Working Paper Series 15/2023

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Czech National Bank —— Working Paper Series —— 15/2023

CZECH NATIONAL BANK

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Modelling Risk-Weighted Assets: Looking Beyond Stress Tests

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Abstract

We propose an improved methodology for modelling potential scenario paths of banks' risk-weighted assets, which drive the denominator of capital adequacy ratios. Our approach centres on modelling the internal risk structure of bank portfolios and thus aims to provide more accurate estimations than the common portfolio level approaches used in top-down stress testing frameworks. This should reduce the likelihood of significant misestimation of risk-weighted assets, which can lead to unjustifiably high or low solvency measures and induce false perceptions about banks' financial health. The proposed methodology is easy to replicate and suitable for various applications, including stress testing and calibration of macroprudential tools. After the methodology is introduced, we show how our proposed approach compares favourably to the methods typically used. Subsequently, we use our approach to estimate the potential increase in risk weights due to a cyclical deterioration in credit parameters and the corresponding setup of the countercyclical capital buffer for the Czech banking sector. Finally, an illustrative, hands-on example is provided in the Appendix.

Abstrakt

V tomto článku navrhujeme zdokonalenou metodiku pro modelování scénářem podmíněných trajektorií rizikově vážených aktiv bank, která ovlivňují hodnotu jmenovatele v ukazatelích kapitálové přiměřenosti. Náš přístup se zaměřuje na modelování interní rizikové struktury bankovních portfolií a jeho cílem je tak poskytnout přesnější odhady než běžné přístupy na portfoliové úrovni běžně používané v top-down zátěžových testech. To by mělo snižovat pravděpodobnost výrazně chybného odhadu rizikově vážených aktiv, který může vést k neopodstatněně vysokým nebo nízkým ukazatelům solventnosti, a tudíž k mylnému vnímání finančního zdraví bank. Navrhovanou metodiku je snadné replikovat a je vhodná pro různé aplikace včetně zátěžového testování a kalibrace makroobezřetnostních nástrojů. Po představení této metodiky ukazujeme, že kvalita výstupů námi navrhovaného přístupu ve srovnání s obvykle používanými metodami vychází příznivě. Poté s využitím tohoto přístupu odhadujeme potenciální nárůst rizikových vah v důsledku cyklického zhoršení úvěrových parametrů a související nastavení proticyklické kapitálové rezervy pro český bankovní sektor. Na závěr v příloze prezentujeme ilustrativní a praktický příklad aplikace představené metodiky.

JEL Codes: E58, G21, G28, G29.

Keywords: Countercyclical capital buffer, credit portfolio structure, risk weighted exposure, stress-testing.

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This work was supported by grant VSE IGS 47/2022 and was developed under the TREA modelling project. The authors would like to thank Libor Holub for his comments and suggestions, which helped to improve the paper significantly. We also appreciate the constructive and insightful comments of the reviewers, Ludek Palan and Aurea Ponte Marquez. The views expressed in this paper are those of the authors and not necessarily those of the Czech National Bank or the European Central Bank.

1. Introduction

Significant efforts have been made to improve the financial sector's stability since the global financial crisis (GFC) of 2008. The Basel accords have played a crucial role in strengthening banking sector regulation[1] as the principles they contain have been gradually implemented into national legislations. The stakeholders' key motivation was to prevent a repeat of the extensive socialization of losses that occurred during the GFC and to promote the necessary stability across the sectors of the economy by addressing the interconnectedness and negative feedback loops observed during the crisis. The banking capital adequacy framework is a crucial regulatory tool for measuring banks' stability. The primary purpose of the framework is to evaluate whether financial institutions currently have sufficient capital in relation to the riskiness of their business activities in order to ensure they stay solvent. This paper focuses on modelling the riskiness of banking portfolios in terms of the risk exposure amount (risk-weighted assets[2]) for credit risk based on the current EU-wide CRR2 regulation.[3]

In today's intricate financial environment, the importance of accurate risk management and forecasting cannot be overstated. Capital adequacy remains a critical metric, but on its own, it does not offer any insights into possible future developments. For instance, it does not reveal how an intense and prolonged crisis may alter the internal structure and risk profile of financial institutions or what the potential implications might be for their future solvency position. To assess this, both the numerator (the volume of capital) and the denominator (risk-weighted assets) of the capital adequacy ratio must be modelled in great detail to achieve sufficient precision (paying due regard to the inherent limitations of any modelling approach).

Risk-weighted assets provide a quantified representation of a bank's assets adjusted for their respective risk levels. The assessment of risk-weighted assets is pivotal not only for banks' internal risk assessments, but also for regulatory bodies tasked with supervising banks and maintaining financial stability. Their goal is to ensure that banks hold adequate capital against potential unexpected losses. Regulatory requirements prescribe methodologies for calculating risk weights and exposure values, which can differ based on factors such as regulatory approach, exposure performance, counterparty, collateral and product type. Consequently, risk-weighted assets can fluctuate over time. Closely monitoring these developments and estimating future values using a range of scenarios is essential. In particular, the evolution of risk-weighted assets is vital for regulatory stress testing exercises that assess the resilience of individual financial institutions and/or the system as a whole. Moreover, it might be useful for calibrating certain macroprudential policy instruments.

