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Credit Loss in Translation: Informing Bank Provisions and Capital Buffer Requirements with Forward-Looking Credit Loss Distributions

Marco Gross and Laurent Millischer

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Credit Loss in Translation: Informing Bank Provisions and Capital Buffer Requirements with Forward-Looking Credit Loss Distributions

Prepared by Marco Gross and Laurent Millischer [*]

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ABSTRACT: We develop a model framework that can be used to derive the forward-looking credit loss distributions for banks' credit exposures, to use it for (1) assessing the adequacy of provisions at the bank-portfolio level; (2) macro stress testing; and (3) informing the sufficiency of capital requirements, both from a micro- and macro-prudential perspective. The model is semi-structural and simulation-based, entailing a large number of simulated macro-financial scenarios instead of employing handpicked scenarios and ad-hoc scenario weights. The way the model-based credit loss distributions are generated can be made compatible with IFRS 9 or any other accounting regime. The model codes are made available online along with this paper.

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Author’s E-Mail Address:	mgross@imf.org, lmillischer@jvi.org

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WORKING PAPERS

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Contents

1. Introduction

We develop a model framework that can be used to derive the forward-looking credit loss distributions for banks' credit exposures with applications for both micro- and macroprudential policy. The model framework serves the purpose of (1) assessing the adequacy of provisions at the bank-portfolio level; (2) conducting stress tests conditional on macro-financial scenarios; and (3) informing the sufficiency of capital requirements, both from a micro- and macroprudential perspective, including with a view to a countercyclical capital buffer (CCyB) and a positive neutral version thereof (PN-CCyB). The model is designed to be "operationalizable" by central authorities such as central banks and micro- and macroprudential oversight institutions, using the data from banks that they have at their disposal.

The motivation and relevance for pursuing this model development stems from revisions to accounting and prudential frameworks over the past 10 to 15 years. First, from an accounting standards perspective—and therefore from the vantage point of credit loss provisioning—expected credit loss (ECL) models have become more relevant amid the reforms to major accounting frameworks following the global financial crisis; considering, for example, the IFRS 9 framework (IASB, 2014) and the CECL framework for the U.S. (FASB, 2016), with the former being relevant for more than 90 percent of the countries worldwide. Second, macroprudential capital requirements have received increased attention with the advent of Basel III capital regulation, and the policy tools such as the countercyclical capital buffer (CCyB), alongside the recently proposed positive-neutral version thereof (PN-CCyB) (BCBS, 2022). The development of conceptual frameworks and models for calibrating such tools is still nascent and ongoing. General discussions of the interplay between provisioning and capital requirements can be found in Borio & Lowe (2001) and Gaston & Song (2014).

Furthermore, supervisory authorities in most countries mostly do not examine the adequacy of accounting provisions thus far. The development of the provisioning models is left to the banks and their auditors. On one hand, this is intended and stipulated by the accounting frameworks, by following a principles-based approach. On the other hand, however, it risks that banks design and calibrate the models inadequately, to potentially underestimate risk to make balance sheets appear more robust than they are, or to tailor provision flows to offset profits and reduce tax bills. Financial incentives to do so arise naturally in a competitive market environment. It should therefore be useful for supervisory institutions to have some insight into the adequacy of such models and challenge the banks' provision coverage. The model framework that we develop can help in this context.

The model framework that we present in this paper is not specific to any one accounting regime. IFRS 9 is just one example with which it can be made compatible. A primer on IFRS 9, its ECL component specifically, is provided in Annex A1.. For switching from an IFRS-9 application to CECL, for example, one would simply switch the horizon for Stage 1 exposures from 12 months to lifetime. This can be a valuable counterfactual exercise also for IFRS 9 regimes.

To our knowledge, no integrated, top-down, simulation-based model framework for generating credit loss distributions exists that can be used to inform loan loss provisioning levels and inform a CCyB calibration. The risk and likely lack of robustness of employing handpicked scenarios and scenario weights—in an IFRS 9 setting—is discussed in Forest & Aguais (2019) and Gross et al. (2020). To avoid this lack of robustness, we instead stochastically *simulate* a large number of scenarios from the macro-financial model engine, which are fed through the remainder of the model suite, to thereby obtain the credit loss distributions. The model comprises various features that are nonlinear in nature. Simulating full distributions helps in this regard, to better account for and reveal such nonlinearities, in turn for certain moments of the ECL distributions (means and tail percentiles) to be more adequately estimated.

The model's use for macroprudential policy purposes is explored. Concerning a CCyB calibration, guidance for macroprudential policy institutions operating a CCyB can be found in BCBS (2010) and BIS (2015). It is generally recommended to employ a suite of indicators and models to judge the cyclical position of an economy, in turn to inform capital-based policies. A model as presented here can be added to such a suite. A regime switching model to assess the cyclical position and inform capital-based policies was proposed in Brave & Lopez (2021). In Pfeifer & Hodula (2021), the estimated, cyclical swings in profitability (excess profitability during booms) was suggested to be used to build buffers during expansions. Our model approach will entail the use of simulated point-in-time and through-the-cycle distributions of losses and capital needs, to inform the CCyB and PN-CCyB.

Our model therefore contributes to the existing literature along three dimensions. First, we devise a simulation-based model, not employing hand-picked scenarios and ad-hoc weights, the latter being stipulated by the IFRS 9 framework, for instance. That is a methodological contribution. Second, the model is operationalizable for top-down oversight institutions, for assessing the adequacy of provisions and microprudential capital requirements, and for scenario conditional stress testing. Third, the model can be used for informing macroprudential capital requirements, including a CCyB and PN-CCyB.

The model has some details that can render it useful for bank solvency stress testing. It is not, per se, a stress testing model to begin with. It computes ECLs for currently outstanding exposures (i.e., not for those that will be originated in the future) and implied provisioning requirements conditional on future scenarios, and hence not the ECLs year by year forward in time in a way it would be done for a stress test. The model suite can easily be adapted to be used for stress test purposes, however.

The paper is structured as follows. Section 2 presents the general model framework. Section 3 lays out the model structure and explains each of its modules in detail. Section 4 presents the quantitative results, using data from the Colombian banking system to illustrate how the model can be used in practice.[1] Section 5 concludes.

[1]The model was set up and operationalized with data for the Colombian banking system in the context of an IMF technical assistance mission (TA) for the Colombian bank supervisory authority in November 2023 and May 2024. The TA report will be online available on the IMF webpage, under the title "An IFRS 9-Compatible Expected Credit Loss Model for Informing the Provision Requirements for Colombian Banks."

2. Conceptual Framework

This section lays out how the model-derived credit loss distribution can be used to inform provisions (section 2.1), to challenge microprudential capital requirements (section 2.2), and to inform the calibration of the Countercyclical Capital Buffer (CCyB, in section 2.3).

2.1 PiT Credit Loss Distribution and Provisioning

We define the *point-in-time (PiT) credit loss distribution* for a bank portfolio as the forward-looking probability distribution of credit losses obtained at a certain point in time, i.e., conditional on the specific position in the business and financial cycle, and all corresponding bank-portfolio risk parameters as of that moment.

How the point-in-time credit loss distributions are to be used for provisioning depends on the accounting regime in place for banks in a jurisdiction. Under IFRS 9, the provisioning is specific to three asset quality stages (see Annex A1. for a primer). In Stage 1, the credit losses are to be computed over a 1-year horizon and the loss distributions to reflect this. In Stages 2 and 3, they should have a lifetime horizon. Under the CECL scheme as adopted in the U.S., provisioning should be based on expected credit losses with a *lifetime* horizon for all asset quality classes. Under the previous IAS 39 accounting regime and many national accounting frameworks, Stage 1 and 2 exposures were not to be provisioned for.

Figure 1 illustrates the credit loss distributions, expressed as a fraction of credit exposures. As credit losses cannot be negative, the distributions are bounded at zero. The middle sub-figure shows the loss distribution in boom times where losses are expected to be lower and the distribution compressed to the left toward zero.[2] In recession times (bottom sub-figure), expected losses are higher and the loss distribution is expanded toward the right. For provisioning under IFRS 9 (and CECL), the *mean* of the point-in-time credit loss distributions is of interest, because that corresponds to the *expected* loss as such, for which provisions are to be held. In Figure 1, the point ECL_{PiT} (dashed vertical blue line) denotes this point.

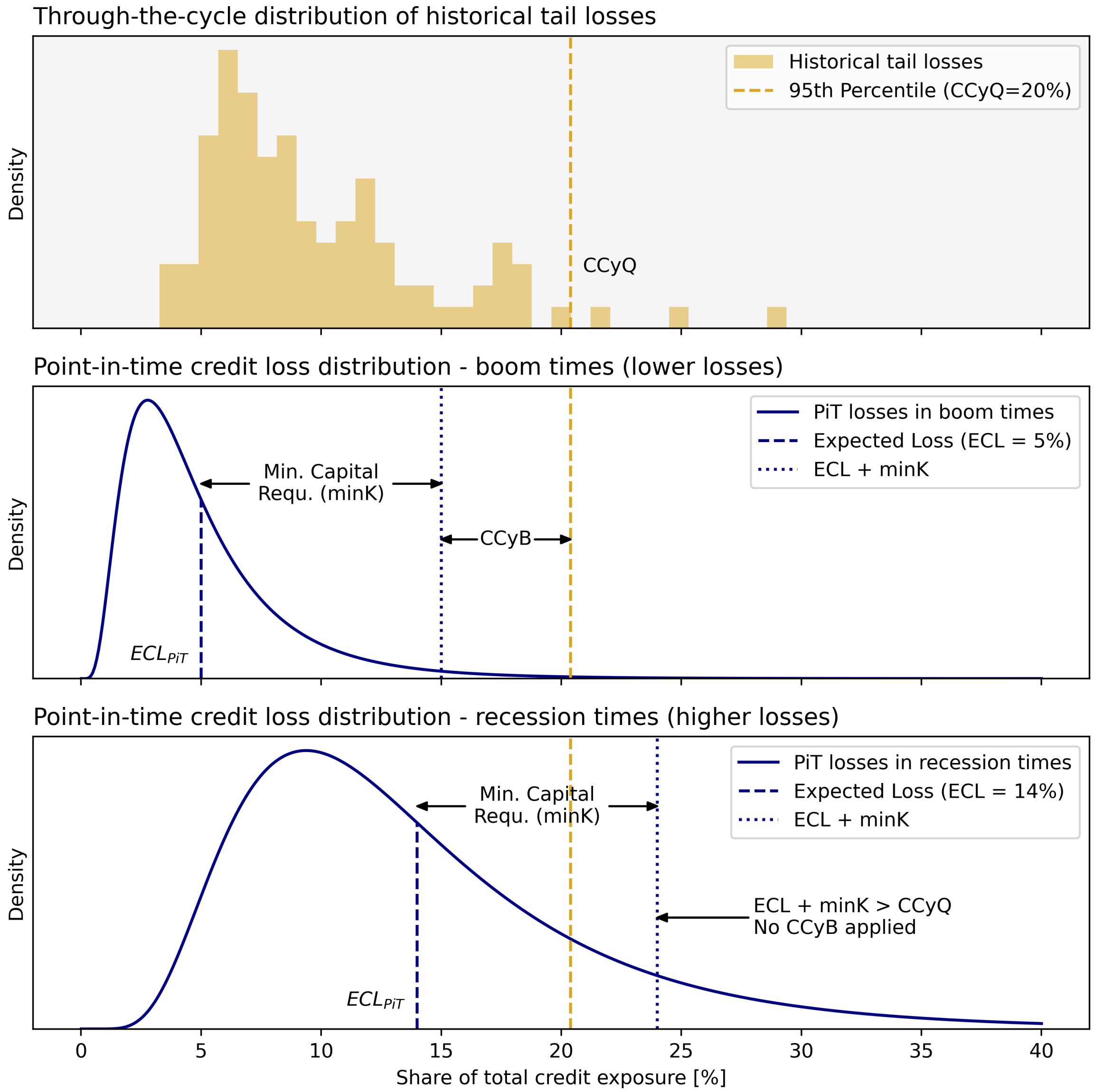
2.2 PiT Credit Loss Distribution and Capital Requirements

While loan loss provisions serve as a buffer for expected credit losses, capital requirements are designed to protect bank balance sheets against "unexpected losses," pertaining to some tail metric of the loss distribution. The Basel Committee on Banking Supervision (2006), for instance, explicitly aims for Pillar 1 requirements to cover the 99.9th percentile under the IRB approach.

Using point-in-time credit loss distributions, it is possible to benchmark capital requirement, i.e., assess what quantile of the point-in-time credit loss distribution the combined buffers of loan loss

[2] The through-the-cycle distribution of historical losses in the top sub-figure is discussed in section 2.3 below.

Figure 1: Through-the-Cycle and Point-in-Time Credit Loss Distributions



Note: The schematic illustrates the use of the mean and a tail percentile of the simulated credit loss distributions from the model for informing the point-in-time provision balance (ECL_{PiT}) and the amount that informs the CCyB ($CCyQ - ECL_{PiT} - minK$).
Source: The authors.

provisions and minimum capital requirements correspond to. This benchmarking can be performed at the level of each bank-portfolio, each bank, and the entire banking system.

Figure 1 illustrates the benchmarking procedure.[3]. First, minimum capital requirements (the sum of Pillar 1 and Pillar 2 requirements as well as the capital conservation buffer and possible buffers for systemically important banks) are expressed as a share of credit exposure. Then the sum of provisions and minimum capital requirements (dotted vertical blue line in Figure 1) can be compared to the point-in-time credit loss distribution and gauge in what fraction of forward-looking loss scenarios the losses

[3]Annex A3. derives the benchmarking mathematically.

are covered by provisions and minimum capital requirements—in particular whether the coverage indeed exceeds 99.9%.

This benchmark should not be interpreted normatively, i.e., whether capital requirements pass or fail a test. The Basel framework makes no quantitative claim as to the quantile of unexpected losses covered by capital requirements under the standardized approach. Furthermore, under the IRB approach, the loan losses are derived using a through-the-cycle PD and downturn (conservative) LGDs. TTC PDs can be higher (lower) than PiT PDs in boom (recession) times. The benchmark simply reveals which quantile of the forward-looking PiT loss distribution is covered by provisions and capital requirements.

2.3 TTC Losses and the Countercyclical Capital Buffer

The Countercyclical Capital Buffer (CCyB) is intended to absorb losses arising in a sudden downturn (as well as to lean against the cycle and dampen it during boom times). It is accumulated during periods of excessive credit growth, when realized point-in-time credit losses tend to be small.

PiT credit loss distributions alone do not convey a banking system's relative position in the credit cycle and hence cannot serve as sole source for the calibration of the CCyB, for which some through-the-cycle (TTC) reference metric is required. The initial BCBS (2010) proposal to use the credit-to-GDP gap to inform the CCyB calibration can be understood as an attempt to do so. This paper puts forward an alternative approach.

Using a TTC distribution of historical tail credit losses can inform a CCyB calibration. This distribution is built from one specific quantile of all historical PiT distributions over a longer time period spanning boom and downturn episodes. Figure 1 assumes quarterly snapshots over 25 years leading to a distribution with 100 observations. A quantile of that distribution (in Figure 1 the 95th percentile is used and denoted as $CCyQ$ – the dashed yellow vertical line) then serves as the anchor point for a calibration. Given its definition, this point is expected to be stable when more (quarterly) data accumulates over time.

The CCyB would then be informed by the amount of capital required to fill the gap between the sum of provisions and capital requirements on one hand and the quantile of the TTC loss distribution on the other. As is illustrated in Figure 1, this mechanism allows for the calibration of a CCyB, setting the buffer to zero in a recession and building it up gradually in neutral or boom phases, including the possibility of a positive neutral CCyB. Annex A3. derives the calibration mathematically.

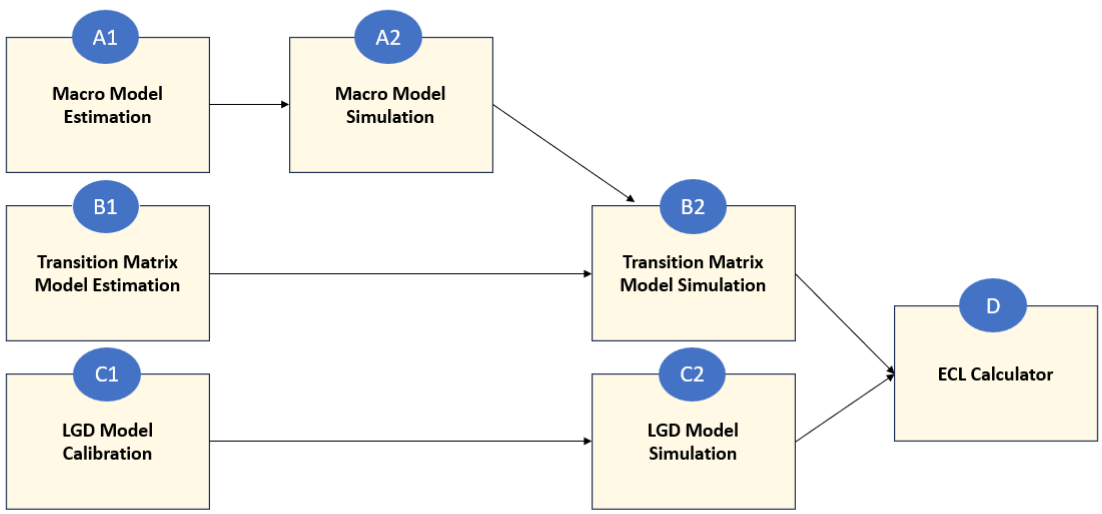
Importantly, credit losses form only one component of overall risk. Since the CCyB applies to total risk-weighted assets (RWA), a calibration should consider not just credit loss dynamics, but also all other components of a profit and loss distribution confronting banks, including interest income and expenses, fee and commission income and expenses, and market risk-related valuation gains and losses.

3. The Model

3.1 Model Structure

The model is composed of four modules. These include a macro-financial model component (Module A in Figure 2), a transition matrix model component (Module B), an LGD module (Module C), and a module that combines all other modules' outputs to obtain an credit loss distribution for all bank-portfolios (Module D). Modules A, B, and C are further split into two sub-components (A1/A2, B1/B2, C1/C2) which are responsible for estimation and simulation, respectively. Figure 3 provides a more detailed outline of the modules and their connections. The modules (or functions) are depicted by yellow boxes, initial data inputs by blue boxes, and intermediate data outputs as black text on white background.

