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EXPECTED CREDIT LOSS MODEL

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BOX 3: EXPECTED CREDIT LOSS MODEL[1]

One critical aspect of stress testing is the consideration of NPLs. At the most general level, it relates to a loan where the borrower is not making repayments as per contractual obligations – usually for a period exceeding 90 days. NPLs can pose significant risks to financial institutions and the overall financial system, resulting in bank losses and an adverse impact on profitability, reducing credit availability, and eroding investor confidence. Thus, the potential impact of NPLs on financial institutions' balance sheets and their ability to absorb losses are a crucial element in banks' stress testing and risk quantification exercises.

The quantification of provisions for credit losses has undergone a significant shift with the implementation of the IFRS 9 for financial instruments, effective from 1 January 2018. IFRS 9 replaces the incurred loss models under IAS 39 with an expected credit loss (ECL) model that looks ahead and factors in potential future losses. IFRS 9 was prompted by the fact that banks worldwide did not adequately set aside provisions in a timely manner during the GFC in 2008. Under the incurred loss model, charges for potential credit losses were kept low until an actual credit loss event occurred. Once loan delinquencies start to rise, the charges sharply increased, thereby further threatening financial system stability.

The implementation of IFRS 9 brings several advantages, including a more gradual adjustment of loss provisions throughout the economic cycle. Under IFRS 9, the ECL recognition follows a three-stage impairment approach, which involves calculating provisions based on the credit quality of financial instruments. Stage 1 (performing) provisions account for expected defaults within the next 12 months for loans with low credit risk. Stage 2 (performing loans that experienced a *significant increase in credit risk*) and Stage 3 (NPLs) provisions are based on the lifetime ECL for loans that have significantly deteriorated or are expected to adversely affect future cash flows.

IFRS 9 allows for the early recognition of low provisions from the loan's origination date, and higher provisions are made as the credit quality of the loan deteriorates. Provisioning may increase substantially as the credit risk worsens, but if the credit quality improves, it can revert to a 12-month ECL level. The following Box provides details on the top-down approach used to estimate banks' ECL provisions and, consequently, determine accurate bank capital projections driven by the extent of credit risk.

Overview

IFRS 9 provisioning requirements are informed by the ECL module of the Bank's loan loss forecasting model. The box is structured as follows. Part A provides an explanation of how the Z-Factor is calculated and showcases the historical time series of the Z-Factor, which is based on aggregated loan portfolios from core domestic banks. Part B outlines the process of connecting the Z-Factor to macro-financial conditions and presents the projected Z-Factor for the time horizon of 2023-2025. Lastly, Part C outlines the specific measures taken to convert the projected transition matrices into loan loss provisions flow amounts. The model flow is depicted graphically in Figure 1. The framework follows ECL methodologies proposed by the IMF in Gross et al. (2020) and model averaging techniques described by Gross and Población (2019). Integral to the ECL stress test framework is the concept of transition matrices that captures the transitions across loan stages. In the first stage of the analysis, the probability of loans progressing among the IFRS 9 stages 1, 2 and 3 will be estimated using the Z-Factor methodology.

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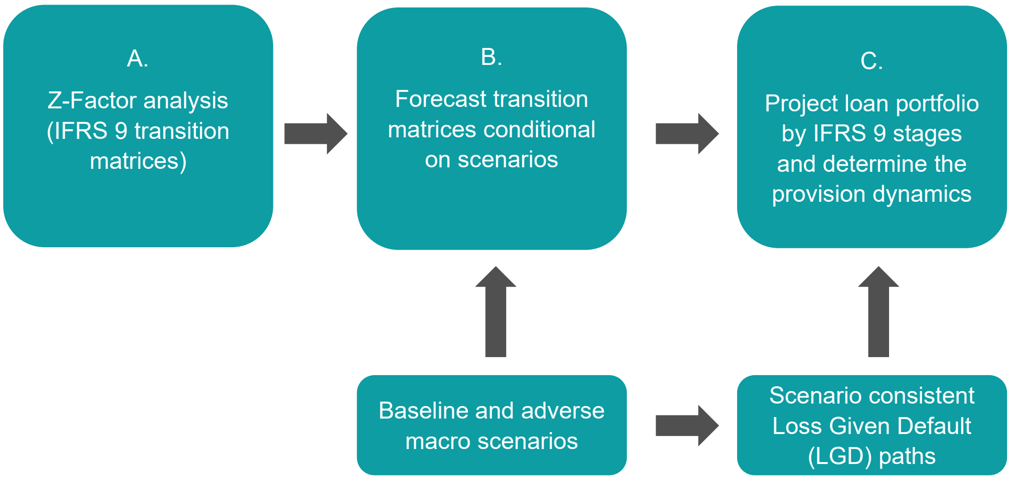
Figure 1
OUTLINE OF THE THREE PARTS OF THE EXPECTED CREDIT RISK MODULE



Source: Central Bank of Malta.

