A FORWARD-LOOKING MACROECONOMIC SCALAR FOR IFRS 9 PD IN DEVELOPING ECONOMIES

Israel Odion E. Idewele (Ph.D)
Department of Banking and Finance
Evangel University. Ebonyi State, Nigeria
idewelei@evangeluniversity.edu.ng
Corresponding Author
And
Associate Professor Dibua, Ekene C
Department of Accountancy,
Paul's University, Awka, Anambra State.
Dibuaekene@gmail.com
And
Ikilidih, Joy N. (Ph.D)
Department of Accountancy,
Paul's University, Awka, Anambra State.
joyikilidih@gmail.com

Abstract
With the introduction of an anticipated credit loss (ECL) framework to account for impairments, IFRS 9 regulates the reporting of financial assets and liabilities. At every reporting date, the ECL model updates recognized ECLs by taking into account historical data, present circumstances, and anticipated information. Usually, ECL is divided into three parts: exposure at default (EAD), loss given default (LGD), and probability of default (PD). In order to improve accuracy, this research suggests a way for creating a macroeconomic scalar to modify PD in the ECL model by including forward-looking data. Datasets from Cameroon and Nigeria are utilized to demonstrate the suggested methodology, and different modeling approaches are employed for validation. Five steps make up the methodology: (1) planning and research, (2) data preparation, (3) model construction, (4) macroeconomic scalar computation, and (5) model validation. Regression, feed forward neural networks, random forest, gradient boosting, and GLM (Logit, Probit) are some of the methods used. For the Nigerian and Cameroonian datasets, the macroeconomic scalar that was constructed successfully adjusted PD within the ECL model. Every modeling strategy offered insightful information, proving the scalar's capacity to enhance ECL forecasts. A reliable technique for adding forward-looking data to the ECL model is to incorporate a macroeconomic scalar. This improves PD accuracy and can take into account the uncertainty, volatility, and sparse data that are characteristics of developing countries.In this study, a scalable method for modifying PD in ECL models with macroeconomic data is presented, with a focus on developing nations.

Keywords: projected credit loss, IFRS 9, probability of default, macroeconomic, and forward-looking
The accounting of financial assets and liabilities is governed by IFRS 9.

INTRODUCTION

The International Financial Reporting Standard (IFRS) 9 was released in 2014 after the International Accounting Standard Board (IASB) and Financial Accounting Standard Board (FASB) collaborated to restructure accounting standards for a better and more straightforward expected credit loss (ECL) framework during the financial crisis (IFRS, 2014). Since comparable metrics are also needed for other risk management purposes, such as the quantification of regulatory or economic capital requirements, the quantification of ECL is frequently divided into its three components: exposure at default (EAD), loss given default (LGD), and probability of default (PD).

ECL = PD × LGD × EAD is a condensed formula for estimating expected credit loss (Breed et al., 2021).

According to the IFRS 9 standard (IFRS, 2014), the PD model must account for how default rates are impacted by the macroeconomic environment both now and in the future. This makes it possible to calculate estimations of impairments for the future. However, certain financial situations (like COVID-19) are challenging and lead to a lot of uncertainty, particularly when it comes to adding forward-looking data to ECL forecasts (IFRS, 2020).

In the context of emerging nations, modeling forward-looking data poses a number of difficulties. First, these countries frequently struggle with the availability and dependability of macroeconomic data, which makes it challenging to predict economic trends accurately and to make successful plans. Financial modeling and risk assessment are further complicated by the volatility of credit defaults, which is made worse by periods of high inflation and variable interest rates. The lack of strong social safety nets is another major obstacle, making customers susceptible to job losses without sufficient assistance and making it more difficult to forecast consumer behavior and economic stability. These difficulties highlight the necessity of adaptive modeling approaches that can take into consideration the limited data, volatility, and uncertainty typical of developing countries. According to the IFRS 9 standard (IFRS, 2014), the PD model must account for how default rates are impacted by the macroeconomic environment both now and in the future. This makes it possible to calculate estimations of impairments for the future.