Figure 2: Model Structure



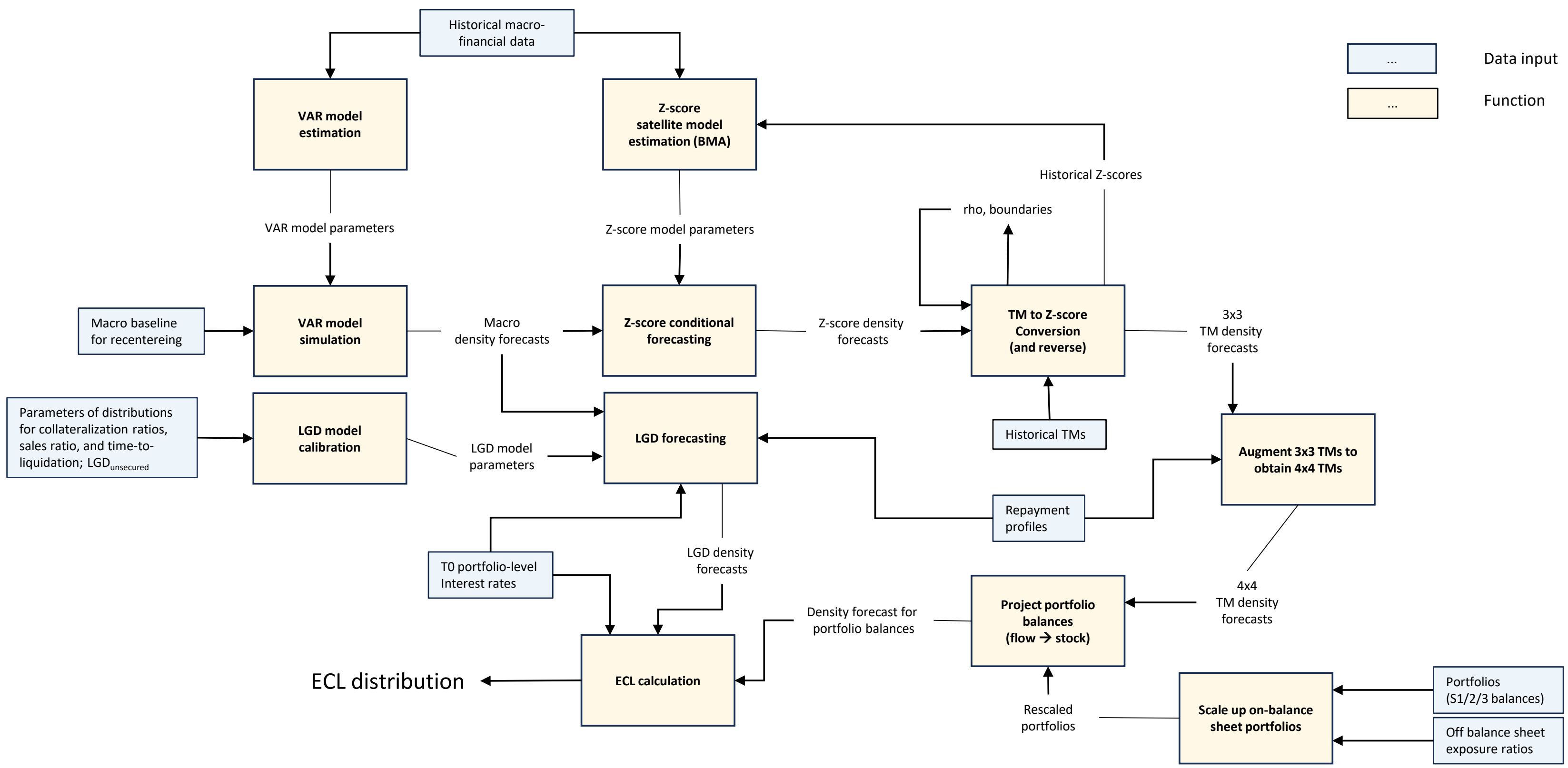
Simulated macro-financial density forecasts are fed through the model suite. A large number of macro-financial scenarios (e.g., 5,000 multivariate paths, 30 years forward in time, with quarterly frequency) are simulated from the macro module (Module A2) which are then fed through all subsequent modules in a consistent manner, all the way through to the credit loss distributions for all banks and portfolios in Module D.[4]

IFRS 9 stipulates that a small number of scenarios is to be designed by banks, which are to be used to imply the ECL estimates, of which, in turn, a weighted average using some self-set scenario weights is

[4]The long simulation horizon may raise concerns over the reliability and robustness of such long-horizon forecasts. We would be less concerned in this regard, however, because the density forecasts of the macro-financial variables as well as the implied bank risk parameters will shortly beyond the short/medium-term horizon converge to their long-run means and historical variance (regarding the width of the density forecast). Such means and variances may of course be subject to uncertainty though, but perhaps not as much as a concrete forecast path in the short-term. The uncertainty of longer-term trends and variance may be more structural in nature.

to be computed. This approach has some drawbacks: the selection of scenarios and the determination of their weights is bound to remain *ad hoc*, and hence it is uncertain whether the resulting ECL estimates come anywhere close to the "true" ECL for a loan portfolio (Section IV in Gross et al. (2020) has a related detailed discussion and analytical treatment). This is why a simulation-based approach is proposed and implemented here. By doing so, no specific small subset of scenarios and their weights are to be devised, but a large number of simulated scenarios covers the whole distribution, while weights remain only implicitly involved. All nonlinearities in the relationships that determine the credit loss distributions are more properly accounted for (assuming the model properly captures them) and the credit loss distributions' mean and other statistical moments more robustly estimated. Overall, adopting the simulation-based approach is meant to avoid operating with specific hand-picked macro-financial scenarios and the associated subjective weights.

Figure 3: Structure of the Model (Detailed)



3.2 Required Data Inputs

The required model inputs comprise historical macro-financial data and bank-portfolio level micro data. The macro Module A requires macro-financial data as input. The transition matrix Module B requires as inputs historical data on transitions between stages, portfolio repayment data, and current interest rates. The LGD Module C necessitates historically observed unsecured LGD rates. All required data inputs are summarized in Table 1.

Table 1: Data Input Requirements

Item	Dimension	Comments
Exposure stocks	B x P x T x S_5 x C	Historical end-of-period t stocks in currency units, by bank and portfolio.
Transition flows	B x P x T x S_3 x S_3	Historical cross-flows between Stages 1/2/3 through period t in % of the end-of-previous-period stock, by bank and portfolio.
Interest rates	B x P	Annualized current interest rates for outstanding stock of exposures, by bank and portfolio.
Repayments	B x P x S_3 x H	Principal repayment distribution of initial Stage 1 and 2 exposures, by bank and portfolio, from current position up to H quarters into the future.
Unsecured LGDs	(B x) P	Unsecured LGDs for recently defaulted loans
Historical macro data	K x T	History of relevant macro-financial variables
Collateralization ratios	B x P x C x S_5	Fitted parameters of the log-normal distribution of portfolio-level collateralization ratios.

Note: The dimensions denote the: B = banks; P = portfolios; T = historical time; S_3 = Stages 1 to 3; S_5 = Stage 1, Stage 2 and the three time-since-default buckets of Stage 3; H = future time horizon; K = macro-financial variables; C = collateral type.
Source: The authors.

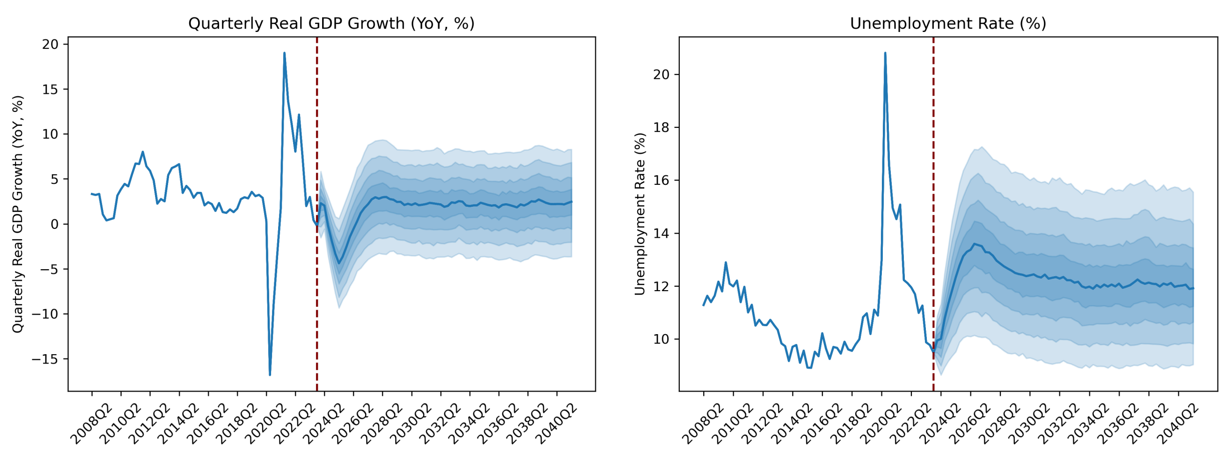
The model is flexible in allowing for different portfolio segmentations. The segmentation should be chosen according to economic and data availability considerations. Exposures with similar characteristics such as similar sensitivities to the macro-financial environment and unsecured loss rates should be included in the same portfolio type. A sufficiently high number of contract-level exposures should be included in each portfolio to observe meaningful historical transition matrices and estimate robust macro-financial relationships. Portfolio types could be defined according to counterparts (large non-financial corporates, SMEs, financial firms, public sector and local government, households), lending purpose (consumer finance, mortgage lending, project finance) and instrument type (micro-finance, loans, bonds).

3.3 Module A: Macro-Financial Model

A conventional vector autoregressive (VAR) model may form the starting point for the simulation-based model suite, though any other macro-financial model can serve the same purpose. Its purpose is to capture the historical dependencies of all relevant macro-financial drivers and produce multivariate, multi-period density forecasts. When using a VAR model, it does so in a reduced-form manner. The macro-financial module is set up to contain two VAR models for the illustration in the paper later on: the first one contains the endogenous domestic macro-financial variables (such as GDP growth, unemployment, and interest rates) plus exogenous international variables (such as the oil price or U.S. interest rates). A second, auxiliary, VAR model endogenizes the relationship between the international variables.

The density forecasts from the VAR models can be generated using conventional resampling methods which account for residual and coefficient uncertainty. This is done by drawing from the coefficient vector mean and covariance matrix estimates to capture coefficient uncertainty, and further adding noise by drawing from the VAR models' residuals to capture *residual uncertainty*. The former uses a parametric bootstrap method, assuming multivariate normality; while the residual drawing can be accomplished in a nonparametric or parametric manner. The width of the final credit loss distributions can later be examined regarding their dependence on accounting for only coefficient uncertainty, coefficient and residual uncertainty combined, and to their dependence on the parametric (normal) versus nonparametric distributional treatment of the residuals. Figure 4 illustrates the density forecasts for some selected macro variables; in this case for Colombia, the example that is chosen for the empirical application later in the paper.

Figure 4: Density Forecasts for Macro-Financial Variables



Note: The chart displays the historical macro-financial variables for Colombia (up until the dashed vertical line in 2023Q3) and the scenario-conditional density of those variables for the ten-year period starting in 2023Q4. Shaded bands show the width of the distribution from the 25th to the 75th percentile.
Sources: Haver and authors' calculations.

The macro model includes all macro-financial variables that are required inputs for the subsequent modules (B, C, and D). The choice of macro-financial variables to include in the macro model depend on the input requirements for all subsequent components of the model, and would usually include variables such as GDP growth, price inflation, the unemployment rate, the relevant bilateral exchange rate (or an effective, i.e., trade weighted, exchanges rate), wage growth, house price growth, a short-term sovereign bond yield, and a term spread (e.g., the difference between a long- and short-term sovereign bond yield). Furthermore, depending on the application, exogenous variables can be included in the VARX model. Possible exogenous variables include: the U.S. Fed Funds or other major central bank policy rates, GDP growth rates of major trading partners, and import or export-related commodity prices such as for oil. All variables will serve as potential inputs to the transition matrix (Z-score) models as described in Section 3.5. House prices should be included in the model as this variable will serve as an important direct input to the LGD module as well, for its portion that is responsible for delivering LGD estimates for the real estate-collateralized part of the banks' loan portfolios.

The exogenous variables are endogenized using a second VAR model. This serves to capture the variation an dependencies across the international variables, which feeds through to uncertainty (the density forecasts) of the domestic macro-financial variables. Density forecasts from the "international VAR" will be simulated first; which are then used as an input to the density forecast simulation with the "domestic VARX."

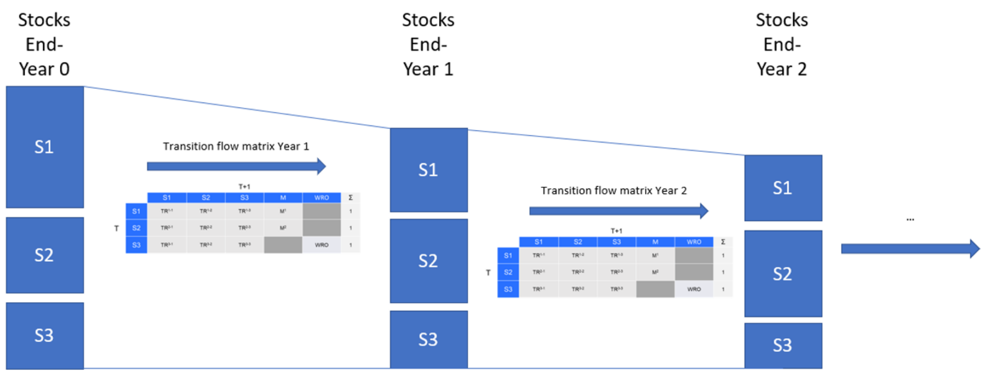
3.4 Module B1: Constructing Z-Scores from Transition Data

Different transition matrix model approaches exist, various of which allow for transition dependence on macro-financial conditions. Examples include the ordered probit model applied to global corporate and sovereign bond rating transition data in Nickell et al. (2000); the regime-switching framework applied to Standard & Poor's rating data primarily focused on North America in Bangia et al. (2002); the multi-factor Markov chain model applied to sovereign ratings from about 200 issuers and a North American-focused corporate rating database in Wei (2003); a factor model applied to corporate bond transition data from the U.S. in Trück (2008); a Markov chain model with macro dependence and an application to consumer credit card portfolios from the UK in Malik & Thomas (2012); a discrete time maximum likelihood estimation with macro dependence applied to the credit exposure data of an Austrian bank in Gavalas & Syriooulos (2014); and Moody's credit transition model, a discrete-time, multiple-destination proportional hazards model in Wang et al. (2017). All these models have in common that they allow for the transition dependence on macro-financial factors.

We employ the Z-score methodology developed by Belkin et al. (1998) for rating transitions, and apply them to credit quality class transitions as relevant under IFRS 9; as suggested in Gross et al. (2020). The Z-scores are then conditioned on macro-financial factors using a Bayesian Model Averaging Method (BMA); see Gross & Población (2017).

Historical transition flow data, collected in the form of transition matrices, need to be generated before modeling them. This requires the definition of stage migration criteria. The balances in Stages 1, 2, and 3 move as a result of the stage migration flows and other factors (new business, repayment of principal, and write-offs) through time (Figure 5). New business inflows into Stage 1 do not need to be considered in the ECL model here, because the aim of the model is to quantify the ECLs and implied provision needs for *currently outstanding* bank portfolios (including off-balance sheet assets). Provisions needs for loans originated in the future will arise after their origination, but these are not to be quantified with the model, given its purpose for informing "today's" provision requirements.

Figure 5: Stage Balances and Stage Transitions



Note: M in the transition flow matrix denotes principal repayment flows. WRO in the transition matrix denotes write-off flows.
Source: The authors.

The IFRS 9 accounting framework (IASB, 2014) stipulates various criteria that can be used to define stage transitions. Indicators for the move from Stage 1 to Stage 2 include: minimal absolute or relative changes in PDs since origination; observed or expected significant changes in operating profits of firm borrowers; rating downgrades; material rises in market-based CDS spreads or credit spreads of bonds of corporate borrowers; modification and restructuring, such as interest payment holidays, interest rate step-ups, or the call for additional collateral or guarantees; a rebuttable presumption of reaching 30 days past due. The move from Stage 2 to 3 is akin to an incurred loss. The related indicators include the outright bankruptcy of a borrower, and a rebuttable presumption of delinquent payments surpassing a 90 days past due counter.

All such indicators correlate in practice. Hence, a smaller subset of indicators should be sufficient for defining the stage transition process. A recent survey of what staging criteria are used by European banks (EBA, 2023) suggests that the most commonly employed criteria by European banks include thresholds related to relative changes in PDs, modification and restructuring, and other watch list criteria.[5]

There are two possible avenues for defining staging criteria when preparing the transition flow data for the model. The first option is to use banks' own historical stage classifications, when available, to derive historical transition matrices. This has the advantage of allowing the model to reflect the staging assumptions of banks but may hamper the comparability of the staging dynamics across banks if they use notably different criteria. The second option is to define a set of criteria in a "top-down" manner, to ensure comparability across banks. In both cases, the data would ideally be generated for the years predating the introduction of IFRS 9 in 2018.

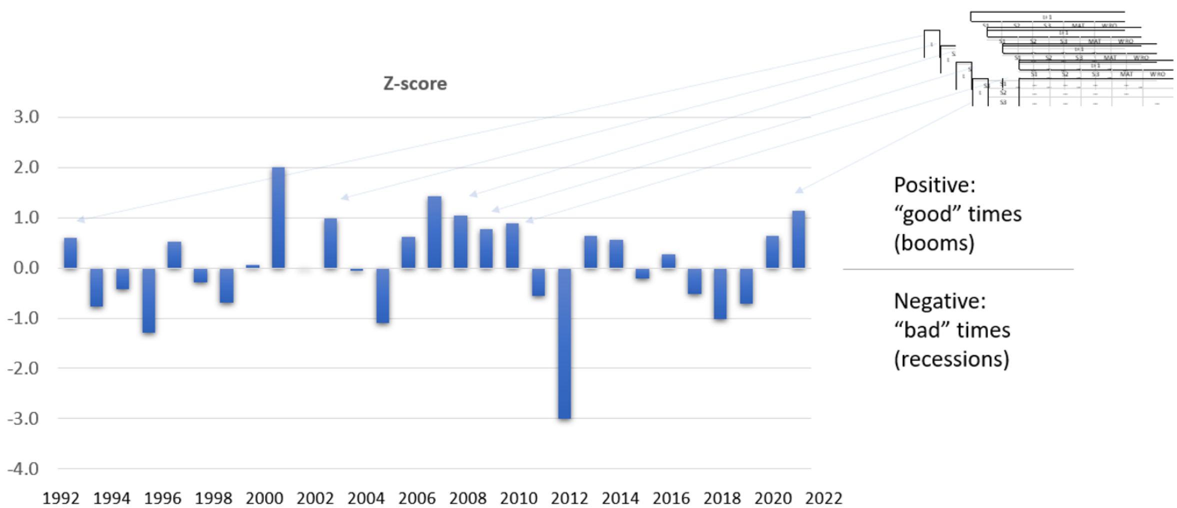
A Z-score methodology (Belkin et al., 1998) lies at the center of the transition matrix module. This

[5] There is no role foreseen for LGDs to directly influence the migration decision, according to the IASB (2014) framework. LGDs may just indirectly relate to and therefore correlate with default risk. A first example for when this can happen is the default risk of commercial real estate firm borrowers which depends, inter alia, on the value of commercial real estate, which therefore drives both default risk and LGDs. A second example relates to the possible strategic default incentives of retail mortgage borrowers when residential house prices drop, in countries where the legal environment is characterized by "less than full recourse."

methodology is often applied by banks for modeling rating transitions. Here, it is used for IFRS 9-type transition matrices; as suggested in Gross et al. (2020). It allows compressing the information contained in a time series of transition matrices—for each bank and portfolio—into one number per point in time (Figure 6). It thereby reduces the dimensionality of the transition data, to make it easier to model the transition process econometrically as a function of macro-financial conditions. For each bank and each portfolio type, historical Z-Scores can be estimated from historical transition rates as illustrated in Figure 7.

