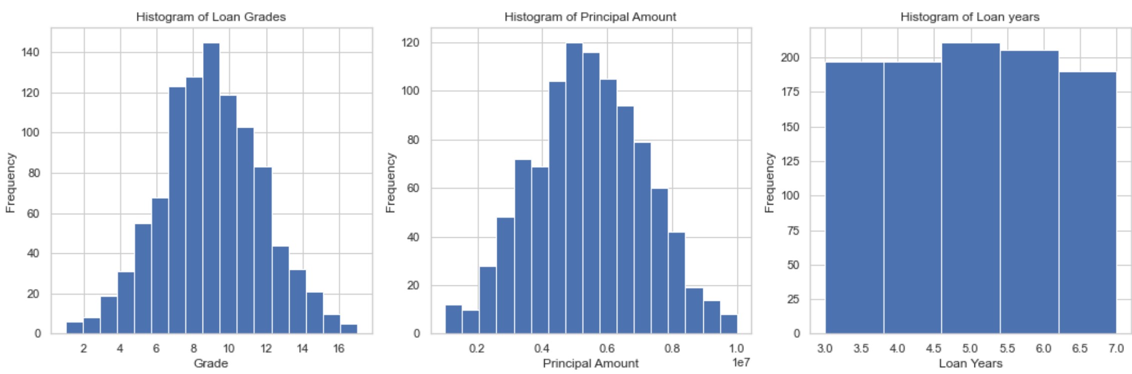

Figure 7: Portfolio Variable Distribution

(a) We use the Kolmogorov-Smirnov test to test that the initial loan grades, principal amount, and lifecycle of each loan follow the assumed distribution. For borrowed amount, the $p - value$ is 0.2346, greater than the threshold of 0.05, so it followed the assumed normal distribution. However, the loan grade and loan duration failed the test of respective normal and uniform distribution since we rounded them to the nearest integer. Even when we increased the sample size to 10,000, they failed the continuous version of the specified distribution. However, we can verify from the above plot that they qualitatively have the desired distribution.

4. **Customer Replacement:** Once a borrower's loan defaults or reaches maturity, we flag them as either defaulted or matured. We remove them from the original portfolio and replace them with the same loan amount to keep the balance sheet the same. However, we follow the rules above to randomly generate its loan length and initial credit rating to keep the portfolio realistic.

5. **The number of borrowers** remains constant at 1000 every quarter to maintain stable calculations. Researchers could also increase the number with better computation capacity.

6. **Borrower's initial credit rating:** We use rating standards from S&P Global Ratings Credit Research, which adopts the 18 ratings: AAA, AA+, AA, AA-, A+, A, A-, BBB+, BBB, BBB-, BB+, BB, BB-, B+, B, B-, CCC, D. There is one additional category NR. In the simulation, we use numeric values to replace letter grades with the following transformation rule.

Grade	**Value**
AAA	1
AA+	2
AA	3
AA-	4
A+	5
A	6
A-	7
BBB+	8
BBB	9
BBB-	10
BB+	11
BB	12
BB-	13
B+	14
B	15
B-	16
CCC/C	17
D	18

7. **Rating migration matrix:** We use the Average one-year transition rates for global corporates by rating modifier (1981-2022) (%) as the initial migration matrix and is used to calculate the transition threshold for each rating.

4.2 Implement the IFRS9 Provision- impairment modelling judgements

1. **Approach to determining a SICR**: To determine whether a bond has experienced a significant increase in credit risk (SICR) and should be classified as a Stage 2 bond, we follow a specific approach. First, we generate a pair of correlated standard normal variables, denoted as std_normal1 and std_normal2, using a covariance matrix of $\begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$. Next, we calculate a new transition threshold using the following formula:

$$\text{new transition threshold} := \Phi\left(\sqrt{\gamma} \cdot \text{cci}[t+1] + \sqrt{1-\gamma} \cdot \text{std\_normal2}\right).$$

   We use the new transition threshold to find the updated credit rating.

   (a) If the updated credit rating minus the initial > 1, we classify the obligor in Stage 2. In this Stage, we compute the lifetime Expected Credit Loss as the provision amount.

   (b) If the initial credit rating minus the updated > 1, we classify the obligor in Stage 1. In this Stage, we compute the 12-month Expected Credit Loss as the provision amount.

2. **The applicable definition of default**: We define our standard to classify a bond in Stage 3. In this Stage, we compute the lifetime Expected Credit Loss as the provision amount. We calculate a new transition threshold using the following formula:

$$\text{new default threshold} := \Phi\left(\sqrt{\rho} \cdot \text{cci}[t+1] + \sqrt{1-\rho} \cdot \text{std\_normal1}\right).$$

   If the new default threshold value is below the next time's default threshold(at t+1), it's marked to be Default and classified in Stage 3. We will replace the defaulted loan using the rules mentioned above.

4.3 Simulation realization

Based on the above portfolio simulation, we discuss how to implement the simulation.

We first calculate the cumulative probability of each rating and their corresponding thresholds by the inverse of the standard normal distribution. We then calculate the new transition matrix for each period using the point-in-time CCI. We then calculate the conditional PD using the historical average Default Rate. Therefore, $1 - PD$ can be multiplied by the threshold I got before. Then the default probability of assets of different levels in different periods can be obtained as rating migration only considers transitions between non-defaulted loans.

We can also calculate new PD and compare it with the above conditional PD matrix. If the new PD is less than the conditional PD, the borrower defaults and is classified as Stage 3.

4.4 Simulation analysis

To verify if the model is efficient enough, we observe if the CCI and default rate has an inverse relationship. If the model is correct, there should be fewer default numbers when the economy is good or vice versa. The following figure testifies to this expectation. The blue line is CCI and the orange line is the number of defaulted customers. We could see a significant drop in CCI during 1992, 2008, and 2020, corresponding to several big financial crises (explained in the Dictionary Section). Correspondingly, there are several rises in the number of defaulted leavers in these periods.

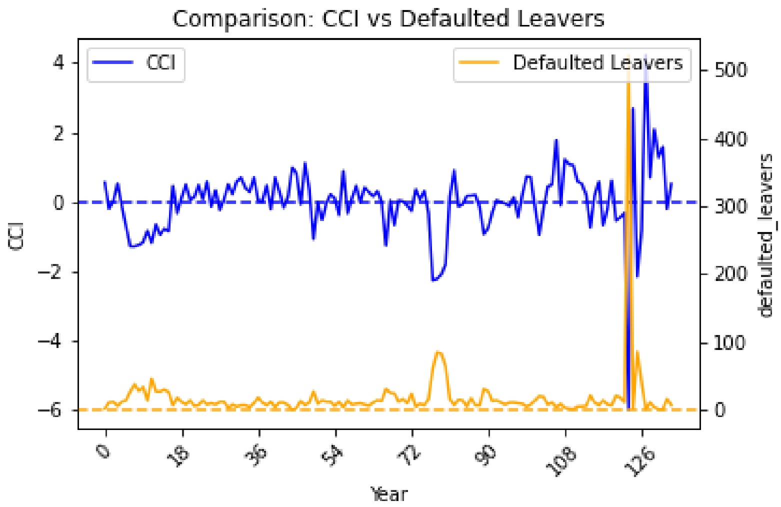

Figure 8: CCI vs Number of Defaulted Leavers

The number of assets due reflects the number of debtors leaving the portfolio due to maturity. Since the loan has the shortest length of 3 years, no loans will be matured until after 3 years. Moreover, since the maturity is regardless of macroeconomic condition and each matured loan is replaced, we should expect a converged behaviour for the loan length. We can see from the figure that maturity leavers appear after several periods and, indeed converges in the long run. Furthermore, joiners and leavers sum to 1000, the total amount of customers every period.

