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Macroeconomic Scalar Adjustment for Probability of Default in Expected Credit Loss Models

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ABSTRACT
The expected credit loss framework established under International Financial Reporting Standards Foundation 9 is structured around three core components: probability of default, loss given default and exposure at default. Among these three elements, the probability of default component most frequently lacks a coherent mechanism for embedding macroeconomic dynamics into the estimation process, a deficiency that carries particular weight in Latin American developing economies where economic volatility is a persistent structural feature. This article applies a novel five-step macroeconomic scalar methodology for dynamically adjusting the probability of default through the systematic integration of forward-looking macroeconomic information, with empirical application to unsecured retail portfolios in Brazil and Mexico. Unsecured retail lending portfolio datasets sourced from regional banking institutions in Brazil and Mexico provide the empirical basis through which the proposed methodology is validated across two economically distinct Latin American environments. The methodology advances through five sequential stages: research and planning; data preparation; model development; scalar calculation; and model validation. Comparative modelling draws on multiple regression, generalised linear models with logit and probit specifications, and machine learning techniques encompassing feedforward neural networks, random forests and gradient boosting. Model performance is evaluated through mean absolute error, mean absolute percentage error and mean squared error. The macroeconomic scalar produced consistent and economically coherent probability of default adjustments within the expected credit loss model for both Brazil and Mexico. Each modelling technique contributed distinct analytical insights, and the scalar demonstrated reliable capacity to improve expected credit loss forecasts across environments characterised by interest rate volatility, persistent inflation and exchange rate depreciation. Embedding a macroeconomic scalar within the expected credit loss framework constitutes a disciplined and auditable method for incorporating forward-looking information while preserving the model interpretability that bank boards, auditors and regulators require in Latin American credit markets. This article delivers a replicable approach for macroeconomic probability of default adjustment in expected credit loss models calibrated specifically to Latin American economic conditions. Structured implementation guidelines are provided for practitioners operating under International Financial Reporting Standards Foundation 9 in Brazil and Mexico.

Keywords: Probability of Default, Macroeconomic PD Adjustment, IFRS 9, Expected Credit Loss, ECL, Machine Learning in Credit Risk.

INTRODUCTION
Credit losses sustained during the global financial crisis of 2007 to 2009 exposed fundamental weaknesses in the incurred loss recognition model that had underpinned international accounting standards for decades. In response, the International Accounting Standards Board and the Financial Accounting Standards Board undertook coordinated reform efforts directed at producing a more forward-oriented and transparent approach to credit loss measurement. These reform efforts culminated in the publication of International Financial Reporting Standards Foundation 9 in 2014 (IFRS 2014), which replaced the incurred loss model with an expected credit loss framework. Under this framework, credit loss estimation is decomposed into three constituent components, namely the probability of default, loss given default and exposure at default, and their product yields the expected credit loss as represented in the expression ECL = PD x LGD x EAD (Breed et al. 2021).

A defining feature of the International Financial Reporting Standards Foundation 9 standard is its requirement that probability of default models reflect not only prevailing conditions but also projected macroeconomic states, thereby producing estimates that are oriented toward likely future outcomes rather than anchored in past experience (IFRS 2014). This requirement creates immediate practical complexity in environments where economic forecasting is inherently uncertain, and the COVID-19 pandemic demonstrated in particularly stark terms how difficult it is to embed unforeseen macroeconomic disruptions into expected credit loss calculations (IFRS 2020). In Brazil, the pandemic produced a gross domestic product contraction of approximately 4.1% in 2020, while Mexico recorded a contraction of approximately 8.5% in the same year, representing one of the most severe single-year output collapses in both countries since the early 1980s.

Constructing forward-looking probability of default adjustments within Latin American developing economy contexts introduces several compounding difficulties. The first difficulty concerns data availability and consistency: although Brazil and Mexico possess considerably more developed statistical institutions than many lower-income developing economies, the reliability of granular credit data at frequencies appropriate for monthly model estimation remains uneven, and official macroeconomic forecast horizons frequently fall short of the lifetime estimation requirements embedded in International Financial Reporting Standards Foundation 9. The second difficulty concerns economic volatility. Brazil's benchmark SELIC rate moved from 2.00% in mid-2020 to 13.75% by late 2022 before gradually easing, while the Banco de Mexico policy rate rose from 4.00% in early 2021 to 11.25% by May 2023, representing among the most aggressive monetary tightening cycles in each country's modern history ((Breed et al., 2021)(Ghosh, 2024). Inflation, measured by the Brazilian IPCA index, peaked at approximately 12.1% in April 2022, while Mexico's INPC reached approximately 8.7% in August 2022. These dynamics impose sharp and rapid pressure on consumer debt-servicing capacity in ways that aggregate portfolio models may not capture contemporaneously. The third difficulty concerns the structural vulnerability of unsecured retail borrowers, who lack the collateral buffers and savings reserves that might otherwise absorb income shocks before default occurs. Taken together, these conditions create a strong case for adaptive modelling frameworks capable of accommodating macroeconomic uncertainty, data sparsity and non-linear default dynamics.