Our paper presents a detailed methodology for estimating risk-weighted assets related to credit risk conditional on a selected scenario. Credit risk is by far the most significant source of risk in the Czech banking sector. The proposed methodology is easily replicable, as regulatory bodies in the EU share the same type of data employed in our approach. Simultaneously, it promotes high granularity, which may reduce model risk and potential deviations from actual future outcomes,

[1] Although we note the relevant critique of extensiveness made by Haldane (2012).
[2] We call the indicator risk-weighted assets (RWA), as is the norm among practitioners.
[3] https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32019R0876

i.e. forecasting errors. In the Appendix, we provide a hands-on example, including direct links to the supervisory common reporting (COREP) framework with row and column identifiers. This promotes transparency and further enhances the replicability of our framework. Furthermore, we suggest that our approach offers certain advantages over the portfolio level methods commonly employed by regulators. Finally, we showcase how our model can be applied to the calibration of macroprudential instruments, providing an example derivation of the absolute capital amount for the countercyclical capital buffer (CCyB) to mitigate cyclical fluctuations in risk-weighted assets for credit risk.

A viable approach to estimating the evolution of risk-weighted assets for credit risk uses structural form equations anchored directly to the IRB regulatory formulas, which are based on the asymptotic single risk factor (ASRF) model. Despite its known limitations, the ASFR model has been globally adopted by regulators and financial institutions. As a result, this method is generally preferred for risk weight modelling over reduced form estimations. This trend is further supported by a lack of sufficiently long time series and the structural approach's capacity to at least partially capture the inherent non-linearities embedded in the regulatory risk weight calculations. Furthermore, this approach naturally accounts for regulatory prescriptions specific to performing and non-performing exposures.

Although the existing approaches often disclose only limited specifics, and the granularity of the portfolios used is rarely discussed in detail, it appears that risk weights and exposure values are predominantly modelled separately in the implementation of IRB formulas using aggregate risk data on either the bank or the portfolio level (e.g. Feldkircher et al., 2013, Schmieder et al., 2011, Daniëls et al., 2017, Budnik et al., 2020, and ECB, 2023). In contrast, resorting to reduced form estimations is not very common, as it can lead to substantial misestimations of risk weights, particularly when simulating prolonged crises, as the internal mechanics are generally not adequately covered. Nevertheless, reduced form estimation has been adopted in specific contexts as a straightforward simplification, such as in bottom-up stress testing (Burrows, 2012). Finally, in certain applications, the risk weights are merely shifted by a pre-defined stressed change (Buncic et al., 2019).

In our methodology, we align with the prevailing trend by directly using the regulatory IRB formulas. However, instead of employing aggregate risk data as in the conventional supervisory stress testing methodologies, we strongly emphasize granular modelling of the internal risk structure of banks' portfolios at the level of individual internal obligor grades. The individual grades within portfolios possess distinct risk characteristics. A detailed representation of these risk profiles allows for more comprehensive assessment of vulnerabilities and tail risks during the stress test. This approach also aims to better capture the inherent non-linearities by enhancing the alignment of the scope of modelling between supervisors and supervised institutions.

Precise modelling of risk-weighted assets may also be of significant importance for appropriate calibration of the countercyclical capital buffer (CCyB), which is aimed at bolstering banks' resilience through financial cycles. Notably, risk weights for credit risk are notoriously pro-cyclical, interwoven with the dynamics of cycles. Consequently, while CCyB adjustments traditionally account for credit growth, we believe it is equally important also to consider fluctuations in risk weights, which can affect capital requirements and bank robustness. Therefore, we also provide an example of a framework for calibrating the CCyB based on the evolution of risk weights using our granular modelling approach, thus extending the contemporary practices.

The paper is organized as follows. The second section introduces the methodology for estimating risk-weighted assets. The third section discusses the model's performance. The fourth section provides an example model application where the evolution of risk-weighted assets during a hypothetical downturn is estimated and subsequently used to calibrate the level of the countercyclical capital buffer necessary to counteract the reduction in the capital ratio. Finally, the last section concludes.

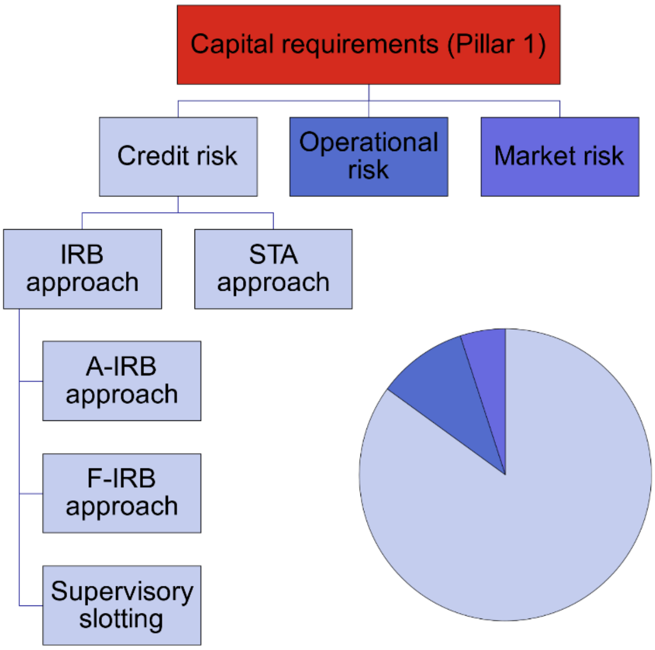
2. Methodology

Basel III requires banks to hold a specific amount of capital in relation to their risk exposures. Risk-weighted assets (RWA), as the denominator of the capital adequacy ratio (CAR), are one of the key components used to determine the minimum amount of capital banks must hold to cover their risk:

$$CAR = \frac{Capital}{RWA} \quad (1)$$

The RWA framework covers multiple types of risk. However, the credit risk area accounts for over 85% of the total RWA in the Czech banking sector. In the credit risk area, banks are allowed to use two main approaches to model credit risk weights: the internal rating based (IRB) approach and the standardized (STA) approach. Further, within the IRB approach, we distinguish the advanced IRB (A-IRB) approach, the foundation IRB (F-IRB) approach and the supervisory slotting approach. An overview of the RWA framework is captured by a stylized diagram in Figure 1 below.

