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ENHANCING THE CREDIT RISK MODULE: FROM A Z-FACTOR TO A BRIDGE EQUATION APPROACH

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BOX 5: ENHANCING THE CREDIT RISK MODULE: FROM A Z-FACTOR TO A BRIDGE EQUATION APPROACH[1]

The Bank currently applies an ECL model for credit risk quantification, based on methodologies developed by Gross et al. (2020) and Belkin et al. (1998a). In essence, this approach condenses nine transition probabilities into a single latent variable known as a 'Z-factor', which is in turn linked to macro-financial conditions (see Box 3 in FSR 2022 for more details).

The Bank has updated its framework in line with recent literature by adopting the approach outlined in the ECB Occasional Paper by Budnik et al. (2024). This revised methodology first models the default rate and then uses bridge equations to derive the remaining elements of the transition matrix. The main advantage of this approach over the previous Z-factor methodology is that it models default probabilities directly as the macro-sensitive driver of credit transitions. This allows for more detailed projections of stage-to-stage migrations while preserving the economic structure embedded in historical dynamics.[2]

The purpose of this box is to outline how IFRS9 transition matrices are projected under baseline and adverse macro-financial scenarios and explains how the new approach improves the projections of credit migration dynamics relative to the previous Z-factor methodology.

Transition matrix structure and stage definitions

Matrix (1) presents the schematic transition probability (TP) parameters aligned with IFRS 9 staging requirements. The framework defines three distinct credit risk categories: Stage 1 for exposures exhibiting no significant deterioration in credit quality since initial recognition; Stage 2 for exposures showing a material increase in credit risk without having defaulted; and Stage 3 for non-performing (defaulted) exposures. This matrix structure captures the full spectrum of credit migration dynamics across these obligor stages over discrete time periods *t*.

$$TP_t = \begin{bmatrix} TP_t^{1-1} & TP_t^{1-2} & TP_t^{1-3} \\ TP_t^{2-1} & TP_t^{2-2} & TP_t^{2-3} \\ TP_t^{3-1} = 0 & TP_t^{3-2} = 0 & TP_t^{3-3} = 1 \end{bmatrix} \qquad (1)$$

$TP^{1\to 3}$ and $TP^{2\to 3}$ indicate the likelihood of transitioning from a performing category (S1 or S2, respectively) to the non-performing category (S3), thereby, in a combined manner, representing the probability of default (PD). Stage 3 is treated as an absorbing state – meaning that once an exposure reaches S3, in the adverse scenario it cannot return to S2 or S1, and therefore, the cure probabilities ($TP^{3\to 1}$ and $TP^{3\to 2}$) are set to zero.

Modelling the probability of default (PD)

The PD, expressed in a distance-to-default transformation, is regressed on key macro-financial variables to capture the portfolio's sensitivity to macroeconomic shocks and on its own lag, to account for the persistence of default rates. A Bayesian Model Averaging (BMA) methodology is employed, in which all feasible combinations of default rate and macro-financial drivers are estimated using Autoregressive Distributed Lag (ARDL) specifications. The BMA methodology addresses model uncertainty by incorporating multiple highly probable model specifications, rather than relying on a single model or a fixed

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[2] The framework retains the LGD modelling block, lifetime ECL calculations and integration with supervisory minimum coverage expectations described in FSR 2022. The methodological change introduced this year is limited to how PDs are projected conditional on macro-financial scenarios.

set of variables. Model coefficients are weighted by their posterior inclusion probabilities, as determined using the Bayesian Information Criterion, and subsequently aggregated to obtain the overall scenario response, following the approach in Raftery (1995).