However, certain financial situations (like COVID-19) are challenging and lead to significant uncertainty, particularly when incorporating forward-looking data into ECL forecasts (IFRS, 2020). Similar to Breed et al. (2023), we take a scalar approach in this research to account for the impact of macroeconomic conditions—both current and future—on default rates. IFRS 9 does not enforce any specific methodology. Nonetheless, by adding a scalar to each of the ECL's components, a financial institution can modify the ECL for future macroeconomic situations if it chooses to use the scalar approach:

$$ECL = PD \times s_{PD} \times LGD \times s_{LGD} \times EAD \times s_{EAD}, \qquad (2)$$

where the terms represent the macroeconomic scalars for PD, LGD, and EAD respectively. The scope of this paper focuses only on the PD scalar. The PDs will generally be on loan-level and the scalars on segment level.

The PD scalar can be estimated by:

$$\hat{s}_{PD} = \frac{Forecasted\ credit\ index}{Base\ default\ rate}$$

where the Forecasted credit index is the credit index predicted using forecasts of macroeconomic variables, and the Base default rate is the average observed default rate of the PD. This credit index serves as a conduit between macroeconomic circumstances and a portfolio's default patterns. It should be noted that segmentation-level scalars are advised.

LITERATURE REVIEW

Models at the loan level

Bellini (2019) lists a number of loan level modeling approaches that can be used to model default while taking macroeconomic factors into account. These include survival analysis, generalized linear models, and numerous machine learning techniques (such as bagging, boosting, and random forests). Loan-level models are more complex to construct (more data), may take longer to deploy than portfolio-level models, and require trustworthy historical loan level data (Black, 2016). Nonetheless, Black (2016) suggests that loan-level models are the most effective approach to addressing the IFRS 9 standard's forward-looking component. Many other sources, such as Xu (2016), Skoglund (2014), Crook & Bellotti (2010), and Bellotti & Crook (2013), identify the use of discrete hazard rates as a common technique to employ in the forward-looking PD IFRS 9 modeling. Generally speaking, loan-level models are more accurate than portfolio-level ones. Engelman (2021) demonstrates the integration of a macroeconomic model at the loan level with one at the portfolio level.

There is a dearth of literature on PD approaches tailored to IFRS 9 that take macroeconomic modifications into account. Nonetheless, Tasche (2013) and Crook & Bellotti (2010) provide a summary of general approaches to integrating macroeconomic circumstances into credit risk modeling.

Even if the particular approach was created for a different use, like Basel regulatory models, several of these might be used in the context of IFRS 9. Our suggested approach is strong enough to handle the difficulties brought on by sparse and erratic macroeconomic data.

To investigate the impact of macro variables on PDs, Tokmak (2020) employs an ARDL (Autoregressive Distributed Lag) bound testing approach using quarterly data on the likelihood of default ratio and other macroeconomic variables. The ARDL cointegration technique determines the long term relationship between series with different integration orders.

The ARDL cointegration technique, also known as the bound test of cointegration, is built around estimating an Unrestricted Error Correction Model (UECM) using the Ordinary Least Squares (OLS) approach. Simons and Rolwes' (2009) list of portfolio-level macroeconomic models includes a variety of methodologies, including logistic regression, econometric models, and vector autoregressive models. Simons and Rolwes (2009) explored the relationship between the default rate and the macroeconomy using a logit model based on macroeconomic parameters. The following are some advantages of this relatively simple model: It is straight forward, very simple to understand, and generates consistent results.

Portfolio-level models are easier to build since they can be implemented faster and require less data (Black, 2016). The economy affects each consumer differently, depending on macroeconomic circumstances. Customers in the tourism sector, for example, suffered tremendously during the COVID-19 epidemic, whereas those in the information technology and pharmaceutical sectors had a different experience.

METHODOLOGY

The model's development, or stage three, is discussed. Step 5 describes how to validate the model, whereas Step 4 derives the macroeconomic scalar.

Step 1: Plan and research

We must ensure that all procedures and actions taken during this research and planning stage are in accordance with IFRS 9. Understanding the theoretical relationship between default rates (Y) and macroeconomic variables (Xs) is critical. For example, rising GDP (gross domestic product) indicates an improved economic environment and increased production of goods, which reduces default rates and economic loss. As a result, we expect default rates to be inversely related to GDP.

At this step, we also select the optimal modeling approach based on the financial institution's technical expertise, software accessibility, and other business considerations. There are numerous approaches available, such as VARMAX, ECM, and linear regression. A detailed examination of the underlying assumptions of the chosen technique is required. Furthermore, a thorough examination of the nation's unique characteristics and sovereign risks is required.

Step 2: Preparing the Data

This stage consists of three sub-steps: determining the credit index, selecting variables, and reducing variables.

