South African Journal of Economic and Management Sciences
ISSN: (Online) 2222-3436, (Print) 1015-8812

A pragmatic macroeconomic default risk adjustment in developing countries

Authors:
Suben Moodley[1]
Tanja Verster[2,3]
Helgard Raubenheimer[2,3]

Affiliations:
[1]Business School, DaVinci Institute, Johannesburg, South Africa

[2]Centre for Business Mathematics and Informatics, Faculty of Natural and Agricultural Sciences, North-West University, Potchefstroom, South Africa

[3]National Institute for Theoretical and Computational Sciences (NITheCS), Potchefstroom, South Africa

Corresponding author:
Tanja Verster,
tanja.verster@nwu.ac.za

Dates:
Received: 05 Nov. 2024
Accepted: 09 Apr. 2025
Published: 29 May 2025

How to cite this article:
Moodley, S., Verster, T. & Raubenheimer, H., 2025, 'A pragmatic macroeconomic default risk adjustment in developing countries', *South African Journal of Economic and Management Sciences* 28(1), a5958. https://doi.org/10.4102/sajems.v28i1.5958

Background: The expected credit loss (ECL) framework of International Financial Reporting Standards Foundation (IFRS) 9 typically comprises three components: probability of default (PD), loss given default (LGD) and exposure at default (EAD). Among these, PD often lacks a systematic approach for incorporating macroeconomic dynamics, particularly in the developing economies.

Aim: This article proposes a novel methodology for dynamically adjusting PD using a macroeconomic scalar that integrates forward-looking information.

Setting: The proposed methodology is illustrated on datasets from Kenya and Mauritius to validate its applicability.

Method: The methodology consists of five steps: (1) research and planning; (2) data preparation; (3) model development; (4) calculation of the scalar; and (5) model validation. Comparative analysis is conducted using multiple regression, generalised linear models (Logit, Probit), and machine learning techniques such as neural networks, random forests, and gradient boosting. Model performance is assessed using key summary statistics and validation metrics.

Results: The proposed macroeconomic scalar effectively adjusted PD within the ECL model for the Kenya and Mauritius datasets. Each modelling approach contributed insights, demonstrating the scalar's ability to improve ECL predictions.

Conclusion: Integrating a macroeconomic scalar into the ECL model offers a robust method for incorporating forward-looking information, improving PD accuracy that can account for uncertainty, volatility and sparse data characteristic of developing economies.

Contribution: This article provides a systematic approach for adjusting PD in ECL models using macroeconomic data offering a scalable solution. Additionally, we provide practical guidelines and step-by-step recommendations for practitioners seeking to implement macroeconomic adjustments in PD estimation.

Keywords: probability of default; PD; macro-economic PD adjustment; IFRS 9 expected credit loss; ECL; machine learning in credit risk; developing countries.

Introduction

Following the financial crisis, the International Accounting Standards Board (IASB) and the Financial Accounting Standards Board (FASB) collaborated to reform accounting standards, aiming for a more transparent and streamlined approach to credit loss recognition. This effort led to the introduction of the International Financial Reporting Standards Foundation (IFRS) 9 in 2014 (IFRS 2014), which established an expected credit loss (ECL) framework. Expected credit loss calculation is typically decomposed into three key components – probability of default (PD), loss given default (LGD) and exposure at default (EAD) – as these metrics are also essential for regulatory and economic capital assessments. A simplified representation of ECL is given by the formula: ECL = PD × LGD × EAD (Breed et al. 2021).

Under IFRS 9 (IFRS 2014), PD models must incorporate both current and projected macroeconomic conditions to ensure that default risk assessments reflect forward-looking estimates, enhancing the accuracy of impairment calculations. However, some financial circumstances (e.g., coronavirus disease 2019 [COVID-19]) are difficult to forecast and create high levels of uncertainty, especially in incorporating forward-looking information into ECL estimates (IFRS 2020).

Modelling forward-looking information in developing country contexts presents several challenges. Firstly, these nations often face limited availability and reliability of macroeconomic data, making it difficult to accurately forecast economic trends and plan effectively. Secondly, the volatility in credit defaults, exacerbated by periods of high inflation and fluctuating interest rates, adds complexity to financial modelling and risk assessment. Thirdly, the absence of robust social safety nets, leaving consumers vulnerable to job losses without adequate support, which further complicates predicting consumer behaviour and economic stability. These challenges underscore the need for adaptive modelling techniques that can account for uncertainty, volatility and sparse data characteristic of developing economies.

In this article, we consider a scalar approach to accommodate the influence of the current and forecasted macroeconomic conditions on default rates, similar to the scalar approach used in Breed et al. (2023). No prescribed method is enforced by IFRS 9. Following Breed et al. (2023), if a financial institution chooses the scalar approach, the ECL can be adjusted for forward-looking macroeconomic conditions by applying a scalar to each of the ECL components (Equation 1):

$$\mathrm{ECL} = \mathrm{PD} \times s_{\mathrm{PD}} \times \mathrm{LGD} \times s_{\mathrm{LGD}} \times \mathrm{EAD} \times s_{\mathrm{EAD}}, \quad \text{[Eqn 1]}$$

where s_{PD}, s_{LGD} and s_{EAD} are the macroeconomic scalars for the PD, LGD and EAD, respectively. This article will focus only on the PD scalar (s_{PD}). The PDs will generally be on account level)and the scalars on segment level. The PD scalar can be estimated by (Equation 2):

$$\hat{s}_{\mathrm{PD}} = \frac{\text{Forecasted credit index}}{\text{Base credit index}}, \quad \text{[Eqn 2]}$$

where the Base credit index is the average observed credit index and Forecasted credit index is the forecasted credit index using macroeconomic variable forecasts. A credit index is defined as a measure derived from historical default data that approximates a loan portfolio's inherent default behaviour concerning macroeconomic conditions. In essence, it links macroeconomic conditions to the default behaviour of a portfolio. A brief literature review on credit indices is provided in the literature study and the mathematical formulation is detailed in the Methods section. Note that segmentation-level scalars are recommended. Typically, the credit index will be on account level and the scalar on segment level. Segment scalars enhance risk measurement by accounting for changes in segment proportions within the portfolio over time. This improvement reduces ECL volatility, as ECL allowances adjust gradually in response to shifts in portfolio composition. Consequently, segment scalars provide a more stable and reliable estimate of credit risk.

As a principles-based accounting standard, IFRS 9 does not mandate a specific approach for adjusting PD estimates to reflect macroeconomic conditions. Instead, the appropriate methodology may vary across different portfolios in the Global Public Policy Committee (GPPC) (2016). The existing literature provides limited guidance on IFRS 9-specific PD adjustment techniques, leaving practitioners to adapt broader credit risk modelling approaches.

Several general methods for incorporating macroeconomic factors into credit risk models have been discussed by Crook and Bellotti (2010) and Tasche (2013). While originally developed for other applications, such as Basel regulatory models, many of these techniques can be adapted to align with IFRS 9 requirements.

Our proposed methodology is robust enough to contend with the challenges posed by limited and volatile macroeconomic data. Additionally, our approach has a significant advantage: the transparency and explainability provided by a separate scalar. This distinct scalar helps differentiate the ECL allowance by current credit performance and forward-looking expectations. Given that IFRS 9 ECL estimates are a substantial item in the income statement, transparent and explainable IFRS 9 methods are essential for bank management, boards, auditors and regulators.

The article's layout is as follows: the Introduction section provides motivation and contains a literature summary. The Methods section includes the proposed methodology that consists of five broad steps. In the Results section, we illustrate how our proposed methodology can be applied by utilising case studies from Kenya and Mauritius, using unsecured retail portfolios. Finally, the Conclusion section concludes and makes recommendations for further research work.