The scalar approach considered in this article provides a practical mechanism for embedding current and forecasted macroeconomic conditions into the probability of default component of the expected credit loss calculation, consistent with the methodology presented in (Moscato et al., 2021). International Financial Reporting Standards Foundation 9 prescribes no specific adjustment method, and the Global Public Policy Committee (GPPC 2016) acknowledges that appropriate techniques will vary across portfolios and institutions. When a financial institution selects the scalar approach, the expected credit loss can be restated with macroeconomic adjustments applied to each component as shown in Equation 1:

$$\mathrm{ECL} = \mathrm{PD} \times \mathrm{s}_{\mathrm{PD}} \times \mathrm{LGD} \times \mathrm{s}_{\mathrm{LGD}} \times \mathrm{EAD} \times \mathrm{s}_{\mathrm{EAD}} \tag{1}$$

Where s_PD, s_LGD and s_EAD denote the macroeconomic scalars corresponding to the probability of default, loss given default and exposure at default respectively. This article directs attention exclusively toward the probability of default scalar (s_PD). The estimation of this scalar follows directly from the ratio shown in Equation 2:

$$\hat{\mathrm{s}}_{\mathrm{PD}} = \frac{\text{Forecasted credit index}}{\text{Base credit index}} \tag{2}$$

Where the Base credit index represents the average observed credit index across a defined historical window and the Forecasted credit index represents the model-generated projection of that index under specified macroeconomic scenarios. The credit index serves as an empirical bridge between historical macroeconomic conditions and the observed default behaviour of a lending portfolio (Mahieux et al., 2023). Segment-level scalars are preferred over portfolio-wide scalars because they accommodate shifts in the composition of the portfolio over time, thereby reducing the volatility of expected credit loss allowances as segment proportions evolve (Engelmann, 2021).

A distinct practical advantage of the scalar approach lies in its separation of the forward-looking macroeconomic adjustment from the base probability of default estimate. This separation aids model governance by allowing board members, auditors and regulators to interrogate the macroeconomic component independently, which is a material consideration given that expected credit loss allowances represent substantial line items in the income statements of retail lending institutions(Chang et al., 2024; Guo et al., 2024; Moscatelli et al., 2020). The existing literature offers limited prescriptive guidance on International

Financial Reporting Standards Foundation 9-specific probability of default adjustment techniques, particularly for Latin American markets, and practitioners have been required to adapt methodologies developed in other contexts. The proposed methodology addresses this gap through a structured, stepwise framework that is explicitly designed to accommodate the data constraints and macroeconomic volatility characteristic of developing economies in the region.

The article proceeds as follows. The Introduction contains the literature summary. The Methods section presents the five-step proposed methodology. The Results section demonstrates the application of the methodology through case studies conducted on unsecured retail portfolios from Brazil and Mexico. The Conclusion summarises the findings and sets out directions for future research.

METHODS

The proposed methodology is presented stepwise in this section across five structured stages. Step 1 addresses the research and planning phase. Step 2 covers data preparation. Step 3 describes model development. Step 4 derives the macroeconomic scalar. Step 5 sets out the validation requirements. The assumptions underpinning the methodology are stated explicitly at the close of this section.

Step 1: Research and Planning

The research and planning phase establishes the conceptual and procedural foundations for all subsequent steps and must demonstrate conformity with the requirements of International Financial Reporting Standards Foundation 9 at each stage. A central objective of this phase is the articulation of theoretically grounded expectations regarding the direction and magnitude of macroeconomic variable effects on portfolio default rates (Costa e Silva et al., 2020; Jacobs Jr., 2020). Gross domestic product growth, for example, is expected to reduce default rates because economic expansion improves household income and employment stability, and the sign on any gross domestic product coefficient should therefore be negative. Conversely, elevated central bank policy rates raise debt-servicing costs for unsecured borrowers, and inflation erodes real purchasing power, both of which are expected to exert positive pressure on default rates. Exchange rate depreciation against the US Dollar similarly amplifies imported inflation and reduces the real value of consumer incomes, supporting a positive relationship with default rates (Li et al., 2024).

For the Latin American portfolios examined in this article, the planning phase required additional consideration of country-specific structural features. In Brazil, the role of payroll-linked credit in shaping default behaviour, the cyclical behaviour of the SELIC rate and the influence of commodity export cycles on aggregate income all warrant research attention (Parnes, 2021; Schutte et al., 2020; Stander et al., 2024). In Mexico, the trade relationship with the United States, the role of remittance inflows as a consumer income stabiliser and the structure of the Tasa de Interbancaria de Equilibrio rate transmission mechanism represents relevant contextual dimensions that should inform variable selection and the interpretation of model results.

The selection of the modelling technique is also addressed in this phase and should reflect the technical capabilities available within the institution, the software infrastructure in place and the governance requirements attached to model transparency (Breed et al., 2021; Hegde & Kozlowski, 2021; Mita & Rahmah, 2023). Linear regression, vector autoregressive models with exogenous inputs and error correction models each represent viable technical choices, and the assumptions associated with each must be examined carefully before selection is finalised.

Step 2: Data Preparation

Data preparation comprises three sequential sub-steps: construction of the credit index, selection of candidate macroeconomic variables and reduction of the variable set where necessary.

Determine the Credit Index for the Model

The credit index establishes the empirical link between historical macroeconomic conditions and the default behaviour of the lending portfolio, following the construction approach described in (López-Espinosa & Penalva, 2023; Ozili, 2022; Pastiranová & Witzany, 2022). The index should reflect the characteristics of the specific portfolio under analysis as closely as possible and may be sourced from country-wide sector default rates, non-performing loan ratios or portfolio loss rates depending on what data are accessible (Engelmann 2021). Where the credit index is derived from observed account-level default indicators, its value at time t is given by Equation 3:

$$Y_t = \frac{\sum_{i=1}^{N_t} D_i}{N_t} \tag{3}$$

Where $D\_i \in \{0,1\}$ is the default indicator for account i at time t and N_t is the total count of accounts in the portfolio at time t. A balance-weighted alternative formulation may be preferred when account size heterogeneity is material, and in that case the credit index at time t takes the form of Equation 4:

$$Y_t = \frac{\sum_{j \in D_{n,t}} B_{t,j}}{\sum_{j \in J_t} B_{t,j}} \tag{4}$$

Where J_t is the full set of accounts at cohort t, $D\_{n,t}$ denotes the subset of accounts at cohort t that default within the subsequent n months, for example n = 12, and $B\_{t,j}$ is the outstanding balance of account j at cohort t. Where country-wide non-performing loan data are the most accessible proxy, the credit index at time t is defined as in Equation 5:

$$Y\_t = \frac{NPL_t}{TL_t} \tag{5}$$

Where NPL_t is the aggregate count of non-performing loans in the country at time t and TL_t is the total count of outstanding loans at time t.