Determine the credit index

To approximate the default behavior of the portfolio, a credit index (Y) is required, which is often derived using past defaults. This credit index should be closely tied to the loan portfolio that a bank is modeling, such as national default rates for a specific loan sector, nonperforming loan rates, or, if available, loss rates (Engelmann, 2021). Schutte et al. (2020) recommend considering the entire economic cycle.

If default rates are volatile, a smoothing method (such as LOESS) may be considered. Stages are assigned based on changes in credit quality since initial recognition. Stage 1 is assigned when the credit risk has not escalated appreciably after initial recognition. Stage 2 is assigned when credit risk has significantly escalated since original recognition. When an account goes into default, it is allocated to Stage 3. A 12-month ECL is recognized for Stage 1 accounts, whereas a lifetime expected loss (EL) is recognized for Stage 2 and Stage 3 accounts.

It is proposed that the macroeconomic scalar be estimated solely for Stage 1 accounts but used for both Stage 1 and Stage 2. The argument for using Stage 1 clients for development is that macroeconomic conditions influence their probability more organically than customers who are already in arrears (Stages 2 and 3).

Variable selection for the model

Numerous macroeconomic variables (X's) can be used in the modeling process. When selecting macroeconomic indicators, two crucial factors to take into account are data reliability and availability. Another crucial consideration is the availability of projections for these variables. Similar to Moody's, these forecasts usually include a base, upside, and negative scenario (PWC, 2017).

Finally, business stakeholders' perspectives should be taken into account. Following their discovery, each accessible macroeconomic indicator undergoes exploratory data analysis. One popular tactic is to plot these variables against time. Any missing values must be imputed (SAS Institute, 2010), and outliers must be smoothed (James et al., 2012). If macroeconomic variables show a lot of time volatility, they should not be employed in modeling (van der Lith, 2019).
Since most macroeconomic data are issued on a quarterly basis, these quarterly figures must be transformed to monthly figures. Spline interpolation, linear interpolation, and piecewise constant interpolation are among the options (Engelmann & Rauhmeier, 2011).

Variable reduction of the X's

Variable clustering can be a helpful technique to minimize the number of variables and eliminate multicollinearity if there are many variables (SAS Institute, 2010). Theoretically, each nation has a wide range of macroeconomic and macroprudential factors.

Step 3: Development of the model

It is necessary to fit a Y = f(X) model (such as linear regression or VARMAX) to every feasible combination of macroeconomic variables. Verifying that the underlying modeling technique's assumptions are fully met is crucial. For example, the following presumptions apply to linear regression (Kutner et al., 2005):

Linearity: There is a linear relationship between X and the mean of Y.
Homoscedasticity: For any value of X, the residual variance remains constant.
Independence: There is no relationship between observations.

Step 4: Calculate the macroeconomic scalar

The macroeconomic variable scalar for the PD is defined as:

$$\hat{s}_{PD} = \frac{\textit{Forecasted credit index}}{\textit{Base default rate}}$$

Where the Base default rate represents the PD's average default rate, and the credit index that is predicated on projections of macroeconomic variables is known as the anticipated credit index. Segment-level scalars are recommended.

The final projected credit index over the next 12 to 24 months will be the predicted credit index, which is created using the model developed in Step 3. The macroeconomic variable projections, which are published quarterly by the bank's internal economics team or an external organization (such as Moody's), provide the best estimated picture of the economy for the next five years (PWC, 2017).

Although more scenarios could be offered, three are typically provided: the base, upside, and downside possibilities. Entering the expected values of specific macroeconomic elements into the model yields the anticipated credit index. After five years, the economic variables are often projected for each instrument's remaining lifetime using a mean reversion approach (PWC, 2017). This indicates that during a period of two to five years, economic indicators gravitate to either a long-term average rate (such as unemployment) or a long-term average growth rate (such as GDP). The fundamental default rate should be the average observed default rate over the preceding 12 to 24 months.

Step 5: Validation

Validating the generated models is crucial (De Jongh et al., 2017). The variables should have a logical explanation, and the models and resulting scalars should make commercial sense. There should be theoretical justification for the macroeconomic variables that are employed.

To demonstrate the aforementioned methods, two datasets are presented as case studies. Both a Kenyan and a Mauritius regional bank's unsecured retail portfolios were used. For current clients, both databases cover January 2008 through June 2022. Please note that all default rates have been normalized in order to maintain confidentiality and avoid revealing the true level of default rates. The observed bank-specific default rate, adjusted for the impact of volatility and seasonality, served as the basis for the CRI for Kenya and Mauritius.