Literature summary

Introduction

The IFRS 9 standard (IFRS 2014) requires that the PD model accommodate the influence of the current and the forecasted macroeconomic conditions on default rates. This enables a determination of forward-looking estimates on impairments (Botha et al. 2025). Crook and Belotti (2010) examined various classes of modelling techniques that can incorporate macroeconomic information, although not in the IFRS 9 context. These classes are broadly categorised into aggregate risk models and individual account assessment approaches. These two classes will be discussed next and then the credit index will be discussed. The credit index aims to establish a link between historical macroeconomic conditions and the corresponding impact on the default behaviour of the portfolio and is usually either the country-wide default rates or the bank-specific default rates (Breed et al. 2023).

Aggregate risk models

Several studies have explored the use of aggregate risk models (i.e., portfolio-level) in credit risk analysis. Crook and Belotti (2010) and Durović (2019) provided examples of such models, while Bellini (2019) highlighted traditional vector autoregression (VAR) and vector error correction (VEC) models as key tools for handling macroeconomic time series. Jacobs (2019) extended this approach by incorporating exogenous variables into vector autoregressive models through VARMAX. Tasche (2015) applied regression techniques to link default rates with macroeconomic indicators.

Evaluation of how macro variables impact PDs is investigated by Tokmak (2020) by employing an Autoregressive Distributed Lag (ARDL) bound testing approach on quarterly data of the PD ratio and other macroeconomic variables. The ARDL co-integration technique is used in determining the long-run relationship between series with different orders of integration. The ARDL co-integration technique or bound test of co-integration is based on the estimation of an Unrestricted Error Correction Model (UECM) with the Ordinary Least Squares (OLS) method.

Simons and Rolwes (2009) outlined various aggregate risk level macroeconomic modelling techniques, including logistic regression, econometric models and vector autoregression. Their study specifically examines the relationship between default rates and macroeconomic conditions by constructing a logit model with macroeconomic variables. This model is particularly appealing because of its simplicity, interpretability and reliable performance.

One of the key advantages of aggregate-level models is their efficiency. As they generally require fewer data points compared to more granular models, they are easier to develop and can be implemented more quickly (Black 2016).

However, Durović (2019) found a low effect of the macro environment on PD development, mainly because of the fast-changing marketplace and a constant increase in the number of participants in this market. This is one of the disadvantages of using aggregate risk models. The economy, measured by macroeconomic variables, does not influence each customer in the same way. For example, the COVID-19 pandemic had a catastrophic effect on customers in the tourism industry, but customers experienced the opposite in the information technology and pharmaceutical industries. An IFRS 9 generalised methodology is given in Van der Lith (2019) for including macroeconomic (ME) forecasts in impairment calculations, focussing on data-challenged environments. A further challenge lies in addressing intrinsic model risk and quantifying its impact. The UK's Prudential Regulation Authority provides guidance on this in its model risk management principles for banks (PRA 2023a, 2023b).

Individual account assessment approaches

Bellini (2019) outlines various individual account assessment modelling approaches that incorporate macroeconomic factors when estimating default risk. These include GLMs, survival analysis and advanced machine learning methods such as bagging, boosting and random forests (RFs).

Developing account-level models presents several challenges. As noticed by Black (2016), these models require extensive and high-quality historical account-level data, making them more complex to construct. Additionally, because of the larger data requirements and computational demands, loan-level models can be more time-consuming to develop and implement compared to portfolio-level approaches.

However, Black (2016) recommends that the best way to address the forward-looking aspect of the IFRS 9 standard is to use account-level models. Many others list the use of discrete hazard rates as a popular method in the forward-looking PD IFRS 9 modelling, for example, Bellotti and Crook (2013), Crook and Bellotti (2010), Skoglund (2014) and Xu (2016). Typically, account-level models will increase the accuracy of the models over aggregate risk models. Engelman (2021) shows how an account-level model can be combined with an aggregate risk macroeconomic model.

Credit index

A connection needs to be made between historical macroeconomic conditions and their effects on the default behaviour of the portfolio (Breed et al. 2023). To achieve this, a credit index is necessary, usually derived from historical default data, to approximate the portfolio's default behaviour. This credit index should be closely linked to the loan portfolio a bank is modelling, for example, country-wide default rates of a particular loan sector, non-performing loan rates or loss rates, if available (Engelmann 2021). The crucial prerequisite for making this approach work is the existence of a macroeconomic model that allows the estimation of an abstract state of the economy that closely reflects the economic conditions of a bank's portfolio (Engelmann 2021). This credit index does not have to be the actual observed default rate, as this default rate might be influenced by business decisions and hide the true link between the default rate experienced and the macroeconomic conditions of a country, for example, payment holidays in the COVID-19 pandemic. Our proposed methodology will develop a scalar that is typically on segment or portfolio level, whereas the PDs are generally on account level. Our focus is on portfolios in developing countries.

Methods

Our proposed methodology is step wise described in this section. We have explained the methodology in five steps. In Step 1, we will discuss the research and planning and in Step 2, the data preparation. In Step 3, the development of the model is explained. Step 4 contains the derivation of the macroeconomic scalar and Step 5 describes how to validate the model. We also highlight the assumptions of the model.

Step 1: Research and planning

In this research and planning phase, we must ensure that all processes and steps comply with IFRS 9. It is essential to understand the theoretical relationship between macroeconomic variables and the default behaviour of the portfolio. For example, if the gross domestic product (GDP) increases, it indicates higher production of goods and a healthier economic scenario, which leads to reduced economic losses and lower default rates. Thus, we expect default rates to be inversely proportional to the GDP. During this phase, we also select the appropriate modelling technique, which depends on the technical expertise available within the financial institution, the availability of software and other business considerations. Various techniques are available such as linear regression, VARMAX and ECM. The assumptions underlying the chosen technique need careful examination. In addition, the unique characteristics and sovereign risks of the country in question should be thoroughly researched.

Step 2: Data preparation

This step comprises three sub-steps: determine the credit index, variable selection and variable reduction.

Determine the credit index for the model

Similarly, according to Breed et al. (2023), a link needs to be established between the historical macroeconomic conditions and their corresponding impact on the default behaviour of the portfolio. A credit index is required, which will typically be derived from the historical defaults to approximate the default behaviour of the portfolio. This credit index should be closely linked to the loan portfolio that the bank is modelling, for example, country-wide default rates of a particular loan sector, non-performing loan rates or loss rates, if available (Engelmann 2021). If the credit index (*Yt*) at time *t*, is derived from the historical default rates, the definition will be as in Equation 3:

$$Y_t = \frac{\sum_{i=1}^{N_t} D_i}{N_t}, \qquad \text{[Eqn 3]}$$

where:

- $D_i \in \{0,1\}$ is the default indicator for loan *i* at time *t* and
- N_t is the total number of loans in the portfolio at time *t*.

Alternative methods to determine the credit index might include a % of the original balance that defaulted in the next *n* months and then the credit index, *Yt* at time *t* is defined as shown in Equation 4:

$$Y_t = \frac{\sum_{j \in D_{n,t}} B_{t,j}}{\sum_{j \in J_t} B_{t,j}}, \qquad \text{[Eqn 4]}$$

where:

- J_t is the set of accounts at cohort *t*.
- $D_{n,t} \subset J_t$ is the set of accounts at cohort *t* that defaults in the next *n* months, e.g. *n* = 12 and
- $B_{t,j}$ is the balance at cohort *t*.

Another measure of credit risk is the non-performing loan rate in a country, then the credit index (i.e., non-performing loan rate), Y_t at time *t* is defined as given in Equation 5:

$$Y_t = \frac{NPL_t}{TL_t}, \qquad \text{[Eqn 5]}$$

where:

- NPL_t represents the total number of non-performing loans in the country at time *t* and
- TL_t is the total number of outstanding loans in the country at time *t*.

If it is not possible to use a country-wide default rate, it should be observed that bank-specific default rates need to be adjusted, for example, business decisions must be stripped out of the observed default rate (e.g., exclude accounts with payment holidays). These business decisions might mask the true macroeconomic link. Seasonality should also be examined and it needs to be determined whether it is specific to the behaviour of the financial institution's portfolio or to the macroeconomic link itself. It should be considered to omit any 'extreme' time period, for example, the COVID-19 pandemic, to ensure that the period considered does not include too extreme events. It is recommended that a complete economic cycle should be considered (Schutte et al. 2020).