Figure 1: Risk-Weighted Assets Framework Overview



Risk-weighted assets can be decomposed into a product of two principal components – the exposure value (EV) and the risk weight (RW):

$$RWA = EV \times RW \tag{2}$$

These two components are often treated separately. Exposure value forecasts are modelled using a dedicated satellite model, while risk weights follow a separate procedure.

Modelling and forecasting risk weights is a complex process. Regulatory formulas involve several risk components, which need to be determined before the formulas can be applied. In particular, these may include (depending on the regulatory approach) the probability of default (PD) and the loss given default (LGD). Our approach focuses predominantly on how these risk parameters can be estimated while ensuring an appropriate level of sensitivity to macroeconomic scenarios, and how to reflect the forecasted evolution of risk weights at the individual obligor grade levels of each portfolio of each bank.

The fundamental logic of our approach to risk weight modelling is in line with the current best practices in the euro area, as described, for example, in Budnik et al. (2020) and ECB (2023). However, our paper makes several contributions to the existing frameworks. Unlike the other commonly used methods, we model risk weights at the individual obligor level, promoting high granularity in risk management practices. The granular approach should lower the model risk and provide further insights into potential vulnerabilities and tail risks, and might reduce forecasting errors due to better alignment with banking sector data. Furthermore, the methodology is described in a sufficiently detailed manner, including a hands-on example with direct links to the COREP framework. This fosters transparency and replicability of our approach. Last but not least, we also demonstrate a possible model application involving the derivation of the CCyB needed to cover a cyclical reduction in the absolute capital requirements during an expansionary phase of the financial cycle (see Section 0). This extends the contemporary CCyB calibration practice, which focuses solely on the potential credit losses affecting the regulatory capital (the numerator of the capital ratio).

For the purposes of this paper, we estimate the model separately for three portfolios which together form the core part of the non-financial private sector (NFPS): (i) loans to non-financial corporations, (ii) loans to households secured by residential property and (iii) residual loans to households.

Overall, the estimation of risk-weighted assets is conducted in several steps. First, satellite models for the point-in-time risk parameters PD PiT and LGD PiT, together with the growth of the loan portfolio, are estimated.[4] The satellite models represent the link between the scenario path and the impact on banks' balance sheet items. Second, the accounting structure of the credit portfolio is estimated based on the scenario to obtain the conditional dynamics of performing and non-performing exposures. Third, risk-weighted assets are modelled using the set of upstream outputs

[4] Note that in the model application section, we do not use credit growth in our projections, as the CCyB is set for the current portfolio only. For stress testing exercises with dynamic balance sheets, however, it should be considered.

from the previous steps. In the remaining part of this section, we will further explore these individual steps in greater detail.

Satellite Models

Satellite models are applied to estimate the impact of the macroeconomic scenario path on banks' balance sheet items. A large variety of frameworks are currently employed to estimate PD PiT, LGD PiT and credit growth, starting with models based on the Merton approach (Merton, 1974), through augmented BMA models such as Panos and Polak (2019a), to large structural models such as Gregor and Hejlova (2020). In practice, any suitable PD PiT and LGD PiT models can be applied to the individual segments, as this is a standard procedure common to most stress testing frameworks. In the case of the Czech National Bank's (CNB) stress testing exercises, PD PiT for "loans to non-financial corporations" are modelled as in Siuda (2020) and those for "loans to households secured by residential property" as in Gregor and Hejlova (2020). The residual loans to households PDs exhibit a high correlation with the loans secured by residential property PDs, so there is no need for comprehensive modelling for the case of the Czech banking portfolio. The path is determined by shifting the PDs of loans to households secured by residential property by a constant term derived from the long-term relationship between the two variables. For LGD PiT, we base our projections for each of the three above-mentioned segments on Gersl et al. (2012). Credit growth for the top-down stress testing exercises is modelled according to Plasil (2021). Next, to estimate the final path of risk-weighted assets for CCyB estimation purposes presented in the next section, we also set the conditional distribution of the parameters using the procedure of Hajek et al. (2017). Using this procedure, we can determine less probable but more severe paths of the risk parameters that are still consistent with the baseline development of the real economy. We do not detail the methodologies for the PD PiT and LGD PiT predictions used in these satellite models, as they are well-documented in the aforementioned literature and are not the focus of this paper.

Modelling the Structure of the Loan Portfolio from the Accounting Perspective

To model the loan portfolio structure, we closely follow the framework outlined by Panos and Polak (2019b), with several specific features. First, the initial transition probability matrices that control the movements between stages are calibrated so that the realized default rates closely follow the projections from the satellite models. Second, the transition probability matrices are modelled with bridge equations, as suggested in Gross et al. (2019).

As established above, the portfolios considered in this paper cover the whole NFPS for each bank in the system. The approach can be extended in the same way to model additional portfolios, but for the purposes of Section 0, we will focus solely on NFPS loans. Each portfolio's initial structure of IFRS9 impairment stages and the calibrated transition probability matrices are retrieved from the supervisory financial reporting (FINREP) framework. The FINREP framework is also used to estimate the bridge equations. Next, the projections from the satellite models are applied to model the evolution of the impairment stages for each quarter and each bank's portfolio, as in Panos and Polak (2019b). Subsequently, the outputs of the model are used to project transitions of loans between performing and non-performing status in the modelling of risk-weighted assets. For this purpose, loans in impairment stages 1 and 2 are treated as performing and those in impairment stage 3 as non-performing.