DATA PRESENTATION AND INTERPRETATION

If any business decisions have an impact on the default behavior, they should be removed. We determined the monthly average default rate (January, February, etc.) and adjusted these to shift each monthly credit index up or down depending on how much the average credit index for the corresponding calendar month deviates from the overall average credit index for the entire sample. This is necessary in order to investigate seasonality. The default rate in Mauritius and Kenya was unaffected by this. The methodology should still include this. Any severe time span, like COVID-19, should be excluded.

We utilized LOESS (locally estimated scatterplot smoothing) regression (Cleveland, 1979) to the PD time series, even though there are other smoothing strategies that should be taken into account. Due to the availability and dependability of data, projections, and business decisions, only four of the numerous macroeconomic variables in Kenya and Mauritius could be employed in the modeling. The entire value of all the products and services produced in a nation during a given year is known as the gross domestic product, or GDP. An increase in GDP indicates that more things are created, which improves the economy and lowers losses. As a result, we anticipate a negative GDP sign. We anticipate a decline in the default rate if GDP rises.

The rate that a nation's bank charges on loans and advances that regulate the money supply in the economy and banking sector is known as the central bank interest rate, or CBR. If this rate rises, it indicates that borrowing will become more expensive and that there will be more economic losses.
Our third variable is inflation (INF). The price of goods rises in response to inflation, increasing the amount of money required to purchase goods and services and resulting in growing economic loss.
The rate at which one currency will be converted into another is known as the foreign exchange rate, or FXR. It is also thought of as the worth of one nation's currency in relation to another. More economic loss results from the country's currency becoming weaker relative to the USD if this value rises.
As a result, we anticipate positive indicators for CBR, INF, and FXR; that is, if any of these factors rise, we anticipate an increase in the default rate. In conclusion, the observed default rate and each macroeconomic variable have the following theoretical relationships:

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

A three-month rolling average was used to transform the quarterly data into monthly data. Analysis of the data was exploratory. There were no missing values found. We looked at outliers. Additionally, we used the Augmented Dickey-Fuller test to determine whether the time series were stationary. There are numerous ways to determine if a time series is stationary. For example, we employed the Augmented Dickey-Fuller test. Both GDP and INF were non-stationary for Mauritius, and FXR and INF were non-stationary for Kenya's GDP. For the sake of illustration, we chose to convert these variables to both year-over-year and quarter-over-quarter changes.

We only chose models that met the following requirements out of all the models that were fitted: economic expectations should be met by the estimated sign of the regression coefficients of the macroeconomic variables. Please take note that we substituted the rank correlation of the partial dependence plot (as a stand-in for the estimated sign) for machine learning models. This requirement was only applied to the Reg, GLML, and GLMP and not to the FNN, RF, or GB. All estimated coefficients must be statistically significant at 5%. MAE (mean absolute error), MAPE (mean absolute percentage error), and MSE (mean squared error) were used to rank the remaining models.

Case study 1: Unsecured retail portfolio of Kenya

The best model for each modelling technique for the unsecured retail portfolio of Kenya is shown in
Table 1(based on the best average rank of MAE, MAPE and MSE).

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	0.010390	0.010363	0.010369	0.009148	**0.006117**	0.008333
MAPE	0.247607	0.246031	0.246151	0.221073	**0.147135**	0.195311
MSE	0.000152	0.000152	0.000152	0.000132	**0.000062**	0.000093
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
Ave rank	5	4	6	3	**1**	2

Along with the variables used in each model, the MAE, MAPE, and MSE are provided. Keep in mind that YOY denotes a change from year to year, QOQ denotes a change from quarter to quarter, and 3 and 6 stand for the three and sixmonth lag, respectively.The rank of MAE, MAPE, and MSE determines the average rank.Interestingly, the GPD is present in every model.The random fore st (RF) model with combination 40, which incorporates the prime rate (PR) and the GPD's annual ch ange (YOY_GPD) as variables, is the best ranking model.The average rank of the GLM using the log it link function utilizing combination 22, which is solely dependent on the YOY_GPD, is 4.After mo re research, the best six models for each technique (unsecured Kenya retail portfolio) are 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.

When the predicted values for the macroeconomic variables were entered into the models, the predicted CRI for Kenya is displayed in Figure 1. Forecasts of an upside, base, and negative scenario form the basis of the projected CRI. The internal economics team of the bank provided these predicted values for the macroeconomic factors.