We define the adjusted credit index at time *t* as Y_t', which incorporates seasonality adjustments, the omission of extreme periods (e.g., COVID-19) and excludes any other business-related factors. Finally, a smoothing technique (e.g., Locally Estimated Scatterplot Smoothing [LOESS]) could be considered if volatility is observed in the default rates. We define Y_t'' as the smoothed credit index at time *t*. Note that within the IFRS 9 context, the forward-looking information will vary between 12 months and the remaining lifetime, depending on the stage that the account is in. A stage is assigned based on changes in credit quality since initial recognition. Stage 1 is assigned when credit risk has not increased significantly since initial recognition. Stage 2 is assigned when credit risk has increased significantly since initial recognition. Stage 3 is assigned when an account defaults. A 12-month ECL is recognised for Stage 1 accounts and a lifetime expected loss (EL) is recognised for Stage 2 and Stage 3 accounts. It is recommended that the macroeconomic scalar is modelled only for Stage 1 accounts, but applied to Stage 1 and Stage 2 accounts. The rationale behind using Stage 1 customers for development is that macroeconomic factors impact the probability of these customers more naturally than those customers who are already in arrears (Stage 2 and Stage 3).

Variable selection for the model

In the same way as Breed et al. (2023), various macroeconomic variables (*X's*) can be used in the modelling process. Several factors should be considered when choosing the macroeconomic variables, for example, the reliability and availability of data. A crucial aspect is the availability of forecasts for the proposed variables. These forecasts usually consist of a base, upside and downside scenarios, for example, the forecasts provided by Moody's (PWC 2017). Finally, business considerations should be taken into account.

If all the available macroeconomic variables are identified, the next step is to perform exploratory data analysis of each variable. A popular way is to plot these types of variables over time. If any missing value exists, these need to be imputed (SAS Institute Inc 2010) and if any outliers are observed, these need to be smoothed (James et al. 2012). If a specific macroeconomic variable is very volatile over time, it should rather not be used in the modelling (Van der Lith 2019). Most macroeconomic variables are published every quarter and these quarterly data need to be converted to monthly frequency. Many options exist, for example, piecewise constant interpolation, linear interpolation and spline interpolation (Engelman & Rauhmeier 2011).

For any time series, it is important to ensure stationarity (Fuller 1996). If a time series is stationary, it has a constant mean. Time series statistical techniques require stationarity as an assumption. There are many methods to test whether a time series is stationary, for example, plotting the data and visually checking for trends or using an Augmented Dickey-Fuller Test. To make a non-stationary series, stationary, various methods can be used, for example, using first differences, growth rates or year-on-year changes (Fuller 1996). Application of the appropriate transformation of the macroeconomic variables contributes to robust models (i.e., using year-on-year change to ensure stationarity). The lags of macroeconomic variables should also be included. Suggested lags to consider are 3, 6, 9 and 12 months, however, business considerations should be taken into account.

We define the set of explanatory variables as $\boldsymbol{X}_t = \{X_{1,t}, X_{2,t}, \dots X_{p,t}\}$, as a vector of macroeconomic variables as well as their lags as $\boldsymbol{X}_{t,l} = \{X_{1,t,l}, X_{2,t,l}, \dots X_{p,t,l}\}$, where l indicates the lag, e.g. $l = \{0, 3, 6, 9, 12\}$.

Variable reduction

If many variables exist, variable clustering can be a useful tool to reduce the set of variables and eliminate multicollinearity (SAS Institute Inc 2010). In theory, numerous macroeconomic variables may exist per country (including both macroeconomic and macroprudential variables).

Step 3: Development of the model

A model (e.g., linear regression or VARMAX) needs to be fitted to all possible combinations of macroeconomic variables. We define $f(\boldsymbol{X}_{t,l})$ as the function mapping the explanatory variables $\boldsymbol{X}_{t,l}$ to the smoothed, adjusted credit index, Y_t'', giving us the following notation as shown in Equation 6:

$$Y_t'' = f\left(\boldsymbol{X}_{t,l}\right) + \epsilon_t, \quad \text{[Eqn 6]}$$

where $\boldsymbol{X}_{t,l} = \{X_{1,t,l}, X_{2,t,l}, \dots X_{p,t,l}\}$ is a vector of macroeconomic variables (with their lags) and ϵ_t is the error term capturing the residual noise.

It is important to ensure that all assumptions of the underlying modelling technique are met. Linear regression, for example, has the following assumptions (Kutner et al. 2005):

- **Linearity**: The relationship between the predictors (i.e., explanatory variables, independent variables or features) and the mean of the response (i.e., target or dependant) is linear.
- **Homoscedasticity**: The variance of residual is the same for any value of the predictors.
- **Independence**: Observations are independent of each other.
- **Normality**: For any fixed value of the predictors the response is normally distributed.

Out of all the models fitted, we should select only those that fulfil the following criteria:

- The estimated signs for the regression coefficients of the macroeconomic variables should align with economic expectations. For example, the estimated sign for the GDP coefficient should be negative as we expect default rates to decrease when GDP increases (see Đurović, 2019).
- All estimated coefficients should be statistically significant at α% significance level, for example, 5% (see Đurović, 2019).
- Ensure multicollinearity is absent, for example, variation inflation factor (VIF) should be less than 10 (Lin 2008).

Note that if a machine learning technique is used in the methodology, such as neural networks, gradient boosting or RFs, it may not be straightforward to determine if the estimated sign of the macroeconomic variable aligns with economic expectations. An alternative approach is to use one of the many explainability tools within machine learning such as the partial dependence plot. A partial dependence plot illustrates the functional relationship between the model inputs and the model's predictions (SAS Institute Inc 2020). If the rank correlation between the response and the partial dependence plot is positive, it can be interpreted as a proxy for a positive relationship, whereas a negative rank correlation can be interpreted as a proxy for a negative relationship.

The remaining models can be ranked using a suitable measure of model fit, for example, the adjusted R-square, MSE (mean square error), MAPE (mean absolute percentage error), MAE (mean absolute error), the Akaike information criterion (AIC) or the Schwarz Bayesian information criterion (SBC). The best model may subsequently be selected, considering other relevant business considerations.

Step 4: Calculate the macroeconomic scalar

Given macroeconomic scenario g, the macroeconomic variable is scalar at time t for the PD as defined in Equation 7:

$$\hat{s}^{g}_{PD,t} = \frac{Y''^{g}_{t}}{\overline{Y}_{t}}, \qquad \text{[Eqn 7]}$$

where $\overline{Y}_t$ is the average observed credit index at time t, usually defined as shown in Equation 8:

$$\overline{Y}_t = \frac{\sum_{i=t-m}^{t} Y''_i}{m} \qquad \text{[Eqn 8]}$$

m is the number of months chosen by business to represent a typical business cycle, usually set to 12 months.

Given macroeconomic scenario g, the forecasted credit index, Y''^{g}_{t} at time t will use macroeconomic variable forecasts (Equation 9):

$$Y''^{g}_{t} = f\left(\boldsymbol{X}^{g}_{t,l}\right) + \epsilon_t, \qquad \text{[Eqn 9]}$$

where $f(\boldsymbol{X}_{t,l})$ is a function (e.g., GLM, RF) mapping predictors $\boldsymbol{X}_t$ to the credit index, $\boldsymbol{X}^{g}_{t,l} = \left\{X^{g}_{1,t,l}, X^{g}_{2,t,l}, \ldots X^{g}_{p,t,l}\right\}$ is a vector of forecasted macroeconomic variables (including their lags) for a given macroeconomic scenario g and ϵ_t is the error term capturing residual noise.

The forecasted credit index will be the resulting forecasted credit index for the next 12–24 months, using the model built in Step 3. The forecasts of the macroeconomic variables are provided quarterly by either an external company (e.g., Moody's) or the bank's internal economics team, offering the best-estimated view of the economy over the next five years (PWC 2017). Typically, three scenarios are provided (upside, downside and base scenarios), although more scenarios may be used. Forecasted values of these macroeconomic variables are plugged into the model to obtain the forecasted credit index.