Building Initial Risk-Weighted Assets

The next step focuses on building the starting point risk-weighted assets for credit risk. Before we start, it is worth reminding that the credit risk RWAs represent only a part of the denominator used to determine capital ratios – the total risk exposure amount ($TREA$).[5] In the case of the Czech banking sector, the risk exposure amount for credit risk (REA_{CR}) accounts for roughly 87% of $TREA$. As we focus on just a part of the loan portfolio, only a part of REA_{CR}, labelled as REA_{CR}^{M}, is modelled. In particular, we choose only exposure classes connected to the NPFS (see Table 1). The rest of $TREA$ is assumed to remain constant. There is, however, no loss of generality, as the proportion of loans modelled with our procedure can be easily extended. Overall, REA_{CR}^{M} makes up 82% of REA_{CR} and over 71% of $TREA$ in our case. Generally, REA_{CR}^{M} is the sum of the products of the exposure values (EV) and risk weights (RW) for the individual portfolios. Our approach to modelling these two components relies on the most granular data available in the regulatory common reporting (COREP) framework, i.e. data at the internal obligor grade level. In the Appendix, we also provide an illustrative example suggesting how to replicate the methodology for stress testing and other purposes. Our hands-on example features detailed references to the COREP framework, including the individual rows and columns of each relevant template. For more details, see the Appendix.

First, we set up the initial regulatory portfolio for REA_{CR}^{M}. To do so, we use data obtained from COREP, which provides granular information at the internal obligor grade level within each exposure class in the internal ratings-based (IRB) approach portfolio and at the exposure class level in the standardized (STA) approach portfolio. Therefore, our approach can be easily replicated across the EU countries, as their regulatory bodies share the same reporting standards. Besides the exposure value and final risk-weighted exposure amount available for both the IRB and STA approaches, the reported data also provide additional items used to derive the final risk weights for the internal obligor grades of each exposure class of the IRB approach. The key variables are the through-the-cycle probability of default (PD TTC), the downturn loss given default (LGD DT) and the average maturity (M).[6] For simplicity, we often refer to the first two parameters simply as PD and LGD. Using these risk parameters, we can derive a calculated risk weight $RW_{Calculated}$ for each internal obligor grade within each IRB portfolio and bank, as shown later in this section.

Next, we determine the implied risk weight by simply taking the ratio of the reported risk-weighted exposure amount to the reported exposure value:

$$RW_{Implied} = \frac{RWA}{EV} \tag{3}$$

Finally, we calculate the ratio ϕ of the implied risk weight to the calculated risk weight:

[5] Sometimes generally denoted as RWA for simplicity (as, for example, in Equation 1).

[6] The PD TTC parameter captures a borrower's credit risk over an entire economic cycle, including both downturns and upturns. Unlike PD PiT, which varies with short-term conditions, PD TTC should provide a more stable, long-term view of default risk. The LGD DT parameter represents the potential loss a bank might face on a defaulted loan during adverse economic conditions or downturns. It should be higher than LGD PiT at most times because recoveries are expected to be lower in challenging economic times. Note that while in the A-IRB approach, the banks themselves are responsible for modelling LGD DT, in the F-IRB approach these risk parameters are prescribed by CRR2.

$$\phi = \frac{RW_{Implied}}{RW_{Calculated}} \quad (4)$$

The ratio ϕ captures in particular non-linearities stemming from the aggregation of individual obligors within a given grade (for more detail on aggregation, see the hands-on example in the Appendix). This effect is especially significant for lumpy portfolios, such as financial institutions, where each institution within a given grade has typically assigned its own PD and LGD. As a consequence, the calculated and implied risk weights tend to be different and ϕ thus deviates from 1. In contrast, the same PD and LGD is typically assigned to the whole pool of obligors within a single grade for many retail portfolios. In such cases, the calculated and implied risk weights match almost perfectly, i.e. $\phi \approx 1$. In addition, ϕ might also capture other adjustments banks apply when calculating the final risk weight which are not sufficiently captured by the reporting framework and thus cannot be considered in the calculation.[7] The ratio ϕ is stored and later applied to scale the risk weight projections to account for non-linearities and additional adjustments as described above.

Parameter ϕ is essential to ensure that the actually reported and model starting points RW (and RWA) are fully aligned, which is necessary for any kind of stress testing or macroprudential policy calibration exercise. A similar calculation for ϕ as in Equation 4 can also be made under the aggregated portfolio level approach to align the starting points. However, as shown in Equation 5 below, the RW function is a non-linear multivariate function and thus can behave very differently in different areas of the function domain. This might result in substantial misestimations of risk weight projections when the values of ϕ deviate significantly from 1, even with matching starting points. Consequently, to achieve optimal results, it is vital to ensure that the implied and calculated starting point risk weights converge as closely as possible, ideally pushing ϕ near to 1.

The formulas used to determine $RWA_{Calculated}$ are conceptually based on Merton's model application by Vasicek (2002), commonly known as the asymptotic single risk factor (ASRF) model. The ASRF model has been central to the IRB approach to credit risk in the Basel frameworks since its introduction within Basel II (the original concept is presented in BCBS, 2005). The model simplifies credit risk by assuming it is driven by a singular systematic factor. While this model enhances risk sensitivity compared to the STA approach, it has inherent drawbacks. Specifically, its reliance on a single risk factor may oversimplify risks and may not capture nuanced influences on credit portfolios stemming from other risk factors. There are also concerns regarding its pro-cyclicality, which might inadvertently amplify economic cycles. Nonetheless, despite these limitations, regulators and financial institutions globally have adopted the ASRF model due to its relative sophistication, its ability to use internal data for more tailored risk weightings and its potential regulatory capital benefits. For these reasons, the ASFR model is also central to our approach to IRB modelling, as we aim to align the core logic of the RWA calculations with those of the regulated banks.