Keep in mind that the values shown in Figure 1 are mostly based on forecasts, which are revised often. The predicted CRI should therefore be based on the most recent projections. It should be noted that prior to July 2022, the baseline, upside, and downside projections are exactly the same because these values are historically observed; only starting in July 2022 do the baseline, upward, and downside forecasts deviate from the predicted values.

It appears that the random forest model (see Figure 1b) more closely captures the peaks and valleys of the historically observed default rate than the GLM model (Figure 1a).

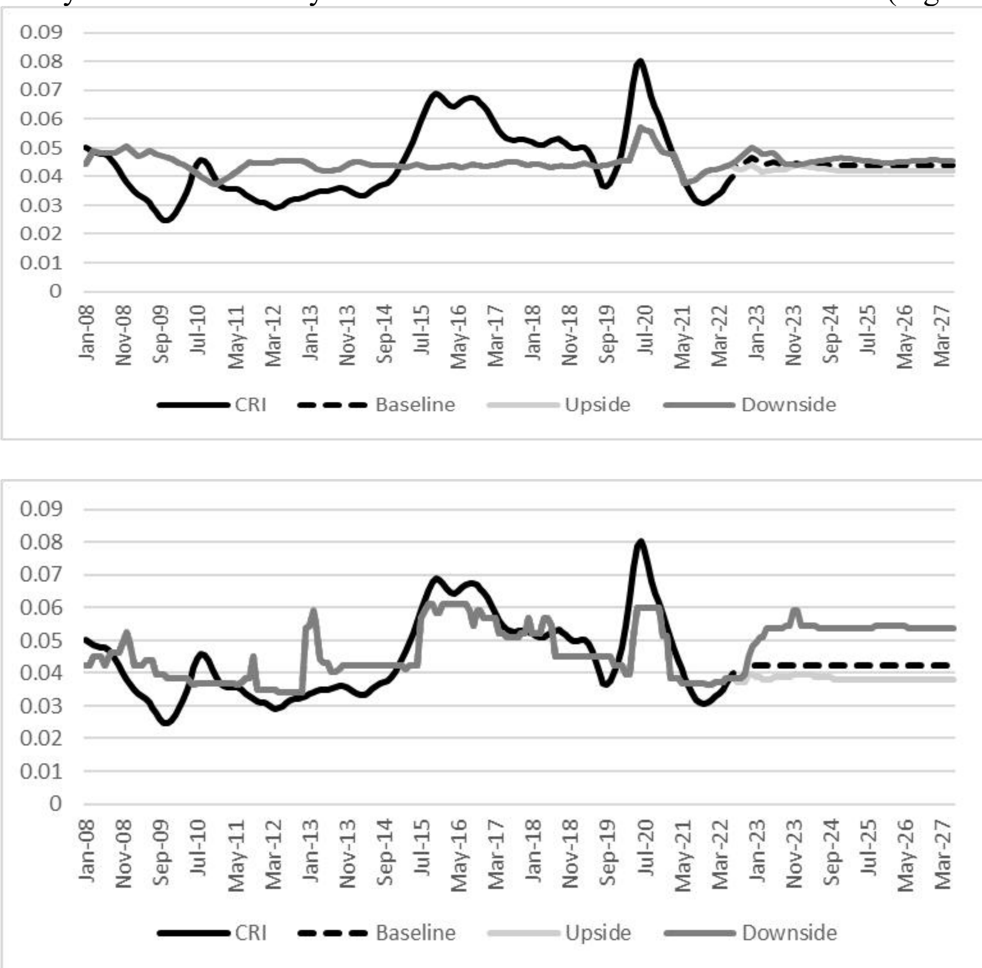


Figure 1: CRI of the unsecured retail portfolio of Kenya: (a) GLM (logit) model 22, (b) RF model 40

Both models are consequently validated since all variables included make commercial sense and a logical explanation for the variables is enforced (by evaluating only models with the estimated sign agreeing with the theoretical relationship). The anticipated scenarios (upside, downside, and base scenario) need to be rational, and the generated scalars are within a suitable range.

Case study 2: Unsecured retail portfolio of Mauritius

Table 2 displays the top models for each modeling technique for Mauritius's unsecured retail portfolio. The average ranks of these models across MAE, MAPE, and MSE measures were used to choose them.