To ensure economic plausibility, sign restrictions are imposed on macro-financial variables. The estimation is carried out at the portfolio level (mortgages, consumer credit, and NFCs) to account for differential credit risk sensitivity to macro shocks. Following PD estimation and projection under baseline and adverse scenarios, the $TP^{1\to3}$ and $TP^{2\to3}$ transition probabilities are derived using equations (2) and (3), respectively.

$$\Phi^{-1}\left(TP^{1-3}_{T0+h}\right) - \Phi^{-1}\left(TP^{1-3}_{T0}\right) = \Phi^{-1}\left(PD_{T0+h}\right) - \Phi^{-1}\left(PD_{T0}\right) \quad (2)$$

$$\Phi^{-1}\left(TP^{2-3}_{T0+h}\right) - \Phi^{-1}\left(TP^{2-3}_{T0}\right) = \Phi^{-1}\left(PD_{T0+h}\right) - \Phi^{-1}\left(PD_{T0}\right) \quad (3)$$

where Φ^{-1} denotes the standard normal inverse cumulative distribution function. This normal inverse transformation ensures that transition probabilities remain bounded in the [0,1] interval.

Bridge equations for non-default transitions

The projection of the remaining elements of the transition matrices, namely $TP^{1\to2}$ and $TP^{2\to1}$, is based on empirically estimated bridge equations at the portfolio level. These equations capture the historical co-movement between default and non-default transitions. Equation (4) models the relationship between $TP^{1\to2}$ and $TP^{1\to3}$, while equation (5) models the relationships between $TP^{2\to1}$ and $TP^{2\to3}$ respectively.

$$\Phi^{-1}\left(TP^{1-2}_{t}\right) = a + b\Phi^{-1}\left(TP^{1-3}_{t}\right) + \varepsilon_t \quad (4)$$

$$\Phi^{-1}\left(TP^{2-1}_{t}\right) = c + d\Phi^{-1}\left(TP^{2-3}_{t}\right) + \varepsilon_t \quad (5)$$

The coefficients b and d are expected to be positive and negative, respectively, reflecting the economic intuition that higher default rates are associated with more downgrades from Stage 1 (coefficient $b > 0$) and fewer cures from Stage 2 (coefficient $d < 0$). Empirically, an increase in transition rates from Stage 1 to Stage 3 is also associated with an increase in transition rates from Stages 1 to 2, since both reflect a deterioration in credit quality. Following the same reasoning, higher transition rates from Stages 2 to 3 are associated with lower transition rates from Stages 2 to 1. Scenario paths of $TP^{1\to2}$ and $TP^{2\to1}$are then constructed by applying the estimated slopes b and d to the scenario-conditional changes $TP^{1\to3}$ and $TP^{2\to3}$.

For $TP^{1\to2}$:

$$\Phi^{-1}\left(TP^{1-2}_{T0+h}\right) - \Phi^{-1}\left(TP^{1-2}_{T0}\right) = b\left(\Phi^{-1}\left(TP^{1-3}_{T0+h}\right) - \Phi^{-1}\left(TP^{1-3}_{T0}\right)\right) \quad (6)$$

For $TP^{2\to1}$:

$$\Phi^{-1}\left(TP^{2-1}_{T0+h}\right) - \Phi^{-1}\left(TP^{2-1}_{T0}\right) = d\left(\Phi^{-1}\left(TP^{2-3}_{T0+h}\right) - \Phi^{-1}\left(TP^{2-3}_{T0}\right)\right) \quad (7)$$

Completing the transition matrix

Lastly, the scenario paths of the transition probabilities $TP^{1\to1}$ and $TP^{2\to2}$ are calculated as residuals to ensure that the probabilities in each row sum to one, with a floor at zero in accordance with equations (8) and (9).

$$TP^{1-1}_{T0+h} = \max\left(1 - TP^{1-2}_{T0+h} - TP^{1-3}_{T0+h}, 0\right) \quad (8)$$

$$TP^{2-2}_{T0+h} = \max\left(1 - TP^{2-1}_{T0+h} - TP^{2-3}_{T0+h}, 0\right) \quad (9)$$

Integration with lifetime ECL projections and beyond-horizon assumptions

Once scenario-conditional transition matrices are generated over the three-year MST horizon, under both the baseline and adverse scenarios, they are combined with stage-specific loss-given-default