For any given bank-portfolio, a Z-Score of zero corresponds to the transition matrix being equal to the long-run average transition matrix, a positive Z-Score to a more "favorable" transition matrix with fewer defaults and more frequent migrations to better stages, and a negative Z-Score to more "unfavorable" transitions.

Figure 6: Z-Score—Illustration



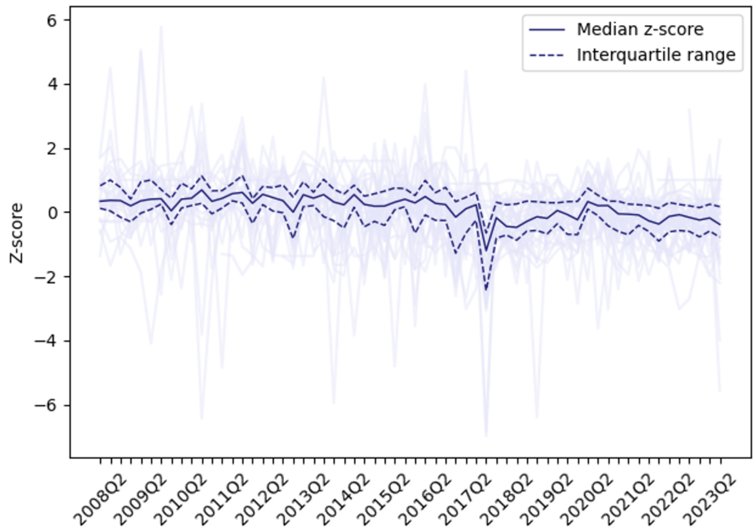
Note: The figure illustrates the meaning and purpose of a Z-score, which is to compress a series of historical transition matrices into one number per point in time.
Source: Gross et al. (2020)

3.5 Module B2: Econometric Models for Z-Scores to Relate them to Macro-Financial Variables

The Z-score time series estimates will be modeled as a function of macro-financial drivers, using a Bayesian Model Averaging (BMA) methodology (Gross & Población, 2019). It is used to avoid "hand-picking" equations and instead to produce robust equations which account for model uncertainty. Hand-picked equations are at risk of resulting in specific, though possibly not robust, scenario conditional forecasts.

In principle, the Z-scores may be included in the VAR model, without the need for separate bridge equations. This is not feasible in practice, however, because there are Z-scores for all banks and portfolios, which likely results in several dozens up to hundreds of Z-score time series in most applications.

Figure 7: Estimated Z-Scores: Illustration



Note: The charts show the estimated historical Z-scores for one specific portfolio (commercial lending) of all Colombian banks (light blue lines), alongside the cross-bank median and interquartile ranges.
Source: SFC and author calculations.

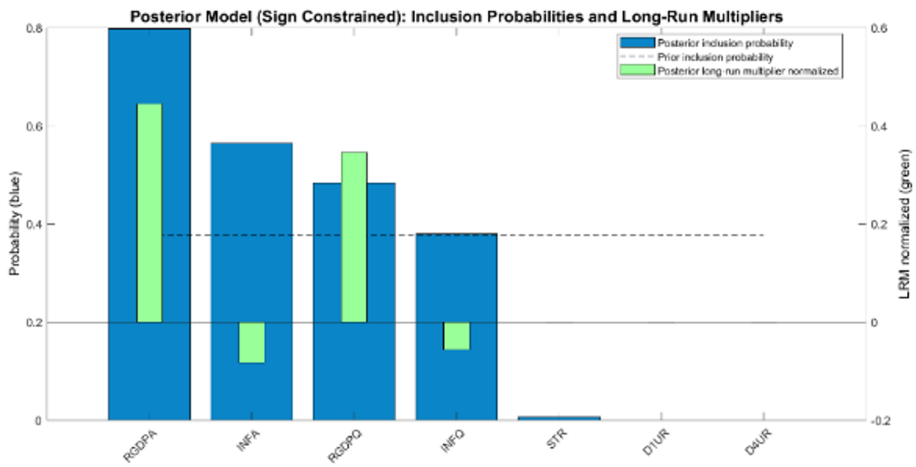
This would render the VAR model too high-dimensional and hence no longer estimable. Having the separate bridge equations, moreover, implies that time contemporaneous macro-Z-score relationships can be considered on top of lagged relationships; which is beneficial. The specific BMA implementation also allows for the imposition of sign constraints on long-run multipliers (LRMs) of the Z-score models' right-hand side variables, to thereby ensure that the coefficients are having the signs that economic theory and common sense suggest (Gross & Población, 2019).

Figure 8 illustrates the output of the BMA methodology. Macro-financial variables are only retained in the individual equations comprised by a "model space" when they had the "right," predefined signs. Each equation in the model space had its empirical weight, which can either be in-sample or out-of-sample criteria-based. The right hand-side variables that are found to be relevant in the Z-score models should be included in the macro module (Module A). This means that one may estimate the transition matrix models first, to then ensure the coverage of all variables in the macro model.

The density forecasts for the Z-scores are then generated from the Z-score bridge equations using the macro-financial density forecasts (Figure 4) as input. This requires (1) the drawing of coefficients from the Z-score models, using the estimated coefficient means and coefficient covariance matrices; (2) drawing from the Z-score model residuals (bank portfolio specific); and (3) the macro-financial density forecasts simulated from the VARX model.

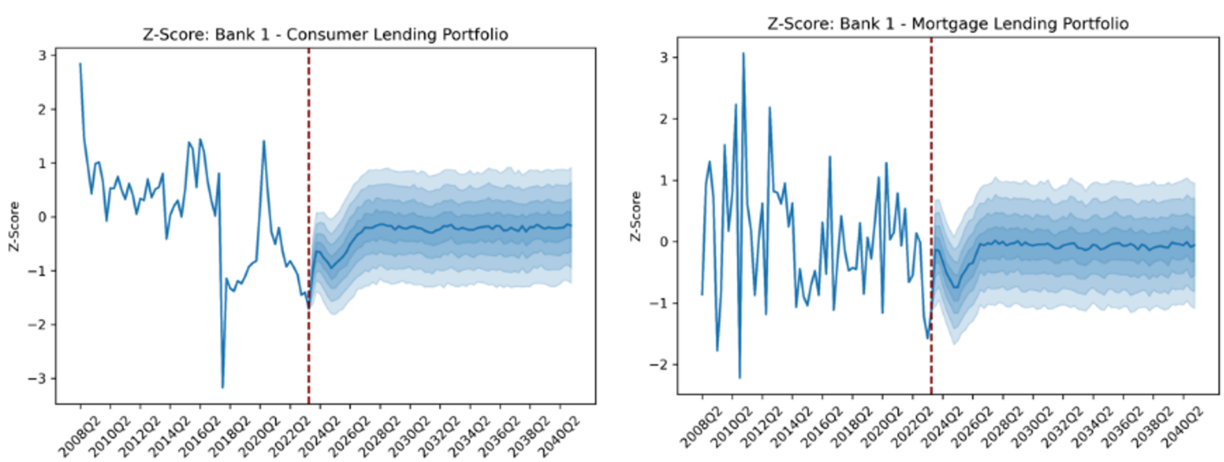
Figure 9 visualizes the Z-score density forecast for two bank portfolios as an illustration. These Z-score distributions can be decomposed into coefficient, model, and residual uncertainty. The model uncertainty dimension can be examined because the BMA methodology is involved. The VARX model density forecasts can be decomposed into only coefficient and residual uncertainty, on the other hand, because there is no BMA method involved for it, and it is just one specific model. The decomposition of the sources of uncertainty can later be analyzed with a view to the final credit loss distributions.

Figure 8: Illustration of BMA Model Estimates



Note: The chart visualizes the model structure of the panel BMA models for the Colombian banks' loan portfolios. The left-hand side variables are the banks' Z-scores. The predictor variables are RGPDA and RGPDQ (real GDP growth QoQ and YoY), INFA and INFQ (QoQ and YoY consumer price inflation), STR the 3-year sovereign bond yield, D1UR and D4UR (the QoQ and YoY absolute difference in unemployment rates). The underlying models involved lags of the right-hand side variables, beyond their time contemporaneous inclusion. The posterior (and prior) inclusion probabilities pertain to the combined inclusion of contemporaneous and lagged terms. The long-run multipliers (green, right axes) represent the sum of the coefficients on a given contemporaneous and lagged predictor variable. They were normalized by multiplying the initial LRMs with the ratio of the standard deviations of the left and right-hand side variables. Therefore, they can be compared across predictors and models.
Source: SFC, Haver, and authors' calculations.

Figure 9: Density Forecasts for Macro-Financial Variables



Note: The chart shows the historical Z-score estimates (up until 2023Q3), followed by the simulated Z-score density forecast until 2040, as an example here for two portfolios (consumer and mortgage lending) of a selected Colombian bank. Shaded bands show the width of the distribution from the 25th to the 75th percentile.
Source: SFC and author calculations.

3.6 Module C: Loss Given Default

The LGD modeling literature is relatively scarce. The negative empirical relationship between default and recovery rates on corporate bonds and an analysis of the macro factors that drive them is documented in Altman et al. (2005). Moody's KMV's LossCalc model has endogenous LGDs, driven by collateral, debt type, firm level financials, industry factors, and macro-financial factors (Gupton & Stein, 2005). An empirical analysis of LGDs for UK bank retail credit portfolios in Bellotti & Crook (2012) uses different model methods, to, likewise, conclude that PDs and LGDs are positively correlated.

We employ two LGD model methods, both structural in nature. For real estate collateralized portfolios, we index the value of collateral with house price trajectories simulated by a macroeconomic model. The indexation with house price paths is considered also in Gross & Población (2017) and Gross et al. (2020).[6] For all other portfolios, we use the Frye & Jacobs (2012) methodology, which establishes a structural link between PDs and LGDs.

In our model, LGDs are modeled depending on the nature of underlying collateral and time-since-default. Loans in default are split in three buckets based on the time-since-default. Thresholds to move from the first bucket (recent defaults) to buckets 2 and 3 can be defined by portfolio and collateral type.[7] For loans that have been in default for long, an LGD of 100 percent is assumed in line with current international practice. For each portfolio, the loan-level collateralization ratio (CR)—the ratio of available collateral to loan exposure—is then fitted using a lognormal distribution. This parametric distribution captures the amount of available collateral at the portfolio level using two parameters only and allows dealing with the numerous combinations of portfolios, banks, collateral types, scenarios and future years in a computationally efficient way.

If no collateral is available, an unsecured LGD (informed by historical recoveries on unsecured parts of loan exposures) is applied. For uncollateralized portfolios, no CR distribution is fitted. In the credit loss simulation, defaults can occur during the first year and in subsequent years. For those instances, projected unsecured LGD rates are applied, which are derived using the Frye-Jacobs (FJ, Frye & Jacobs, 2012) methodology that links LGDs to scenario-specific PDs. Annex A4..1 summarizes the logic of the FJ methodology.

For collateral other than real estate, the CR distribution is translated into a portfolio-level LGD. The fitted CR distribution allows to compute the fraction of overcollateralized loans (for which an LGD of 0 percent is applied). For the remainder of the portfolio, the unsecured LGD rates are applied to the uncollateralized part of each loan. The logic is depicted in Figure 10 and captured by equation (1)[8]. The resulting LGD is derived in Annex A4..2.

$$\begin{aligned} LGD &= \int_0^{\inf} loss(CR) \cdot pdf(CR) \cdot dCR \\ &= LGD_{unsec} \cdot \left[\Phi_{LN}(1) - e^{\mu+\sigma^2/2} \Phi_N \left(-\frac{\mu+\sigma+\sigma^2}{\sigma} \right) \right] \end{aligned} \tag{1}$$

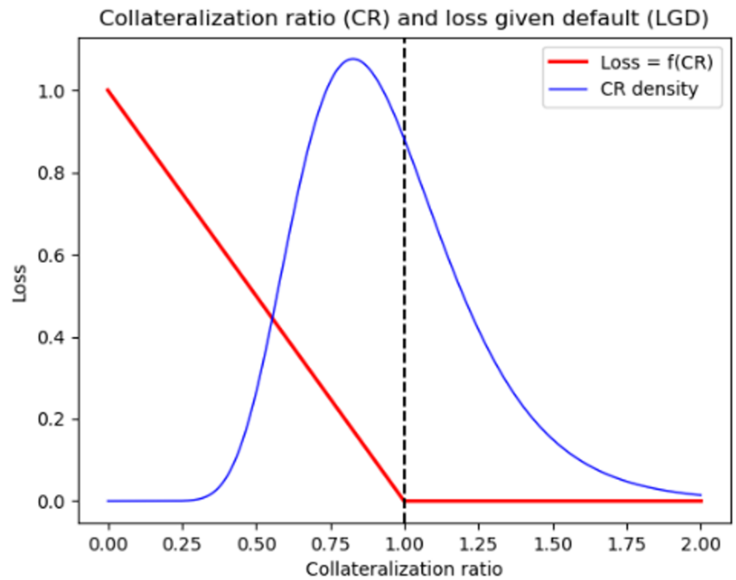
For defaults occurring after the first year in the simulation, unsecured LGDs are projected using

[6] The latter uses the indexation approach in a micro(-macro) simulation model at the household level.

[7] The thresholds for the application of the model to the Colombian banking sector are provided in Annex A4..5.

[8] The red term in the equation represents the loss rate and is shown in red on the Figure. The blue term in the equation represents the probability density and is shown in blue on the Figure.

Figure 10: Distributional Logic Underlying the LGD Model



Note: The blue line represents the portfolio distribution of loan-level collateralization ratios. The part of that distribution above 1 (black, dotted, vertical line) represents overcollateralized loans, while the part below 1 represents loans with collateral values below the exposure value (CR<1). The red line shows the loss as a function of the collateralization ratio: overcollateralized loans incur no losses (Loss=0), while undercollateralized loans incur losses in case of default, the loss is 1 in case there is no collateral (CR=0).
Source: The authors.

the FJ methodology and the CR distributions are shifted according to portfolio amortization (reflecting higher credit risk when exposures decrease). As time passes, principal repayment decreases the credit exposure and, assuming collateral values remain unchanged, pushing collateralization ratios higher.[9]

For real estate collateral, the CR distribution is adjusted to account for the uncertainty regarding the time to collateral liquidation and the future sales price (SP). In a first step, the distribution is multiplied by a lognormal distribution reflecting the uncertainty concerning the time from default to foreclosure and the simulated change in average house prices along the scenario horizon. The distribution of time-to-foreclosure (TTF) is informed by empirical moments. The fluctuations of the house price index along the horizon are captured by the change in the house price index comprised by the macroeconomic model, then discounted back to the time of default, and finally fitted with a lognormal distribution. In a second step, the CR distribution is multiplied by a lognormal distribution which reflects the uncertainty about the precise sale price, which could be higher or lower than a bank's collateral valuation at present.[10] Finally, as for other collateral types, the loan amortization is considered to project future CR distributions.

$$CR \sim LN(\mu, \sigma^2) \quad \longrightarrow \quad CR \sim LN(\mu + \mu_{TTF} + \mu_{SP}, \sigma^2 + \sigma^2_{TTF} + \sigma^2_{SP}) \tag{2}$$

The resulting lognormal CR distribution of equation (2) can be translated into a portfolio-level LGD

[9] Annex A4..3 derives how the collateralization ratio distributions are affected by this.
[10] The resulting CR distribution is derived in Annex A4..4.

according to equation (1). For defaults occurring after the first year in the simulation, unsecured LGDs are projected using the FJ methodology and the CR distributions are shifted according to scenario-specific changes in the house price index.

3.7 Module D: Expected Loss Distributions

Lifetime ECL calculations are relevant under the new IFRS 9 and CECL accounting frameworks. Conceptual and practical discussions regarding the relevant formula can be found in Skoglund (2016), Gross et al. (2020), and Engelmann (2021). We calculate expected credit loss distributions separately for exposures in Stages 1, 2, and 3.

Stage 1 ECLs are computed as shown in equation (3) using the scenario-conditional exposures, transition rates, and LGD distributions. For Stage 1, the ECL is calculated over a 1-year (i.e., 4-quarter) horizon by multiplying the flow-to-default ($EXP \cdot TR$) by the LGD. Over the first four quarters, the exposure that rests initially in Stage 1 will transition to Stage 2 and 3. To compute expected losses for the outstanding Stage 1 portfolio, the exposure in Stages 2 and 3 at the beginning of the first quarter is set to 0. Hence, equation (3) sums over two stages and four quarters.

The actual flow-to-default is computed as the product of the EAD, the exposure in Stage X=1/2 (denoted by $EXP^{S_X}_{t=q-1}$ in the equation below) and the PD, i.e., the transition rate from Stage X=1/2 to 3 (denoted $TR^{X\rightarrow 3}_{t=q}$). The exposure at the end of quarters 1, 2, and 3 is determined by setting the initial exposure values in Stage 2 and 3 to 0 and multiplying the vector $[EXP^{S_1}_{t=0}, 0, 0]$ with the full scenario-specific transition matrix. Given that the precise moment of default within the quarter is unknown, the losses are assumed to happen in the middle of the quarter. To reflect this assumption, the exponent in the denominator of equation (3) involves the term -0.5. The interest rate r for discounting is a quarterly rate (not annual) because the time steps that the ECL formula entails are quarterly.

$$ECL^{S_1} = \sum_{X=1}^{2} \sum_{q=1}^{4} \frac{EXP^{S_X}_{t=q-1} \cdot TR^{X\rightarrow 3}_{t=q} \cdot LGD^{S_X}_{t=q}}{(1+r)^{q-0.5}} \tag{3}$$

Stage 2 ECLs are calculated in the same way as for Stage 1 with one difference: Losses are summed over the lifetime of the loans up to quarter M (in which the portfolio is fully repaid), instead of considering just $M = 4$ quarters as for Stage 1. The initial exposure at the beginning of quarter 1 is set to zero for Stages 1 and 3, to then multiply the vector $[0, EXP^{S_2}_{t=0}, 0]$ with the full scenario-specific transition matrix. The interest rate r is a quarterly rate.

$$ECL^{S_2} = \sum_{X=1}^{2} \sum_{q=1}^{M} \frac{EXP^{S_X}_{t=q-1} \cdot TR^{X\rightarrow 3}_{t=q} \cdot LGD^{SX}_{t=q}}{(1+r)^{q-0.5}} \tag{4}$$

Stage 3 ECLs are calculated for each time-since-default bucket. For each bucket, the Stage 3 exposure in that bucket which does not cure is multiplied with the LGD of that stage and bucket.

$$ECL^{S_3} = \sum_{b=1}^{3}(1 - TRC_b^{3\to 1} - TRC_b^{3\to 2}) \cdot EXP_{b,t=0}^{S_3} \cdot LGD^{b,t=1} \tag{5}$$

The cure rate ($TRC_b^{3\to X}$) is computed from the scenario-specific, simulated transition matrices. For the first bucket (those exposures with the shortest time-since-default), the cure rate is computed over a three-year horizon, for the second bucket over a one-year horizon and for the longest time-since-default bucket, the cure rate is set to 0.[11]

3.8 Point-in-time and Through-the-cycle distributions

The model as described above generates point-in-time (PiT) credit loss distributions, i.e., using any current position in the economic cycle as a starting point. The mean of such a distribution is the expected credit loss of a portfolio and informs the level of required provisions. To compute the PiT credit loss distribution, the model inputs are the last observations of the macro-financial variables as well as all portfolio parameters (Z-scores and actual observed Stage composition).