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	0.0036740	0.0036625	0.0035842	**0.0032883**	0.0057172	0.0049885
MPE	0.1377796	0.1310375	0.1274247	**0.1206683**	0.2316228	0.2146604
MSE	0.0000263	0.0000401	0.0000379	**0.0000204**	0.0000534	0.0000430
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					
Ave rank	**4**	**3**	**2**	**1**	**6**	**5**

Once more, the variables included in each model are listed along with the MAE, MAPE, and MSE. Interestingly, GDP is included in every model, and the prime rate (PR) is included in the majority of models.

The feedforward neural network (FNN) model with combination 60, which incorporates the interpolated prime rate lagged three months (I_PR_3) and the GDP lagged six months' year-over-year change (YOY_GDP_6) as variables, is the best-ranking model. The GLM with the probit link function employing combination 378, which is based on three variables—the I_PR, YOY_EXR_3, and YOY_GDP_6—is the second-best model.

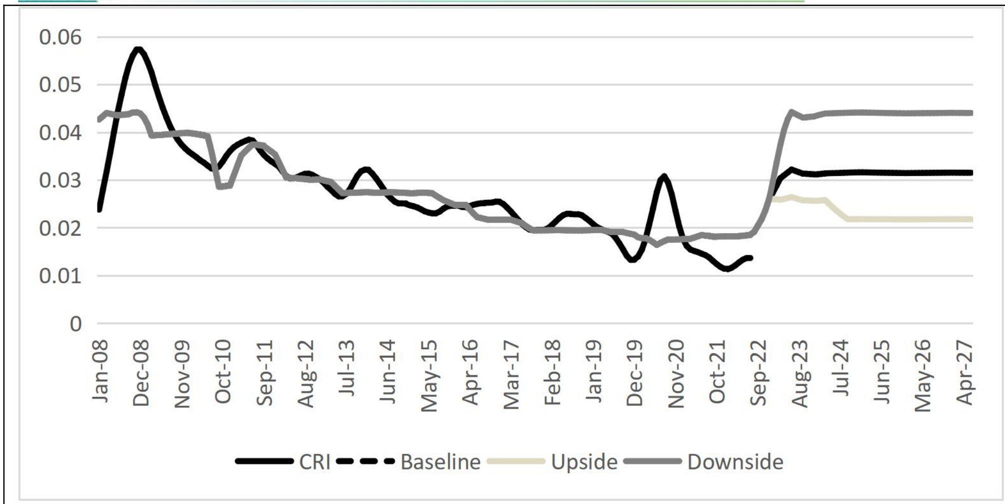
A closer look shows that Table 3 lists the top six models for each approach, with model combinations 60 and 378 appearing frequently.

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

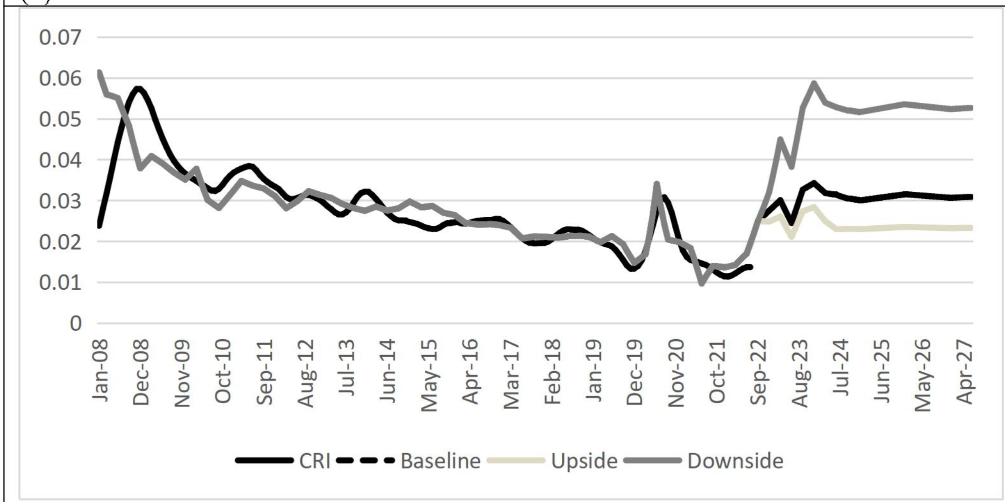
Rank	**Reg**	**GLML**	**GLMP**	**FNN**	**RF**	**GB**
1	1590	402	**378**	**60**	1313	318
2	402	42	402	1805	220	310
3	1554	**378**	42	1560	1306	1782
4	384	492	492	1752	1288	1895
5	372	1788	1788	425	1330	1559
6	1524	**60**	**60**	1554	1312	1913

When the predicted values for the macroeconomic variables were entered into the models using the FNN 60 and the GLMP 378, respectively, the predicted credit index for Mauritius is displayed in Figure3. Once more, projections of an upside, base, and downside scenario form the basis of the Projected credit index.Both the GLMP and the FNN models appear to do a good job of capturing the

Fluctuations in the historical observed default rate.