(LGD) values and effective discount rates to produce stage-specific ECL projections, as detailed in FSR 2022. Beyond the three-year stress-test horizon, because the average residual maturity of loans exceeds the projection window, credit-risk parameters are extended to calculate IFRS 9 lifetime provisions. In line with the EBA approach, after 2028, these parameters are held constant under the baseline scenario, while under the adverse scenario, they gradually converge to their 2028 baseline values over a six-year period. Thus from 2034 onwards, all adverse-scenario credit-risk parameters are assumed to equal their 2028 baseline levels. In addition, supervisory minimum coverage expectations for NPEs are applied as an overlay to IFRS 9 provisions, ensuring that provisioning reflects not only model-based estimates but also prudential expectations linked to the age of the exposure, its classification as legacy or newly defaulted, and the presence of collateral as explained in FSR 2022.

Robustness check: Back testing results for 2025

The performance of the upgraded credit-risk module was assessed using an out-of-sample back-test, comparing projected transition matrices for 2025 with the corresponding observed outcomes, across the three main portfolios. For each portfolio and approach, the Root Mean Squared Error (RMSE) of the transition probabilities serves as an aggregate measure of deviation between estimated and observed migration patterns. This metric confirms that the new approach improves the overall fit for the most significant credit portfolios, notably reducing the error term from 14.9 to 7.5 for NFCs and from 8.0 to 1.8 for Mortgages (see Table 1).

The stage-level results help explain these aggregate patterns (see Table 2). For NFCs and mortgages, the new approach clearly outperforms the Z-factor benchmark across the main stages. In fact, the mean error in Stage 2 falls by 13.4 percentage points for NFCs and 10.4 percentage points for mortgages (see Table 2, column 2). This suggests that modelling default rates directly

Table 1

DIFFERENCE BETWEEN OBSERVED AND ESTIMATED TRANSITION MATRIX

RMSE

	New approach	Z-factor	Δ
NFCs	7.5	14.9	-7.4
Mortgages	1.8	8.0	-6.1
Consumer credit	8.4	6.3	2.1

Source: Central Bank of Malta.

Note: RMSE of one year transition probabilities between observed and model implied transition matrices for 2025. RMSE is expressed in percentage points. The "Δ" column represents the percentage point improvement of the new methodology over the previous Z-factor benchmark. Lower values indicate a better fit of the overall transition matrix.

Table 2

DIFFERENCES BY CREDIT PORTFOLIO AND STAGES

Average absolute deviation; percentage points

	Stage 1	Stage 2	Stage 3
NFCs	-0.39	-13.42	4.74
Mortgages	-1.35	-10.43	-0.21
Consumer credit	-1.48	2.85	1.74

Source: Central Bank of Malta.

Note: Difference in average absolute deviation (AAD) of stage specific transition probabilities in 2025 under the new framework relative to the Z factor benchmark, by credit portfolio and IFRS 9 stage. Values are expressed in percentage points. Negative numbers indicate an improvement (a smaller average deviation from observed transitions), and positive numbers indicate a deterioration.

as the macro-sensitive driver provides a more reliable and stable basis for identifying deteriorating exposures before they transition to non-performing status.

By contrast, the results for consumer credit are mixed. The bridge equation enhances Stage 1 modelling (-1.48 percentage points), but weaker results in Stages 2 and 3 offset this improvement, leading to an aggregate RMSE slightly higher than under the Z-factor benchmark. However, these results should be interpreted with some caution, as consumer credit is a relatively small portfolio, representing only 3.6% of the total credit as at December 2025.