The Z-Factor methodology provides a way of summarising the nine transition values into one. The second stage of the analysis involves linking the Z-Factor to macroeconomic variables and then forecasting the loan transitions conditional on EBA scenario forecasts under both baseline and adverse scenarios. The Bayesian Model Averaging (BMA) techniques are utilised when establishing a link between macroeconomic variables and the Z-Factor. BMA accounts for model uncertainty explicitly by using several highly probable models to estimate the forecasts rather than relying on a singular model and variable specification. The third stage of the analysis assesses the impact of the Z-Factor forecasts (that would have been transformed back to IFRS 9 transition matrices) on the provisioning requirements of banks to quantify the extent of provisions required by them under the baseline and adverse scenarios for the three loan stages.

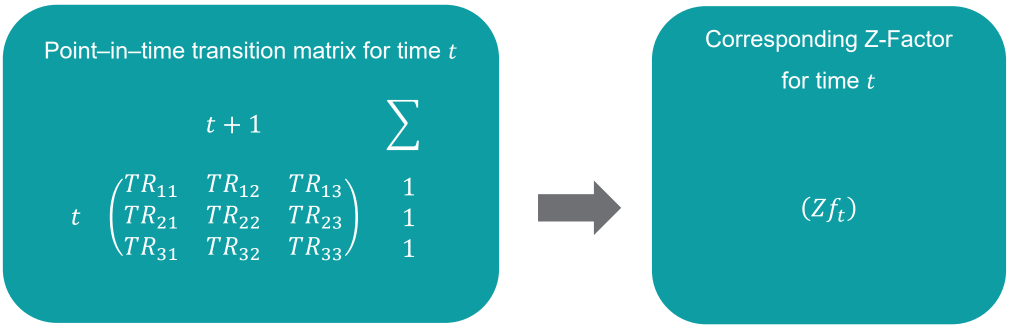
Data requirements

The data involved in the ECL modelling exercise includes i) granular loan data for core and non-core banks, ii) historical macroeconomic data and iii) macroeconomic projections. The first category of input data is needed to calculate the Z-Factor, with loan volumes sourced from FINREP and loan portfolio characteristics sourced from the Central Credit Register (CCR). Specifically, quarterly reports were generated from the CCR to track the share of loans to households and non-financial corporations (NFCs) experiencing changes in their performance status over the tested period. In addition, balance sheet data was required to calculate credit risk parameters, including loan loss provisions and risk exposure amounts at their respective starting points as of 2022 (more information on the risk parameters is provided later in part C of this box). The second type of data pertains to historical time series of macro-financial variables between 2016 and 2022, sourced from the National Statistics Office and ECB SDW (detailed in Table 1 of part B). And finally, baseline and adverse scenario macro forecasts were sourced from the EBA's 2023 EU-wide stress test.

Part A: Z-Factor and transition matrices

The analysis employs a one-parameter representation of credit rating transition matrices in line with the work of Gross et al. (2020) and Belkin et al. (1998a). The Z-Factor provides a way of summarising the 9 transition values into a single value as shown in Figure 2. IFRS 9 came into effect in 2018; however, the analysis is extended back to 2016 to improve the accuracy of the forecasts.

Figure 2
POINT-IN-TIME TRANSITION MATRIX CONVERTED TO A SINGLE Z-FACTOR



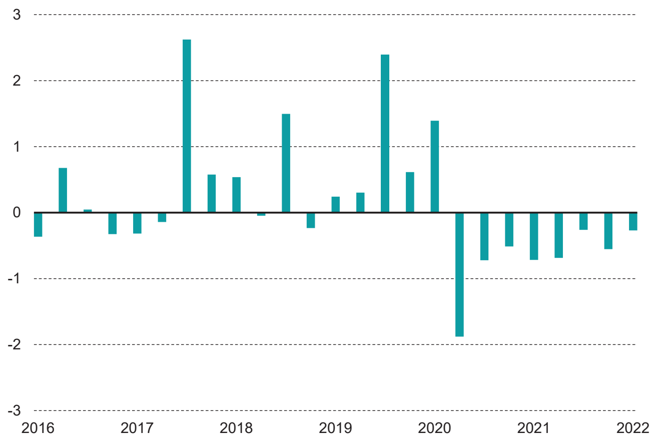
Source: Central Bank of Malta.