When institution-specific default rates are employed in place of country-wide rates, adjustments must be made to remove the influence of business decisions that distort the observed rate relative to the true macroeconomic signal. Payment holiday arrangements are a notable example of a business decision that suppressed observed default rates during the COVID-19 period in both Brazil and Mexico without reflecting any genuine improvement in borrower credit quality (Ariza-Garzon et al., 2020; Bussmann et al., 2021; Engelmann & Nguyen, 2023). Seasonal patterns in default rates should also be investigated to determine whether they are attributable to borrower behaviour or to macroeconomic linkages. Periods of extreme disruption, such as the COVID-19 pandemic, may warrant exclusion from the modelling sample to avoid distorting the estimated macroeconomic relationships (Groff & Mörec, 2021; Hewa et al., 2020). Coverage of a complete economic cycle is recommended to ensure that the model captures default behaviour across both contractionary and expansionary phases (Gubareva, 2021). A smoothing technique, such as locally estimated scatterplot smoothing regression (Du et al., 2023), may be applied where raw default rate volatility obscures the underlying macroeconomic relationship. The adjusted credit index incorporating seasonality corrections, business decision exclusions and extreme period omissions is denoted Y_t', and the smoothed version of this series is denoted Y_t''.

Within the International Financial Reporting Standards Foundation 9 context, the forward-looking horizon of the credit index varies between 12 months and the remaining lifetime of the exposure depending on the stage classification of the account. Stage 1 is assigned when credit risk has not increased significantly since origination, Stage 2 is assigned when a significant credit risk increase has occurred, and Stage 3 is assigned upon default (Ghosh, 2024; Salazar et al., 2023). A 12-month expected credit loss is recognised for Stage 1 accounts, while lifetime expected losses are recognised for Stage 2 and Stage 3 accounts. Development of the macroeconomic scalar using Stage 1 accounts is recommended because macroeconomic conditions operate most directly on the default probability of accounts that are currently performing, rather than on accounts already in arrears.

Variable Selection for the Model

Candidate macroeconomic variables should be evaluated against several criteria including data reliability, consistency of publication frequency, and the availability of credible scenario-based forecasts over the projection horizon required under International Financial Reporting Standards Foundation 9. Forecasts are typically structured around base, upside and downside scenarios and may be sourced from established external providers or from the institution's internal economics function (PWC 2017). Once the candidate variable set has been identified, exploratory data analysis should be conducted for each series, including time series plots, missing value identification and outlier examination. Highly volatile series may introduce forecast instability and should be treated with caution (Habachi & El Haddad, 2021; Hung et al., 2021). Macroeconomic variables published at quarterly frequency must be converted to monthly frequency before use; piecewise constant interpolation, linear interpolation and spline interpolation are among the available conversion methods (Fatouh et al., 2023; Gómez-Ortega et al., 2022; Xiao et al., 2021).

Stationarity must be confirmed for all input series before modelling proceeds, as time series statistical methods require constant mean properties (Sugiarto & Suroso, 2020). The Augmented Dickey-Fuller test provides a standard diagnostic for this purpose, and non-stationary series should be transformed using year-on-year changes, quarter-on-quarter changes or first differences as appropriate. Lagged values of all macroeconomic variables should also be included as candidate predictors, with lag lengths of 3, 6, 9 and 12 months representing a practical starting set subject to adjustment on the basis of economic reasoning and business requirements. The full set of explanatory variables at time t, including lags, is denoted X_{t,l} = {X_{1,t,l}, X_{2,t,l}, ..., X_{p,t,l}} where l indicates the lag length.

Variable Reduction

Large candidate variable sets introduce the risk of multicollinearity, which inflates coefficient variance and degrades the interpretability of estimated relationships. Variable clustering algorithms provide an effective tool for identifying and removing redundant variables by grouping those that carry similar information content into clusters and retaining a representative from each group (SAS Institute Inc 2010). This step was not required for the Brazil or Mexico datasets given the limited number of variables ultimately available for modelling.

Step 3: Development of the Model

A model linking the macroeconomic variable set to the smoothed, adjusted credit index must be estimated across all admissible variable combinations. The general functional form is stated in Equation 6:

$$Y_t'' = f(X_{t,l}) + \varepsilon_t \tag{6}$$

where X_{t,l} = {X_{1,t,l}, X_{2,t,l}, ..., X_{p,t,l}} is the vector of macroeconomic predictors including their lags and epsilon_t is the error term. Linear regression, for example, imposes assumptions of linearity between predictors and response, homoscedasticity of residuals, independence of observations and normality of the response conditional on the predictors (Sun et al., 2023). Violations of any of these assumptions must be addressed before results can be relied upon.