In particular, the calculations of risk weights for each performing internal obligor grade within IRB portfolios[8] are based on the following formula prescribed by the CRR2 regulation:

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[7] For example, banks must apply a correlation multiplier for large (over EUR 70 billion in total assets) or unregulated financial entities, and in the case of companies with total annual sales below EUR 50 million, banks can adjust the correlation coefficient for a given company by a term dependent on its total annual sales.

[8] The formulas are identical for both the foundation IRB (F-IRB) and the advanced IRB (A-IRB) approaches.

$$RW_{calculated} = \left(LGD \times N\left\{ \frac{1}{\sqrt{\left(1 - R(PD)\right)}} \times G(PD) + \sqrt{\frac{R(PD)}{1 - R(PD)}} \times G(0.999) \right\} - LGD \times PD \right) \times Z(M, PD) \times 1.06 \times 12.5 \times SME\ SP \quad (5)$$

where $N\{X\}$ is the cumulative distribution function for a standard normal random variable, $R(PD)$ is the coefficient of correlation dependent on PD, $G\{X\}$ is the inverse cumulative distribution function for a standard normal random variable, $Z(M, PD)$ is the maturity adjustment dependent on maturity M and PD, and $SME\ SP$ is the small and medium-sized enterprises (SME) supporting factor.

The particular form of the $R(PD)$ equation depends on the given exposure class. In general, for exposures to corporates, institutions, central governments and central banks, the formula takes the following form:

$$R(PD) = 0.12 \times \frac{1 - e^{-50 \times PD}}{1 - e^{-50}} + 0.24 \times \left(1 - \frac{1 - e^{-50 \times PD}}{1 - e^{-50}} \right) \quad (6)$$

As mentioned above, this formula can be further adjusted depending on various factors. For instance, for large or unregulated financial sector entities, $R(PD)$ is additionally multiplied by 1.25. In contrast, for companies with total annual sales below EUR 50 million, $R(PD)$ is reduced by the term:

$$0.04 \times \left(1 - \frac{min(max(5, S), 50) - 5\ )}{45} \right) \quad (7)$$

where S is total annual sales in millions of EUR. However, COREP reporting does not allow for determining for what exposure volume in which specific grades these adjustments were applied; therefore, we abstract from it in our approach.

For retail exposures, the correlation coefficient takes the following form:

$$R(PD) = 0.03 \times \frac{1 - e^{-35 \times PD}}{1 - e^{-35}} + 0.16 \times \left(1 - \frac{1 - e^{-35 \times PD}}{1 - e^{-35}} \right). \quad (8)$$

The exceptions are qualified revolving exposures, where $R(PD) = R = 0.04$, and exposures secured by immovable property collateral, where $R(PD) = R = 0.15$. In contrast to the special cases for financial sector entities and companies with total annual sales below EUR 50 million, we consider the special cases for qualified revolving exposures and exposures secured by immovable property in our approach, as they are reported separately.

The maturity adjustment $Z(M, PD)$ is simply $Z = 1$ for all retail exposures. In all other cases, it takes the following form:

$$Z(M, PD) = \frac{1 + (M - 2.5) \times b(PD)}{1 - 1.5 \times b(PD)}, \quad (9)$$

where b is the maturity adjustment factor calculated as follows:

$$b(PD) = (0.11852 - 0.05478 \times \ln(PD))^2. \quad (10)$$

Note that, under CRR2, $SME\ SP$ ranges between 0.7619 and 0.85 when the counterparty is a small or medium-sized enterprise to counterbalance the rise in capital resulting from the capital conservation buffer. The exact value depends on the total amount of the exposure to the bank. We determine the $SME\ SP$ values for each obligor grade, exposure class and bank from the ratio of the reported RWA after and before applying the SME supporting factor. The resulting parameters thus represent the average of the $SME\ SP$ values applied by the bank for individual obligors within each grade. It follows that the ratio is equal to 1 when no SME exposures are present.

A different methodology for calculating risk weights is prescribed for non-performing exposures within the IRB approach. In the foundation IRB (F-IRB) approach, the risk weight for non-performing exposures always equals 0. In the advanced IRB (A-IRB) approach, the formula takes the form

$$RW = \max(EL_{BE} - LGD; 0) \quad (11)$$

where EL_{BE} is the expected loss best estimate. In our approach, we assume a constant spread between LGD and EL_{BE}, resulting in constant projections for the risk weights for A-IRB non-performing exposures.

We also need to set up the risk weights applied to STA portfolios and portfolios under the supervisory slotting approach.[9] For each STA exposure class, the ratio $RW_{implied}$ of the risk exposure amount to the exposure value is calculated as in Equation 3, and this value is kept stable for the whole scenario period. Thus, we do not consider a credit deterioration within STA exposure classes, and the overall STA risk weight dynamics stem only from the evolution of the exposure values in the individual portfolios. This also holds for STA non-performing exposures and supervisory slotting portfolios. This represents one of the potential weaknesses of our approach, as STA risk weights also tend to show some sensitivity to the macroeconomic scenarios due to the internal portfolio structure dynamics caused, for example, by migrations between credit quality steps. A possible way to model STA risk weights is outlined in ECB (2023). We are also considering adding more detailed STA modelling to our framework in future updates.

As part of this step, we need to establish a connection between the accounting and the regulatory loan portfolio (see Table 1). This will facilitate PD, LGD and exposure value scenario development. To do so, we need to map the set of counterparties from the accounting perspective (based on the FINREP framework) to the collection of regulatory IRB and STA exposure classes (based on the COREP framework). Although some minor misspecification may occur, the mapping procedure presented below provides a robust outcome in terms of exposure values assigned at the level of the whole banking sector. We also cross-checked the matched portfolios and classes with the AnaCredit database, and the established links were reaffirmed.