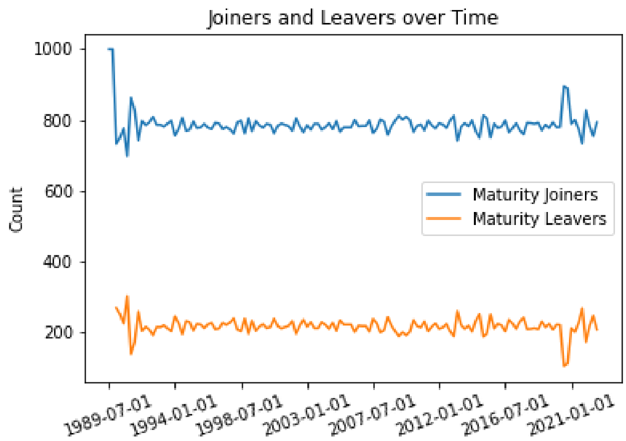

Figure 9: Maturity Joiners & Leavers

We then analyze how the IFRS9 regulation affects the bank's PnL through the breakdown of Stages over time. As seen from the figure below, the number of debtors at each Stage has a similar movement with the CCI. Furthermore, during financial crises, the number of Stage 1 customers drops while the number of Stage 3 customers increases. The total loan amount classified by Stages has a similar moving tendency by the same logic.

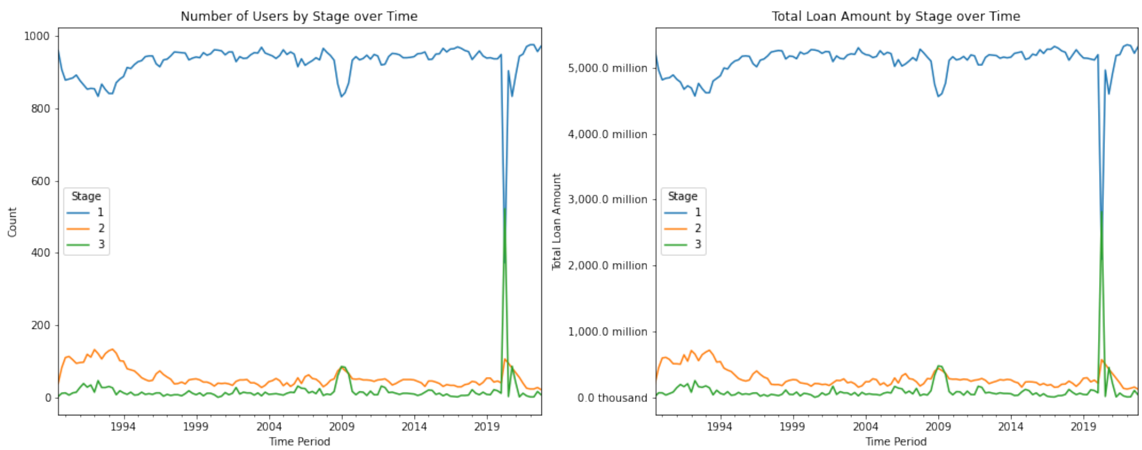

Figure 10: Number of Users & Total Loan Amount by Stage under IFRS9

5 Backtesting

Reasons for Backtesting: We want to use the portfolio migration and future economic forecasts to predict the IFRS9 provision in the upcoming years (2023-2025). However, we do not know the efficiency of the prediction. Therefore, we conduct backtesting to validate what we have done. We assume we stand at the end of 2018, and the task would be to forecast the estimated credit losses that result from customers declaring a default. We compare the estimated credit loss with the actual credit loss from the original simulated portfolio.

5.1 Backtesting Methodology

We don't have CCI values in the future that describe the economy. However, the Bank of England publishes expected values of the Unemployment Rate (UR) in the upcoming years based on multi-factor non-public models. Since the unemployment rate has a similar moving tendency to the historical insolvency rate, we use future predictions of the unemployment rate to predict the CCI.

We first predict the CCI values for upcoming years. Using the available data for the percentage change of $UR(\Delta UR)$, we build the simple linear regression model to predict the future CCI.

$$CCI_t = a + b \cdot \Delta UR$$

We then use the statistical package in Python and the historical data of the unemployment rate from 1989 to 2018 to build this model. The model coefficients are summarized in the table below. We can see from the table below that $p - value$ for both intercept and slope are near 0, smaller than threshold 0.05. Therefore, the relationship between CCI and ΔUR is statistically significant. The $adjustedR - squared$ is 61.7%, indicating that the model has a relatively good linear fit.

Table 4: Coefficient Estimates

	coef	std err	t	P> $\|t\|$
const	-0.0887	0.041	-2.174	0.032
Delta_UE	-15.3359	1.134	-13.520	0.000

We assume that the realistic forecast matches the real unemployment rate published by the Office of National Statistics. Using the regression coefficients and the ΔUR in the next several years, we have the estimated CCI. In the figure below, the orange dot is the estimated IR. We could see that the estimation values of CCI lie within the reasonable range of the original data, indicating that the estimation is reasonable. We could observe that the 99% prediction interval contains most of the real data.

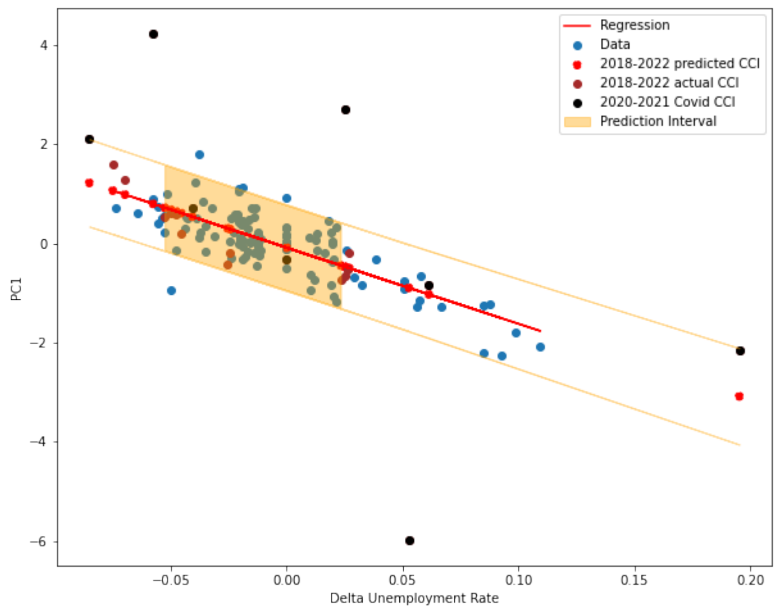

Figure 11: Linear Regression for CCI

In addition to performing the linear regression, we conducted a residual analysis to evaluate the model's assumptions. The results indicate that the residuals conform to a normal distribution, as evident from the normal quantile-quantile (QQ) plot and the histogram of residuals. This suggests that the assumption of normality is generally satisfied.

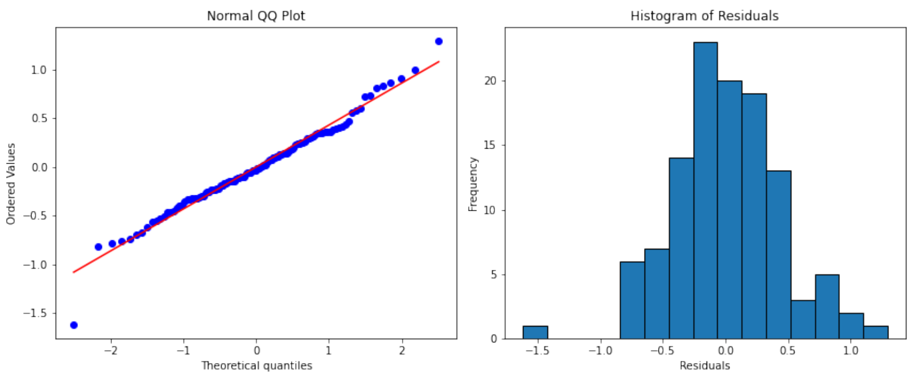

Figure 12: Residual Distribution

Furthermore, the four plots generated from the residual analysis provide insights into the linearity, homoscedasticity, and overall goodness-of-fit of the linear regression model. We observed that the residuals do not exhibit a systematic pattern concerning the explanatory variable, and they have a mean value of 0. These findings lead us to conclude that the residuals do not display heteroscedasticity, indicating that the assumption of constant variance is satisfied. Based on these analyses, we can validate the linear regression model and conclude that it meets the necessary assumptions. This gives us confidence in the model's ability to accurately estimate the relationship between the variables and make reliable predictions.