The loan stages are applied retrospectively whereby banks' loans are classified according to the following: Stage 1 – performing with a stable risk profile (those without or up to 30 days past due), Stage 2 – exposures with a significant increase in credit risk (forborne performing or performing with days past due between 30 and 90 days), and Stage 3 (all NPEs with days past due exceeding 90 days).

Chart 1 provides a visual representation of the calculated historical Z-Factor. The Z-Factor is negative during economic downturns due to downgrades between Stages 1 and 2 or defaults into Stage 3. Conversely, the Z-Factor is positive during economic upturns when the transition probabilities referring to the downward movement of loans stand below their long-term average, corresponding to loans reverting to previous stages. The Z-Factor can be interpreted as representing one standard deviation of stage transitions from the historical average of stage transitions. The occurrence of the negative Z-Factor period in Chart 1 follows the COVID-19 period. Several European governments, including that of Malta, implemented a range of fiscal and macroprudential policies, such as moratoria, to alleviate the economic repercussions of the pandemic on households and businesses. These measures introduced during the initial phase of the pandemic might partly account for the delayed response observed in the Z-Factor series.

The process of converting the stage transitions shown in Figure 2 to the Z-Factor series in Chart 1 is done by assuming that the probability density of loan transitions X depends on two independent normal random variables: an idiosyncratic driver Y and a systematic economy-wide driver *Zf*. The correlation between *Zf* and X is captured by the parameter ρ, with *Zf* explaining a fraction of the variance of X noted in equation 1.

Chart 1
HISTORICAL Z-FACTOR SERIES
(standard deviations)



Source: Central Bank of Malta calculations.

$$X_t = \sqrt{1-\rho} Y_t + \sqrt{\rho} Zf_t \quad (1)$$

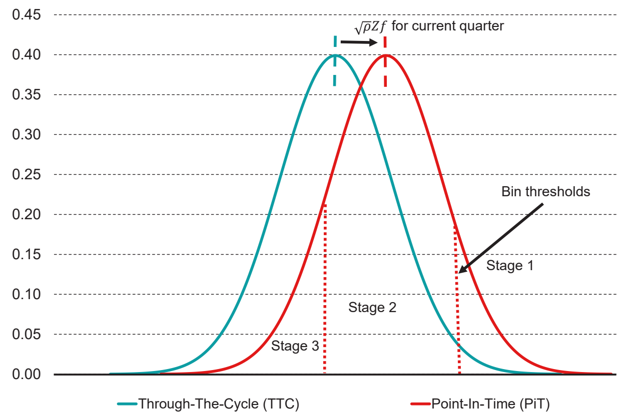
Since the portfolio consists of many obligors, the idiosyncratic component *Y* can be assumed to be eliminated through diversification as in Belkin et al. (1998b). The method calculates fitted transition probabilities based on bin boundaries and a long-term average transition matrix as depicted in Chart 2.

The fitted transition probabilities, Δ_t can be expressed mathematically as follows:

$$\Delta_t\left(X_{g+1}^G, X_g^G, Zf_t, \rho\right) = \Phi\left(\frac{X_{g+1}^G - \sqrt{\rho} Zf_t}{\sqrt{1-\rho}}\right) - \Phi\left(\frac{X_g^G - \sqrt{\rho} Zf_t}{\sqrt{1-\rho}}\right) \quad (2)$$

The function *Φ* represents a cumulative distribution of a standard normal variable. The term X_g^G are the "bin boundaries" (represented by the vertical lines in Chart 2), which are calculated using the inverse of the standard normal cumulative distribution function, referencing a long-term average transition matrix. The historical deviation between observed and fitted transition matrices can be computed using a minimisation function for each point in time that minimises the expression in equation 3.