The model can also produce a through-the-cycle distribution of historical tail losses, i.e., the accumulation of a tail metric of historical PiT credit loss distributions, as described in section 2.3.

3.9 Model Extensions

Various model extensions can be considered. Four examples include:

- Splitting portfolios by their fixed vs. variable rate parts. The stage balances and transition flow matrices can be generated with this split for all portfolios. The Z-scores and Z-score bridge equations would then be estimated separately. The economic drivers of credit risk can in this way be captured in a more nuanced manner, not just for the aggregate of the portfolios with regard to the fixed-variable rate feature. One may expect the various interest rate variables to be significant drivers of variable rate portfolios' Z-scores, because rising interest rates would make it harder for borrowers to service their debt. The write-up of the model as presented above is generic enough to encapsulate such an extension, as this extension just entails an additional portfolio split.
- Endogenizing the discounting of recovery values and expected losses. The discounting of recovery values and losses in the LGD and ECL calculation module are currently based on the loan portfolios' T0 interest rates. These could be endogenized with the interest rate paths that are

[11] This is to reflect the fact that loans in the second bucket have been in default for up to two years. The cure horizon is therefore reduced.

already endogenous in the VARX model component. This would make the discounting more economics-related.[12]

- Estimating Z-scores for each row of the bank-portfolio transition matrices. The Z-scores are currently estimated for the full transition matrix per bank-portfolio (Wei, 2003). Alternatively, one can estimate the Z-scores for each row of a transition matrix history separately. This would be appropriate in situations where the dynamics of the three stages are not synchronized and periods exist where, for instance, Stage 1-loans default more frequently than usual while many Stage 3-loans cure.

- Employing nonlinear macro models for the scenario simulations. A linear macro model core is currently used. A nonlinear macro model may better capture possible nonlinearities in the relationship among the macro-financial variables. Regime-switching VAR(X) models will be one example of a nonlinear model format that can be explored.

[12] Some accounting frameworks, such as IFRS 9, stipulate the use of interest rates from the time of loan origination for discounting throughout the lifetime of the credit exposure.

4. The Model in Use: An Illustration

4.1 Colombia: Bank Sample and Portfolios

An illustration of the model to Colombia is presented in this section. The sample comprises 55 Colombian banks, implying close to 100 percent banking system coverage. The banking system represents 71 percent of financial system assets at end-2023 (Figure 11). It represents about 64 percent of nominal GDP in 2023. The banking system is to an extent concentrated: the largest three, eight, and 13 of 55 banks operating at end-2023 represent 50, 75, and 90 percent share of banking system assets, respectively (Figure 11).

Four bank portfolio types were defined: a commercial portfolio, microcredit, consumer lending, and mortgage credit. The former two cover lending to corporate borrowers; the latter two are retail lending portfolios. The commercial portfolio comprises large and small firms, public sector entities, and financial firms. The distinction into the four headline portfolios follows a standing convention at the Superintendencia Financiera de Colombia (SFC), in its databases, and the models it has for informing the provision needs for banks so far. The largest share of the banking system loan book represents commercial lending (Figure 11). The shares of commercial lending, consumer lending, mortgages, and microcredit in that order stood at 50, 30, 16, and 4 percent, respectively, at end-2023.

The focal criteria for the generation of stage balances and stage transition flow data for the model include past due criteria and the modification and restructuring of the exposures. The 30-days and 90-days past due criteria were chosen as the primary indicators that imply the move from Stage 1 to 2, and Stage 2 to 3, respectively. Exposures whose contracts are restructured are defined to move to Stage 3. When repayment of principal and payment of interest (i.e., the combined annuity) of Stage 2 exposures resume, they migrate back to Stage 1. When annuity payments of Stage 3 exposures resume, they move first back to Stage 2, and only when they pay for at least three months in sequence after leaving Stage 3, they then move from Stage 2 to Stage 1. Modified or restructured exposures need to comply with additional cure periods before moving one stage up.

Default flow rates were historically most material for the small microcredit portfolio and the more sizable consumer credit portfolio (Figure 12). The default rates in all portfolios rose notably in 2017 (the only exception being the retail mortgage portfolio), thereby rendering the implied NPL stock to gross loan stock ratios higher. The workout and write-off process take time, as indicated by the only slowly decaying NPL ratios since 2017. The consumer credit portfolio has experienced a further deterioration since 2022.

The model as developed here for the Colombian banks pertains to their domestic lending and foreign lending through branches, but not through subsidiaries. The Colombian banks' domestic loan book, foreign lending through branches, and the foreign loan book of subsidiaries amounts to 89, 1, and 10 percent at end-2023.[13] The branch-based foreign lending (1 percent of total, through foreign

[13] The aforementioned "close to 100 percent coverage of Colombian banks" refers to the banks' total assets, i.e., the coverage is about 90 percent when excluding the banks' foreign business through subsidiaries abroad, as we do.

branches that exist at only three banks) could not be excluded from the data and the current model implementation due to data reporting constraints in this regard. Lending through foreign subsidiaries is excluded from the model's scope, on purpose, for the time being. Extending the scope to foreign subsidiary-based lending will require that the model be operated with macro-financial data and bank portfolio data for the foreign jurisdictions.

Colombian solo bank entities' bond exposures were not yet included in the exposure stocks as a basis for the model. At end-2023, the solo banks' domestic bond exposures amount to 13 percent of a total of the domestic loan book and domestic and foreign bonds held by the solo banks (Figure 13). The 13 percent splits into 9 and 4 percent for public and private corporate bond exposures. The 4 percent corporate bond exposures can be added by the SFC later on to the commercial loan portfolio in the model. Another 8 percent share for foreign bonds are excluded from the model's scope for now, on purpose, on the same grounds as the foreign subsidiary-based lending, which are a function of macro-financial conditions outside Colombia.

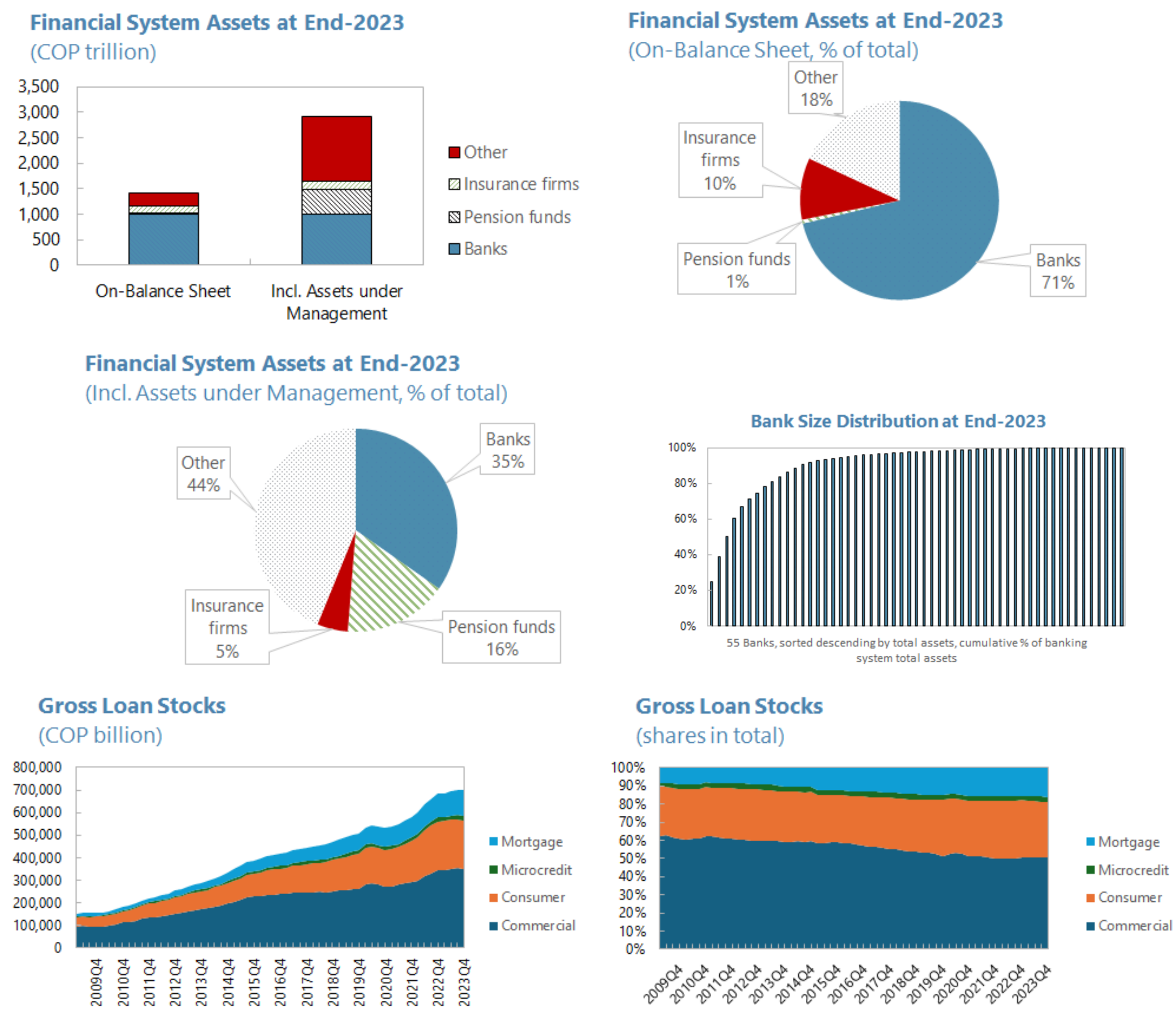
4.2 Z-Score Model Component

A panel version of the BMA was used for the application to Colombia, with the banks being the cross-section dimension, and the bank portfolio level Z-scores being the dependent variables. The Z-score estimates for the four portfolios are presented in Figure 14. The set of variables defining the predictor pools and the LRMs for the four portfolios is summarized in Table 2. The unemployment rate was excluded from the predictor set for the commercial and microcredit Z-score models because unemployment is seen as resulting from firm defaults, and hence including them in the Z-score models would mistakenly reverse this causal relationship. House prices were excluded from the retail mortgage portfolio model because Colombia's legal system is designed to have a full recourse structure. This means that borrowers with real estate collateralized debt have no incentive to strategically default as a function of house price drops specifically. Hence, there is no structural relationship (ceteris paribus) between house price dynamics and mortgage default rates. The consumer lending portfolios were assumed to not be driven by house price dynamics.

The pandemic period was excluded from all estimations (2020Q2—2022Q2, nine quarters). Its inclusion would bias the coefficients toward zero, given that default transitions and other adverse transition flows were significantly dampened due to an unprecedented policy support during the pandemic; while macro-economic variables experienced a significant downturn dynamic. The inclusion of dummies (intercept/step dummies) would not be sufficient to address this issue, because slope coefficient would remain relevant for an entire sample period including the pandemic and hence be at risk of downward bias.

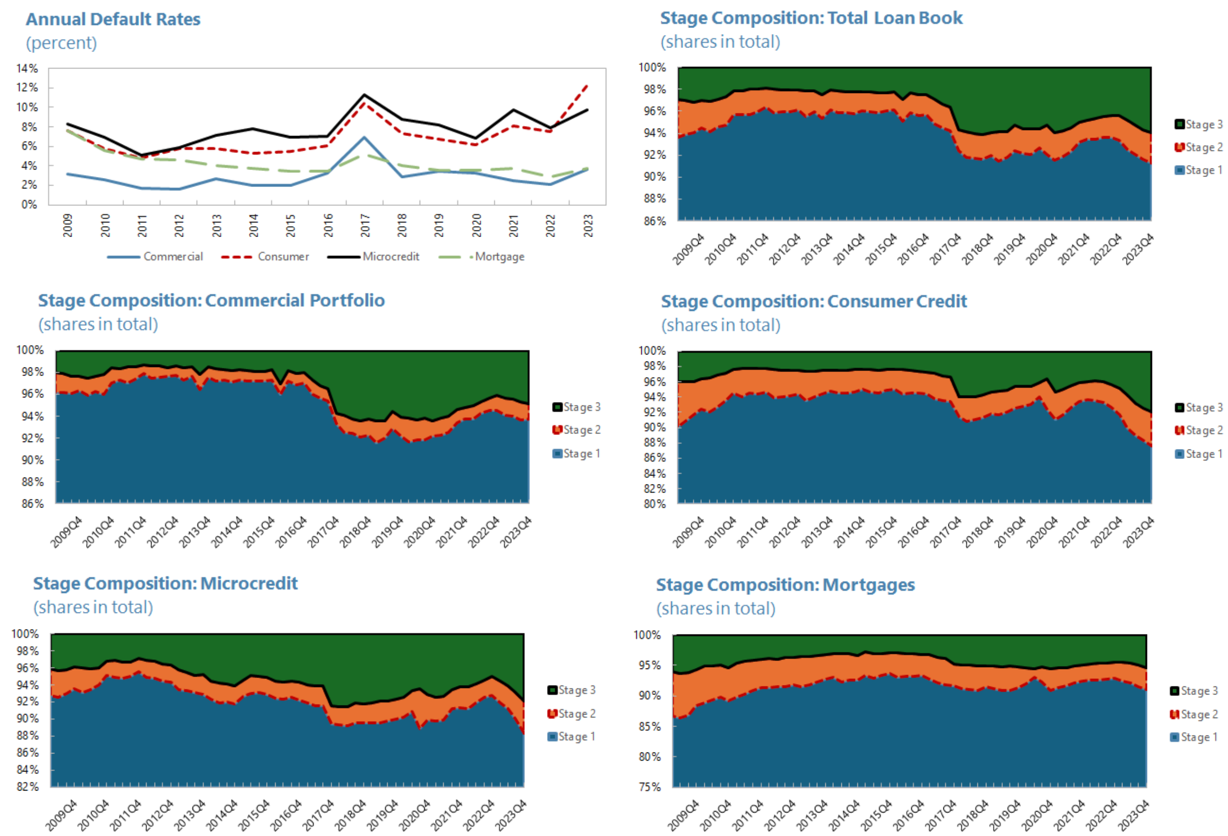
The resulting BMA model structures are shown in Figure 15, model residuals in Figure 16, and the historical contributions in Figure 17. The model fit was produced also for the pandemic period, confirming that the macroeconomic performance-implied Z-scores would have been notably worse than observed; and hence the model residuals in 2020Q2—22Q2 are significantly positive (defined as observed minus fit; Figure 16). Exactly this warranted the exclusion of the pandemic period from the estimation sample.

Figure 11: Colombia: Banking System and Loan Book Structure



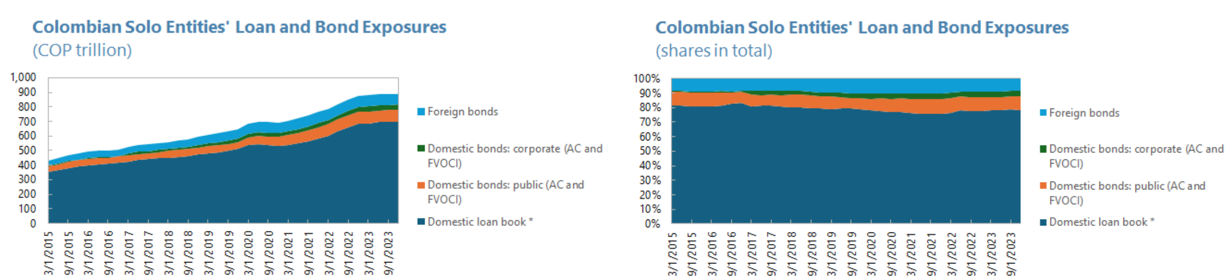
Note: The Colombian banking system is composed of 55 banks at end-2023. This includes one state-owned bank and 54 private commercial banks. "Other" financial institutions comprise brokers, dealers, trust companies, and other residual NBFIs.
Source: SFC and author calculations.

Figure 12: Colombia: Banking System Loan Book—Credit Risk Metrics



Note: Default rates are defined as the flow of Stage 1 and 2 exposures to Stage 3 through year t, divided by the beginning of year t stock of Stage 1 and 2 exposures. The Stage 1/2/3 stock shares are measured at end-quarter positions. The defining criteria for the migration between and prevalence within Stages 1/2/3 are discussed in Section 4.1.
Source: SFC and author calculations.

Figure 13: Colombia: Solo Banks' Loan and Bond Exposures



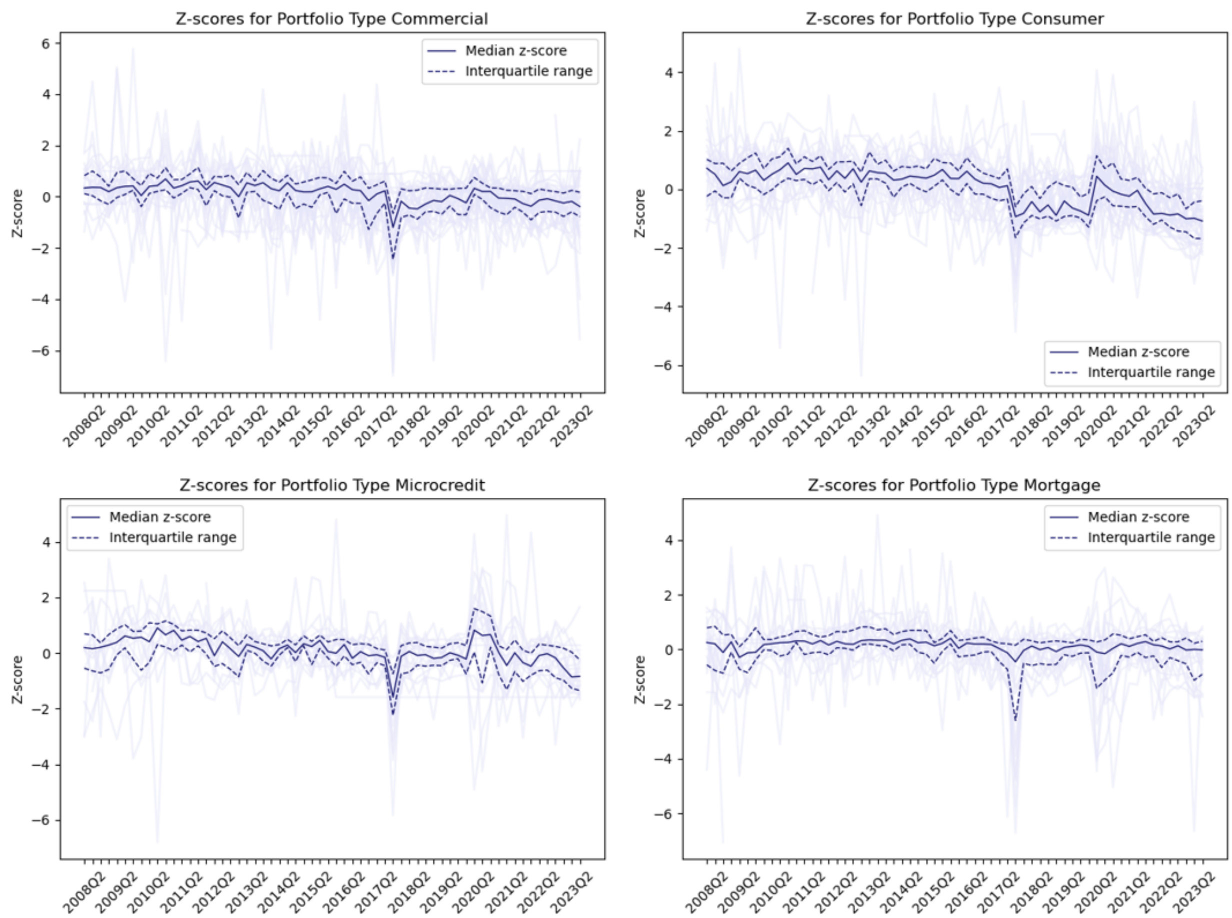
Note: The charts show the evolution of the Colombian solo banks' domestic loan book size alongside domestic and foreign bond exposures. As a caveat, the domestic loan book comprises foreign branch-based lending, which represents only a negligible share, however, at the aggregate banking system level. Banks here comprise all credit institutions ("establecimientos de crédito").
Source: SFC and author calculations.