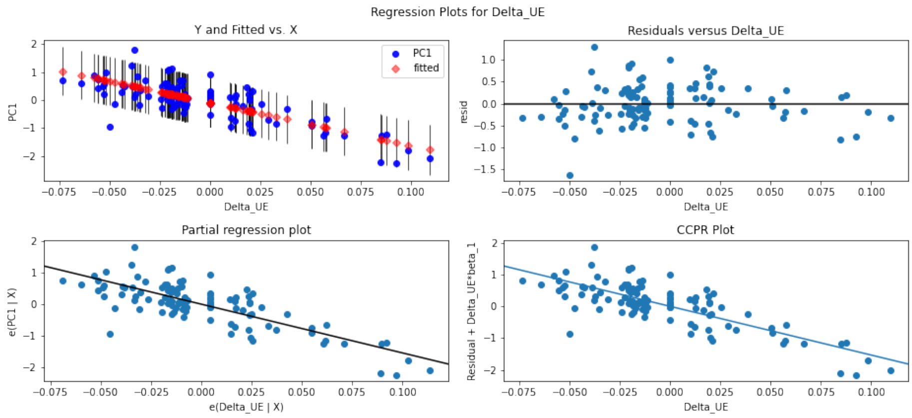

Figure 13: Regrssion Plots

We then compare the predicted CCI and our original CCI. The figure below indicates that the predicted CCI has a similar trend as the original CCI. The predicted and the actual CCI have roughly the same drop or same rise at around the same time. However, using prediction methods other than PCA, it is unrealistic to expect our predicted Credit Cycle Index (CCI) to match the actual CCI perfectly. Due to the unexpected shock in covid era, the single-factor unemployment rate does not capture such shock and causes the estimated CCI to be less volatile.

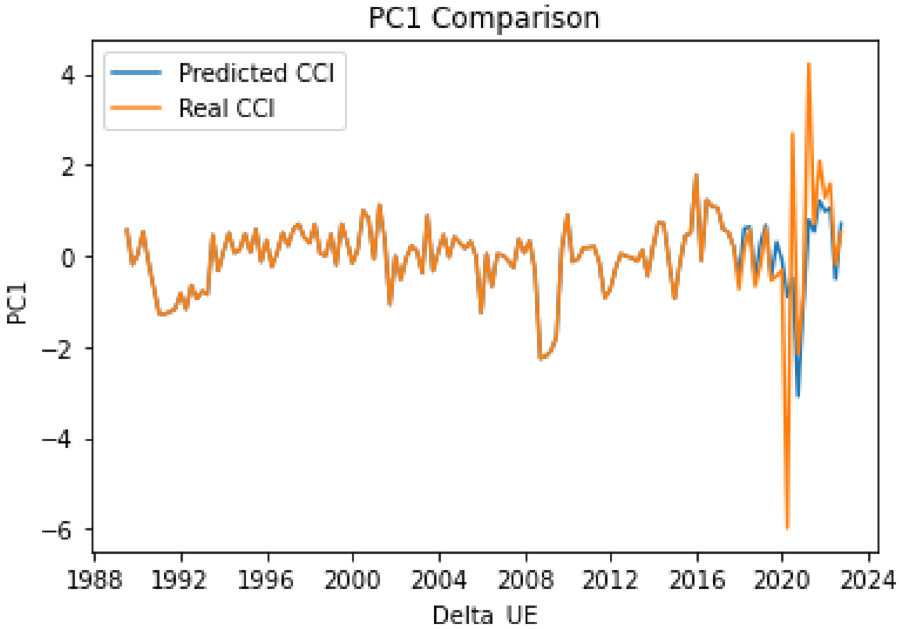

Figure 14: Actual CCI: 1989-2018 vs Prediction for CCI:2018-2022

5.2 Other methodologies for predicting CCI:

It's worth mentioning that Economic predictions involve uncertainties and various factors that can affect the accuracy of the forecast. Different prediction methods have strengths and limitations, and it is important to consider contextual factors when choosing an appropriate forecasting approach. This helps to set realistic expectations regarding the accuracy of economic predictions.

Future researchers could try Autoregressive Integrated Moving Average (ARIMA) on the CCI data with external regressors such as the unemployment rate to predict the CCI. Multiple linear regression can also be a choice which accounts for multiple predictors and improve model fit. Kalman filter is also possible and Kalman filter's benefits and disadvantages are mentioned in an earlier section when we mentioned multiple choices to calculate CCI.

5.3 Portfolio DR and Vasicek MLE

In the backtesting simulation, we need Vasicek parameters. We first use historical portfolio data from 1989 to 2017 to calculate the portfolio level default rate DR_t by weighting the total loan balance corresponding to loans at each grade and calculating the weighted average:

$$DR_t = \frac{\sum_g PD_{g|Z_t} \times EAD_{g,t}}{\sum_g EAD_{g,t}}.$$

Here the $EAD_{g,t}$ is the sum of borrowed amounts at grade g at time t. This formula is preferred over simply dividing the number of defaulted loans by the total number of loans because it considers the credit quality (PD) and the size (EAD) of each loan. Incorporating PD and EAD provides a more accurate measure of credit risk and reflects the potential losses that may occur. It allows for a more granular analysis by taking into account the individual characteristics of each loan group, providing a more meaningful default rate estimation. We can see from the graph below that the CCI has an inverse relationship with the portfolio-level default rate, corresponding to the original logic.

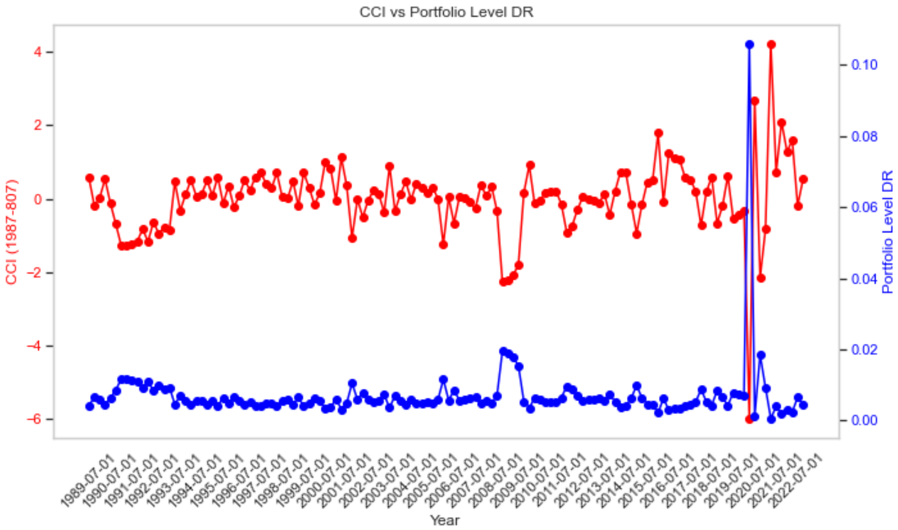

Figure 15: CCI vs Portfolio Level Default Rate: 1989-2017

We then use the DR_t and Vasicek MLE to calculate two parameters. The $\rho_{forecast} = 0.01952$ and the $\lambda_{forecast} = 0.005469$. These Vasicek parameters and the predicted CCI values after 2017 will give us the predicted conditional probabilities on the portfolio level

$$\text{PD}|Z_t = E(DR_t) = \frac{\phi(\phi^{-1}(\lambda_{\text{forecast}}) - \rho_{\text{forecast}} Z_t)}{\sqrt{1 - \rho_{\text{forecast}}}} \tag{7}$$

, where ϕ is the standard normal cumulative distribution function.