Chart 2
PROBABILITY DENSITY FUNCTIONS FOR IFRS 9 STAGES
(per cent)



Source: Central Bank of Malta
Adapted from: Belkin et al. (1998a); Gross et al. (2019).

$$min_{Zf_t} \sum_G \sum_g w_{tg} \left(P\,(G,g) - \Delta\left(X_{g+1}^G, X_g^G, Zf_t, \rho\right)\right)^2 \quad (3)$$

Assuming ρ and the bin boundaries from the long-term average transition matrix, a Z-Factor was computed for each point in time that minimises equation 3. However, since ρ and *Zf* are unknown, a double-loop approach as suggested by Belkin et al. (1998a) was adopted by searching for both ρ and the time series Z-Factor while ensuring that the resulting variance of Z-Factor is equal to one.

B. Linking the Z-Factor to macroeconomic conditions and projecting scenario conditional paths

Selecting a single equation to connect risk metrics such as the Z-Factor to macroeconomic variables can notably affect a bank's requirements for loan loss provisioning and anticipated capital standing. Even rational equations from an economic and statistical standpoint can produce a broad spectrum of results based on scenario analyses. To mitigate this problem, a BMA methodology is employed akin to that of Gross et al. (2019), that explicitly attempts to address model uncertainty. This approach assumes that every model is only partially accurate, and thus it operates with a set of models. These models are assigned weights in the form of probabilities that reflect their relative predictive performance. The individual models are then combined to form a posterior model that relates the Z-Factor to contemporaneous and lagged macroeconomic variables. This posterior model acts as an econometric bridge equation and is created using the assigned probability weights.

To limit the number of models used in the BMA approach, the maximum number of predictors are restricted to three out of *K* possible predictors. The equations used in the model structure follow the Autoregressive Distributed Lag (ARDL) model format, as shown in equation 4. The Z-Factor, denoted by Y_t, is the dependent variable, while the macroeconomic variables in Table 1 are the *K* predictors. The model space is formed by examining all potential combinations of predictors from the pool of *K* variables. Due to the limited time series data from Q4 2016 to Q4 2022 at a quarterly frequency, the lag structure for the exogenous predictors is "closed" without any gaps, and the lag length is fixed at one. The Bayesian Information Criterion (BIC) showed that all models required a single autoregressive lag, a common feature among all the equations in the model space, before considering various predictor combinations to define the model spaces.

$$Y_t = \alpha + \rho_1 Y_{t-1} + \cdots + \rho_1 Y_{t-p} + \sum_{k=1}^{k_i} (\beta_0^k X_t^k + \cdots + \beta_{q^k}^k X_{t-q^k}^k) + \varepsilon_t \tag{4}$$

The posterior coefficient means $E(\beta|D)$ are a weighted average of the individual equations' coefficients, with the weights $P(M_i\,|D)$ being implied by BIC performance measure based on data D, as in Raftery (1995). See equations 5 and 6, respectively.

$$E(\beta|D) = \sum_{i=1}^{I} P(M_i\,|D)\check{\beta}_i \tag{5}$$

$$P(M_i|D) \approx \exp\left(-1/2\,BIC_i\right) / \sum_{l-1}^{I} \exp\left(-1/2\,BIC_l\right) \tag{6}$$

Sign constraints are imposed to ensure that the signs of the predictors have the desired effect on the Z-Factors in the macroeconomic stress scenario. The predefined sign criteria are detailed in Table 1. The BMA estimation and sign constraint findings indicate that house prices, inflation, and interest rate play a significant role in driving the Z-Factor. Furthermore, all equations in the final model space exhibit well-behaved residuals with Durbin Watson values near 2.

The subsequent step involves using the posterior model to predict scenario-dependent paths for Z-Factors over the three-year stress test horizon (12 quarters). The EBA's 2023 stress test scenarios