As the macroeconomic forecasts are externally provided, our model does not explicitly compute long-term projections beyond this period. However, in line with the standard industry practice, these forecasts often follow a mean reversion approach (PWC 2017). This means that economic variables tend to return to a long-term equilibrium over time. Specifically, macroeconomic variables, such as unemployment rates tend to revert to their historical average level, while variables such as GDP growth gradually align with their long-run trend growth rate over a horizon of two to five years.

For our case study, we directly use these externally provided forecasts without further adjustments. However, the base default rate in our framework is set as the average observed default rate over the past 12–24 months. Additionally, macroeconomic scalars are segmented by risk characteristics (Black 2016) and segment-level scalars are recommended to ensure better risk differentiation.

Step 5: Validation

It is very important to validate the resulting models (De Jongh et al. 2017). The models as well as the resulting scalars should make business sense and there should be a clear and logical explanation for the inclusion of specific variables. The macroeconomic variables used should be theoretically justifiable. The model should reflect a variety of macroeconomic variables and represent different aspects of the economy. Variables should not be too volatile, as this increases forecast uncertainty. The model should not contain too many variables as this increases the likelihood of multicollinearity and complicates the interpretability of results. The forecasted scenarios (upside, downside and base scenario) must also be validated to ensure they are logical. For instance, when upside forecasts are entered into the model, the forecasted credit index should decrease relative to the base scenario. Conversely, if downside forecasts are entered into the model, the forecasted credit index increases relative to the base scenario. In the long-term trend, the business expected the scenarios to converge with one another and to a realistic PD in the long term, close to the expected range for PD.

The resulting scalar should be within a reasonable range. It is crucial to consider the region (upper and lower bounds) of each variable before a model breakdown, for example, the GDP year-on-year change, may not be less than −10% and more than +10% before the scalar becomes unreasonable. This proposal is a structured approach to determine where models will break down and in these regions of breakdown, a management adjustment needs to be triggered.

Assumptions

The proposed methodology assumes adherence to the underlying assumptions of the selected modelling approach, including those relevant to linear regression. It further requires the availability of a suitable credit index, such as observed and country-wide default rates, to ensure that the relationship between macroeconomic conditions and the default behaviour is captured correctly. In addition, both historical and forecasted macroeconomic data must be accessible to effectively incorporate forward-looking information. Finally, the methodology presupposes technical proficiency in advanced modelling techniques, facilitating the use of machine learning and traditional statistical models to enhance predictive performance.

Ethical considerations

Ethical clearance to conduct this study was obtained from the North-West University and Faculty of Natural and Agricultural Sciences Ethics Committee (No. NWU-01478-24-A9).

Results

Two datasets are used as case studies to illustrate the proposed methodology. An unsecured retail portfolio from a regional bank in Kenya and another from Mauritius were analysed. Both datasets span the period from January 2008 to June 2022, covering up-to-date customer data available at the time of analysis. We acknowledge that the data are now somewhat dated. However, these were the only data made available by the bank under strict confidentiality agreements. Additionally, all the default rates have been normalised to protect the actual levels of default.

The credit index for both Kenya and Mauritius was based on the observed bank-specific default rate, controlled for the effects of seasonality and volatility. Any business decision should be excluded if this influences the default behaviour. Seasonality must be investigated: we calculated the monthly average default rates (e.g., default rates of January, February, etc.) and adjusted these so that each monthly credit index is shifted up or down based on how far the average credit index for the respective calendar month deviates from the overall average credit index for the entire sample. This adjustment did not influence the Kenya or Mauritius default rate, but still remained an important part of the overall methodology. We should consider omitting extreme time periods, such as the COVID-19 pandemic. Smoothing should be considered and several smoothing techniques exist, however, we applied LOESS regression (Cleveland 1979) to the PD time series.

Although Kenya and Mauritius have many macroeconomic variables, only four were available to be used in the modelling because of the reliability and availability of data and forecasts as well as business decisions. The GDP is the total value of all the goods and services produced within a country over the course of a year. If the value of GDP increases that indicates more goods are produced, the improved economic scenario and a reduction in economic losses. Therefore, we expect a negative sign for GDP. If GDP increases, we expect the default rate to decline. The central bank interest rate (CBR) is the rate that is charged by a country’s bank on loans and advances that control the money supply in the economy and the banking sector and if this rate increases, which indicates an increased cost of borrowing and hence more economic loss. Inflation (INF) is our third variable. An increase in inflation leads to the rise in the prices of goods, making goods more expensive, hence more money needs to be paid for goods and services, leading to increasing economic loss. The foreign exchange rate (FXR) is the rate at which one currency will be exchanged for another. It is also regarded as the value of one country’s currency concerning other currencies. Here, this value is captured per US Dollar (USD). If this value increases, the country’s currency becomes weaker in comparison to the USD, indicating more economic losses. Therefore, we expect positive relationships between CBR, INF and FXR, that is, if any of these increases, we expect the default rate to rise. In summary, the theoretical relationships between each of the macroeconomic variables and the observed default rate are as follows:

- GDP – Negative
- CPI – Positive
- PR – Positive
- EXR – Positive

The quarterly data were converted into monthly data using a three-month rolling average. Exploratory data analysis was performed. No missing values were observed. Outliers were studied. We also investigated whether the time series were stationary using the Augmented Dickey-Fuller Test. Many methods exist to test whether a time series is stationary. We used the Augmented Dickey-Fuller Test for illustrative purposes. For Mauritius, both GDP and INF were non-stationary and, for Kenya, GDP, INF and FXR were non-stationary. We decided for illustrative purposes to transform these variables into year-on-year change as well as quarter-on-quarter change. This ensured stationarity (confirmed by the Augmented Dickey-Fuller tests). When analysing macroeconomic variables, it is important to take the time lags associated with them into account. For illustration, we considered three- and six-month lags. However, the business should determine the most suitable set of lags. The data provided by the bank were limited, particularly in terms of available forecasts for the given time span, partly because of the impact of COVID-19. As a result, variable reduction was not necessary for these two datasets.

We chose regression (Reg), GLM (Logit), GLM (Probit), feedforward neural network (FNN), random forest (RF) and gradient boosting (GB) as our modelling techniques. We tested 3429 combinations for each technique (we considered four macroeconomic variables and used lags zero, three and six). Variable combinations could include lags but were restricted not to include both a variable and its lag in the same combination. Out of all the models fitted, we selected only the models that fulfil the following criteria:

- The estimated signs of the regression coefficients for macroeconomic variables should align with expected economic principles. Note that for machine learning models we used the rank correlation of the partial dependence plot (as a proxy for the estimated sign).
- All estimated coefficients must be statistically significant at 5% (this was only applied for the Reg, GLML, GLMP and not for the FNN, RF and GB).

The remaining models were ranked by mean absolute error (MAE), mean absolute percentage error (MAPE) and mean squared error (MSE).

Case study 1: Unsecured retail portfolio of Kenya

The best model for each modelling technique for the unsecured retail portfolio of Kenya is as shown in Table 1 (based on the best average rank of MAE, MAPE and MSE). Note that all the estimated coefficients of the Reg, GLML and GLMP are significant at 5% and that the final variables included in this table already adhere to the correct estimated sign and rank correlation. Table 1 therefore does not contain regression statistics (such as significant values or coefficients). However, summary statistics are provided.