5.4 Log-odd Adjustments

We need a split-by-grade conditional probability of default to simulate the portfolio for the next several years. We will adjust the forecast so that the weighted average default point is as close to the forecasted portfolio-level conditional probability of default. Then the credit grade-level default thresholds are adjusted following the predicted state of the macroeconomy. The adjustment logistics are as follows:

We first introduce the logit function for any logistic regression:

$$\text{logit}(p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \sum_{i=1}^{n} \beta_i y_i, \tag{8}$$

where $ln(\cdot)$ denotes the natural log function and n denotes n explanatory variables. In the current study, we choose $n = 1$. We assume p is the probability of survival so that $p = 1 - PD$. So our equation is

$$\text{logit}(p) = \ln\left(\frac{Pr(Survival)}{Pr(Default)}\right) = \ln\left(\frac{1 - PD}{PD}\right) \tag{9}$$

So we can write $\log(\text{odds}_\text{g}) = \beta_0 + \beta_1 \cdot g$ where g is the credit grade.

Furthermore, from the equation 9, we can write $e^{(\text{ln-odds})} = \frac{1}{\text{PD}} - 1$, so

$$\text{PD}_g = \frac{1}{e^{\log(\text{odds}_\text{g})}} + 1, \tag{10}$$

where both PD and the ln (odds) are defined with respect to all credit grades g from 1 to 17.

We need to adjust the forecast grade-level conditional probability of default so that the weighted average probability of default approaches the forecasted portfolio-level values. We do not adjust β_1, the amount of ln-odds change for one unit of increase in g. Therefore, we only adjust β_0 by a series of x such that

$$\log(\text{odds}_\text{g}) = (\beta_0 + x) + \beta_1 \cdot g, \tag{11}$$

implemented into equation 10 so that

$$\text{PD}_\text{adj} = \frac{\sum_{g=1}^{17}(\text{PD}_g \cdot \text{EAD}_g)}{\sum_{g=1}^{17} \text{EAD}_g} \tag{12}$$

so that $PD|Z_t$ and PD_{adj} satisfy $|PD|Z_t - PD_{adj}| \leq \epsilon$, where ϵ is pre-defined precision tolerance close to 0. Although any value sufficiently small will increase the accuracy of the model, it's set to 0.02 in the current study due to the computation limit.

In addition to this adjustment, the rating migration matrix will be re-scaled following the cumulative survival likelihood. The probability of an obligor associated with credit grade will be the transition matrix's entry multiplied by a $\frac{Pr(\text{survival at time } t)}{Pr(\text{Long-Run Average Survival})}$ multiplier.

The algorithm for future years' PD calculation:

1. Set $t = 2017$. We then increase the t every time we reach the end of one loop. The loop terminates in 2022.

2. Forecast the portfolio level conditional probability of default by 7 and set those as targets in the iterative process.

3. Input the 18-by-18 rating migration matrix and form the base matrix for $t = 2017$.

4. Define $PD_g, \log(\text{odds}_\text{g}), PD_{adj}$. β_0 *and* β_1 are calculated using the long-run average default thresholds. Use the EAD values from the last 2017 portfolio to calculate PD_{adj}.

5. Construct the annually revised rating migration matrix for $t+1$ by multiplying $\frac{Pr(\text{survival at time } t)}{Pr(\text{Long-Run Average Survival})}$. We then calculate the cumulative transition matrix by multiplying the cumulative matrix at time t by the annual matrix at time $t+1$ we just derived.

6. Run the loop starting from an initial value of x, and we increment x by a very small amount until $|PD|Z_t - PD_{adj}| \leq \epsilon$ is met. Once the optimal adjustment coefficient x is found, calculate everything from step 5.

7. Store the transition matrices and go to step 1.

At each time t from 2018 to 2022, the annual transition matrices and respectively the PD_{adj} are only calculated with a 5-year horizon ahead advised by this study's supervisors. After year 5, the long-run average base values will be used instead.

5.5 IFRS9 Provision

After we derive the adjusted probability of default for the forthcoming years until maturity and the 12-month transitional probabilities, the portfolio evolution follows the same logic as the historical portfolio simulation. 12-month transitional matrices will be thresholds to determine which credit grade the customer will be in at the end of the respective year, which will depend on the state of the macroeconomy in the current time cycle.

Now we have the estimated portfolio evolution, we can calculate the Lifetime Expected Credit Loss for Stage 2 and 3 customers and the 12-month Expected Credit Loss for Stage 1 obligors. The sum of these values for all obligors is the provision amount reserved for potential losses under IFRS9 regulation. 12-month ECL and lifetime ECL(LECL) has expression as below:

$$\text{12-month ECL} = \text{12-month PD} \times \text{LGD} \times \text{EAD}$$

and

$$\text{LECL} = \sum_{t=1}^{m} \text{LPD}_t \times \text{LGD}_t \times \text{EAD}_t \times \text{DF}_t. \tag{13}$$

Here m is the remaining years until maturity, and DF_t is the discount factor at year t and represents the future value of money. We choose the annual inflation rate to be 2% so that $DF_1 = 1.02, DF_2 = 1.02^2$.

Inflationary Considerations in IFRS 9 Modeling during Covid: The COVID support measures implemented during the pandemic, such as fiscal stimulus packages and low-interest rates, often necessitated the central banks to engage in money printing or monetary expansion. The objective behind the central bank's money printing was to provide financial relief, boost liquidity, and stimulate economic recovery. However, this increase in the money supply can potentially lead to inflationary pressures. Consequently, in the context of provision forecasting under IFRS 9, the impact of inflation on the discounting process becomes significant, as adjustments may be required to account for higher expected inflation. Future researchers can enhance the accuracy of their IFRS 9 modelling by incorporating realistic projections of inflation rates and adjusting them accordingly. Fluctuations in inflation rates would also result in adjustments to the value of floating payment-type mortgages.

5.6 Analysis and Discussion

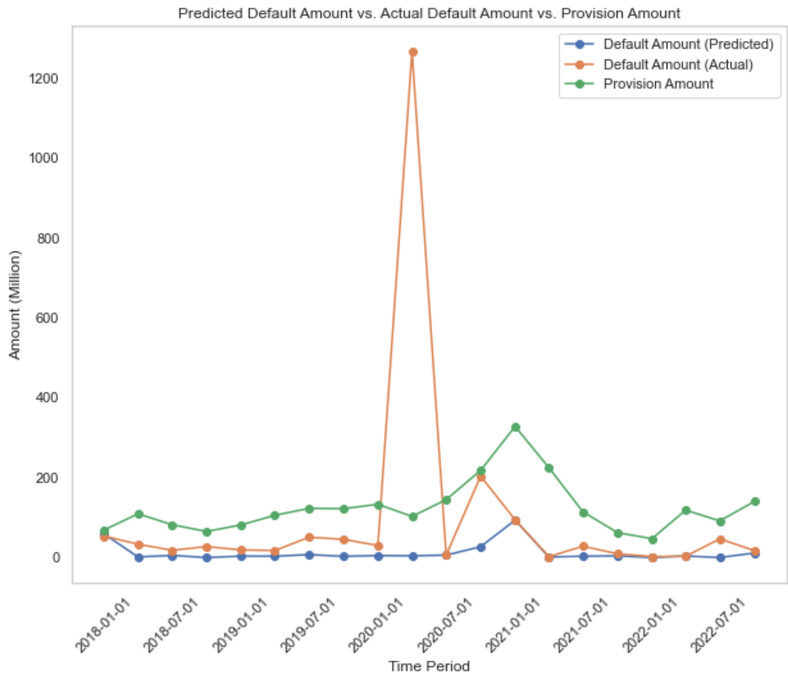

Figure 16: Backtested Default Amount vs Provision Amount vs Actual Default amount: 2018-2022

We can see from the above graph that the predicted and actual write-off amounts are not the same shape and may differ at specific points, such as during the Covid time. The reason that the expected default amount and provision amount are not as significant as the actual default amount is that the unemployment rate itself does not fully predict a significant drop in the economy. So the predicted CCI does not have a significant drop as the real one (recall Figure 14). As a result of the less volatile predicted CCI, the predicted default amount is insignificant. It's worthwhile noting that this risk is not included in the analysis. Therefore, if central banks didn't do anything to rescue the financial market, the IFRS9 provision would be insufficient for banks to cover the credit losses. In addition to the earlier CRR quick fix amendments that relax regulations mentioned in the section, the UK government implemented several other things to alleviate the impact of Covid on credit losses:

1. UK government introduced the Furlough scheme to subsidize employee wages, protecting jobs and easing the burden on businesses that eased the credit pressure.