Table 1
TRANSFORMATIONS AND SIGN CONSTRAINTS FOR MACROECONOMIC VARIABLES

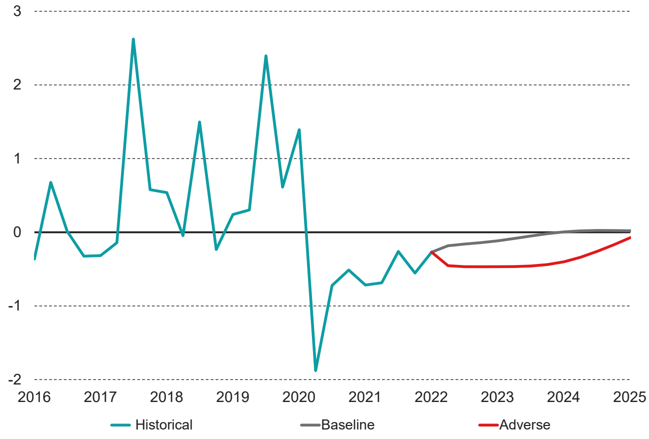
Variable	MT GDP	MT Unemployment	MT Sovereign spread	MT House prices	MT Inflation	Risk free rate (Ten-year Bund rate)
Transformation	YoY	Level	Level	YoY	YoY	Level
Sign constraint	1	-1	-1	1	-1	-1
EBA Baseline 2025	+ 11.2%	+ 0.3 pp	+ 0.2 pp	+ 11.3%	+ 9.0%(1)	- 0.1 pp
EBA Adverse 2025	- 5.5%	+ 7.8 pp	+ 0.6 pp	- 9.7%	+ 9.0%	+1.5 pp

Source: Central Bank of Malta and EBA 2023 EU-wide stress macro financial scenario.

(1) Although the three-year cumulative impact for HICP is the same, the increases are frontloaded in the case of the adverse scenario.

for the baseline and adverse figures are integrated with the path created with the posterior model. The EBA's annual figures are integrated were temporally disaggregated into quarterly frequency for the analysis. The predicted conditional paths for Z-Factors are presented in Chart 3, displaying both the posterior baseline and adverse paths. The Chart shows a smooth recovery under the baseline scenario to the historic average loan transition rate, with an even slower recovery under the adverse scenario.

Chart 3
HISTORICAL SERIES AND SCENARIO PROJECTIONS FOR Z-FACTOR
(standard deviations)



Source: Central Bank of Malta calculations.

A transition matrix forecast can be derived from the conditional Z-Factor projections in the same way as the historical fit is produced at the estimation stage, using the formulae given by equation 3 above. The parameter ρ and the bin boundaries previously estimated are used; only Zf as an input variable varies conditional on the outcome of the baseline or adverse scenario forecasts.

C. Loan loss provisions

With the transition matrices obtained, the next step concerns the derivation of the implied S1, S2 and S3 loan stocks and the corresponding provisions. In line with the static balance sheet assumption, there is no explicit control over maturity, new business flows and write-offs. The stock-flow dynamics for the loans are presented in the set of Equations 7:

$$S1_t = S1_{t-1} + \underbrace{(TR_t^{21}S2_{t-1} + TR_t^{31}S3_{t-1})}_{(inflows\ to\ S1)} - \underbrace{(TR_t^{12}S1_{t-1} + TR_t^{13}S1_{t-1})}_{(outflows\ from\ S1)} \quad (7)$$

$$S2_t = S2_{t-1} + \underbrace{(TR_t^{12}S1_{t-1} + TR_t^{32}S3_{t-1})}_{(inflows\ to\ S2)} - \underbrace{(TR_t^{21}S2_{t-1} + TR_t^{23}S2_{t-1})}_{(outflows\ from\ S2)}$$

$$S3_t = S3_{t-1} + \underbrace{(TR_t^{13}S1_{t-1} + TR_t^{23}S2_{t-1})}_{(inflows\ to\ S3)} - \underbrace{(TR_t^{31}S3_{t-1} + TR_t^{32}S3_{t-1})}_{(outflows\ from\ S3)}$$

Loan loss provisions must be assigned to exposures in all three stages, which vary over time due to various risk factors under the ECL approach. These risk factors include the probability of default (PD) (12-month and implied lifetime), a discount factor, and LGD. Specifically for real estate collateralised portfolios, which represent the majority share of the loan book, the LGD component is estimated for each bank in a separate module. The LGD is connected to the EBA house price trajectories for both the baseline and adverse scenarios via equation 8.

$$LGD_t = 1 - \left(\frac{HP_t}{HP_0} \times RE_{Collateral}\right) - Other_{Collateral} \tag{8}$$

$RE_{Collateral}$ refers to real estate collateral. Therefore, HP, representing house prices, are an influential factor both for projecting loan migrations and determining the value of collateral.