Table 2: Z-Score Models—Predictor Set and Sign Constraints for Panel BMA

Variable alias	Variable	Commercial	Consumer	Microcredit	Mortgages
RGDP	Real GDP growth (denoted RGDPQ and RGDPA for QoQ and YoY, resp.)	1	1	1	1
INF	Consumer price inflation (INFQ and INFA for QoQ and YoY, resp.)		-1		-1
UR	Unemployment rate (level, abs. QoQ, abs. YoY)		-1		-1
SOV3	3-year sovereign bond yield	-1	-1	-1	-1
TS	Term spread	-1	-1	-1	-1
HP	Residential property price growth (denoted HPQ and HPA for QoQ and YoY, resp.)	1		1	
FX	USD-COP exchange rate (FXQ and FXA for QoQ and YoY, resp.)	-1			
WAG	Wage inflation (QoQ and YoY)		1		1
OIL	Brent crude oil price in USD (QoQ and YoY)	1			
FFR	Fed funds rate	-1			

Note: The table summarizes the inclusion settings and LRM (long-run multiplier) sign constraints for the panel BMA models that are estimated for the Z-scores of four portfolios of all banks. Empty cells denote the exclusion of a variable from the predictor pool. 1: inclusion allowed with a positive sign constraint. -1: inclusion allowed with a negative sign constraint. 0: would indicate the inclusion allowed with no sign constraint (not relevant in this application). Various variables were included in the predictor pool with different transformations, such as QoQ and YoY. These transformations contain different economic information.
Source: IMF staff.

Figure 14: Historical Bank-Portfolio Level Z-Score Estimates



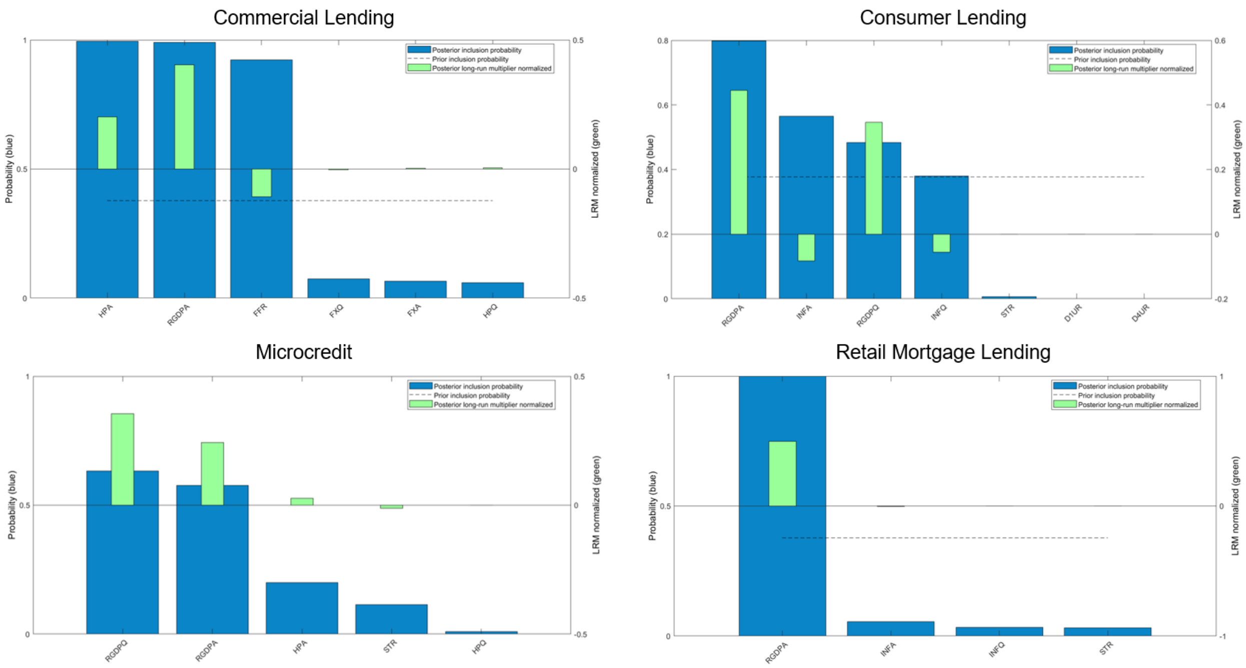
Note: The charts show the estimated historical Z-scores for the four portfolios of all banks in the sample (light blue lines), alongside the cross-bank median and interquartile ranges.
Source: SFC and author calculations.

4.3 Point-in-time credit loss distributions

The banking system's total PiT provision stocks correspond well to the existing PiT provisions for the commercial lending portfolio, and deviates on the up- and downsides for the other portfolios to an extent (Figure 18). Expressed as a percentage of end-2023 loan book exposures, the model's estimated provision coverage stands at 4.4 percent, compared to 4.5 percent for the banks, for the commercial portfolio. The consumer lending portfolio appears to be under-provisioned to an extent according to the estimates; the microcredit and mortgage lending portfolios are over-provisioned according to the estimates. The provisional nature of the estimates should be kept in mind.

The provision coverage estimates and actual coverage differ with a view to the underlying stages (Figure 19). One pattern concerns Stage 2 provisioning, for which the model estimates all point to a notable underprovisioning for all four portfolios. For Stage 3, the commercial, microcredit and consumer

Figure 15: BMA Model Structure



Note: The charts visualize the model structure of the panel BMA models for four portfolios. The left-hand side variables are the banks' Z-scores. The predictor variables' abbreviations are listed in Table 2. The underlying models might involve lags of the right-hand side variables, beyond their time contemporaneous inclusion. The posterior (and prior) inclusion probabilities pertain to the combined inclusion of contemporaneous and lagged terms. The long-run multipliers (green, right axes) represent the sum of the coefficients on a given contemporaneous and lagged predictor variable. They were normalized by multiplying the initial LRMs with the ratio of the standard deviations of the left and right-hand side variables. Therefore, they can be compared across predictors and models.
Source: SFC, Haver, and author calculations.

portfolios appear to all be adequately provisioned (to an extent overprovisioned according to the model estimates), while the mortgage portfolio's coverage appears to be just adequate.

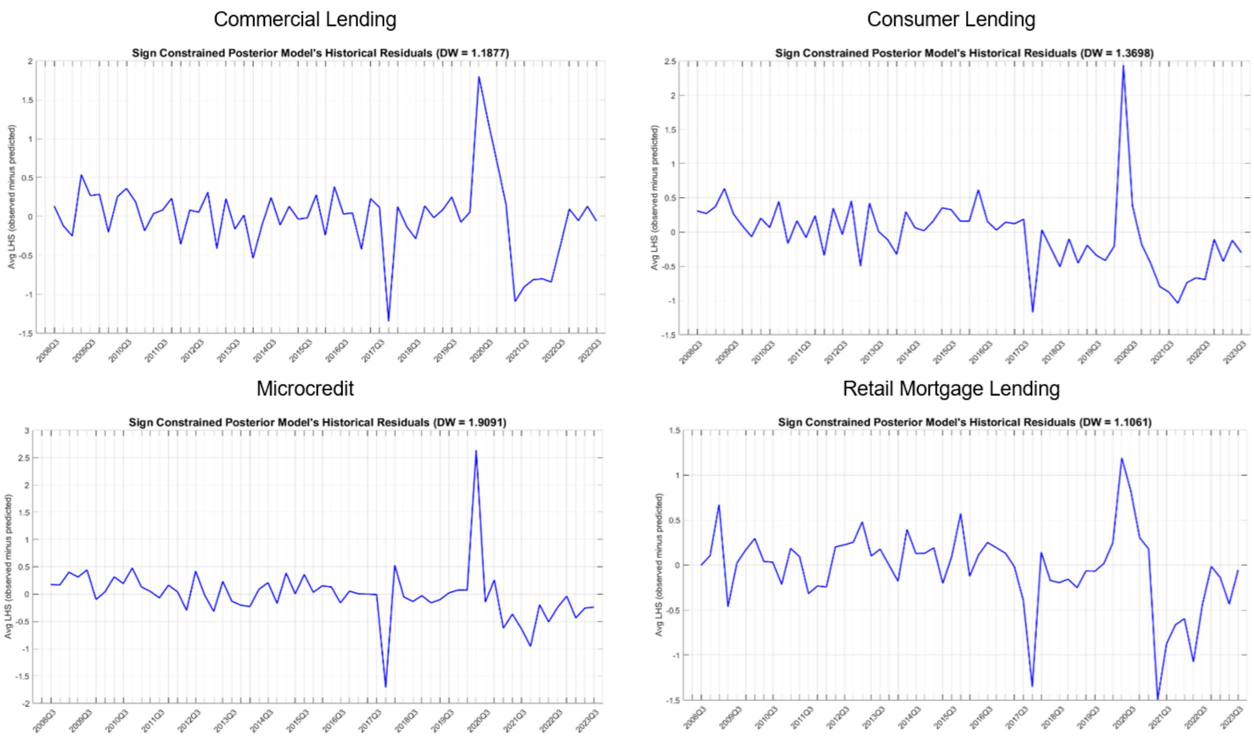
The differences in model-based provision coverage and observed coverage, expressed relative to RWAs, reveals a notable cross-bank-portfolio heterogeneity and potential capital impact from a transition (Figure 20). The median levels of the provision coverage differentials point to a downward move in capitalization in particular for the commercial lending portfolio. The capital ratios impacts of individual banks cover a broad range from about -7 to +12 percentage points.

4.4 Counterfactual and Sensitivity Analyses

Sensitivity 1: VAR(X) Model—Excluding the Pandemic Period

Excluding the pandemic period from the domestic VARX and auxiliary foreign VAR estimation sample results in tighter credit loss distributions. The credit loss distributions are tighter when excluding the pandemic period due to the VAR(X) model's inferior ability to explain the co-dependencies of all macro-financial variables during the pandemic, resulting in more sizable model residuals and hence a

Figure 16: BMA Model Residuals



Note: The charts show the residuals from the bank cross-section average fit and the bank cross-section observed Z-scores historically. The pandemic period (2020Q2-2022Q2) was excluded from the estimation; the fit and residuals were computed here for this period nonetheless.
Source: SFC, Haver, and author calculations.

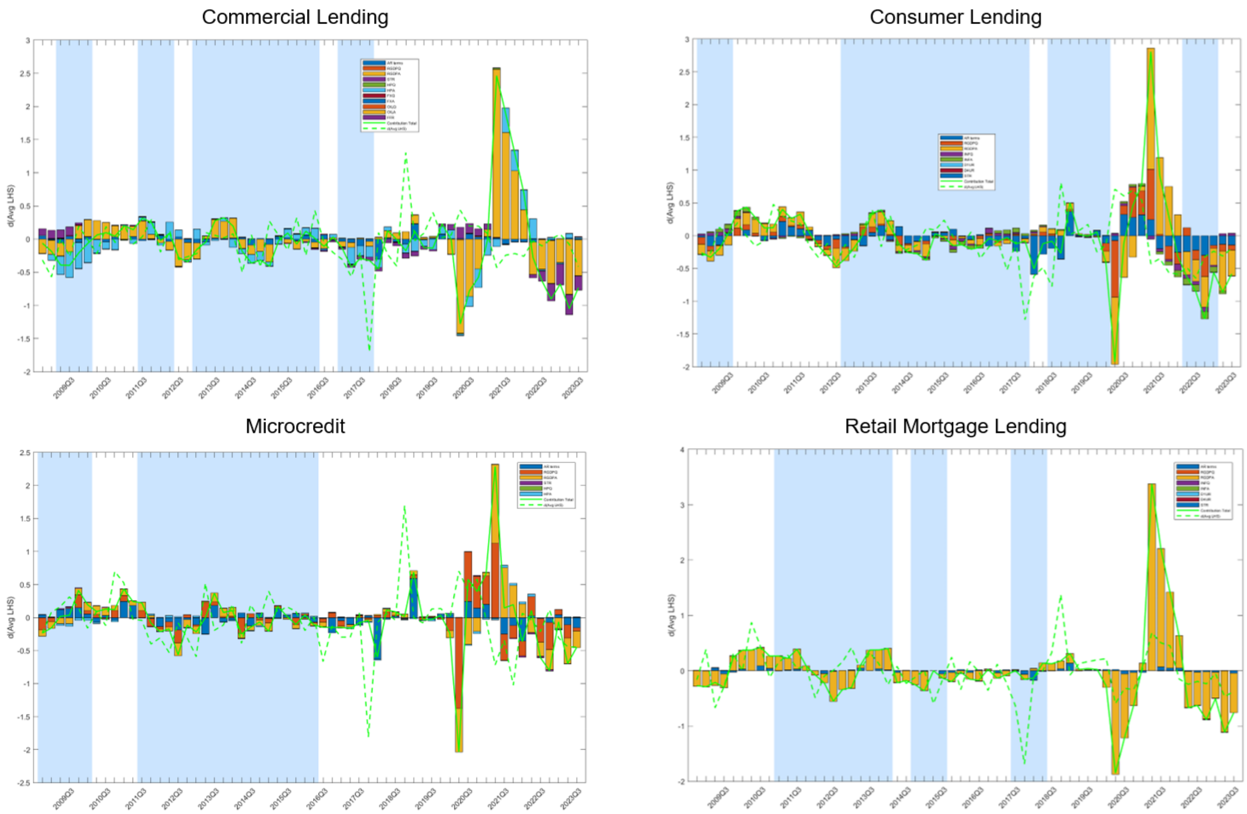
wider density forecast. While the means of the PiT distributions and hence the PiT provisions are not overly sensitive to the inclusion of the pandemic period (Figure reffig:24), the total provisions informed by the upper tails of the distributions are more sensitive.

Sensitivity 2: Residual and Model Uncertainty Off

A first counterfactual analysis in this context entails the deactivation of residual uncertainty from all relevant model components, which results in tighter credit loss distributions. This includes the residuals from the domestic VARX, the auxiliary foreign VAR, and the four Z-score econometric panel equations. As an illustration for this counterfactual, we show the PiT credit loss distributions, with and without account for residual uncertainty in the density forecast simulations (Figure 22). The distributions become tighter, to a sufficiently strong extent so that even their means shift to the left. The tails of the distributions are, of course, sensitive too.

When switching the model uncertainty component of the BMA model elements off, the resulting credit loss distributions do not—in this application—change notably. When switching off the model uncertainty component of the BMA equations for the Z-scores (for the four portfolios), the credit loss distributions do not become notably tighter at the aggregate banking system level (Figure 23). This is not always the case; as in other applications for other banking systems, the model uncertainty

Figure 17: BMA Models—Historical Contributions



Note: The charts show the historical contributions from the models' predictor variables. Contemporaneous and lagged terms of the predictor variables were combined. Blue areas denote the periods when the data for the underlying bank cross-section coverage increases (an unbalanced panel underlies the models). The pandemic period (2020Q2-2022Q2) was excluded from the estimation; the historical contributions were computed and included in the charts for this period, nonetheless.
Source: SFC, Haver, and author calculations.

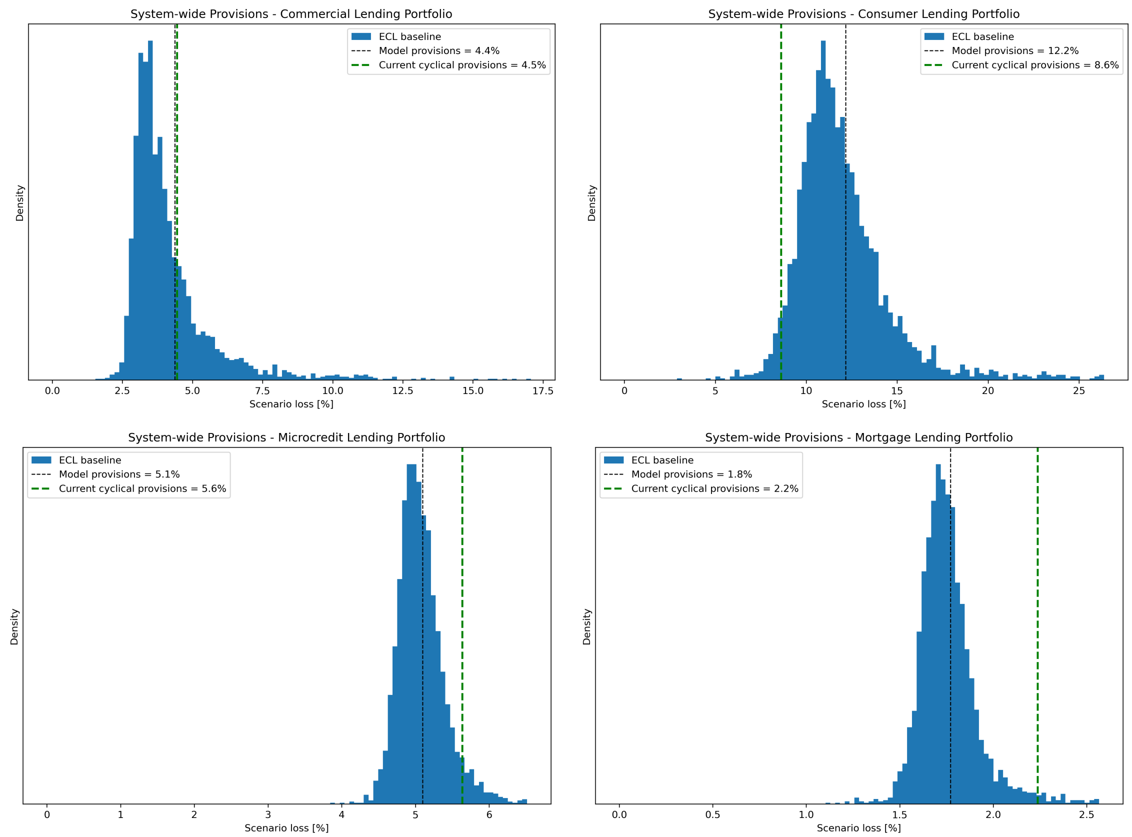
component does play a quantitatively more relevant role.[14]

Sensitivity 3: Re-Anchoring Macro-Financial Baseline Paths

The model allows the user to re-anchor the baseline paths, which has the directionally expected impacts on the resulting credit loss distributions. The re-anchoring feature has been used, as an illustration, for three macro variables in the domestic VARX: real GDP growth, the unemployment rate, and CPI inflation. They were re-anchored from the VARX model-based raw density forecasts to an IMF WEO baseline forecast (October 2023) for Colombia (Figure reffig:27). It implies an economically more favorable trajectory for GDP growth and unemployment rates, alongside lower inflation, than the domestic VARX model. Hence, the credit loss distributions involving the re-centered macro density forecasts are, correspondingly, shifted to the left, i.e., pointing to lower PiT credit losss and provisioning

[14] Any finding in this regard is fine. I.e., the finding that the model uncertainty component is not sizable does not obviate the appeal and rationale for employing the BMA methodology. Its value still stems from the ability to impose sign constraints and to do aim to obtain robust models that are not subject to the concern of being "hand-picked." The fact that model uncertainty may be small can, furthermore, not be known upfront.