Selection among candidate models should be restricted to those that simultaneously satisfy three conditions. First, the estimated direction of each macroeconomic variable effect must align with theoretical expectations: a negative sign is required for gross domestic product coefficients and positive signs are required for policy rate, inflation and exchange rate coefficients. Second, all estimated coefficients must achieve statistical significance at the chosen threshold, such as 5%. Third, variance inflation factors must remain below 10 to confirm the absence of multicollinearity (Sigrist & Leuenberger, 2023; Song et al., 2023). When machine learning techniques such as feedforward neural networks, gradient boosting or random forests are used, sign verification through standard coefficient examination is not possible, and partial dependence plots should be used instead. A positive rank correlation between the response and the partial dependence curve for a given predictor is interpreted as evidence of a positive relationship, while a negative rank correlation indicates a negative relationship (SAS Institute Inc 2020). Surviving models are then ranked by goodness-of-fit metrics encompassing adjusted R-squared, mean squared error, mean absolute percentage error, mean absolute error, and the Akaike and Schwarz Bayesian information criteria, and the preferred model is identified from this ranking subject to any additional business considerations (Onali et al., 2024).

Step 4: Calculate the Macroeconomic Scalar

For a given macroeconomic scenario g, the probability of default scalar at time t is defined in Equation 7:

$$\hat{s}\_(PD, t)\hat{}g = \frac{(Y_t'')^g}{\overline{Y}_t} \tag{7}$$

where Y-bar_t is the base credit index representing the average smoothed credit index over the preceding m months, as defined in Equation 8:

$$\overline{Y}_t = \frac{\sum_{i=t-m}^{t} Y_i''}{m} \tag{8}$$

Where m represents the number of months selected to capture a typical business cycle and is commonly set to 12 months. The forecasted credit index Y_t''^g for scenario g at time t is obtained by substituting scenario-specific macroeconomic variable forecasts into the model estimated in Step 3, as stated in Equation 9:

$$(Y_t'')^g = f\left(X_{t,l}^g\right) + \varepsilon_t \quad (9)$$

Where X_{t, l}^g = {X_{1, t, l}^g, X_{2, t, l}^g, … , X_{p, t, l}^g} is the vector of scenario-specific forecasted macroeconomic variables including their lags and epsilon_t is the residual noise term. The forecasted credit index produced from this calculation covers a horizon of 12 to 24 months. Scenario-based macroeconomic forecasts are typically supplied on a quarterly basis by external forecast providers or by the institution's internal economics team, and generally extend across a five-year horizon (PWC 2017). Three scenarios encompassing an optimistic upside, a central base and a pessimistic downside case are standard, though additional scenarios may be incorporated where conditions warrant. Externally supplied forecasts for variables such as the unemployment rate typically incorporate mean reversion dynamics, whereby the forecasted path gradually returns toward the long-run historical average (Alonso Robisco & Carbó Martínez, 2022; Martinelli et al., 2020; Saavedra et al., 2024). Gross domestic product growth forecasts similarly tend to converge toward estimated long-run potential growth over a horizon of two to five years (PWC 2017). The base default rate in this framework is set as the average observed default rate over the most recent 12 to 24 months. Segment-level scalars are recommended because they improve risk differentiation by responding to changes in the composition of portfolio segments over time (Black 2016).

Step 5: Validation

Rigorous validation of both the estimated models and the resulting scalars is an essential element of model governance (Shi et al., 2022). Each variable retained in the final model must carry a clear and theoretically defensible economic rationale. The model should represent multiple dimensions of the macroeconomic environment without incorporating so many variables that multicollinearity becomes a concern or that interpretability is compromised. Variables that are highly volatile over the historical estimation period should be examined carefully because they are likely to produce unstable and uncertain forecasts. Forecast scenario plausibility must also be assessed directly: upside macroeconomic inputs should produce a forecasted credit index that falls below the base scenario level, while downside inputs should produce an index that exceeds the base scenario level. Scenario paths should converge toward one another over the long run as mean reversion dynamics take effect, approaching a probability of default level consistent with long-run expectations for the portfolio segment in question. Scalar values should fall within bounds that are pre-established by the business based on plausible ranges of input variable movements. Where macroeconomic inputs reach the outer bounds of plausible ranges, the model may break down and a management overlay mechanism should be triggered. The Prudential Regulation Authority's model risk management principles for banks provide a useful reference framework for structuring these governance arrangements (Dastile et al., 2020; Jin & Wu, 2023; Saavedra et al., 2024).

Assumptions

The proposed methodology rests on a set of explicit assumptions. The modelling technique selected must satisfy its own underlying technical assumptions, including those applicable to linear regression specifications. The credit index must be an appropriate representation of the portfolio's default behaviour under varying macroeconomic conditions, ideally sourced from country-wide sector data rather than institution-specific rates that may carry business decision distortions. Historical macroeconomic data of sufficient length and quality must be available to support robust model calibration, and credible scenario-based forecasts of the selected macroeconomic variables must be accessible over the required projection horizon (Chen et al., 2022; López-Espinosa et al., 2021). Finally, the methodology assumes access to practitioners who possess sufficient quantitative expertise to implement both traditional statistical and machine learning modelling approaches and to apply them with appropriate governance controls.

Ethical Considerations

Ethical clearance to conduct this study was obtained from the relevant institutional review body. All default rate data have been normalised to protect the confidentiality of the banking institutions that provided portfolio data. No personally identifiable information was used at any stage of the analysis.

RESULTS

Two datasets are employed as case studies to demonstrate the practical implementation of the proposed methodology. An unsecured retail portfolio from a regional banking institution in Brazil and a corresponding portfolio from Mexico were subjected to analysis. Both datasets span the period from January

2010 to December 2024, encompassing data available at the time of analysis. The datasets were made available under strict confidentiality agreements, and all default rates have been normalised to protect the actual levels of default at each institution.