The MAE, MAPE and MSE are given and the variables used in each model. Note that YOY indicates a year-on-year change; QOQ indicates a quarter-on-quarter change and 3 and 6 refer to the three- and six-month lags. The average rank is determined by the rank of MAE, MAPE and MSE. It is interesting to note that each model contains the GDP. The best ranking model is the RF model using combination 40, which includes the year-on-year change of the GDP (YOY_GDP) and the prime rate (PR) as variables. The GLM with the logit link function using combination 22 which is based only on one variable, namely the YOY_GDP, has an average rank of four. Further investigation reveals the top six models per technique (unsecured Kenya retail portfolio) as follows:

- Reg: 610; 76; 286; 586; 502 and *22*.
- GLML: *22*; 292; *40*; 400; 262 and 286.
- GLMP: *22*; 292; *40*; 400; 262 and 286.
- FNN: 1809; 2209; 671; *22*; 767 and 3.
- RF: *40*; 340; 370; 394; 1516 and 341.
- GB: 1558; 1824; 1516; *40*; 384 and 1597.

We see that model combinations 22 and 40 appear quite often. The forecasted credit index for Kenya is as shown in Figure 1, where the forecasted values for the macroeconomic variables were plugged into the models. The forecasted credit index is based on the forecasts of upside, base and downside scenarios. These forecasted values for the macroeconomic variables were obtained from the bank's internal economics team. Note that the values depicted in Figure 1 are heavily dependent on the forecasts provided and these forecasts are regularly updated. The latest forecasts should inform the forecasted credit index. Note that before July 2022 the forecasts of baseline, upside and downside are identical (as these values are historically observed values) and only from July 2022 do the values for baseline, upside and downside differ based on the forecasted values. The GLM model (Figure 1) does not capture the ups and downs of the historically observed default rate as close as, for example, the RF (refer to Figure 1).

The resulting scalars for the GLM and RF models are shown in Figure 2. Recall that the GLM with the logit link function used combination 22 is based only on one variable, namely the YOY_GDP and the random forest used combination 40, which includes the year-on-year change of the GDP (YOY_GDP) and the prime rate (PR) as variables. The range of a reasonable scalar needs to be determined by the business and should be in line with the expectations of the forward-looking scenarios. For both the models, the macroeconomic scalars make sense, as we expect a scalar of around 1 for the baseline, on the upside we expect the scalar should be less than the baseline scalar and for the downside we expect a scalar higher than the baseline scalar.

Both the models are therefore validated as all variables included make business sense and a logical explanation for the variables is enforced (by considering only models with the estimated sign aligning with the theoretical relationship). The forecasted scenarios (upside, downside and base scenarios) need to be logical and the resulting scalars are within a reasonable range.

Case study 2: Unsecured retail portfolio of Mauritius

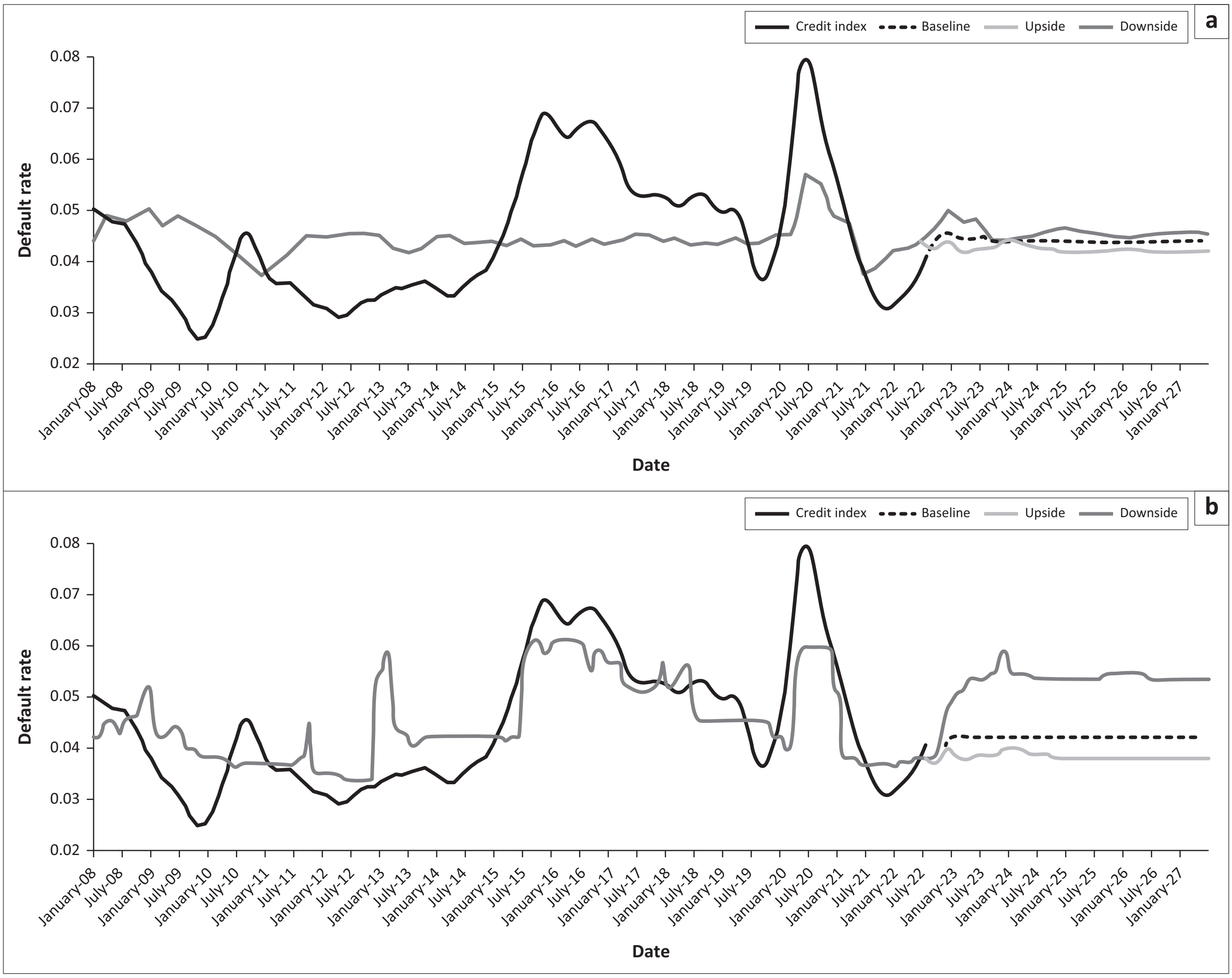
The best models for each modelling technique for the unsecured retail portfolio in Mauritius are presented in Table 2. These models were selected based on their average ranks across MAE, MAPE and MSE metrics.

Again, the MAE, MAPE and MSE are given and the variables used in each model. It is interesting to note that each model contains the GDP and most models contain prime rate (PR). The best ranking model is the feedforward neural network (FNN) model using combination 60, which includes the interpolated prime rate lagged three months (I_PR_3) and the year-on-year change of the GDP lagged six months (YOY_GDP_6) as variables. The second-best model is the GLM with the probit link

TABLE 1: Top-performing model for each technique (Kenya unsecured retail portfolio).

Model	Reg	GLML	GLMP	FNN	RF	GB
Model number	610	22	22	1809	40	1558
MAE	0.010	0.010	0.010	0.009	0.006	0.008
MAPE	0.248	0.246	0.246	0.221	0.147	0.195
MSE	0.00015	0.00015	0.00015	0.00013	0.00006	0.00009
Variable 1	PR_6	YOY_GDP	YOY_GDP	PR_3	PR	PR
Variable 2	QOQ_EXR_3	-	-	YOY_CPI_6	YOY_GDP	YOY_CPI_6
Variable 3	YOY_GDP	-	-	QOQ_EXR_6	-	YOY_EXR
Variable 4	-	-	-	QOQ_GDP_6	-	YOY_GDP
Average rank	5	4	6	3	1	2

MSE, mean square error; MAPE, mean absolute percentage error; MAE, mean absolute error; GLML, generalised linear model Logit; GLMP, generalised linear model Probit; FNN, feedforward neural network; RF, random forest; GB, gradient boosting; Reg, regression.



The forecasted credit index for Kenya is shown in Figure 1 where the forecasted values for the macroeconomic variables were plugged into the random forest model using combination 40. The random forecast follows the historically observed default rates closer than the GLM (refer to Figure 1).