Figure 18: System-Level PiT Provisions: Models vs. Existing



Note: The credit loss distributions were based on a point-in-time simulation anchored in end-2023 starting point parameters, with a sufficiently long horizon (30 years) to cover the residual maturities of the longest-dated loans (relevant for mortgages). The distributions represent the total across stages 1/2/3 and across banks.
Source: SFC and author calculations.

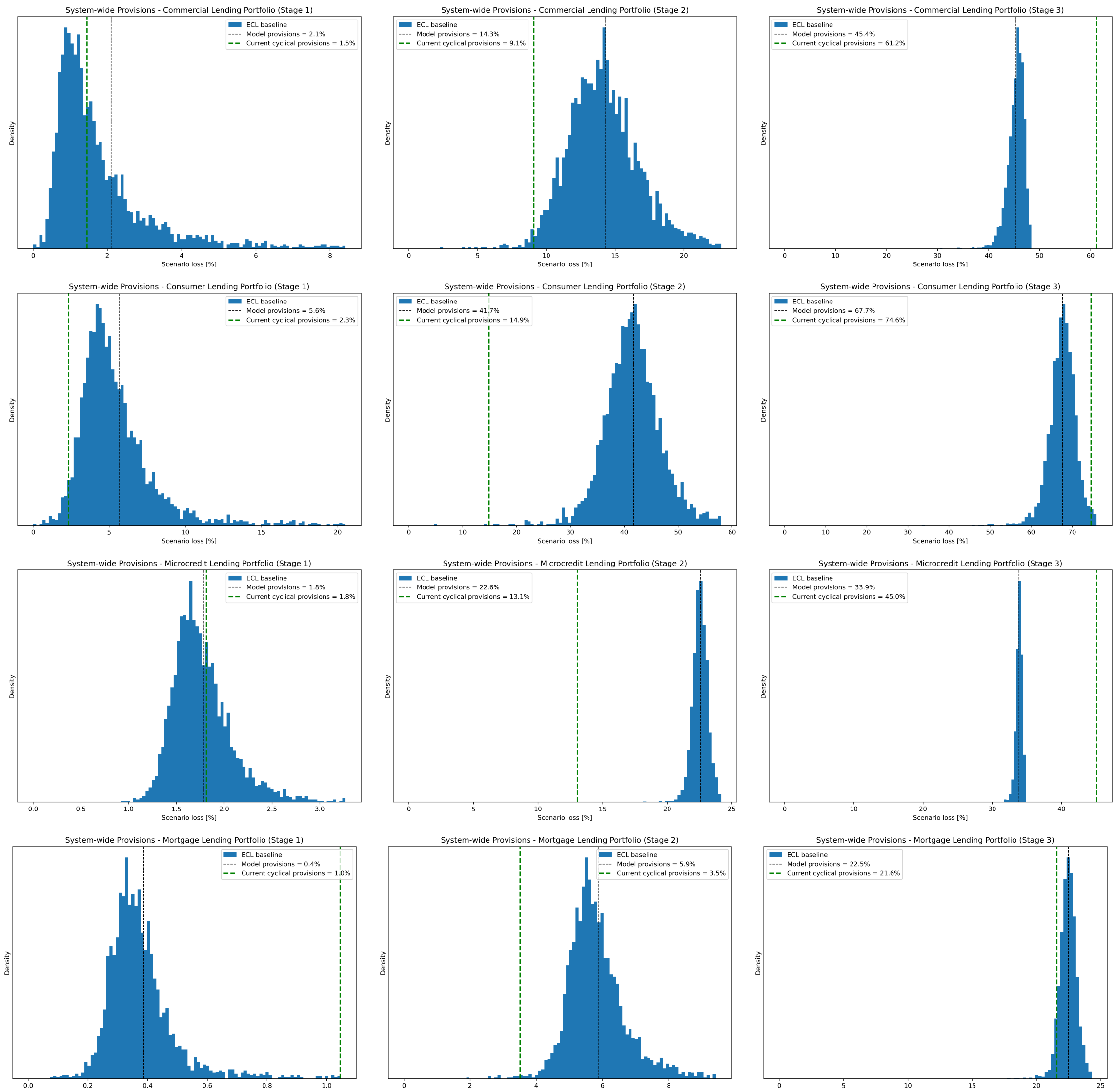
needs (Figure 25).

Sensitivity 4: Stage 1 Provisioning with Lifetime Horizon

Switching the ECL horizon for Stage 1 exposures from 1-year to lifetime increases the provisioning needs as expected, and most notably in relative terms for the longer duration mortgage portfolios. The horizon for the Stage 1 ECL and provisioning calculations can be switched from 1-year to any other longer horizon, including a lifetime horizon, in the model (to recall, the CECL provisioning scheme in the U.S. is an example that considers a lifetime horizon for Stage 1 exposures).

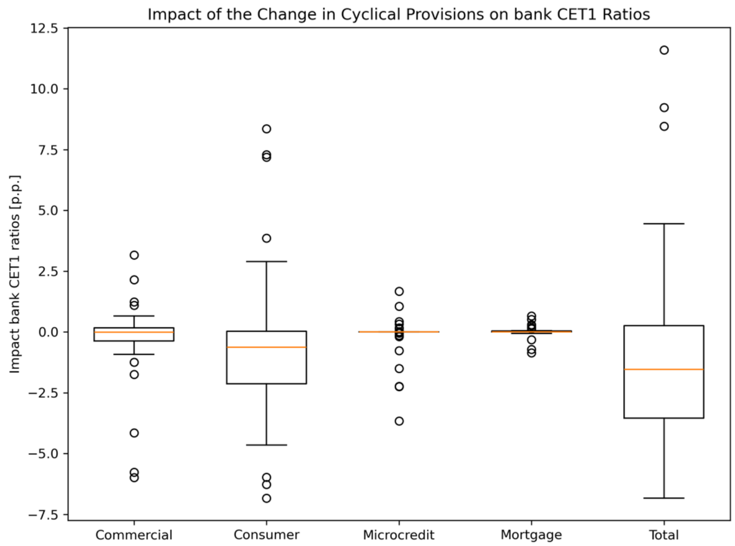
The resulting provisioning coverage increases for all portfolios when switching to the lifetime horizon (Figure 26). In absolute percentage point terms, the shift is most pronounced for the consumer credit portfolio; yet, its absolute provision coverage is the highest in the first instance. More relevant to examine are, therefore, the relative changes in the coverage ratios. They amount to 1.7x, 1.5x, 1.2x, and 2.2x for the commercial, consumer, microcredit, and mortgage portfolios, respectively. The largest multiple at 2.2x for mortgages is the natural consequence of the mortgage loans' longest average duration in a cross-portfolio comparison.

Figure 19: System-Level PiT Provisions by Stages: Model Vs. Existing



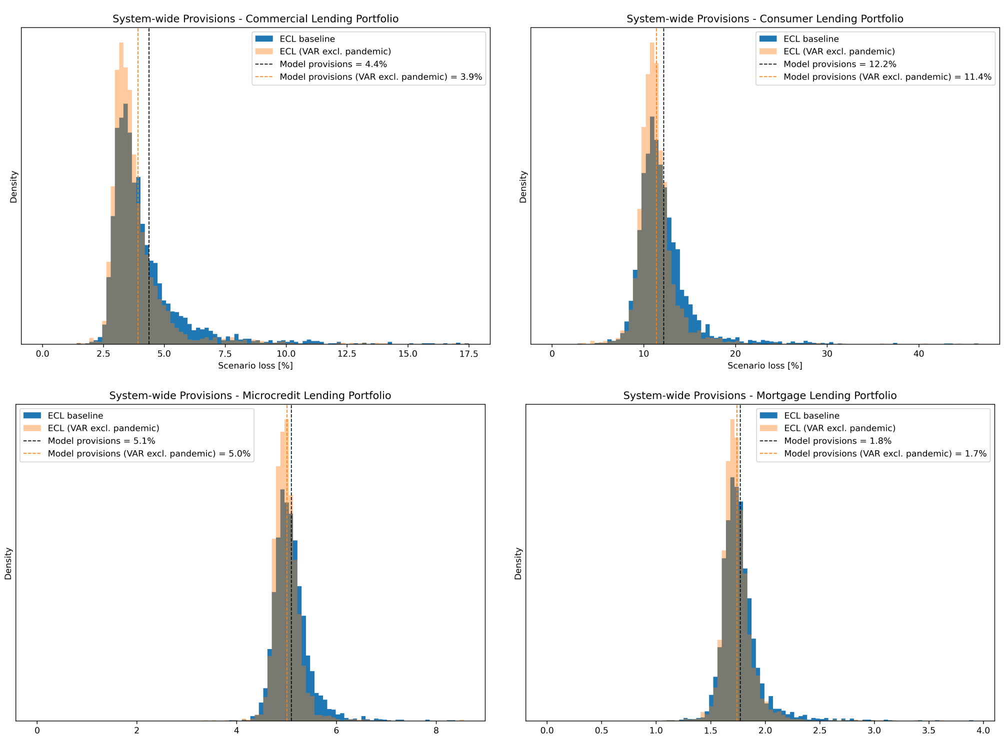
Note: The credit loss distributions were based on a point-in-time simulation anchored in end-2023 starting point parameters, with a sufficiently long horizon (30 years) to cover the residual maturities of the longest-dated loans (relevant for mortgages in particular). The distributions represent the total across stages 1/2/3 and across banks.
Source: SFC and author calculations.

Figure 20: Change in PiT Provision Stocks—Capital Impacts



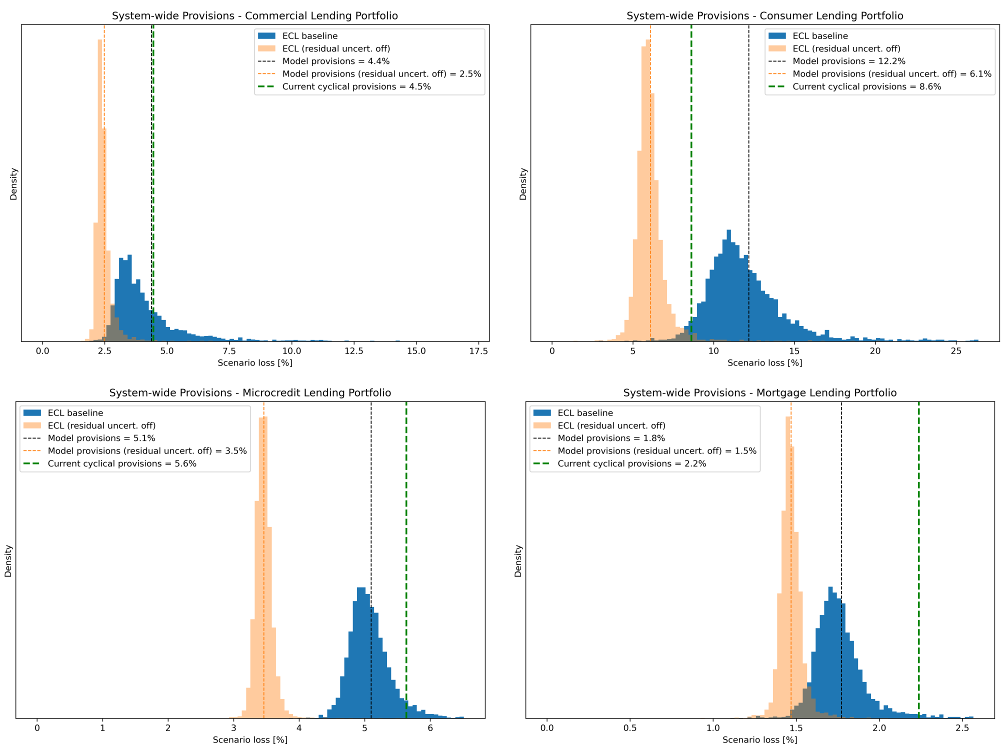
Note: The box plots show the cross-bank distribution of capital ratio shifts, in percentage points, resulting from a hypothetical move from existing provision stocks to the model-based ones. A positive (negative) shift implies that capital ratios move up (down), corresponding to current overprovisioning (underprovisioning) relative to the model-based estimates.
Source: SFC and author calculations.

Figure 21: Sensitivity 1: PiT Credit Loss Distributions—Excluding Pandemic Period



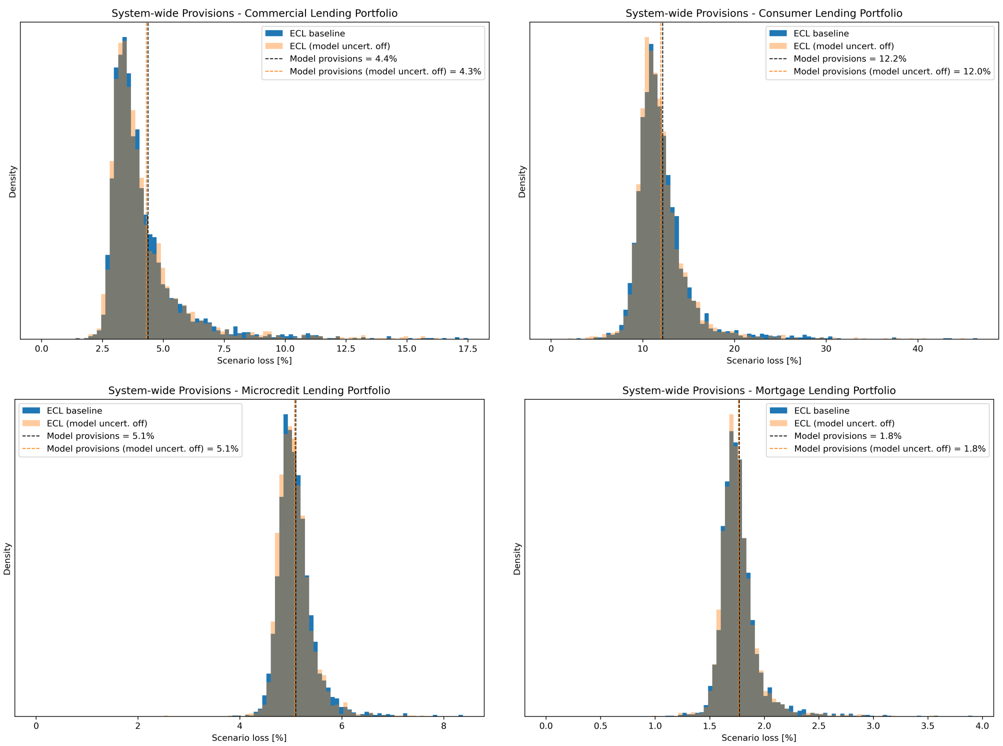
Note: The charts show the PiT credit loss distributions for the four portfolios under the base case (blue) and a counterfactual under which the pandemic period was excluded from the domestic VARX and the auxiliary foreign VAR (orange).
Source: SFC and author calculations.

Figure 22: Sensitivity 2a: PiT credit loss distributions—Switching Residual Uncertainty Off



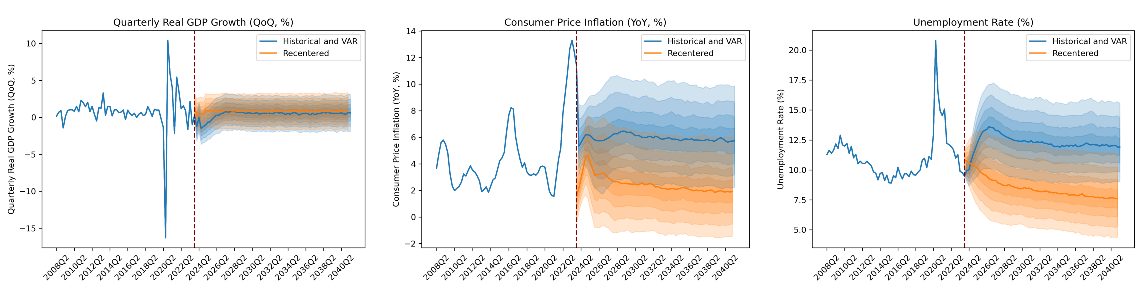
Note: The charts show the point-in-time credit loss distributions for the four portfolios under the base case (blue) and a counterfactual under which the residual uncertainty component of the density forecast for all underlying model components was switched off (orange).
Source: SFC and author calculations.

Figure 23: Sensitivity 2b: PiT credit loss distributions—Switching Model Uncertainty Off



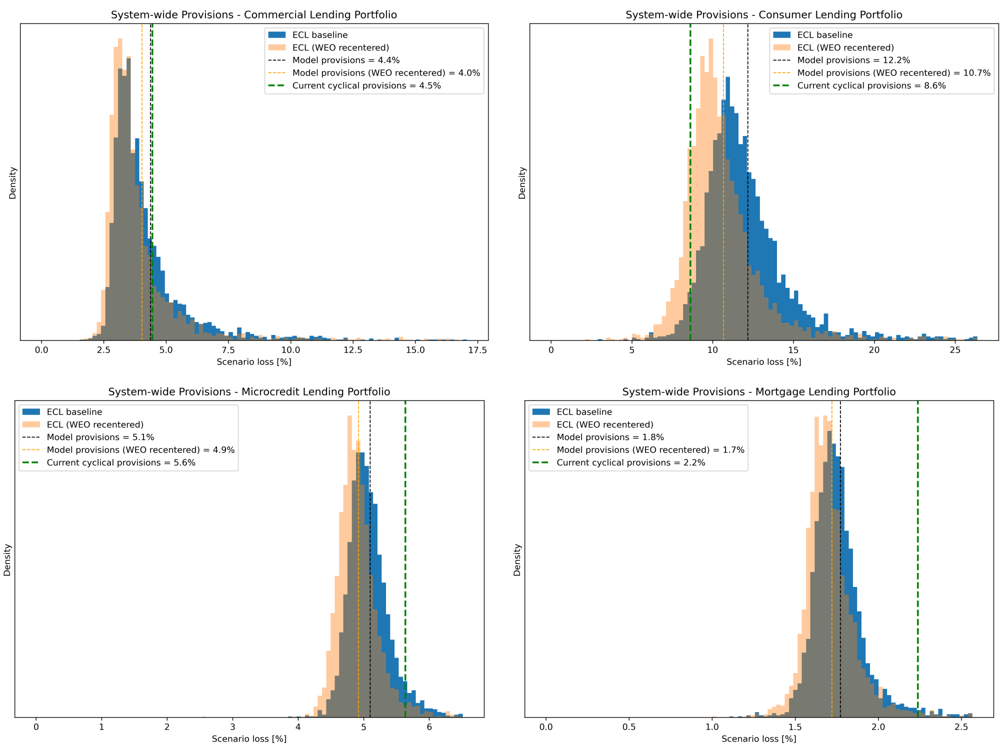
Note: The charts show the point-in-time credit loss distributions for the four portfolios under the base case (blue) and a counterfactual under which the model uncertainty component of the density forecast for all underlying model components was switched off (orange).
Source: SFC and author calculations.