(a)



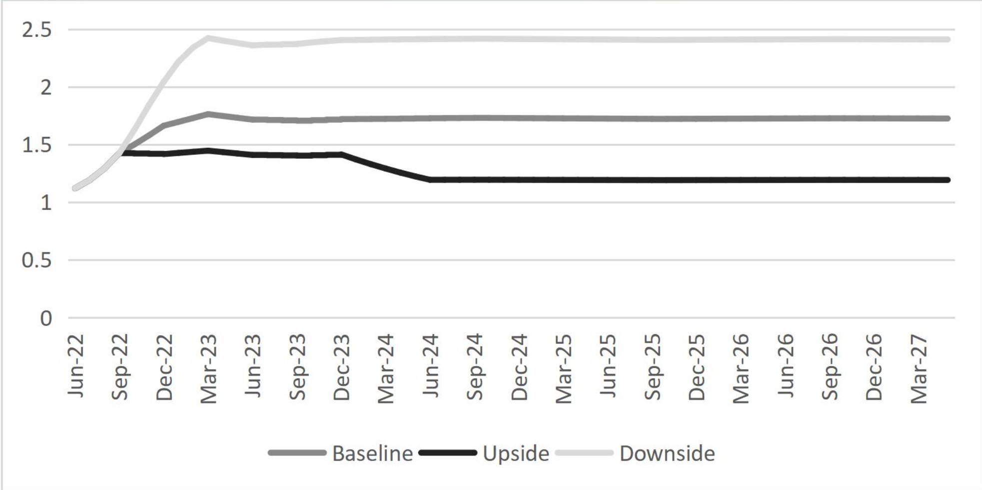
(b)

Figure 3: CRI of the unsecured retail portfolio of Mauritius: (a) FNN model 60, (b) GLM (Probit) model 378

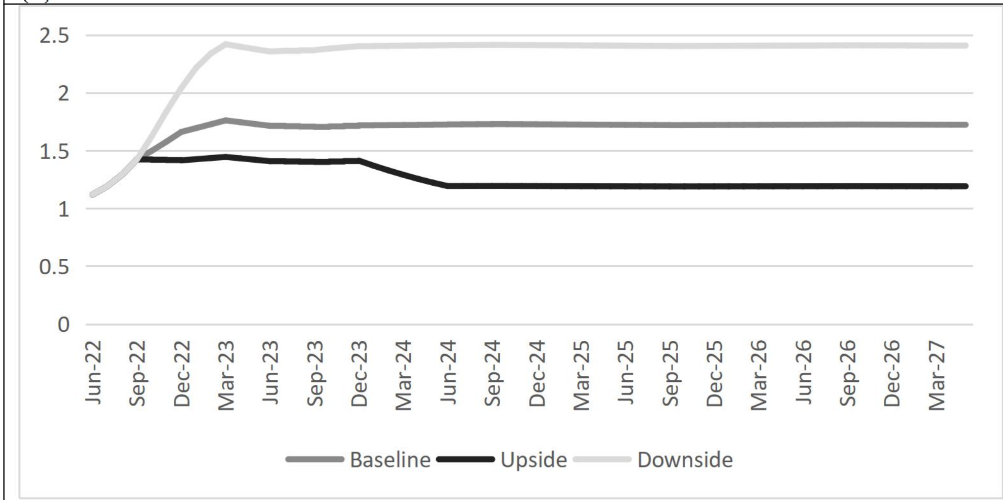
Figure 4 displays the generated scalars for the GLMP and FNN models. Remember that the FNN utilized combination 60, which is based on two variables: the year-over-year change of the GDP lagged six months (YOY_GDP_6) and the interpolated prime rate lagged three months (I_PR_3).