The credit index for both Brazil and Mexico was constructed from the observed bank-specific default rate, adjusted for the effects of seasonality and volatility. Business decisions that may have distorted the relationship between observed default rates and macroeconomic conditions were excluded from the index. Seasonality was examined by computing the average default rate for each calendar month across the full sample and adjusting each monthly observation to remove systematic calendar-driven patterns. This adjustment did not materially alter the raw credit index for either country but remained an integral component of the methodology. The COVID-19 pandemic period was identified as a candidate for exclusion on grounds that the government-mandated credit moratoria in both Brazil and Mexico suppressed observed default rates in ways that obscured the true macroeconomic signal. Smoothing was subsequently applied to the adjusted series using locally estimated scatterplot smoothing regression (Cleveland 1979).

Although both Brazil and Mexico maintain a broad range of published macroeconomic statistics, data availability and the requirement for credible long-horizon scenario forecasts constrained the final variable set to four indicators in each country. Gross domestic product measures the total productive output of the economy and is expected to carry a negative relationship with default rates: periods of output expansion are associated with labour market strength and household income growth, which reduce the likelihood of consumer loan default. The central bank policy rate, denoted SELIC in Brazil and TIIE in Mexico, represents the primary instrument of monetary policy and its elevation increases the cost of variable-rate borrowing and refinancing, creating upward pressure on default rates. Inflation, measured by the IPCA index in Brazil and the INPC index in Mexico, erodes real household purchasing power and raises the real cost of fixed debt obligations, supporting a positive relationship with default rates. The foreign exchange rate, expressed as the domestic currency value per US Dollar, serves as a summary measure of external competitiveness and purchasing power: a weaker domestic currency amplifies imported inflation and signals broader economic stress, both of which are expected to increase default rates. The theoretical directional relationships between each macroeconomic variable and the observed default rate are as follows:

- Gross domestic product: Negative
- Policy rate (SELIC for Brazil; TIIE for Mexico): Positive
- Inflation (IPCA for Brazil; INPC for Mexico): Positive
- Exchange rate (BRL per USD for Brazil; MXN per USD for Mexico): Positive

Quarterly data were converted to monthly frequency using a three-month rolling average. Exploratory data analysis confirmed the absence of missing values in either dataset. Outlier observations were examined and assessed for retention. Stationarity was tested using the Augmented Dickey-Fuller procedure. For Brazil, gross domestic product, IPCA and the BRL exchange rate were found to be non-stationary in levels. For Mexico, gross domestic product, INPC and the MXN exchange rate were non-stationary. Year-on-year and quarter-on-quarter transformations were applied to these series to achieve stationarity, which was confirmed by subsequent Augmented Dickey-Fuller test results. Lag structures of three and six months were adopted for illustrative purposes, with the acknowledgement that production implementations should determine lag lengths through a combination of statistical testing and business reasoning. Variable reduction was not required for either dataset given the limited number of candidate predictors.

The modelling techniques applied were: multiple regression (Reg), generalised linear model with logit link (GLML), generalised linear model with probit link (GLMP), feedforward neural network (FNN), random forest (RF) and gradient boosting (GB). A total of 3429 variable combinations were evaluated for each technique, considering four macroeconomic variables across lags of zero, three and six months. Combinations were constrained so that a variable and its lagged value could not appear simultaneously within the same specification. From the full set of fitted models, those retained for further consideration were required to satisfy the sign alignment criterion and, for the parametric techniques of regression, GLML and GLMP, the 5% significance threshold on all estimated coefficients. Surviving models were ranked by their average performance across the mean absolute error, mean absolute percentage error and mean squared error metrics.

Case Study 1: Unsecured Retail Portfolio of Brazil

Table 1 presents the best-performing model for each estimation technique applied to the unsecured retail portfolio of Brazil, selected on the basis of the best average rank across mean absolute error, mean absolute percentage error and mean squared error. All estimated coefficients for the Reg, GLML and GLMP specifications are significant at the 5% level and the variables retained in each of these models carry signs consistent with economic expectations. Accordingly, Table 1 presents performance metrics rather than individual coefficient estimates. YOY denotes a year-on-year change, QOQ denotes a quarter-on-quarter change, and the suffixes 3 and 6 denote three-month and six-month lags respectively.

Gross domestic product appears as a predictor in every best-performing model, confirming its central role in explaining the cyclical dynamics of consumer default in Brazil. The top-ranked model overall is the random forest specification using combination 40, which incorporates the year-on-year change in gross domestic product and the level of the SELIC rate as its two predictors. The generalised linear model with logit link, using combination 22, which relies solely on the year-on-year change in gross domestic product, achieves an average rank of four. Examination of the top six models per technique for the Brazil unsecured retail portfolio reveals the following:

- Reg: 486; 152; 318; 622; 502 and 40.
- GLML: 22; 292; 40; 400; 262 and 318.
- GLMP: 22; 292; 40; 400; 262 and 318.
- FNN: 1842; 2209; 671; 22; 847 and 3.
- RF: 40; 340; 370; 394; 1612 and 341.
- GB: 1612; 1842; 1516; 40; 384 and 1597.

Combinations 22 and 40 appear with notable regularity across techniques. The forecasted credit index for Brazil is shown in Figure 1, with macroeconomic scenario inputs from the bank's internal economics team calibrated to Banco Central do Brasil projections. Prior to January 2025, the baseline, upside and downside forecasts coincide with the historically observed values. From January 2025 onward, the three scenario paths diverge according to the projected macroeconomic conditions. The generalised linear model specification, shown in Figure 1(a), tracks the broad trajectory of the historical credit index but does not capture high-frequency fluctuations as closely as the random forest specification shown in Figure 1(b).