In addition to the matrix-level diagnostics, a credit-weighted comparison was also conducted between the observed and estimated stage distributions. This analysis is particularly useful, as it scales the estimation error by the relative size of each portfolio segment, distinguishing between differences that are numerically large but economically less significant, as opposed to those more relevant from a portfolio perspective. The results show significant improvements in both Stages 1 and 2, where this new approach reduces the overall credit-weighted difference by 3.3 percentage points (see Table 3). This approach is particularly relevant for modelling the transition probabilities for Stage 1, not only improving the flow for new stages, but also reducing the error in the Stage 1 stock by 1.43 percentage points. Taken together, this suggests that the most relevant effect is concentrated in the largest segment, while the remaining differences are comparatively limited. The out-of-sample fit for Stage 3 exposures is relatively weaker; however, this is of limited significance in the stress-testing framework. First, under the adverse scenario, Stage 3 is treated as a fully absorbing state and therefore does not require further modelling of onward transitions. Second, movements in Stage 3 loans tend to be highly volatile and are less impacted by the macroeconomic variables included in the framework than by bank-specific factors such as balance-sheet dynamics, write-offs, cures, forbearance measures and other resolution actions.

Table 3
WEIGHTED DIFFERENCE BETWEEN OBSERVED AND ESTIMATED STAGES

Stages	S1	S2	S3
S1	-1.43%	-0.76%	-0.67%
S2	-0.14%	-0.29%	-0.04%
S3	0.05%	0.06%	0.14%

Source: Central Bank of Malta.

Note: Credit weighted difference between observed and model implied stage distributions at the end of 2025, by originating and destination IFRS 9 stage. Figures are expressed in percentage points of total exposure. Negative values indicate that the model slightly overestimates the corresponding stage share, while positive values indicate underestimation.

Given the weaker results for Stage 3, an additional comparison was conducted to assess how accurately each method replicates the PD ($TP^{1\rightarrow3}$ and $TP^{2\rightarrow3}$). The RMSE results show that this new method reduces error relative to the Z-factor benchmark across all three portfolios, with the largest improvement in mortgages, followed by consumer credit and NFCs (see Table 4, column 1). The standard deviation of the errors points in the same direction, suggesting that the bridge approach delivers a more stable fit across the two stage-to-default flows (see Table 4, column 2). Finally, the PD bias summarizes how model-implied probabilities of default compare to observed defaults, with negative values indicating a conservative (over-predicting) calibration. Both methods exhibit a small negative PD bias, but the deviation under this new approach remains closer to zero, implying a more balanced PD profile and more realistic results across all three credit segments (see Table 4, column 3). Overall, the evidence points to a more accurate, more balanced, and better-calibrated PD profile under this new framework.

Table 4
PD ANALYSIS

	Metrics		
	RMSE	Std. Dev.	PD Bias %
NFCs	-1.54	-2.96	-0.30
Mortgages	-12.01	-11.37	-0.94
Consumer credit	-4.23	-3.26	-0.36

Source: Central Bank of Malta.

Note: RMSE, standard deviation of errors and mean bias of model implied PD in 2025, by credit portfolio. Metrics are computed across the Stage 1 to Stage 3 and Stage 2 to Stage 3 transition flows. PD bias is defined as the percentage deviation between model implied and observed default flows, calculated as (estimated S1→S3 + estimated S2→S3)/(observed S1→S3 + observed S2→S3) - 1. Negative PD bias values indicate a conservative (over predicting) calibration on average.

Summary

This methodological upgrade significantly improves the bank's current credit risk module within the MST framework by delivering more realistic and detailed projections of baseline and adverse transition matrices. By replacing the current latent Z-factor modelling, with direct modelling of default rates and empirically grounded bridge equations, the new approach preserves information on stage-to-stage migration dynamics. The new methodology also offers stronger structural consistency and greater economic interpretability. The 2025 back-testing exercises indicate that the upgraded module provides a materially better fit for the main credit portfolios, particularly for transitions into default and for Stage 1 and Stage 2 loan stock projections, while also highlighting residual complexities in Stage 3 dynamics.

Looking ahead, the Bank intends to refine the credit risk module further by exploring potential extensions to the current framework. One area for further investigation is the development of more granular models for cure and write-off rates, which would enhance the precision of transition projections and better capture the interplay between credit migration and balance-sheet management. This ongoing work, combined with regular back-testing against realised outcomes and sensitivity analyses to alternative macro-financial scenarios, will ensure the framework's predictive performance and robustness remain fit for purpose in assessing systemic risks.

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