FIGURE 1: Credit index of the unsecured retail portfolio of Kenya: (a) GLM (logit) model 22, (b) RF model 40.

function using combination 378 that is based on three variables, namely the I_PR, YOY_EXR_3 and YOY_GDP_6. Further investigation reveals the top six models per technique as shown in Table 3 and we see the model combination 60 and 378 appearing quite often.

The forecasted credit index for Mauritius is shown in Figure 3, where the forecasted values for the macroeconomic variables were plugged into the models, using the FNN 60 and the GLMP 378, respectively. Again, the forecasted credit index is based on the forecasts of upside, base and downside scenarios. Both models, the FNN and the GLMP, capture the ups and downs of the historically observed default rate quite well.

The resulting scalars for the FNN and GLMP models are shown in Figure 4. Recall that the FNN used combination 60 that is based on two variables, namely the interpolated prime rate lagged three months (I_PR_3) and the year-on-year change of the GDP lagged six months (YOY_GDP_6). The GLM (using the probit link function) is based on combination 378 and this model used three variables: the prime rate, the year-on-year exchange rate lagged for three months and the year-on-year GDP lagged for six months. Similarly, as with Kenya, in both the models the macroeconomic scalars for Mauritius make sense as we expect a scalar around 1 for the baseline (although this is consistently above 1). For the upside scenario, we expect the scalar should be less than the baseline (usually below 1, although in this case, it is consistently above 1) and for the downside scenario, we expect a scalar higher than the baseline scenario.

Conclusion

In this article, we proposed a methodology to develop a macroeconomic scalar to adjust the PD in the ECL model to incorporate forward-looking information. This methodology is pragmatic and robust. The methodology consists of five steps: Research and planning; Data preparation; Development of the model; Calculation of the macroeconomic scalar and, lastly, Validation of the model. Our proposed methodology effectively addresses the challenges faced by developing countries with limited and volatile macroeconomic data, providing a reliable method to adjust the PD in an ECL model for forward-looking information. The use of a separate scalar aids in differentiating the ECL allowance by current credit performance and forward-looking expectations. Given that IFRS 9 ECL estimates significantly impact the income statement, having transparent and explainable methods is crucial and the proposed scalar offers the necessary transparency and explainability.

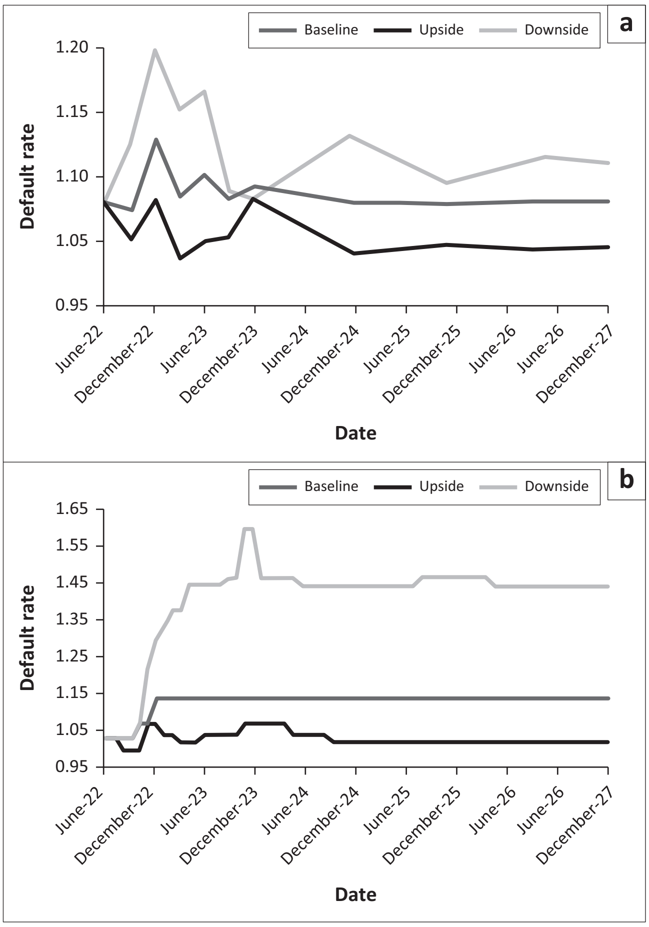


FIGURE 2: Macroeconomic scalar for unsecured retail portfolio of Kenya: (a) generalised linear model (logit) model 22, (b) random forest model 40.

The methodology was illustrated on two unsecured retail portfolios from Kenya and Mauritius. The resulting models were both practical and intuitive (ensured by enforcing business sense as a criterion), with forecasted credit indices for different scenarios that were easily interpretable. Some recommendations to ensure that reasonable values are achieved for the resulting macroeconomic scalars included that the business determines specific regions (upper and lower bounds) for the forecasts of macroeconomic variables.

A key strength of the methodology is the integration of both statistical and machine learning techniques. We employed traditional statistical models, such as multiple regression and GLMs, alongside advanced machine learning methods, including neural networks, random forests and gradient boosting. This dual approach provided a more comprehensive understanding of the dynamics at play and enhanced the predictive accuracy of our models. In some situations, the machine learning techniques outperformed the traditional statistical models, indicating the complex relationship between the macroeconomic environment and the default rates. In Case Study 1, the winners were the GLM and the RF, while in Case Study 2, the FNN and the GLM.

Some specific recommendations were made when implementing the above methodology. A controlled method is recommended to determine which regions should trigger

TABLE 2: Top-performing model for each technique (Mauritius unsecured retail portfolio).

Model	Reg	GLML	GLMP	FNN	RF	GB
Model number	1590	402	378	60	1313	318
MAE	0.004	0.004	0.004	0.003	0.006	0.005
MPE	0.138	0.131	0.127	0.121	0.232	0.215
MSE	0.00003	0.00004	0.00004	0.00002	0.00005	0.00004
Variable 1	I_PR	I_PR	I_PR	I_PR_3	YOY_CPI_3	I_PR
Variable 2	YOY_CPI_6	QOQ_EXR_6	YOY_EXR_3	YOY_GDP_6	YOY_EXR_3	YOY_CPI_3
Variable 3	QOQ_EXR_6	YOY_GDP_6	YOY_GDP_6	-	YOY_GDP_3	YOY_GDP_6
Variable 4	YOY_GDP_6	-	-	-	-	-
Average rank	4	3	2	1	6	5

MSE, mean square error; MAPE, mean absolute percentage error; MAE, mean absolute error; GLML, generalised linear model Logit; GLMP, generalised linear model Probit; FNN, feedforward neural network; RF, random forest; GB, gradient boosting.

TABLE 3: Top six models per technique (unsecured Mauritius retail portfolio).

Rank	Reg	GLML	GLMP	FNN	RF	GB
1	1590	402	378†	60†	1313	318
2	402	42	402	1805	220	310
3	1554	378†	42	1560	1306	1782
4	384	492	492	1752	1288	1895
5	372	1788	1788	425	1330	1559
6	1524	60†	60†	1554	1312	1913

Reg, regression; GLML, generalised linear model Logit; GLMP, generalised linear model Probit; FNN, feedforward neural network; RF, random forest; GB, gradient boosting.
†, Model combinations that appear often.