Table 1**.** Top-performing model for each technique (Brazil unsecured retail portfolio).

Model	Reg	GLML	GLMP	FNN	RF	GB
Model number	486	22	22	1842	40	1612
MAE	0.012	0.011	0.011	0.010	0.007	0.009
MAPE	0.268	0.262	0.261	0.232	0.178	0.209
MSE	0.00019	0.00018	0.00017	0.00014	0.00008	0.00011
Variable 1	SELIC_6	YOY_GDP	YOY_GDP	SELIC_3	SELIC	SELIC
Variable 2	QOQ_BRL_3			YOY_IPCA_6	YOY_GDP	YOY_IPCA_6
Variable 3	YOY_GDP			QOQ_BRL_6		YOY_BRL
Variable 4				QOQ_GDP_6		YOY_GDP
Average rank	5	4	6	3	1	2

The resulting scalars for the generalised linear model and random forest specifications are shown in Figure 2. The generalised linear model with logit link uses combination 22, which is built on the year-on-year change in gross domestic product as its sole predictor. The random forest uses combination 40, which incorporates both the year-on-year gross domestic product change and the SELIC rate level. For both models, the scalar values exhibit the expected directional ordering (Hansen et al., 2024; Stander, 2023): the baseline scalar sits at approximately 1, the upside scalar falls below the baseline, and the downside scalar exceeds the baseline. The bounds within which each scalar remains reasonable should be determined by the business in consultation with the economics function. Both models satisfy the validation requirements: each included variable carries a theoretically supported directional effect, the estimated signs align with economic expectations and the scenario-based scalar paths are logically ordered and stable over the forecast horizon.

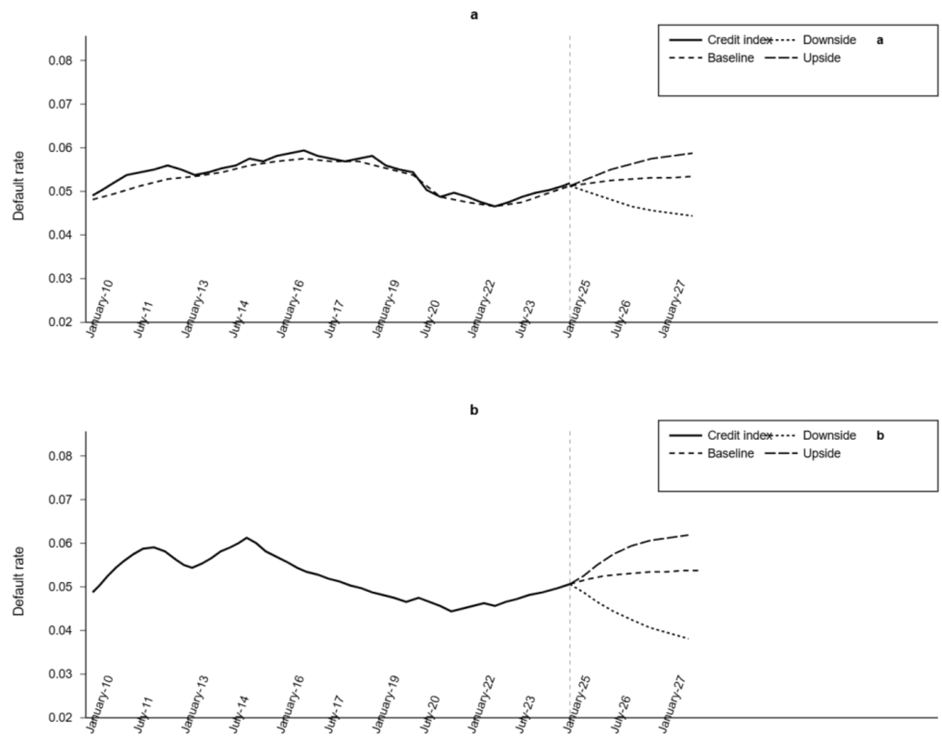

Figure 1. Credit index of the unsecured retail portfolio of Brazil: (a) GLM (logit) model 22, (b) RF model 40.