Figure 24: Sensitivity 3: Re-Anchoring the Macro-Financial Baseline Scenario



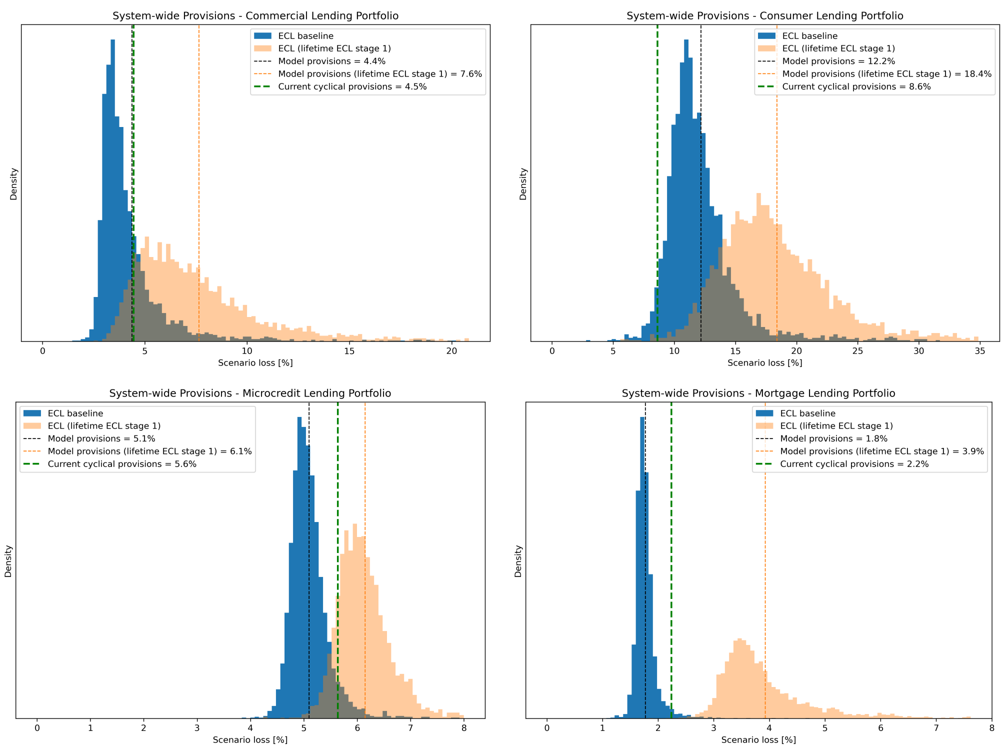
Note: The charts compare the initial domestic VARX-based density forecasts (blue shaded) and their implied baseline medians (blue line) alongside the re-anchored distributions (orange) whose mean was informed by the IMF WEO of October 2023.
Source: SFC and author calculations.

Figure 25: Sensitivity 3: PiT Credit Loss Distributions—Re-Anchoring Macro-Financial Baseline



Note: The charts show the point-in-time credit loss distributions and their means based on the initial base case simulation (blue) alongside the credit loss distributions for which the macro density forecasts were re-anchored to match an alternative baseline (IMF WEO in this case).
Source: SFC and author calculations.

Figure 26: Sensitivity 4: PiT Credit Loss Distributions for Stage 1—Lifetime Horizon for Stage 1



Note: The charts show the PiT credit loss distributions for Stage 1 exposures specifically, comparing the base case for which the ECL horizon is set to 1-year (blue), alongside the counterfactual of a lifetime horizon (orange).
Source: SFC and author calculations.

5. Conclusions

This paper presents a simulation-based ECL model designed to generate credit loss distributions which are generated using a multitude of macro-financial scenarios. The model is modular, integrating macroeconomic density forecasting, a transition matrix module, an LGD module, and an ECL calculator. By being simulation-based, it avoids ad hoc scenario selection and enables a robust and forward-looking estimation of provisioning needs and capital buffers.

The framework supports both micro- and macroprudential use cases. It can be used for assessing the adequacy of credit loss provisions, a task that should be of interest for microprudential bank supervision. It can further be embedded in macro stress testing frameworks, and be employed to inform macroprudential policy calibration, such as a CCyB. An illustrative application to Colombia demonstrates the model's practicality for policy institutions.

Future extensions of the model can and should be considered. These include, for example, differentiating fixed and variable rate exposures and nuancing the model's inner structure in this regard, endogenizing discount factors, and moving from a linear to a nonlinear macro-financial model core.

Annexes

A1. IFRS 9—A Primer

The primary reference for the IFRS 9 principles is the framework published by the International Accounting Standards Board (IASB) in 2014 (IASB, 2014). It was the result of aiming to overhaul the accounting principles after the global financial crisis (GFC), which was judged to have been partially driven by the shortcomings of the previously prevalent accounting framework (IAS 39). IAS 39 was deemed to be too backward-looking and deferring the recognition of loan losses. It thereby was judged to have contributed to procyclical macro-financial dynamics in general and the emerging imbalances that led to the GFC specifically. About 90 percent of the countries in the world (including Colombia) follow IFRS, and hence its revised IFRS 9 component is relevant for them since it became effective in January 2018.

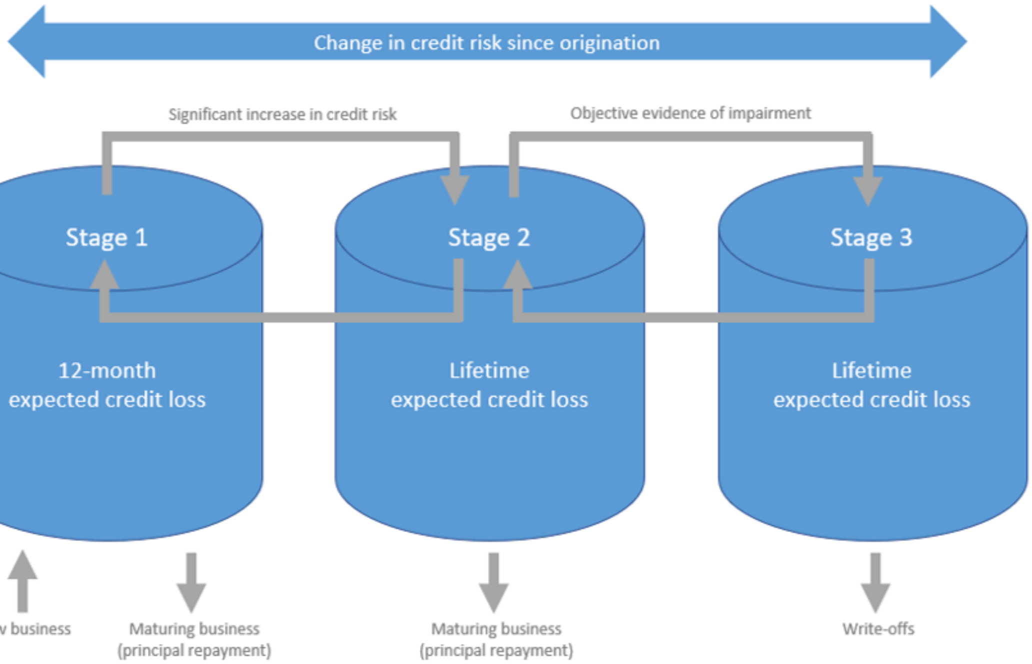
IFRS 9 comprises three areas of reform. They include: (1) the classification and measurement of financial assets and liabilities; (2) the expected credit loss (ECL)-based impairment model principles; and (3) hedge accounting. The first two of these three components, and with a strong weight on the second, are the ones most relevant for the model development in this paper.

At the heart of the ECL-based impairment model under IFRS 9 lies its risk-based categorization (staging) of financial assets along with stage-specific provisioning. Figure 27 visualizes these staging principles. Exposures generally enter Stage 1 upon origination, regardless of their initial "absolute" level of default risk. Depending then on their change in default risk since origination, they may move to Stage 2 or 3. IFRS 9 is principle-based, implying that here—as in numerous other respects—banks can decide how to define the criteria for such stage transitions, subject to guidance provided by the IASB (IASB, 2014). Stage 1 assets are to be provisioned for with a 12-month horizon; Stages 2 and 3 assets with a lifetime horizon. The previous IAS 39 accounting framework did not entail any provisioning for Stages 1 and 2. The move to ECL provisioning for stages other than Stage 3, and the lifetime horizon for Stage 2, was a step to address the "too little, too late" concerns with provisioning under the previous accounting regime. Under IFRS 9, the provisioning can be characterized as "more and earlier."

The ECL-based provisioning is meant to apply to exposures that are measured at amortized cost (AC) and fair value through other comprehensive income (FVOCI). The classification and measurement of financial assets is one of the areas that was reformed under IFRS 9. The IFRS 9 classification scheme is summarized in Figure 28. The details of the criteria and tests to decide which assets map into which measurement category are omitted here; IASB (2014) has the details. AC and FVOCI exposures (involving loans and bonds) are subject to the ECL provisioning scheme.[15]

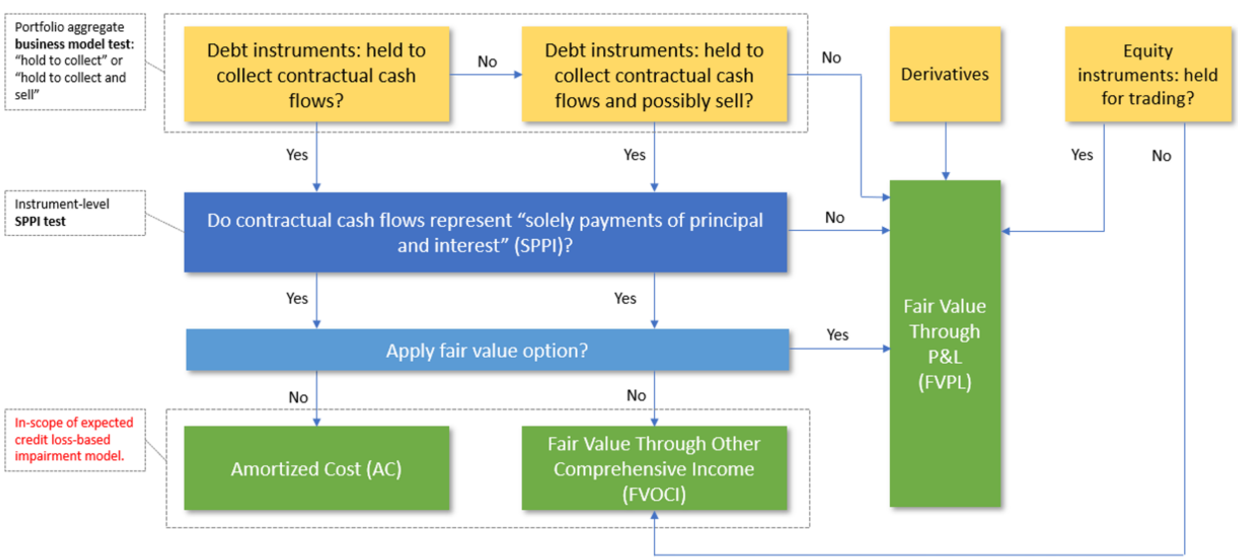
[15]The classification and measurement under IAS 39 accounting rules compare to IFRS 9 as follows: loans and receivable and held-to-maturity bonds under IAS 39 were measured at AC. Fair value through the P&L (FVPL) exposures were measured at FV through the P&L. The previously relevant notion of available-for-sale (AfS) exposures were measured at FV through the OCI account. The concepts of HtM and AfS exposures do not exist anymore under IFRS 9. There are just three classification/measurement principles remaining: AC, FVOCI, and FVPL. Valuation changes of AfS exposures under IAS 39 were to be recorded only through FVOCI, while for FVOCI exposures under IFRS 9, the credit risk-related provision charges for these exposures need to be accounted

Figure 27: Stage Transition Process Under IFRS 9



Note: The schematic summarizes the staging scheme and provision requirements (12-month vs. lifetime) as defined by IFRS 9 (IASB, 2014).
Source: Figure 1 in Section 2 in Gross et al. (2020).

Figure 28: Classification and Measurement of Financial Assets Under IFRS 9



Note: The schematic summarizes the classification and measurement principles for financial assets as defined under IFRS 9 (IASB, 2014). Orange boxes depict types of financial assets (the classification). Green boxes depict the measurement principles. For additional details, including regarding the "tests" involved (business model text, SPPI test), see IASB (2014).
Source: The authors.

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for through the P&L, alongside the full valuation change through the FVOCI account.

A2. CCyP vs. CCyB—A Comparison

The objectives of countercyclical provisioning (CCyP) and countercyclical capital buffers (CCyB) are essentially identical. They aim to (1) let the banking system accumulate buffers during economic boom times, to thereby enhance their resilience through the availability of releasable buffers during economic downturns; and (2) thereby also lean against the build-up of imbalances ("lean against the cycle"), i.e., to counteract an overly exuberant credit growth and associated price inflation (at the economy level and in market segments such as real estate) during boom times and therefore to reduce the potential for and extent of downturns.[16]

For achieving these objectives, the CCyP and CCyB operate through different transmission channels. The CCyP operates through the build-up of provision stocks, which have a direct bearing on actual capital ratios of banks, not primarily their capital requirements, but secondarily so.[17] The CCyB instead operates primarily through letting capital requirements move dynamically. In the latter case, actual capital ratios would be affected secondarily if a change in a capital requirement induces banks to change their actual capital ratios, to maintain a voluntary buffer that separates required and actual capital ratios.

The CCyP in Colombia entails the use of accumulation and release triggers. The accumulation phase prevails as long as no economic downturn arises. A set of quantitative indicators signal a downturn and thereby trigger the release phase. These indicators and hence the downturn signals are bank-specific. They include the quarterly change of individual provisions, the quarterly cumulative provisions net of recoveries, the real annual growth rate of the gross portfolio, and provisions net of recoveries relative to a gross financial margin; for all four of which, specific thresholds are set in the regulation. After the release phase starts for a bank when all four indicators' thresholds are surpassed, it can use up to 70 percent of its standing countercyclical provision stock to counter-balance periodic losses that result from the specific provision build-up and losses from NPL write-offs whose realized loss may exceed the specific provisions previously built for them. Table 3 provides a brief comparison of the CCyP and CCyB scheme, including regarding the release and re-accumulation phase of the CCyP. The description of CCyP is to an extent specific to its design in Colombia (apart from the notes placed under the objective and transmission dimension).

[16]Provisions are meant to cover expected losses. Capital is meant to cover unexpected losses. Loan loss provisions shall cover an expected loss, whether with a short horizon or a longer term—up to lifetime—horizon of banks' credit exposures, but in any case not exceeding their lifetime horizon. A countercyclical provision stock, however, would be informed by the tail of the credit loss distribution, not its mean, which makes it more sizeable and pertain to an unexpected loss. A CCyB would leave the intended rationale of point-in-time provisions intact and reflect a countercyclical provision component through capital requirements.

[17]One secondary effect is that the amount of risk weighted assets would be influenced by a CCyP as risk weights apply to exposures net of countercyclical provisions (and specific provisions)—a buildup of countercyclical provisions would therefore reduce capital requirements, all else equal. Risk weights may further be indirectly influenced, especially when banks employ the IRB approach and if the countercyclical provisioning would have an impact on the risk parameters that feed the IRB risk weight formulas. Overall, this means a secondary impact also through capital requirements, as they build on risk weighted assets.

Table 3: Countercyclical Provisioning (CCyP) vs. Capital Buffer (CCyB)

	CCyP	**CCyB**
Objective	Enhance banking system resilience and lean against the cycle, i.e., make booms less exuberant and recessions less likely and less deep.	
Transmission	Primarily through actual capital through the build-up of provision stocks. Secondarily through capital requirements.	Primarily through capital requirements. Secondarily through actual capital.
Tax treatment	The cost of building CCyP and specific provisions is tax deductible. The cost of building general provisions is not tax deductible.	No direct relevance for tax effects.
Accumulation	Countercyclical provision stock computed based on difference between a downturn credit risk parameter set and point-in-time credit risk parameter set.	Based on aggregate economic cyclical indicators such as credit to GDP gaps, numerous other macro-financial data and indicators, early warning models, growth-at-risk type models, etc. The release phase would further be informed by indicators of financial stress and metrics that may indicate that capital buffer requirements are becoming binding.
Release	Four threshold-based indicators need to jointly provide a "downturn signal" to trigger the release. Release then means that up to 70 percent of then-arising point-in-time provisions/losses (including through specific provision build-up and loss differentials from NPL write-offs with LGL above provision coverage ratios) can be counter-buffered with a release of the previously built countercyclical provision stock.	
Move from release back to accumulation phase	After the release phase lasted up to six months, the normal-times CCyP coverage is to be reached after no more than 18 subsequent months.	

Note: The description of the tax treatment and the accumulation and release dynamics as summarized here is specific to Colombia. The CCyP design in these dimensions may differ across jurisdictions that use a CCyP.

Source: The authors.

A numerical example helps illustrating how a CCyP and CCyB would influence capital, RWAs, and capital requirements. It is discussed here under the assumption that the banks follow the standardized (STA) approach, as relevant for the Colombian banks, for example, at present.[18] As recalled earlier,

[18] A separate discussion can be devised for the case when the IRB approach would be in place, for some or all banks. This would involve the role that the IRB shortfall mechanism and the treatment of risk weights and

the cost of building provisions subtracts from capital; and STA risk weights apply to exposures net of specific provision balances, which include countercyclical provisions. Moving to the new ECL model, while maintaining a the CCyP mechanism and assuming that the model will be applied to all portfolios, will imply that general provisions as currently relevant for some of the portfolios will become irrelevant. The numerical example (further below in this section) explains what the CCyP and a CCyB scheme would imply.

Countercyclical provision balances would (1) not subtract from capital anymore, and (2) not subtract anymore from the exposures before applying the STA risk weights. Only the PiT provisions would still mean a subtraction in these two regards. An additional buffer requirement—the CCyB—would then result as a function of what was previously denoted as the CCyP.

implied capital requirements for nonperforming exposures will play.