[9] Supervisory slotting is used to calculate risk weights for certain specialized lending exposures. The logic of the calculations is similar to that for STA exposures.

Table 1: FINREP and COREP Mapping Set

Portfolio used in FINREP	**Assigned exposure class from COREP**
Loans to non-financial corporations	- Corporate – SME (IRB Approach) - Corporate – Specialized lending (IRB Approach) - Corporate – Other (IRB Approach) - Claims on institutions and corporates with a short-term credit assessment (STA Approach) - Exposures to corporates (STA Approach) - Items associated with particularly high risk (STA Approach)
Loans to households secured by residential property	- Retail – Secured by immovable property SME (IRB Approach) - Retail – Secured by immovable property non-SME (IRB Approach) - Exposures secured by mortgages on immovable property (STA Approach)
Residual loans to households	- Retail – Qualifying revolving (IRB Approach) - Retail – Other SME (IRB Approach) - Retail – Other non-SME (IRB Approach) - Retail exposures (STA Approach)

Modelling the Risk Weights and Exposure Values of the Regulatory Portfolio

This step builds on the estimated loan portfolio structure from the accounting perspective together with the initial risk weights constructed in the previous step and projects the evolution of the risk-weighted assets for credit risk. In the previous section, we presented formulas for calculating the initial risk weights.

The IRB risk weights depend strongly on banks' estimates of PD (for both the A-IRB and F-IRB approaches) and LGD (for the A-IRB approach only, as in the F-IRB approach, the LGD values are prescribed by the regulator). While these parameters were originally intended to be stable, empirical evidence shows that PD values, in particular, fluctuate over time, often being constructed as moving averages of one-year PD PiT with a minimum 5-year window (as allowed by CRR2). Thus, to model the PD and LGD parameters which can be used to estimate the scenario-conditional risk weight evolution, we need to link their dynamics to those of the macroeconomic variables. To achieve this, we take advantage of the PD PiT and LGD PiT parameters already estimated via the satellite models in the first step of the process.

To estimate the PD values, we use PD PiT[10] to construct 36-quarter (9-year) moving averages representing satellite through-the-cycle variables labelled as $PD\,TTC^{SAT}$. The optimal window length was set based on the correlations with the historical PD values and reaffirmed with supervisory experts at the Czech National Bank. The shifts of PD in time are generated via the distance-to-default (DtD) transformation using the inverse CDF of the standardized normal

[10] Note that for this purpose, the PD PiT values need to represent the 12-month probability of default. Since we estimate the parameters as 3-month variables, they are converted via the following transformation to 12-month values: $PiT\ PD_t = 1 - \prod_{i=0}^{3}(1 - PiT\ PD_{t+i})$.

distribution. The DtD transformation for PD is thus, in principle, equivalent to the probit transformation, and for any time t, it is generally defined as:

$$DtD_t = \Phi^{-1}(PD_t) \tag{12}$$

The shift of PD for each performing internal obligor grade i of an exposure class at time T_n is then defined as:

$$PD_{T_n}^{Grade\ i} = \Phi\left(\Phi^{-1}\left(PD_{T_0}^{Grade\ i}\right) + \Phi^{-1}\left(PD\ TTC_{T_n}^{SAT}\right) - \Phi^{-1}\left(PD\ TTC_{T_0}^{SAT}\right)\right) \tag{13}$$

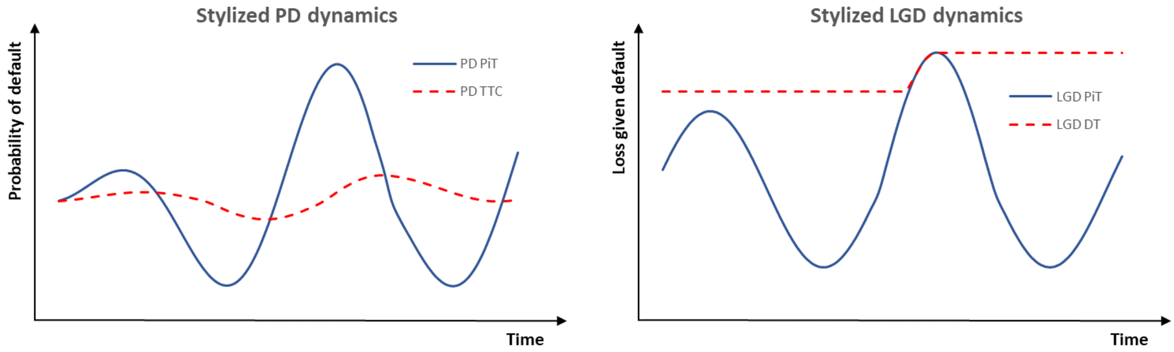
where parameters at T_0 represent the starting point values. This approach is employed quite often in stress test modelling when dealing with bounded variables. The DtD transformation has the advantage of shifting low values proportionally more than high values and ensures that values stay within the $(0,1)$ interval, which is essential given the probabilistic nature of PDs.