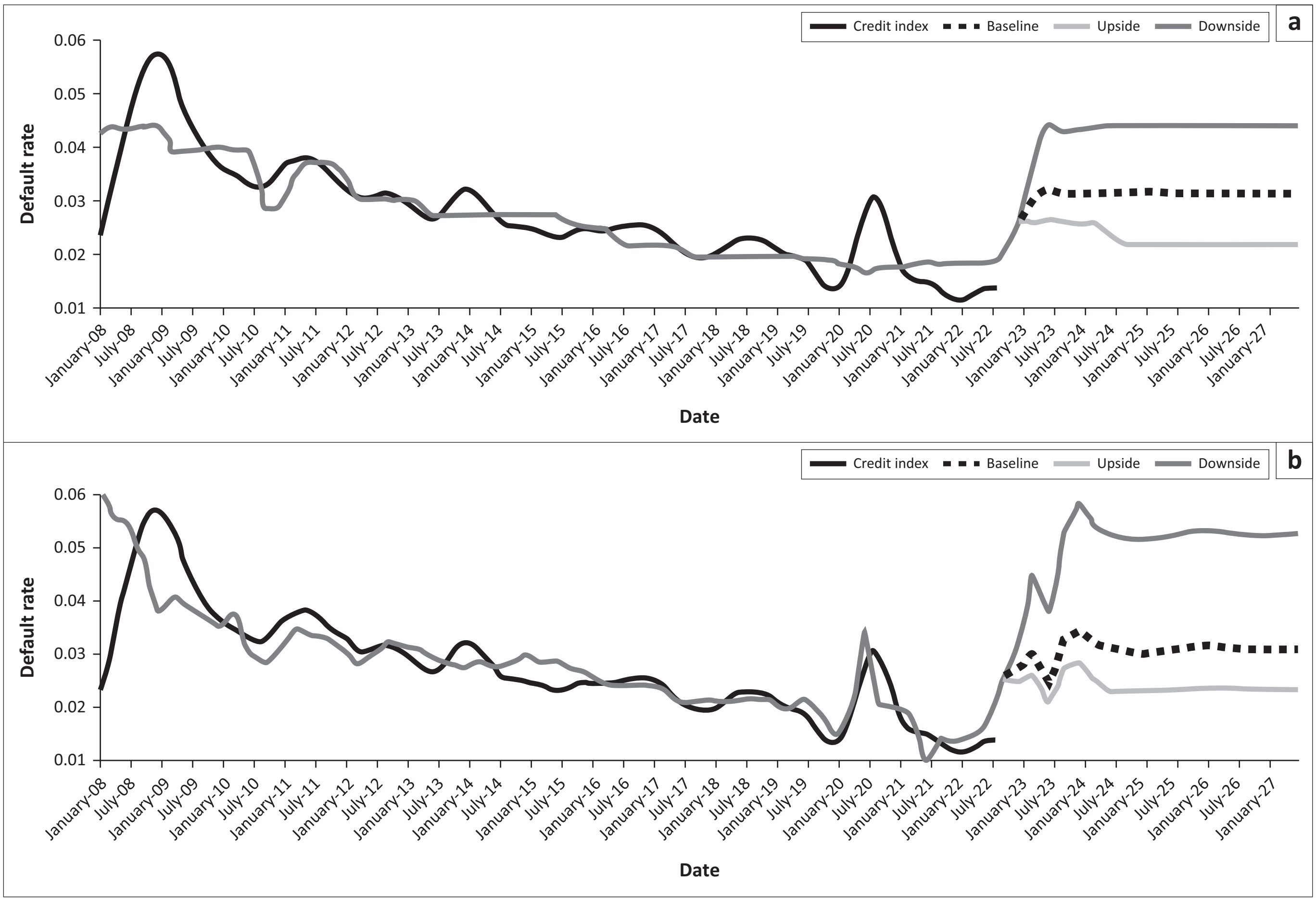


FIGURE 3: Credit index of the unsecured retail portfolio of Mauritius: (a) feedforward neural network model 60, (b) generalised linear model (Probit) model 378.

management adjustments. This should be driven by business. It was recommended that risk characteristics segment the proposed scalars. As mentioned before, segment scalars offer the benefit of improving risk measurement by adapting to changes in segment proportions within the portfolio over time. Segment scalars could deliver a more stable and dependable estimate of credit risk, facilitating more effective financial planning and decision-making.

A limitation of our study was that we had access to only a few number of macroeconomic variables. We recommend that the models be improved by using a wider range of possible macroeconomic and macroprudential variables with reliable forecasts as using only the four variables is not optimal. We found that the use of proper transformations (e.g., QOQ, YOY and lags) of the predictor variables (i.e., macro variables) contributes to stronger models. We recommend that a minimum of 60 time periods be used in this methodology. Another limitation of our study is the lack of country-wide default rates. We recommend that country-wide default rates or alternative proxies should be used as the credit index and not bank-specific default rates that tend to create limitations.

A future idea for research is to investigate alternative methods for converting quarterly data to monthly data, preferably including a full economic cycle. We also recommend that further research should be performed on the use of alternative variables for forecasts of forward-looking information, that is, rather than using GDP consider using the Big Mac Index. The Big Mac Index was invented by *The Economist* in 1986 as a light-hearted guide to whether currencies are at their 'correct' levels (The Economist 2022), but has since been used as a measure to determine the economic health of a country. Many other such alternative measures of economic strength are available, see for example the Human Development Index, the Happy Planet Index and the Better Life Index as specific alternatives to GDP (Hawkes 2021). According to the Men's Underwear Indicator Index, if there is a decline in men's underwear sales, the economy is suffering a slump and if there is an upswing in sales, the economy is likely to improve (The Economic Times 2022). An article on the 'International Monetary Fund' website states that satellite images of the Earth at night reveal the pace of economic growth and much more (Yao 2019). We recommend future research into these alternative measures that might be used to adjust the ECL model's PD levels. The biggest challenge will be to obtain reliable forecasts for these alternative measures.

Further future research could explore how credit performance in many developing economies, often linked to government borrowing or the financial stability of government employees, might benefit from incorporating sovereign debt levels as a forward-looking information indicator. Additionally, future

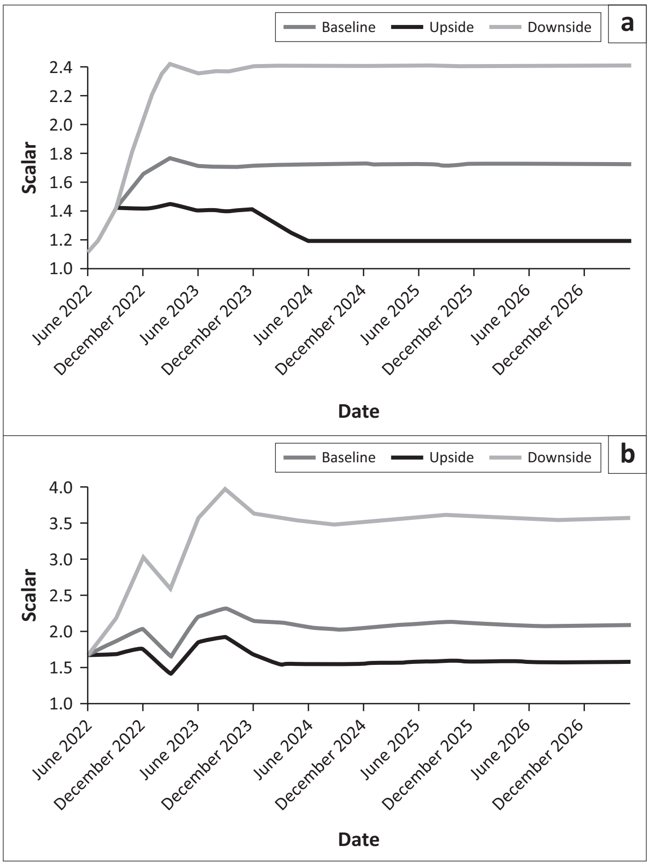


FIGURE 4: Macroeconomic scalar of the unsecured retail portfolio of Mauritius: (a) feedforward neural network model 60, (b) generalised linear model (Probit) model 378.

research could focus on improvements in the methodology to better manage the ECL volatility stemming from forward-looking impairments, particularly in the light of significant challenges such as those experienced during the COVID-19 pandemic.

Acknowledgements

Competing interests

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article.

Authors' contributions

S.M., H.R. and T.V. contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

Funding information

This work is based on the research supported wholly or in part by the National Research Foundation of South Africa (Grant Numbers: 126885, 126877).

Data availability

The data presented in this study are not publicly available because of confidentiality.

Disclaimer

The views and opinions expressed in this article are those of the authors and do not necessarily reflect the official policy or position of any affiliated agency of the authors.