2. Furthermore, the UK government introduced Government-backed loan schemes, Coronavirus Business Interruption Loan Scheme (CBILS) and the Bounce Back Loan Scheme (BBLS), to provide financial support and favourable loan terms to pandemic-affected businesses.

3. Regulatory authorities, including the Bank of England and the Financial Conduct Authority, implemented various measures to ensure the stability of the financial system. This included providing liquidity support to financial institutions, relaxing regulatory requirements, and encouraging lenders to offer forbearance measures to borrowers facing financial difficulties.

4. The government introduced mortgage payment holidays, allowing homeowners to temporarily pause their mortgage payments if they experienced financial hardship due to the pandemic. This measure aimed to alleviate the burden on individuals and prevent widespread mortgage defaults.

5. Mortgage payment holidays: The government introduced mortgage payment holidays, allowing homeowners to temporarily pause their mortgage payments if they experienced financial hardship due to the pandemic. This measure aimed to alleviate the burden on individuals and prevent widespread mortgage defaults.

Nevertheless, the Provision amount could cover the predicted and actual default amount in most cases, meaning that the IFRS9 provision is adequate when we impose the above assumptions in our classification methodologies. We also tested the modelling when we assumed the Covid did not happen by replacing all the Covid data with regularized values and see what would the model result be in a natural environment. We describe the without-Covid modelling in the following subsection.

5.7 P&L Charge

The table Pnl Charge below summarizes the portfolio across the backtested years. The actual write-off amount represents the total loss caused by defaults, calculated as the product of LGD (Loss Given Default) and EAD (Exposure at Default). The Delta Provision represents the change in the predicted provision at the beginning of each year, either adding or subtracting funds to the existing reserve. It is worth noting that the provision calculation assumes that no funds were set aside before 2018, as we want to analyze the net change.

Increasing the provision for a bank has a two-sided impact. On the one hand, it reduces the funds available for profit-generating activities like lending to others. On the other hand, it helps cover potential losses from defaulted loans, enhancing the bank's financial stability. Balancing provisions with profit generation is a crucial challenge for banks.

The Profit & Loss (P&L) charge provides an alternative perspective on assessing the bank's stability and readiness to face credit losses. It is calculated as the sum of the actual write-off amount and the change (delta) in the impairment provision from the previous period to the current one.

The P&L charge reflects the bank's each time cycle position compared to the previous one. During worsened macroeconomic conditions, more obligors default, leading to higher write-off amounts and more enormous P&L charges. Figure 17 illustrates significant P&L charges occur when the macroeconomy's state deteriorates. Around 2020, the substantial increases in the P&L charge can be attributed to the recession's macro conditions (Covid), resulting in higher incurred losses and a rapid escalation in the provision change. The case in 2021 is also essential: whenever a significant amount of unexpected losses appear on the balance sheet, the P&L charge is higher, due to the insufficient level of preparation for it.

Table 5: P&L Charge (Unit: Pounds)

Year	EAD of Defaulted Actual	Writeoff Actual	Provision Amount	Delta Provision at the beginning of the year	P&L Charge
2018-01-01	118,950,673	53,527,803	69,141,128	69,141,128	122,668,931
2018-04-01	74,143,340	33,364,503	109,320,326	40,179,197	73,543,700
2018-07-01	40,062,794	18,028,257	82,122,100	-27,198,226	-9,169,969
2018-10-01	60,556,840	27,250,578	65,252,578	-16,869,522	10,381,056
2019-01-01	42,210,254	18,994,614	81,662,255	16,409,676	35,404,291
2019-04-01	38,856,264	17,485,319	105,647,031	23,984,776	41,470,095
2019-07-01	112,933,670	50,820,152	123,019,886	17,372,855	68,193,006
2019-10-01	101,099,820	45,494,919	122,251,484	-768,401	44,726,518
2020-01-01	66,862,465	30,088,109	133,218,771	10,967,286	41,055,396
2020-04-01	2,816,303,626	1,267,336,632	102,740,417	-30,478,354	1,236,858,278
2020-07-01	12,959,240	5,831,658	144,885,971	42,145,554	47,977,212
2020-10-01	452,704,734	203,717,130	218,068,575	73,182,604	276,899,735
2021-01-01	209,528,685	94,287,908	328,279,663	110,211,088	204,498,996
2021-04-01	4,855,850	2,185,132	224,909,343	-103,370,321	-101,185,188
2021-07-01	62,727,507	28,227,378	114,395,730	-110,513,612	-82,286,234
2021-10-01	20,600,647	9,270,291	62,408,572	-51,987,159	-42,716,868
2022-01-01	5,068,315	2,280,742	47,116,979	-15,291,593	-13,010,851
2022-04-01	6,827,586	3,072,414	118,589,538	71,472,559	74,544,973
2022-07-01	103,677,575	46,654,909	91,704,112	-26,885,427	19,769,482
2022-10-01	38,622,349	17,380,057	140,257,204	48,553,092	65,933,149

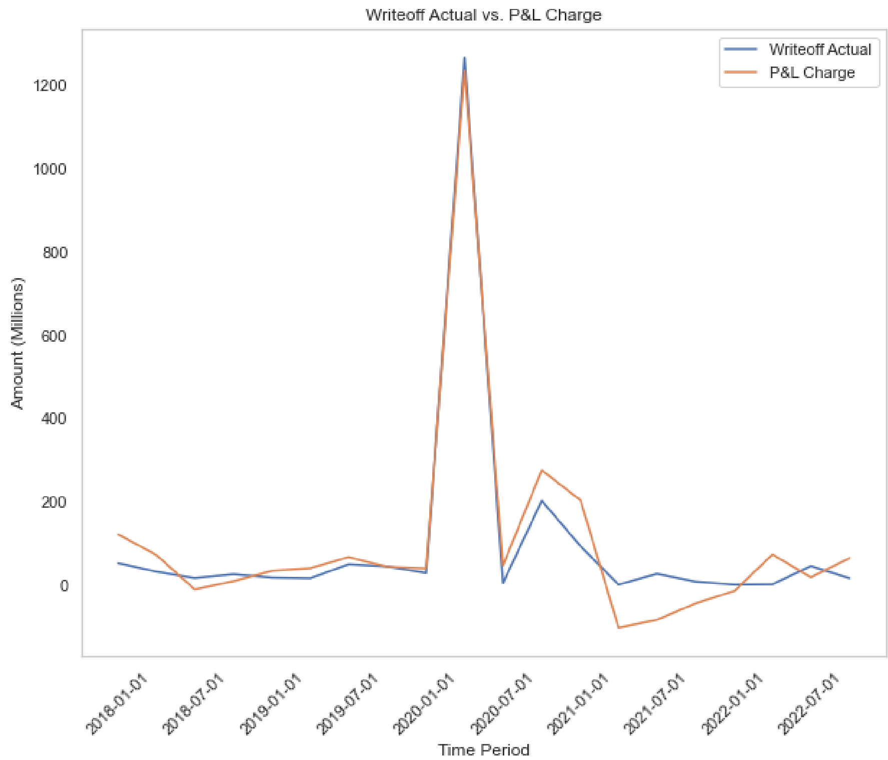

Figure 17: P&L charge and Write-off: 2018-2022

5.8 Without Covid Modelling

Given the significant impact of Covid on the economy, we want to check our model as if the Covid impact did not occur(in a natural environment). To achieve this, we pre-process the CCI data from 2019 to 2021 (3 years of data) using the min-max scalar technique. This scaling transforms the CCI values into the range of [-1, 1], effectively reducing the significant variations observed during the Covid period.