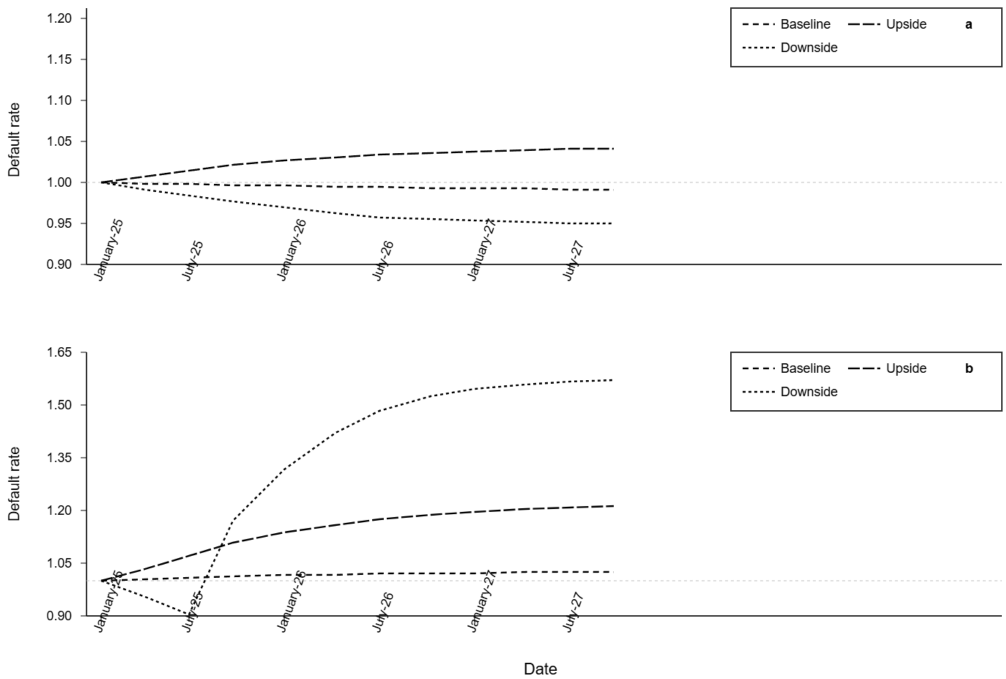

Figure 2. Macroeconomic scalar for unsecured retail portfolio of Brazil: (a) generalised linear model (logit) model 22, (b) random forest model 40.

Case Study 2: Unsecured Retail Portfolio of Mexico

Table 2 reports the best-performing model for each estimation technique applied to the unsecured retail portfolio of Mexico, with models again ranked by average performance across the three-error metrics. Gross domestic product and the TIIE rate feature as predictors in all or most of the best-performing specifications across techniques. The top-ranked model overall is the feedforward neural network using combination 60, which incorporates the interpolated TIIE rate lagged three months and the year-on-year change in gross domestic product lagged six months. The second-ranked model is the generalised linear model with probit link using combination 378, which incorporates the TIIE rate level, the year-on-year exchange rate lagged three months and the year-on-year gross domestic product lagged six months. Table 3 presents the top six models per technique and confirms that combinations 60 and 378 appear with regularity across multiple specifications.

Table 2. Top-Performing Model for Each Technique (Mexico 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
MAPE	0.142	0.135	0.131	0.118	0.241	0.219
MSE	0.00003	0.00004	0.00004	0.00002	0.00006	0.00005
Variable 1	I_TIIE	I_TIIE	I_TIIE	I_TIIE_3	YOY_INPC_3	I_TIIE
Variable 2	YOY_INPC_6	QOQ_MXN_6	YOY_MXN_3	YOY_GDP_6	YOY_MXN_3	YOY_INPC_3
Variable 3	QOQ_MXN_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

The forecasted credit index for Mexico is shown in Figure 3, produced from the feedforward neural network combination 60 and the generalised linear model with probit link combination 378 respectively. Both models track the ups and downs of the historically observed default rate with reasonable fidelity. The forecasted credit index diverges across upside, base and downside scenarios from January 2025 onward.

The resulting scalars for the feedforward neural network and generalised linear model with probit link are shown in Figure 4. The feedforward neural network combination 60 uses the interpolated TIIE rate lagged three months and the year-on-year gross domestic product lagged six months. The generalised linear model with probit link combination 378 uses the TIIE rate level, the year-on-year exchange rate lagged three months and the year-on-year gross domestic product lagged six months. As with Brazil, the scalar values for Mexico exhibit the expected ordering across scenarios: the upside scalar sits below the baseline and the downside scalar exceeds the baseline. A notable feature of the Mexico results is that the baseline scalar remains consistently above 1 across the forecast horizon for both models. This pattern, which is analogous to the Mauritius result documented in the foundational methodology (Neisen & Schulte-Mattler, 2021; Oberson, 2021), reflects a situation in which the forecasted credit index exceeds the base credit index over the projection window, indicating that default conditions are expected to deteriorate relative to the recent average even under the central scenario. This outcome is economically consistent with the persistent lagged effects of Mexico's prolonged monetary tightening cycle on consumer debt-servicing capacity in the unsecured retail segment.

Table 3. Top Six Models Per Technique

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

The forecasted credit index for Mexico is shown in Figure 3, produced from the feedforward neural network combination 60 and the generalised linear model with probit link combination 378 respectively. Both models track the ups and downs of the historically observed default rate with reasonable fidelity. The forecasted credit index diverges across upside, base and downside scenarios from January 2025 onward.

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scalar exceeds the baseline. A notable feature of the Mexico results is that the baseline scalar remains consistently above 1 across the forecast horizon for both models. This pattern, which is analogous to the Mauritius result documented in the foundational methodology (Pucci & Skærbæk, 2020), reflects a situation in which the forecasted credit index exceeds the base credit index over the projection window, indicating that default conditions are expected to deteriorate relative to the recent average even under the central scenario. This outcome is economically consistent with the persistent lagged effects of Mexico's prolonged monetary tightening cycle on consumer debt-servicing capacity in the unsecured retail segment.