For S1 exposures under IFRS 9, the provisions stocks are equal to the 12-month ECL, given by:

$$Prov_{t,S1} = ECL_{t,S1} = TR^{13}_{t+1|t} \times LGD_{t+H|t} \times S_1 \tag{9}$$

Equation 9 follows the familiar *PD x LGD x EAD* structure for ECL. The term $TR^{13}_{t+1|t}$ is the expected default rate for S1 exposures conditional on end of period t. The $LGD_{t+H|t}$ term has a t+H|t to denote the fact that the LGD is forward looking.

For S2 exposures, the lifetime ECL is:

$$Prov_{t,S2} = ECL^{LT}_{t,S2} = \sum_{s=t+1}^{M} \frac{TR^{23*}_s \times LGD_{s+H|s} \times S2_{s-1}}{(1-r)^s} \tag{10}$$

With *M* denoting the average residual term to maturity of each bank's households and NFC portfolio. The denominator of the formulae involves a bank specific average interest rate for both their households and NFC portfolios, that is used for discounting the ECL along the residual maturity.

The term TR^{23}_s is the unconditional transition probability for S2 stocks, which links to the outcome of the transition matrix forecast path in part B. While this unconditional PD TR^{23}_s moves over the lifetime of a loan portfolio in an "unrestricted" manner, and in relation to macro-financial conditions, the incremental PD TR^{23*}_s measures the PD in period *s* conditional on not having defaulted up to period *s-1* and approaches zero over time. The lifetime horizon as measured by *M* is considerably longer than the stress test horizon. To reconcile this, the framework follows the methodological assumptions employed by the EBA, which require the credit risk parameters to remain constant for the baseline scenario after 2025 (including stage transition probabilities and corresponding loss rates). Conversely, those under the adverse scenario revert to the 2025 baseline parameters, following a linear path over a period of six years. This means that each credit risk parameter for the adverse scenario beyond 2031 is equal to the 2025 baseline parameters.

For S3 exposures, the lifetime ECL is computed taking into consideration the probability of remaining in S3:

$$Prov_{t,S3} = ECL^{LT}_{t,S3} = \sum_{s=t+1}^{M} \frac{TR^{33*}_s \times LGD_{s|t} \times S3_{s-1}}{(1-r)^s} \tag{11}$$

The total provisions stock equals the sum of the stage-specific provisions:

$$Prov_t = Prov_{t,S1} + Prov_{t,S2} + Prov_{t,S3} \tag{12}$$

The new provisions which would need to be set aside correspond to the loan loss provisions flow given by:

$$Prov\_Flow_t = Prov_t - Prov_{t-1} \tag{13}$$

Supervisory minimum coverage expectations

Another aspect of relevance to the calculation of provisions is the supervisory minimum coverage expectations for NPEs. These are set out by the respective supervisor, with a communication issued by ECB banking supervision, applicable to the three domestic Significant Institutions (SIs), and BR 09 applicable to the banks supervised by the MFSA (refer to Chapter 5). These expectations set up minimum coverage expectations for "legacy" and "new" NPLs, with a dedicated approach to deal with existing (stocks) of legacy NPLs, issued and classified as such prior to a cut-off date (April 2018 for SIs and April 2019 for other banks), as well as new NPLs for those issued after the respective date. These coverage expectations vary by the vintage count (i.e. number of years the loan has been classified as NPL) and the collateral underlying the loan. This means that the applicable coverage expectations are staggered and will go beyond the three-year stress test horizon. Indeed, a legacy ratio was defined for the share of S3 loans for which minimum coverage expectations apply from 2026. On average, this amounts to 36.5% of the stock of S3 loans reported in December 2022 by the twelve banks in scope of the MST.

To complement the findings of the IFRS 9 credit risk module, the incremental coverage expectations under the supervisory approach for the years 2023, 2024 and 2025 are calculated for each bank. This is done by determining which loans were classified as NPLs in December 2022 and with their loan identifier (provided in the CCR), trace back the first instance when these loans are first reported in the CCR as NPLs. This provides an estimate as to how long these loans have been classified as NPLs and ultimately determine the respective minimum coverage expectations. These requirements for existing NPLs are included in both the baseline and adverse scenarios. In addition, 2023 projections of new NPLs are in scope for incremental provisions given that by 2025 these would have been classified as such for a minimum of two years. In this respect, incremental provisions are added on to the provision requirements of 2025, calculated on the basis of the share of unsecured Stage 3 loans projected for 2023 under the respective scenario.

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