The downturn LGD for each internal obligor grade i within the A-IRB approach is determined based on the absolute values of LGD PiT. According to the guidelines provided by the European Banking Authority (EBA, 2019), the downturn LGD should not be lower than the corresponding PiT LGD values. To adhere to this guidance, we construct a downturn LGD satellite series that, at each time point, represents the maximum value between the initial exposure value (EV) weighted average of the downturn LGDs ($wLGD_{T_0}$) and the maximum value of LGD PiT over the projection horizon until the given time point. It is important to note that this newly constructed series is non-decreasing, as per the EBA guidelines. The resulting series is then used in a manner similar to the $PD\ TTC^{SAT}$ approach:

$$\begin{gathered} LGD\ DT_{T_n}^{SAT} = \max\left(wLGD\ DT_{T_0}; \max(\{LGD\ PiT_t : t = T_0, T_1, \dots, T_n\})\right) \\ wLGD\ DT_{T_0} = \frac{\sum_i^n EV_{T_0}^{Grade\ i} \times LGD_{T_0}^{Grade\ i}}{\sum_i^n EV_{T_0}^{Grade\ i}} \\ LGD_{T_n}^{Grade\ i} = \Phi\left(\Phi^{-1}\left(LGD_{T_0}^{Grade\ i}\right) + \Phi^{-1}\left(LGD\ DT_{T_n}^{SAT}\right) - \Phi^{-1}\left(LGD\ DT_{T_0}^{SAT}\right)\right) \end{gathered} \tag{14}$$

To better illustrate our approach to converting the PiT risk parameters estimated by the satellite models to risk parameters that can be used for the RW calculations, Figure 2 shows stylized dynamics for PD and LGD.

Figure 2: Stylized Through-the-Cycle PD and Downturn LGD Dynamics



The downturn LGDs for the F-IRB approach are prescribed by regulation (CRR2) and depend inter alia on the classification and seniority of the exposures. Thus, we keep the starting point LGDs for F-IRB portfolios constant throughout the period modelled.

The resulting PD and LGD for each internal obligor grade are plugged into the regulatory RW formula, which is then multiplied by the corresponding $\phi^{Grade\ i}$ calculated in the previous step. In this way, we obtain the evolution of the risk weights in the given internal obligor grade starting from the initial point $RW_{T_0}^{Grade\ i}$ exactly matching the $RW_{Implied}^{Grade\ i}$ reported by the bank. The risk weight $RW_{T_n}^{Grade\ i}$ at time T_n for each internal obligor grade thus takes the following form:

$$RW_{T_n}^{Grade\ i} = \left(LGD_{T_n}^{Grade\ i} \times \Psi\left(PD_{T_n}^{Grade\ i}\right) - LGD_{T_n}^{Grade\ i} \times PD_{T_n}^{Grade\ i}\right) \times Z\left(M^{Grade\ i}, PD_{T_n}^{Grade\ i}\right) \times 1.06 \times 12.5 \times SME\ SP \times \phi^{Grade\ i}$$

$$\Psi\left(PD_{T_n}^{Grade\ i}\right) = N\left\{\frac{1}{\sqrt{\left(1 - R\left(PD_{T_n}^{Grade\ i}\right)\right)}} \times G\left(PD_{T_n}^{Grade\ i}\right) + \sqrt{\frac{R\left(PD_{T_n}^{Grade\ i}\right)}{1 - R\left(PD_{T_n}^{Grade\ i}\right)}} \times G(0.999)\right\} \tag{15}$$

For the non-performing IRB internal obligor grades, the risk weights are kept constant throughout the scenario period. This is, in fact, a conservative assumption, as the distance between EL_{BE} and the downturn LGD for defaulted exposures is actually expected to decrease in times of crisis.

Similarly, for the individual STA exposure classes and supervisory slotting exposures, the risk weights also stay constant throughout the scenario horizon. Historical evidence from the Czech banking sector partially supports this approach, as the aggregate STA risk weights vary just slightly, mostly due to changes in the portfolio structure.

Besides the risk weights, to estimate the risk-weighted assets, we must also estimate the exposure value dynamics throughout the scenario period. As the overall evolution of the loan portfolio from the accounting perspective is already known, we can use the link established between the accounting and regulatory perspectives (see Table 1). For each scenario period, a percentage change to the starting point of the accounting portfolio loan value is allocated to the corresponding regulatory exposure classes proportionally across the obligor grades. This results in a stable internal structure of each portfolio regarding the distribution of the exposure value across the obligor grades (for more details, see the example in the Appendix). Note that we project the performing and non-performing volumes separately. For this purpose, impairment stages 1 and 2 are treated as performing and impairment stage 3 as non-performing. In addition, the exposure values for IRB portfolios and supervisory slotting are estimated in gross terms, while for STA portfolios they are estimated net of corresponding provisions (as prescribed by the regulation).

At this stage, we have calculated the scenario paths for both the risk weights and the exposure values. We multiply both values (see Equation 2) to obtain the risk-weighted assets for each internal obligor grade in the IRB approach and for each exposure class in the STA approach and then sum all the RWA projections to obtain REA_{CR}^{M} for each period. In the final step, we add the constant terms for the non-modelled part of REA_{CR} (labelled as REA_{CR}^{NON-M}) and the risk exposure amounts for other risks (REA_{Other}) to get the final $TREA$ for each bank and scenario period:

$$TREA_{T_n} = REA^{M}_{CR,T_n} + \overbrace{REA^{NON-M}_{CR} + REA_{Other}}^{constant\ terms} \qquad (16)$$

The Appendix provides a detailed hands-on example of applying the methodology described in this section with fictitious data points and with references to the COREP templates.