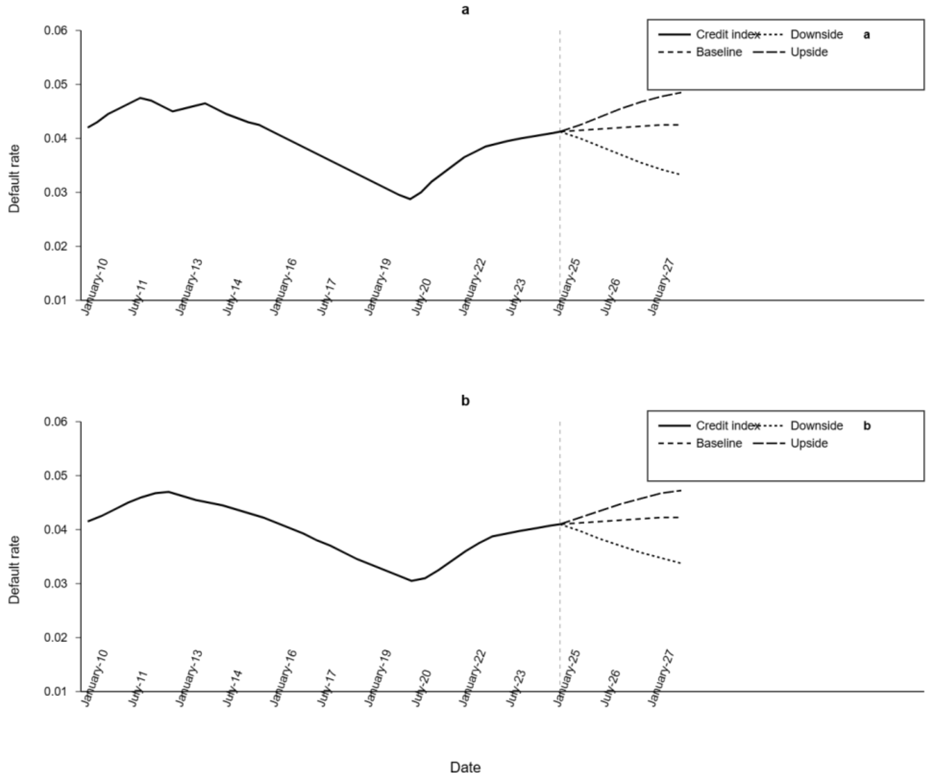

Figure 3. Credit index of the unsecured retail portfolio of Mexico: (a) feedforward neural network model 60, (b) generalised linear model (Probit) model 378.

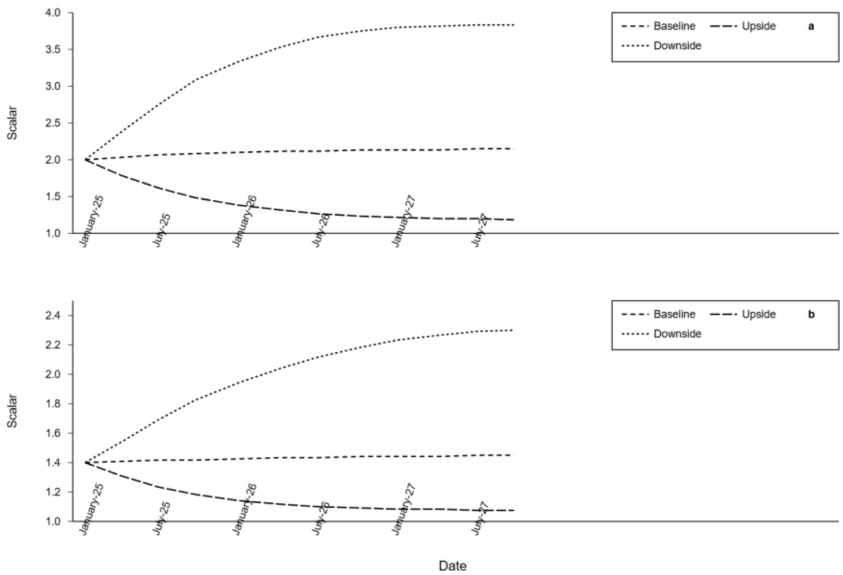

Figure 4. Macroeconomic scalar of the unsecured retail portfolio of Mexico: (a) feedforward neural network model 60, (b) generalised linear model (Probit) model 378.

CONCLUSION

This article has applied a macroeconomic scalar methodology to the task of adjusting the probability of default within the expected credit loss model, demonstrated through two case studies from Latin American developing economies: Brazil and Mexico. The methodology is structured across five steps encompassing research and planning, data preparation, model development, scalar calculation and model validation, and is both pragmatic and adaptable to the data constraints and economic volatility that characterise the Latin American financial environment. The use of a separate scalar component delivers meaningful governance benefits by separating the forward-looking macroeconomic adjustment from the base probability of default estimate, enabling bank management, boards, auditors and regulators to assess each component with transparency. This property is of particular value in markets where expected credit loss allowances represent material income statement items and where regulatory scrutiny of model assumptions is intensifying (PRA 2023a).

The methodology was applied to unsecured retail portfolios from Brazil and Mexico spanning January 2010 to December 2024. The resulting models were practically interpretable and economically coherent, with the enforcement of directional sign constraints ensuring that all retained specifications aligned with established macroeconomic theory. Forecasted credit indices under upside, base and downside scenarios were logically ordered in both case studies. Recommendations include the pre-specification of upper and lower bounds for each macroeconomic variable beyond which the scalar calculation would trigger a management adjustment, the segmentation of scalars by risk characteristic, and the regular updating of macroeconomic scenario inputs as new projections become available.

A key strength of the methodology as applied to these portfolios is the concurrent deployment of traditional statistical and machine learning estimation techniques. Multiple regression and generalised linear models were applied alongside feedforward neural networks, random forests and gradient boosting, providing a richer characterisation of the macroeconomic default relationship than any single technique would deliver in isolation. In some instances, the machine learning approaches surpassed the predictive accuracy of the parametric models, reflecting the nonlinear and interactive nature of macroeconomic effects on consumer default behaviour. In the Brazil case study, the preferred models were the generalised linear model with logit link and the random forest, while in the Mexico case study the feedforward neural network and the generalised linear model with probit link delivered the strongest performance.

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