References

Bellini, T., 2019, *IFRS 9 and CECL credit risk modelling and validation: A practical guide with examples worked in R and SAS*, 1st edn., Elsevier, London.

Bellotti, T. & Crook, J., 2013, 'Forecasting and stress testing credit card default using dynamic models', *International Journal of Forecasting* 29(1), 563–574. https://doi.org/10.1016/j.ijforecast.2013.04.003

Black, B., 2016, *Probability-weighted outcomes under a macroeconomic approach*, viewed 04 November 2024, from https://www.moodysanalytics.com/webinars-on-demand/2016/probablility-weighted-outcomes-macroeconomic-approach.

Botha, A., Oberholzer, E., Larney, J. & De Jongh, R., 2025, 'Defining and comparing SICR-events for classifying impaired loans under IFRS 9', *Annals of Operations Research* 1–36. https://doi.org/10.1007/s10479-025-06546-3

Breed, D.G., Hurter, J., Marimo, M., Raletjene, M., Raubenheimer, H., Tomar, V. et al., 2023, 'A forward-looking IFRS 9 methodology, focussing on the incorporation of macroeconomic and macroprudential information into expected credit loss calculation', *Risks* 11(59), 1–16. https://doi.org/10.3390/risks11030059

Breed, D.G., Van Jaarsveld, N., Gerken, C., Verster, T. & Raubenheimer, H., 2021, 'Development of an impairment point in time probability of default model for revolving retail credit products: South African case study', *Risks* 9(208), 1–22. https://doi.org/10.3390/risks9110208

Cleveland, W.S., 1979, 'Robust locally weighted regression and smoothing scatterplots', *Journal of the American Statistical Association* 74(368), 829–836. https://doi.org/10.1080/01621459.1979.10481038

Crook, J. & Bellotti, T., 2010, 'Time-varying and dynamic models for default risk in consumer loans', *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 173(2), 283–305. https://doi.org/10.1111/j.1467-985X.2009.00617.x

De Jongh, P., Larney, J., Mare, E., Van Vuuren, G. & Verster, T., 2017, 'A proposed best practice model validation framework for banks', *South African Journal of Economic and Management Sciences* 20(1), 1–15. https://doi.org/10.4102/sajems.v20i1.1490

Durović, A., 2019, 'Macroeconomic approach to point in time probability of default modeling – IFRS 9 challenges', *Journal of Central Banking Theory and Practice* 8(1), 209–223. https://doi.org/10.2478/jcbtp-2019-0010

Engelman, B. & Rauhmeier, R., 2011, *The basel II risk parameters: Estimation, validation, and stress testing*, 2nd edn., Springer, Berlin.

Engelmann, B., 2021, 'A simple and consistent credit risk model for basel II/III, IFRS 9 and stress testing when loan data history is short', *International Journal of Financial Engineering* 11(3), 2441002. https://doi.org/10.1142/S2424786324410020

Fuller, W.A., 1996, *Introduction to statistical time series*, Wiley & Sons, New York, NY.

Global Public Policy Committee (GPPC), 2016, 'The implementation of IFRS 9 impairments by banks', *Considerations for those charged with governance of systemically important banks,* viewed 10 March 2022, from https://www.deloitte.com/ch/en/Industries/financial-services/research/2016-gppc-the-implementation-of-ifrs9-impairment-requirements-by-banks.html.

Hawkes, H., 2021, *GDP alternatives: 8 ways of measuring economic health,* viewed 27 August 2023, from https://intheblack.cpaaustralia.com.au/economy/8-ways-of-measuring-economic-health.

IFRS, 2014, *IRFS9 financial instruments: Project summary*, viewed 31 January 2016, from http://www.ifrs.org/Current-Projects/IASB-Projects/Financial-Instruments-A-Replacement-of-IAS-39-Financial-Instruments-Recognitio/Documents/IFRS-9-Project-Summary-July-2014.pdf.

IFRS, 2020, *IFRS 9 and COVID-19*, viewed 25 November 2021, from https://www.ifrs.org/content/dam/ifrs/supporting-implementation/ifrs-9/ifrs-9-ecl-and-coronavirus.pdf.

Jacobs, M., 2019, 'An analysis of the impact of modeling assumptions in the Current Expected Credit Loss (CECL) framework on the provisioning for credit loss', *Journal of Risk & Control* 6(1), 65–112.

James, G., Witten, D., Hastie, T. & Tibshirani, R., 2013, *An introduction to statistical learning: With applications in R*, Springer, New York, NY.

Kutner, M.H., Nachtsheim, C.J., Neter, J. & Li, W., 2005, *Applied linear statistical models*, 5th edn., McGraw-Hill/Irwin, New York, NY.

Lin, F.J., 2008, 'Solving multicollinearity in the process of fitting regression model using the nested estimate procedure', *Quality and Quantity* 42(3), 417–426.

PRA, 2023a, *Prudential Regulation, PS6/23–Model risk management principles for banks*, Bank of England, London, viewed 10 March 2024, from https://www.bankofengland.co.uk/prudential-regulation/publication/2023/may/model-risk-management-principles-for-banks.

PRA, 2023b, *Prudential Regulation, SS1/23–Model risk management principles for banks*, Bank of England, London, viewed 27 May 2024, from https://www.bankofengland.co.uk/-/media/boe/files/prudential-regulation/supervisory-statement/2023/ss123.pdf.

PWC, 2017, *In-depth IFRS 9 impairment: How to include multiple forward-looking scenarios*, PWC, London.

SAS Institute Inc, 2010, *Predictive modelling using logistic regression*, SAS Institute Inc, Cary, NC.

SAS Institute Inc, 2020, *Machine learning using SAS® Viya® course notes (LWCPML35/CPML35)*, SAS Institute Inc, Cary, NC.

Schutte, W.D., Verster, T., Doody, D., Raubenheimer, H. & Coetzee, P.J., 2020, 'A proposed benchmark model using a modularised approach to calculate IFRS9 expected credit loss', *Cogent Economics & Finance* 8(1), 1–27. https://doi.org/10.1080/23322039.2020.1735681

Simons, D. & Rolwes, F., 2009, 'Macroeconomic default modeling and stress testing', *International Journal of Central Banking,* 5(3), pp. 177–204.

Skoglund, J., 2014, 'Credit risk term-structures for lifetime impairment forecasting: A practical guide', *Journal of Risk Management in Financial Institutions* 10(2), 177–195. https://doi.org/10.69554/ICHC6682

Tasche, D., 2013, 'The art of probability-of-default curve calibration', *Journal of Credit Risk* 9(4), 63–103. https://doi.org/10.21314/JCR.2013.169

Tasche, D., 2015, *Forecasting portfolio credit default rates*, viewed 22 April 2022, from https://www.bayes.city.ac.uk/__data/assets/pdf_file/0015/256101/TASCHE-Dirk-10.02.2015.pdf.

The Economic Times, 2022, *Unconventional economic indicators that might surprise you*, viewed 14 March 2023, from https://economictimes.indiatimes.com/news/economy/unconventional-economic-indicators-that-might-surprise-you/mens-underwear-indicator/slideshow/94961917.cms.

The Economist, 2022, *The big mac index*, viewed 05 June 2023, from https://www.economist.com/big-mac-index.

Tokmak, B., 2020, *Probability of default modelling using macroeconomic factors*, The Graduate School of Social Sciences of Middle East Technical University, Ankara

Van der Lith, R., 2019, *IFRS 9 probability of default modelling in data challenged environments focusing on emerging markets (BWIR828: Industry Directed Research Project for Absa, BMR9462)*, North-West University, Potchefstroom.

Xu, Xin, 2016, *Estimating lifetime expected credit losses under IFRS 9*, viewed 17 February 2022, from https://ssrn.com/abstract=2758513 or https://doi.org/10.2139/ssrn.2758513.

Yao, J., 2019, *Illuminating economic growth*, viewed 12 May 2023, from https://www.imf.org/Publications/fandd/issues/2019/09/satellite-images-at-night-and-economic-growth-yao.