The GLM (using the probit link function), which is based on combination 378, utilized three variables: the prime rate, the year-over-year exchange rate lagged three months (YOY_EXR_3), and the year-over-year GDP lagged six months (YOY_GDP_6).

Similar to Kenya, the macroeconomic scalars for Mauritius make sense in both models. For the baseline, we anticipate a scalar of about 1, but in this case it is consistently above 1. For the upside scenario, we anticipate a scalar that is lower than the baseline (typically below 1, but in this instance it is consistently above 1), and for the downside scenario, we anticipate a scalar that is higher than the baseline scenario.



(a)



(b)

Figure 4: Macroeconomic scalar of the unsecured retail portfolio of Mauritius: (a) FNN model 60, (b) GLM (Probit) model 378

FINDINGS, CONCLUSION AND RECOMMENDATION

In this work, we suggested a way for creating a macroeconomic scalar that would modify the PD in the ECL model to account for information about the future. This approach is sound and practical. The approach is broken down into five steps: planning and research; data preparation; model development; macroeconomic scalar calculation; and model validation.

Our suggested methodology offers a dependable way to modify the PD in an ECL model for forward-looking data, successfully addressing the difficulties faced by developing nations with sparse and unstable macroeconomic data. It is easier to distinguish the ECL allowance based on past credit performance and future projections when a distinct scalar is used. The suggested scalar provides the required openness and explainability, which is essential given the substantial impact that IFRS 9 ECL estimates have on the income statement.

Two unsecured retail portfolios from Mauritius and Kenya served as examples of the methodology. The anticipated credit index for various scenarios may be described, and the process produced models that made financial sense. It was suggested that the company identify particular bounds for macroeconomic forecasts to ensure suitable values for resulting scalars.

We advise enhancing models by incorporating a larger range of macroeconomic and macroprudential factors with trustworthy forecasts. Stronger models are produced when macro variables are properly transformed (QOQ, YOY, lags). We recommend using at least 60 time periods. Lastly, rather than using default rates unique to individual banks, we suggest using nationwide default rates as the credit index.

REFERENCES

Bellini, T., 2019. *IFRS 9 and CECL Credit Risk Modelling and Validation: A Practical Guide with Examples Worked in R and SAS.* 1st ed. London: Elsevier.

Bellotti, T. & Crook, J., 2013. Forecasting and stress testing credit card default using dynamic models. *International Journal of Forecasting,* Volume 29, pp. 563-574.

Black, B., 2016. *Probability-Weighted Outcomes Under A Macroeconomic Approach.* [Online] Available at: https://www.moodysanalytics.com/webinars-on-demand/2016/probablility-weighted-outcomes-macroeconomic-approach

Breed, D. G. et al., 2021. Development of an Impairment Point in Time Probability of Default Model for Revolving Retail Credit Products: South African Case Study. *Risks,* 9(208).

Breed, D. 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).

Cleveland, W. S., 1979. Robust Locally Weighted Regression and Smoothing Scatterplots. *Journal of the American Statistical Association,* 74(368), pp. 829-836.

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), pp. 283-305.

Durović, A., 2019. Macroeconomic Approach to Point in Time Probability of Default Modeling – IFRS 9 Challenges. *Journal of Central Banking Theory and Practice,* Volume 1, pp. 209-223.

Engelman, B. & Rauhmeier, R., 2011. *The Basel II Risk Parameters: Estimation, Validation, and Stress Testing (second edition).* 2nd ed. Berlin: Springer.

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

Hawkes, H., 2021. *GDP alternatives: 8 ways of measuring economic health.* [Online] Available at: https://intheblack.cpaaustralia.com.au/economy/8-ways-of-measuring-economic-health

IFRS, 2014. *IRFS9 Financial Instruments: Project Summary.* [Online] Available at: 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[Accessed 31 January 2016].

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), pp. 65-112.

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

Kutner, M. H., Nachtsheim, C. J., Neter, J. & Li, W., 2005. *Applied Linear Statistical Models.* 5th ed. New York: McGraw-Hill/Irwin.

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

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

SAS Institute Inc, 2020. *Machine Learning Using SAS® Viya® Course Notes (LWCPML35/CPML35).* NC: SAS.

SAS Institute, 2010. *Predictive Modelling Using Logistic Regression.* NC: SAS Institute Inc.

Schutte, W. D. et al., 2020. A proposed benchmark model using a modularised approach to calculate IFRS9 expected credit loss. Accepted in Cogent Economics & Finance. *Cogent Economics & Finance.*