After pre-processing the CCI data, we proceed with the same modelling steps outlined in the previous sections. We obtain all the results as before, but with the modified CCI data that eliminates the pronounced fluctuations caused by Covid.

One notable change can be observed in the graph depicting the total loan amount by Stage over time. In the absence of a significant drop in the Stage 1 distribution caused by Covid, the graph shows a more stable pattern.

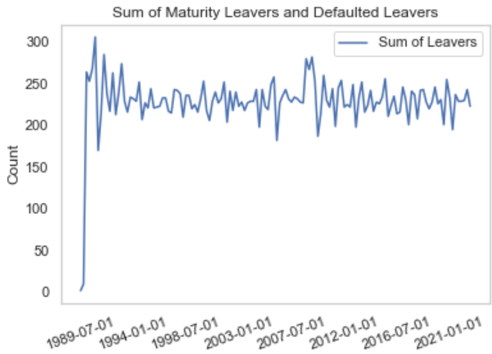

Figure 18: Sum of Maturity and Defaulted Leavers

Figure 19: Number of Joiners and Leavers

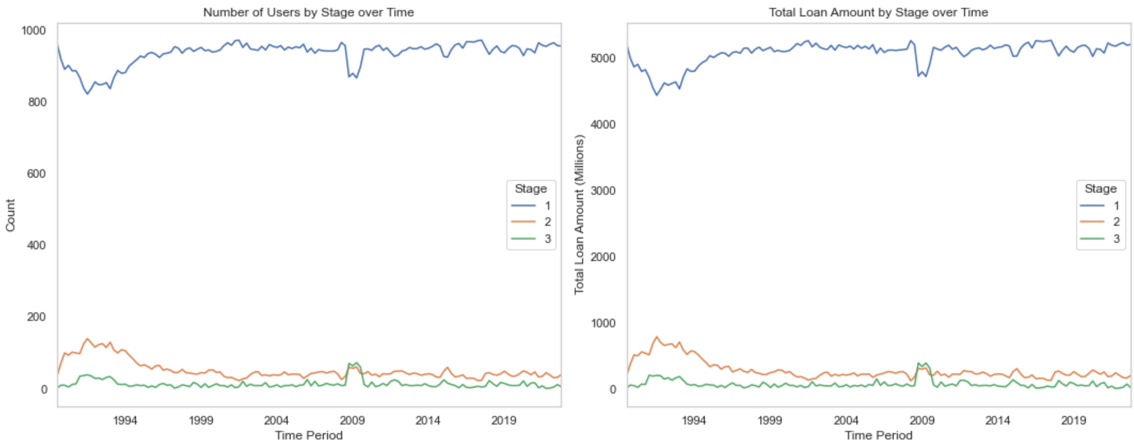

Figure 20: Stage Distribution: Number of Users and Loan Amount

Furthermore, when comparing the CCI values to the number of defaulted leavers, we can see a spike centred around the 2008 financial crisis. This spike is due to the relatively negative value of CCI around that period, which indicates the challenging economic conditions at the time.

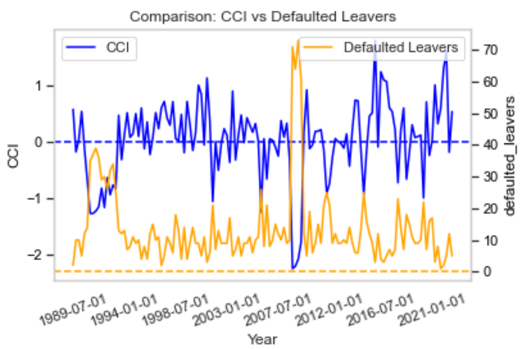

Figure 21: CCI vs Defaulted Leavers

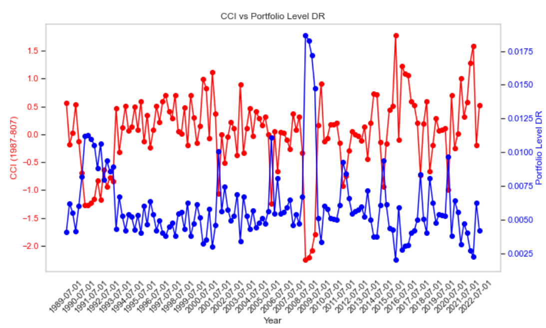

Figure 22: CCI vs Portfolio Default Rate

Using this modified model, we conduct backtesting and observe from figure 23 that the projected provision amount is sufficient to cover the actual default amount over time. Therefore, the IFRS9 is sufficient in a stable economic environment. This result holds when no significant spikes in the actual default amount, such as those caused by the Covid pandemic.

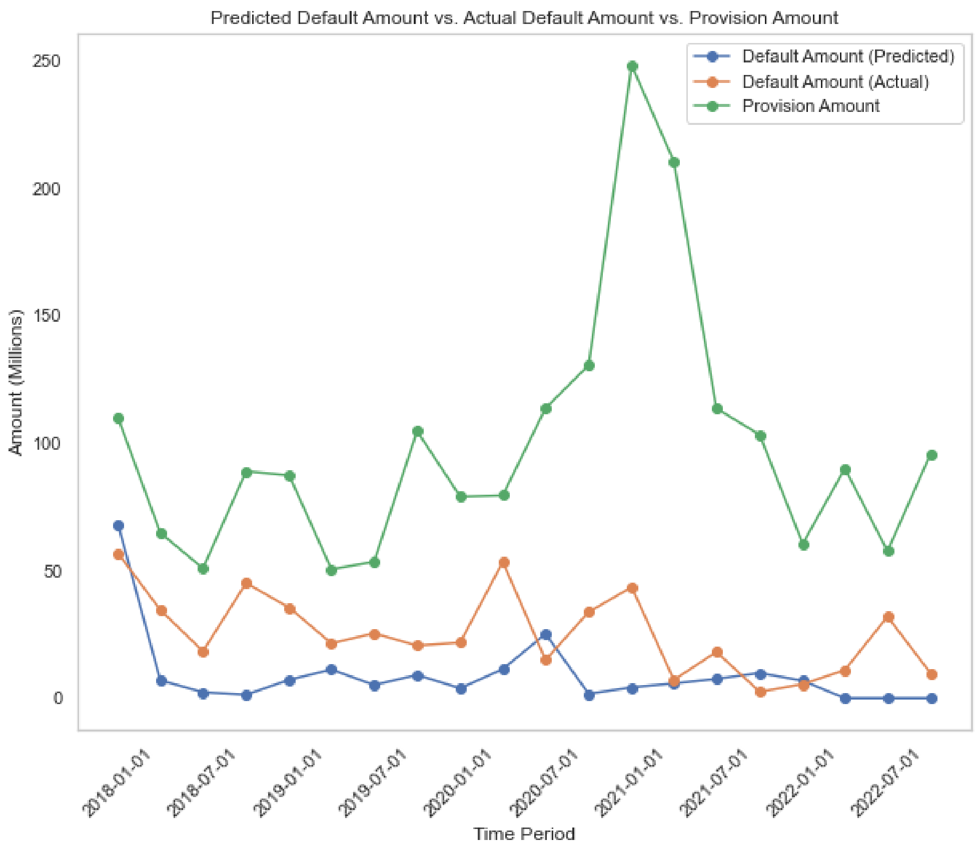

Figure 23: Backtesting: 2018-2022

Overall, by simulating a scenario without the extreme Covid impact and considering a more stable CCI trend, our model provides more reliable forecasts and demonstrates the adequacy of the projected provision amount to cover potential defaults in a less turbulent economic environment.

6 Forecasting

6.1 UK economy outlook overview

The UK economic outlook indicates a reduced probability of recession. However, following GDP growth of 4.0% in 2022, we anticipate a contraction of -0.3% in 2023 due to decreased household incomes and the lingering effects of previous interest rate hikes [39]. Growth is expected to remain modest at 0.6% in 2024. Looking ahead, structural challenges pose significant long-term risks to the economy. These challenges include skill shortages, declining workforce participation, and the ageing population, which require attention and strategic planning [39].