A3. Informing a CCyB from the Through-the-Cycle Loss Distribution

We can express the capital requirements a bank faces as follows:

$$\frac{K}{RWA} \geq \rho^*, \tag{6}$$

where K is a bank's available capital, RWA its risk-weighted assets (both in currency units), and ρ^* the capital requirement (e.g., 14 percent). For the purposes of this analysis, we split ρ^* in two parts, the countercylcical capital buffer $CCyB$ and all other requirements (Pillar 1, Pillar 2, capital conservation buffer, systemically important bank buffers), which we denote by ρ:

$$\rho^* = \rho + CCyB. \tag{7}$$

We further split risk-weighted assets in those arising from credit risk (RWA_{CR}) and those pertaining to other sources such as market risk, operational risk, and others (denoted by $RWA_{\overline{CR}}$):

$$RWA = RWA_{CR} + RWA_{\overline{CR}}. \tag{8}$$

Equation (6) can then be reformulated as:

$$K \geq (\rho + CCyB) \cdot (RWA_{CR} + RWA_{\overline{CR}}). \tag{9}$$

A sufficient condition for equation (9) to hold is that enough capital is available to cover RWA from credit risk *and* RWA from other sources. We will assume the latter condition is fulfilled exactly and focus on the following capital requirement:

$$K_{CR} \geq (\rho + CCyB) \cdot RWA_{CR}. \tag{10}$$

We can now express RWA_{CR} as the product of $\widehat{A}_{CR}$, the total prudential exposure amount for credit risk (the sum of exposure amounts to which risk-weight densities are applied),[19] and $\widehat{RW}$ the effective risk-weight.[20] Equation (10) then becomes:

$$K_{CR} \geq (\rho + CCyB) \cdot \widehat{RW} \cdot \widehat{A}_{CR}. \tag{11}$$

[19]In the STA approach, specific provisions are deducted from exposure and some credit risk mitigation techniques (such as collateral and guarantees) can also reduce the exposure amount. Off-balance sheet exposures are added via credit conversion factors. See CRE20 and CRE22 in BCBS (2023).

[20]Defined such that $\widehat{RW} \cdot \widehat{A} = RWA_{CR}$

By normalizing the equation with the size of total credit risk assets A_{CR}, defining the ratios $k_{CR} = K_{CR}/A_{CR}$ and $\widehat{a}_{CR} = \widehat{A}_{CR}/A_{CR}$, and making explicit that both these terms are a function of provision stocks p,[21], we obtain:

$$k_{CR}(p) \geq (\rho + CCyB) \cdot \widehat{RW} \cdot \widehat{a}_{CR}(p). \tag{12}$$

Based on equation (12), one can show how a model predicting macro scenario-conditional "credit loss densities"[22] can inform essential components of bank solvency requirements. The principle behind these requirements is to have banks hold credit loss provisions (a contra-asset with negative value), alongside capital for covering unexpected losses.[23] While *provisions* are set to cover the expected losses, capital is held by banks to cover losses going beyond those expected losses, covering a quantile of the probability distribution of losses. For the purposes of deriving the calibration of a CCyB, we split capital requirements into a *"minimum"* and a *countercyclical* component. In equation (12), they are driven by ρ (the sum of Pillar 1, Pillar 2, and other buffer requirements) and the $CCyB$, respectively.

Provisions An appropriate level of provisions can be derived for each bank based on the model output, as illustrated in Figure 1. By deriving the PiT loss distribution, one can compute its mean, the *expected losses* that need to be covered by provisions.

Whether they are derived with the model or through other approaches, provisions are pro-cyclical, i.e., they decrease in booms and increase in recession periods. This is shown in Figure 1: in the subfigure on the bottom (illustrating a recession), the loss distribution, shown as a fraction of total credit risk exposures, stretches out further to the right than in the subfigure in the middle (depicting a boom). The mean values of the distributions, showing the required level of provisions, vary accordingly.

Actual levels of provisions affect both the right- and the left-hand side of equation (12). Provisions are deducted from available capital, thus affecting $k_{CR}(p)$, and are also deducted from the exposure value in the standardized approach,[24] thus affecting $\widehat{a}_{CR}(p)$.[25]

Minimum capital requirements Once the appropriate level of provisions has been determined and thus the available capital $k_{CR}(p)$ and exposure $\widehat{a}_{CR}(p)$ are set, the minimum capital requirements (kr_{CR}^{min}) can be computed. Expressed as a fraction of total credit risk exposures, they are given by:

[21] Provisions are deducted from capital and—in the STA approach—from exposure, hence linearly reduce k_{CR} and $\widehat{a}_{CR}$

[22] That is credit losses expressed as a fraction of credit exposure.

[23] For simplicity, this section will not discuss different types of capital. The argument holds for Core Equity Tier 1 capital as for Tier 1 and total capital.

[24] The effect is similar in the case a bank uses the IRB approach to computing risk-weights (CRE30 to CRE36 in BCBS, 2023), which is not further elaborated on here, to simplify the exposition.

[25] Expected losses can be computed over different time horizons, typically over one year or over the lifetime of the exposures, see Section 2.2. All else equal, the longer the chosen time horizon, the further the loss distribution would be stretched to the right and the more its mean may increase. Once the horizon is set, the provisions can be computed with the model and other components of the solvency requirements (minimum capital requirements and the CCyB, see below) derived.

$$kr_{CR}^{min} = \rho \cdot \widehat{RW} \cdot \hat{a}_{CR}(p). \tag{13}$$

Conditional on the level of provisions p, none of the parameters in equation (13) are informed by the model. Risk-weights $\widehat{RW}$ in the standardized approach are given by the BCBS (2023) framework and the minimum capital ratio ρ is constant as per regulation (Pillar 1 requirements, capital conservation buffer) or determined by the supervisory authorities (bank-specific Pillar 2 requirement and buffer for systemically important banks).

However, while minimum capital requirements are not informed by the model, they can be represented on the loss distribution of Figure 1. Whether minimum capital requirements are pro-cyclical, counter-cyclical or do not exhibit a cyclical pattern at all is not straightforward to predict. ρ is expected to be somewhat pro-cyclical (driven by bank-specific Pillar 2 requirements), $\widehat{RW}$ pro-cyclical (driven by deteriorating credit ratings in downturns) and, as explained above, $\hat{a}_{CR}$ slightly anti-cyclical (driven by pro-cyclical PiT provisions that are deducted from exposures). However, the combined effects of provisions and risk weights is expected to be decidedly pro-cyclical. Building new provisions decreases both sides of equation (12) but the effect is stronger on capital, because the right-hand side is weighted.[26] This is illustrated in Figure 1 with the second vertical bars, denoted by $ECL_{PiT} + CyK$, that are further to the right in the sub-figure illustrating recession times.[27]

The countercyclical capital buffer (CCyB) The CCyB is a macroprudential tool aiming to ensure that capital requirements take account of the macro-financial environment, specifically the position in the cycle and protect the banking system from the buildup of system wide risk in upturns (BCBS, 2010). It is meant to help dampen exuberant booms (leaning against the wind) and to provide releasable buffers during downturns, thereby contributing positively to banking system resilience and upholding bank lending potential during recessions.

A CCyB for credit risk exposures can be calibrated within the model framework.[28] The first step entails deriving the system-wide through-the-cycle distribution of historical tail losses. This distribution is illustrated in Figure 1 and represents the probability density of bank credit risk tail losses expressed as a fraction of total credit risk exposure.

By setting a percentile with regard to the TTC distribution of historical tail losses, denoted by $CCyQ$ in Figure 1, policymakers can infer a CCyB. The policy instrument is the choice of this percentile which determines how "deep" a recession the CCyB should protect against. For instance, by choosing the 99.9th percentile, the total capital requirements (including provisions, minimum capital requirements, and the CCyB) would imply the system-wide accumulation of loss-absorbing buffers that would prove insufficient in only one scenario out of one thousand.

[26] $\rho + CCyB$ is of the order of 15 percent and $\widehat{RW}$ between 70-100 percent, so the effect of an increase in provisions on the right-hand side of equation (12) is only about 10-15 percent of the effect on the left-hand side.

[27] The expected loss (and therefore the provision) would increase when an exposure defaults. As defaults are pro-cyclical, the same reasoning applies as above: the sum of provisions and capital requirements (expressed as a fraction of total exposure) is expected to increase in recession times.

[28] A CCyB, once imposed, pertains to all risk-weighted assets, not just credit risk RWAs, as shown in equation (9). Calibrating a CCyB for non credit risk exposures is beyond the scope of this article.

The CCyB would then be derived from the distance that separates the sum of provisions (the expected value of the PiT credit loss distribution, denoted ECL_{PiT} in Figure 1) and the minimum capital requirements (derived from regulation, not from the loss distribution and represented in Figure 1 as CyK) from the TTC quantile $CCyQ$ and would be floored at zero.

In other words, if the sum of provisions and minimum capital requirements are insufficient to cover the chosen quantile of the through-the-cycle distribution, a CCyB would be imposed, thereby increasing banks' capital requirements. Mathematically:

$$k_{CR} \geq CCyQ - ECL_{PiT}. \tag{14}$$

Using equation (12), we can write:

$$(\rho + CCyB) \cdot \widehat{RW} \cdot \hat{a}_{CR} = CCyQ - ECL_{PiT} \tag{15}$$

Noticing that $ECL_{PiT} = p/A_{CR}$, this yields:

$$CCyB \cdot \widehat{RW} \cdot \hat{a}_{CR} = CCyQ - p/A_{CR} - \rho \cdot \widehat{RW} \cdot \hat{a}_{CR} \tag{16}$$

$$CCyB = max\left[0, \frac{CCyQ}{\widehat{RW} \cdot \hat{a}_{CR}} - \frac{p}{\widehat{A}_{CR}} - \rho\right]. \tag{17}$$

Figure 1 illustrates that the CCyB would be positive in boom times, zero in downturns and, depending on the choice of the quantile for deriving $CCyQ$, in neutral times, a *positive neutral* CCyB can be derived.

A4. LGD Model Component—Details

A4..1 Frye-Jacobs Methodology

The LGD model methodology of Frye & Jacobs (2012) can be used to project LGDs conditional on PDs. It exploits the inherent relationship between PDs and LGDs. The primary assumption regarding this relationship is that a greater rate of credit loss accompanies a greater default rate (or in more technical terms: the asymptotic distributions of default rates and loss rates are comonotonic). Frye & Jacobs (2012) show that despite the model's simplicity, it performs well in capturing historical LGD dynamics in situations when historic LGD data was available to allow for back-testing.

Historical LGD data, with a time series dimension, are often not easily available. This means that econometric model structures are not really an option, and imply the value of structural approaches such as the Frye-Jacobs method, which can endogenize LGDs based on scenario-specific default probabilities without relying on long time series of LGD observations.

In principle, the FJ model is applicable to LGDs of any kind of portfolio, but here it is used only for portfolios which are not real estate-collateralized. For real estate collateralized portfolios, structural models can be employed that take account of the evolution of real estate collateral prices (see Annex A4..4). For portfolios that are backed by collateral other than real estate, however, it is harder to devise structural models, e.g., to model the evolution of future income streams. Hence, a simpler model such as FJ methodology is instrumental for such portfolios.

The FJ LGD formula is derived under the assumption that the relationship between PDs and LGDs follows a Vašíček distribution. The LGD formula based on the Vašíček distribution reads as follows:

$$LGD_{t_0+h} = \frac{\Phi\left(\Phi^{-1}(PD_{t_0+h}) - k\right)}{PD_{t_0+h}}, \tag{18}$$

where PD_{t_0+h} and LGD_{t_0+h} are the point-in time (PiT) PDs and LGDs, Φ and Φ^{-1} are the standard normal cumulative and inverse cumulative distribution functions, and k is the so-called "LGD risk index", which is computed as a function of through-the-cycle (TTC) PDs and LGDs (denoted with bars):

$$k = \frac{\Phi^{-1}(\overline{PD}) - \Phi^{-1}(\overline{PD} \cdot \overline{LGD})}{\sqrt{1-\rho}}, \tag{19}$$

where ρ is a default correlation parameter.

Distributions other than Vašíček may be assumed but they do not share the same useful properties as Vašíček. Unlike the beta distribution, the Vašíček formula has closed form solutions for the cumulative and inverse cumulative probability density functions. Unlike the lognormal distribution, Vašíček constrains the rates to be less than 100 percent.

There are different ways to apply the FJ methodology. Its use depends on data availability and the purpose of its application:

- Case 1: Given are PD TTC for T0, LGD TTC for T0, and PD PiT for T0 and along a scenario horizon. Derived are LGD PiT for T0 and along the scenario horizon, conditional on the PD PiT scenario.
- Case 2: Given are PD TTC for T0, LGD PiT for T0, and PD PiT for T0 and along a scenario horizon. First, the LGD TTC for T0 is imputed for the model to match the LGD PiT for T0. Second, the LGD PiT path along the horizon is derived conditional the PD PiT scenario.
- Case 3: Given are LGD TTC for T0, LGD PiT for T0, and PD PiT for T0 and along a scenario horizon. First, the PD TTC for T0 is imputed for the model to match the LGD PiT for T0. Second, the LGD PiT path along the horizon is derived conditional the PD PiT scenario.
- Case 4: A PiT loss rate path is given, alongside a PD TTC and LGD TTC. PD PiT and LGD PiT as of T0 and along a scenario horizon are implied by the model.

Cases 2 and 3 involve an "optimization," i.e., a calibration step to first match an observed LGD PiT for T0. Case 4 is different from the other three cases in that it starts from a loss rate path to then use the FJ method to decompose the loss rate into a PD PiT and LGD PiT path.

Case 2 is the one that is embedded in the ECL model described in this paper. The LGD PiT is equated conceptually to the unsecured LGDs (because they are the ones that are used for provisioning). The LGD TTC is implied to make the FJ module match the PiT LGDs. The PiT and TTC PDs in the equations are the transition rates TR1-3, TR2-3, and TR3-3, for the three stages. The TTC parameters are computed as long-run averages over the historical transition matrices of the respective banks and portfolios.

A4..2 Translating Collateralization Ratios Into Loss Rates

Collateralization ratios (the ratio of collateral value C and loan exposure E) at the portfolio level are modeled to follow a lognormal distribution:

$$CR = \frac{C}{E} \sim LN(\mu, \sigma^2). \tag{20}$$

The portfolio-level distribution of collateralization ratios is translated into loss rates by assuming that collateral is liquidated and reduces losses. Overcollateralized loans (at the time of sale) lead to a loss of 0 while undercollateralized loans incur losses in case of default. The uncollateralized part of the loan is assumed to lead to a loss corresponding to the unsecured LGD.

$$\text{loss(CR)} = \begin{cases} \text{LGD}_{\text{unsec}}(1-\text{CR}), & \text{CR} < 1 \\ 0, & \text{CR} \geq 1. \end{cases} \tag{21}$$

The loss can therefore be computed as the probability-weighted expectation of the function in equation (21) above, which is modeled as following a lognormal distribution.

$$\begin{aligned} LGD &= \int_0^{\inf} loss(CR) \cdot LN_{pdf}(CR) \cdot dCR & (22) \\ &= LGD_{unsec} \int_0^1 (1 - CR) \cdot LN_{pdf}(CR) \cdot dCR & (23) \end{aligned}$$

The analytical properties of the lognormal distribution allow re-writing this expression as:

$$LGD = LGD_{unsec} \left[\int_0^1 LN_{pdf}(CR) \cdot dCR - \int_0^1 CR \cdot LN_{pdf}(CR) \cdot dCR \right]. \quad (24)$$

Using the property of the partial expectation of the lognormal distribution, one can write:

$$LGD = LGD_{unsec} \left[\Phi_{LN}(1) - exp\left(\mu + \frac{\sigma^2}{2}\right) \Phi_N \left(-\frac{\mu + \sigma + \sigma^2}{\sigma} \right) \right], \quad (25)$$

where Φ_{LN} and Φ_N are the lognormal and normal cumulative distribution function (CDF), respectively.

A4..3 Loan Amortization and Collateralization Ratios

Collateralization ratios (the ratio of collateral value C and loan exposure E) are modeled to follow a lognormal distribution:

$$CR = \frac{C}{E} \sim LN(\mu, \sigma^2). \quad (26)$$

When principal loan balances are amortized, the exposure decreases. If collateral values remain unchanged, this amounts to a scalar multiplication of the distribution. If a fraction α is paid back, then E becomes $E(1 - \alpha)$, and, according to the properties of the lognormal distribution, CR then follows:

$$CR = \frac{C}{E(1 - \alpha)} \sim LN(\mu - ln(1 - \alpha), \sigma^2). \quad (27)$$

For each bank portfolio, the amortization rates are known, i.e., by how much the initial portfolio size shrinks through time. This results from principal repayment (which let loan exposures drop and push up CRs) and from loans maturing (which lead to the exposure approaching zero, as through the regular principal repayment process, and the collateral "leaving" the portfolio and does not contribute to increasing CRs). In the model, it is assumed that half of the amortization is linked to repayments and half to maturing loans.

A4..4 Collateralization Ratio Distributions with Time-to-Foreclosure and Future House Prices

Collateralization ratios (the ratio of collateral value C and loan exposure E) are modeled to follow a lognormal distribution:

$$CR = \frac{C}{E} \sim LN(\mu, \sigma^2). \tag{28}$$

Real estate collateral, as opposed to financial collateral, takes time to be liquidated. In Colombia, the sale takes on average four years with a standard deviation of about five years. To determine what the expected effect on losses is, the time-to-foreclosure in years is simulated. The resulting distribution of time-to-foreclosure is then combined with the house price distribution (from the macro model) N years forward to obtain the price at foreclosure. This price is then discounted back to time of default. The resulting distribution is fitted with a lognormal distribution with parameters μ_{TTF} and σ_{TTF}.

Second, the model accounts for the fact that real estate collateral (depending on the region or the specific situation of the house) might not be actually worth the value estimated by the bank (and typically carried forward using the house price index). This uncertainty is modeled using a lognormal distribution with parameters μ_{SP} and σ_{SP} for "sale price" (SP). These parameters should be estimated with actual data.

Similarly, when computing the defaults occurring in future years, the change in house prices is accounted for, using the simulated house price index, which results in a shift of the CR distribution by μ_{HP}.

The product of independent lognormal distributions is a lognormal distribution and the parameters can be analytically derived as follows:

$$CR \sim LN(\mu, \sigma^2) \quad \longrightarrow \quad CR \sim LN(\mu + \mu_{TTF} + \mu_{SP} + \mu_{HP}, \sigma^2 + \sigma^2_{TTF} + \sigma^2_{SP}). \tag{29}$$

A4..5 Definition of Time-Since-Default Buckets

Table 4: Definition of Time-Since-Default Buckets by Portfolio and Collateral Type

Portfolio	**Collateral type**	**Limit bucket 1–2** *(days since default)*	**Limit bucket 2–3** *(days since default)*
Commercial/Micro	None	210	420
Commercial/Micro	Real Estate	540	1080
Commercial/Micro	Financial	360	720
Commercial/Micro	Other	360	720
Consumer/Mortgage	None	30	90
Consumer/Mortgage	Real Estate	360	720
Consumer/Mortgage	Financial	360	720
Consumer/Mortgage	Other	270	540

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