Similarly, another website concluded that the UK economy has significantly improved, avoiding a technical recession [25]. This can be attributed to three key factors: lower natural gas prices, a stronger Sterling, and the successful reopening of the Chinese economy.

Inflation is expected to fall sharply during the year, reaching single digits by the middle of the year and settling around 3-4% by the end of the year. The report attributes this decline to the expiration of previous energy and goods price increases and the softening of tradable goods inflation.

Economic inactivity, driven by health reasons and other factors, has remained elevated since the beginning of the pandemic. However, the report warns that population ageing will contribute to a rise in economic inactivity by 2.4 million by 2030, with 90% of this increase coming from the 65+ age group. Policymakers and businesses are urged to address this challenge by enhancing workforce productivity and refining recruitment strategies.

6.2 Forecasting Methodology

To estimate the performance of the provision on the default amount in various future economies, we employ a forecasting methodology. Our focus is on estimating the Credit Cycle Index (CCI) for the years 2023-2025.

In the backtesting Stage, we utilize historical data on the delta unemployment rate to establish a regression relationship with the historical CCI. This allows us to estimate the future CCI between 2018 and 2022 using realistic projections for the delta unemployment rate. However, we encounter a challenge in generating future quarter CCI due to unreliable estimates for the quarter delta unemployment rate.

To address this issue, we turn to the projected quarter GDP figures provided in two growth scenarios by [25]. In the "prolonged damage" scenario, assuming the materialization of risks such as persistently high inflation and strikes, the economy could contract by around 0.9% in 2023 and experience slower growth in subsequent years.

In the "subdued growth" scenario, the UK economy is expected to grow by 0.1% in 2023, 1.0% in 2024 and 1.8% in 2025. Notably, these figures closely align with the average forecast for GDP growth in 2023-2025 from the UK government website [45]. Consequently, we consider the subdued growth scenario as the average forecast and calculate the optimistic forecast as the average forecast plus the difference between the average and pessimistic forecasts.

After obtaining the forecasted GDP growth rates, we choose not to standardize the data. Standardization can have unintended consequences, transforming relatively small positive values in the optimistic scenario into negative CCI values. This would inaccurately represent the scenario as more negative than intended. Therefore, we proceed with the same backtesting steps using the unstandardized GDP growth rates to determine the evolving portfolio and provision from 2023 to 2025. This approach ensures that the forecasted CCI values maintain their original meaning and align with the projected economic scenarios.

Table 6: Projected annual average real GDP growth by scenario. *Cited from [25]*

	Subdued growth	Prolonged damage
2023	0.1%	-0.9%
2024	1.0%	-0.4%
2025	1.8%	1.9%

Table 7: Projected quarter average real GDP growth by scenario. *Cited from [25]*

	Neutral (Subdued growth)	Negative (Prolonged damage)	Positive
2023Q1	0.100000	0.100000	0.100000
2023Q2	-0.050000	-0.770000	0.670000
2023Q3	0.070000	-1.300000	1.440000
2023Q4	0.090000	-1.740000	1.920000
2024Q1	0.350000	-1.800000	2.500000
2024Q2	0.830000	-0.830000	2.490000
2024Q3	1.230000	0.090000	2.370000
2024Q4	1.540000	0.870000	2.210000
2025Q1	1.730000	1.410000	2.050000
2025Q2	1.810000	1.810000	1.810000
2025Q3	1.830000	2.110000	1.550000
2025Q4	1.910000	2.190000	1.630000

6.3 Analysis and Discussion

In the projected average scenario, the default amount and provision amount rise at the end of 2023 due to a challenging economic environment reflected by a low CCI. However, as the economy improves from 2024 onwards, the default amount gradually decreases. Despite this decrease, the provision amount remains relatively stable due to the significant contribution of Stage 2 users, who have a more considerable impact on the Lifetime Expected Credit Loss (LECL) than the 12-month ECL. In summary, the trends indicate a reduction in defaults with improving economic conditions, while the provision amount remains steady due to the influence of Stage 2 users.

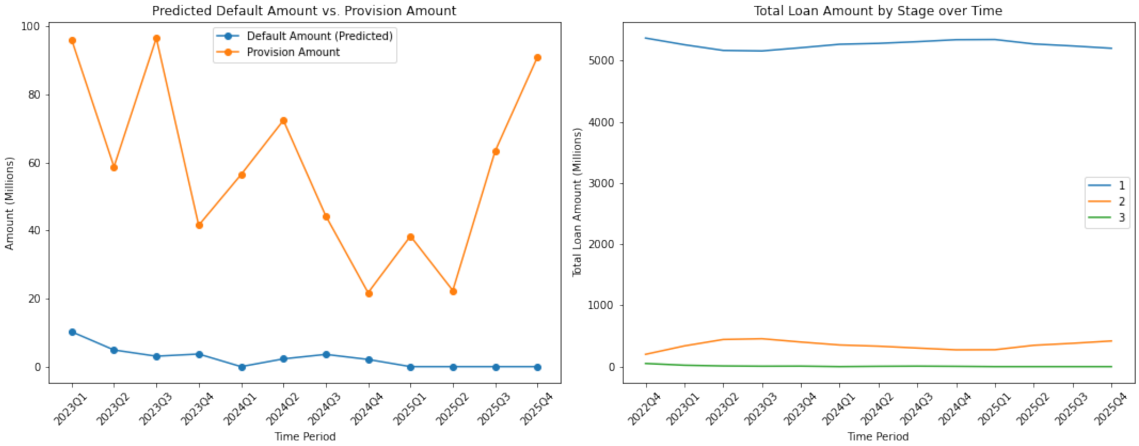

Figure 24: Average Scenario: Forecast Default vs Provision Amount & Staging Distribution: 2023-2025

In the positive scenario, the increasing Credit Cycle Index (CCI) results in a decrease in the defaulted amount. The slight spike in the defaulted amount in 2024 Q4 is a reasonable fluctuation caused by a temporary decline in the CCI value. Overall, the positive trend in the scenario highlights the inverse relationship between the CCI and defaulted amount, reflecting an improvement in the economic conditions and the credit environment. We can check the P&L charge corresponds to the forecasted GDP trend. GDP first increases but later decreases, so the P&L charge first decreases and then increases.

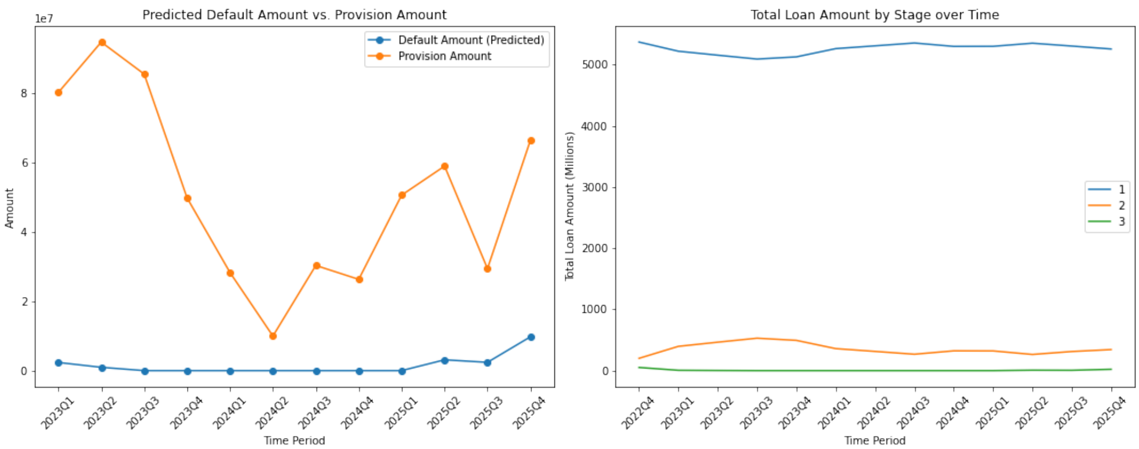

Figure 25: Positive Scenario: Forecast Default vs Provision Amount & Staging Distribution: 2023-2025

Table 8: Positive Scenario: P&L Charge (Pounds)

Year	Writeoff Predicted	Provision Amount	Delta Provision at the beginning of the year	P&L Charge
2023Q1	2,349,641	80,076,109	80,076,109	82,425,750
2023Q2	950,567	94,601,493	14,525,384	15,475,951
2023Q3	0	85,386,280	-9,215,213	-9,215,213
2023Q4	0	49,727,550	-35,658,730	-35,658,730
2024Q1	0	28,243,339	-21,484,211	-21,484,211
2024Q2	0	9,949,499	-18,293,840	-18,293,840
2024Q3	0	30,280,593	20,331,094	20,331,094
2024Q4	0	26,271,311	-4,009,282	-4,009,282
2025Q1	0	50,531,378	24,260,068	24,260,068
2025Q2	3,110,577	58,881,108	8,349,730	11,460,307
2025Q3	2,386,031	29,355,066	-29,526,042	-27,140,011
2025Q4	9,733,291	66,333,027	36,977,961	46,711,252

The negative CCI 2024 leads to an increasingly high default amount in the negative scenario. Then the increasing CCI leads to the reduction of Stage 2 and Stage 3 users, reducing the provision amount. We can check the P&L charge corresponds to the forecasted GDP trend. GDP first decreases but later increases, so the P&L charge first increases and then decreases.

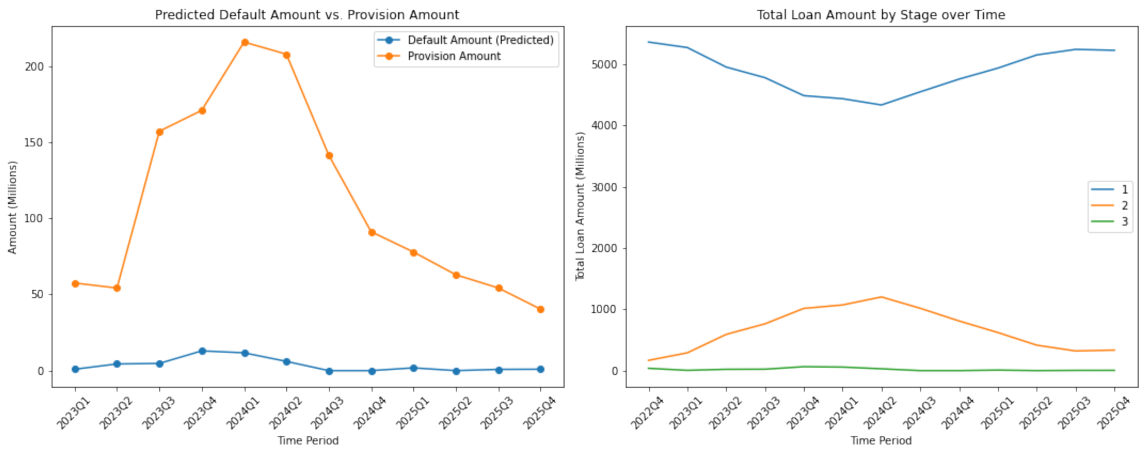

Figure 26: Negative Scenario: Forecast Default vs Provision Amount & Staging Distribution: 2023-2025

Table 9: Negative Scenario: P&L Charge (Pounds)

Year	Writeoff Predicted	Provision Amount	Delta Provision at the beginning of the year	P&L Charge
2023Q1	898,177	57,511,827	57,511,827	58,410,004
2023Q2	4,381,003	54,232,162	-3,279,665	1,101,338
2023Q3	4,717,000	157,148,472	102,916,310	107,633,311
2023Q4	12,958,219	170,851,557	13,703,085	26,661,304
2024Q1	11,688,317	215,711,892	44,860,335	56,548,651
2024Q2	6,055,821	207,734,320	-7,977,572	-1,921,751
2024Q3	0	141,491,434	-66,242,886	-66,242,886
2024Q4	0	91,200,447	-50,290,987	-50,290,987
2025Q1	1,816,137	77,870,911	-13,329,537	-11,513,400
2025Q2	0	62,945,759	-14,925,152	-14,925,152
2025Q3	809,585	54,301,365	-8,644,393	-7,834,808
2025Q4	923,054	40,375,495	-13,925,871	-13,002,817

6.4 Improvement to the methodology

We observed some findings in Figure 16. Firstly, the predicted default amount has a value of 0. Additionally, the predicted default amount in Figure 16 is slightly lower than the actual default amount, though the difference is insignificant. One possible explanation could be that the forecasting CCI, generated by a simple linear regression model, results in a relatively stable CCI that doesn't fluctuate much. Consequently, this stability may lead to fewer bad credit situations and defaults.

Furthermore, when examining Tables 8 and 9, we notice that the predicted write-off amounts are also 0. We suspect this is due to the forecasted GDP values in Table 7, which consistently exhibit highly positive values across all three scenarios. Even though there are variations in the magnitude of these changes, the values do not fall below 0 in neutral and optimistic scenarios. As a result, the overall economic conditions during the predicted year do not indicate a deterioration in creditworthiness, making it highly unlikely for substantial default amounts to occur. Another possible reason could be the limited dataset size, comprising only 1000 simulated loans.

We could employ time series modelling of the CCI, which serves as an indicator of the general performance of the economy. By utilizing time series analysis, future researchers can develop models to project the CCI for different scenarios. The average scenario can be obtained as the prediction, while the upper and lower 95% confidence intervals can serve as the positive and negative scenarios, respectively.

Moreover, if additional data points are available, more advanced machine-learning techniques can be utilized to model the CCI more sophisticatedly. This approach would enhance the accuracy and reliability of the forecasts, providing a more robust basis for estimating the provision's performance on the default amount in different projected economies.

7 Summary and Conclusion

In this research, we have provided a detailed explanation of how to model a synthetic mortgage portfolio, incorporating credit migration using the One-factor Vasicek model, and details for the IFRS9 provision. Additionally, we have outlined the process of conducting backtesting and utilizing this model to make predictions, allowing banks to anticipate future changes in asset allocation while considering the complex geopolitical and economic landscape.

Our findings demonstrate that by employing robust modelling techniques in portfolio credit management and economic variable modelling, it is possible to obtain reliable projections for future provisions, thereby enhancing credit risk management practices.

Our research explores how the International Financial Reporting Standard 9 (IFRS9) performs during the Covid pandemic. As discussed earlier, the IFRS9 framework imposes stringent asset allocation requirements, which are based on certain assumptions regarding portfolio migration and self-defined impairment judgments. However, it is crucial to acknowledge that these assumptions underscore the dynamic nature of credit risk management, which only becomes genuinely reliable when supported by substantial evidence justifying parameter choices and modelling methodologies. Furthermore, our analysis reveals that banks can leverage the flexible definition of modelling rules under IFRS9 to manipulate provision amounts to align with their specific goals.

Given the unpredictable nature of unexpected economic shocks like Covid, our research also highlights the possibility of the predicted provision amount occasionally being insufficient. In such cases, external regulations and financial support would be necessary to mitigate severe credit losses from these shocks. However, it is worth noting that the accumulation of excess capital over previous years can act as a potential buffer during such circumstances.

Additionally, our research includes an examination of future projections for IFRS9 provisions. Based on our analysis of three different scenarios, we have observed that the projected provision amounts would be sufficient as they cover potential default amounts.

However, it is essential to acknowledge the limitations of this research. The simulation size is small, and the portfolio may not be entirely representative of real-world conditions. The modelling techniques employed may not encompass the full spectrum of potential scenarios. To enhance the analysis, future researchers could explore model stability by simulating the entire model multiple times. Additionally, conducting sensitivity analysis to understand how variations in each model parameter impact IFRS9 results would provide valuable insights. Future studies could also explore alternative credit risk modelling techniques and economic modelling methodologies to determine IFRS9 provisions for different types of credit assets.

Overall, this research serves as a foundation, but further investigations are necessary to address these limitations and expand our understanding of credit risk modelling and IFRS9 provision modelling in diverse contexts.

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