3. Model Performance

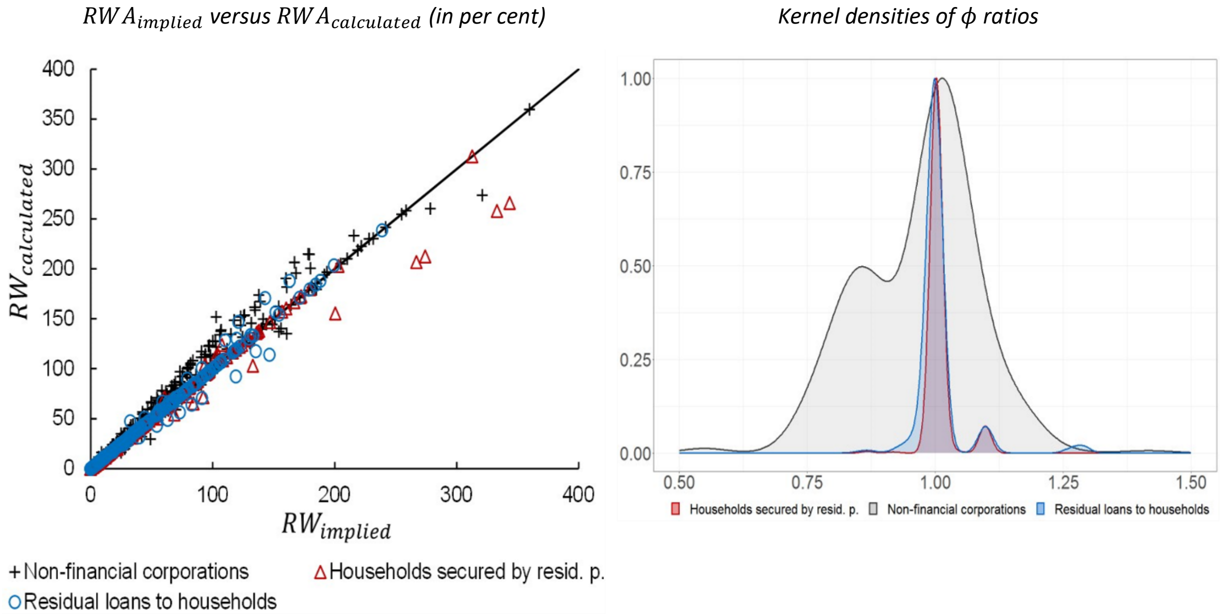
Evaluating the performance of a model is integral to ensuring its reliability, efficacy and applicability in real-world contexts. Such an assessment not only sheds light on the strengths and weaknesses of the model, but also provides valuable insights into its robustness amidst various uncertainties. Testing the model also allows us to develop a better understanding of its limitations and can guide us regarding further enhancements. In this section, we first evaluate the convergence of the ratio ϕ to 1 (see Equation 4), as this convergence is one of the key features of our proposed methodology. Second, we use banks' submissions from the supervisory stress test to assess the model's ability to capture the evolution of risk weights during an economic downturn.

Our methodology relies on using obligor grade level data available in the COREP reporting framework. By aligning the granularity of our approach more closely with banks' calculations, we can expect a significant narrowing of the gap between $RWA_{implied}$ and $RWA_{calculated}$ compared to conventional portfolio level approaches. Such convergence should drive ϕ towards 1. Our testing confirms these expectations. Although the values across banks and portfolios may vary, we achieved an average reduction of the absolute gap between ϕ and 1 of approximately 76%[11] across the sample, a notable improvement over the portfolio level benchmark model. Furthermore, the gap was reduced for essentially all banks and portfolios, underscoring that the proposed methodology provides consistently better alignment.

The capability of our model regarding $RWA_{implied}$ and $RWA_{calculated}$ convergence is further explored in Figure 3. The left panel presents a scatterplot of $RWA_{implied}$ and $RWA_{calculated}$ against the axis of the first quadrant. While several outliers can be detected, the vast majority of the portfolios, particularly those of households, align almost perfectly. This is confirmed by the estimated kernel densities depicted in the right panel, where the ϕ ratios for household portfolios are strongly concentrated around 1. The average ϕ ratio for household portfolios stands at 1.01, with the absolute gap reduced by approximately 95%. For multiple reasons outlined in the previous section, NFC portfolios generally exhibit a less precise match, resulting in a considerably wider kernel density and an average ϕ ratio of 0.97. The reduction of the absolute gap exceeds 68% in comparison to the portfolio level benchmark model in the NFC portfolio case. Although this is a less pronounced improvement than for the household portfolios, it remains substantial.

[11] This also includes non-NFPS portfolios like institutions or central banks and central governments.

Figure 3: Assessing Convergence between $RWA_{implied}$ and $RWA_{calculated}$ by NFPS Portfolios



Note: Both charts are based on individual obligor grade level data. The kernel densities in the right panel are scaled such that the maximum value on the vertical axis is 1. The value of the smoothing parameter is 1.25 and 15 for the non-financial corporations and household portfolios respectively.

In the next part, we focus on evaluating the performance of our approach in the context of the Czech National Bank's supervisory bottom-up stress testing exercise. Given the historical data constraints, marked by a predominance of "good times" and a lack of extended trends, traditional quasi-out-of-sample forecasts are deemed inappropriate for this exercise. By analysing banks' projections disclosed during the stress tests, we assess the model's ability to capture more pronounced risk weight shifts, particularly during periods of elevated macroeconomic stress.

The data were sourced from the 2023 supervisory bottom-up stress testing exercise, with the participation of 12 out of the 15 banks in the Czech banking sector, representing approximately 99% of total bank assets. This exercise resembles the EU-wide stress test conducted by the European Banking Authority, adopting similar templates and methodology in general. Participating banks were tasked to assess the impact of the baseline and adverse macroeconomic scenarios on their capital and RWAs from 2022 to 2025. We extracted average point-in-time (PiT) values for PD and LGD for each asset class disclosed. These served as input data for projecting RWAs using our proposed model. The derived projections were then compared against the banks' original disclosures.[12] Due to the confidential nature of the data, the results provided are restricted to the aggregate level.

To comprehensively assess our model's performance, we contrast its results with two benchmark models that use fully aggregated data, disregarding the internal obligor grade portfolio structure.

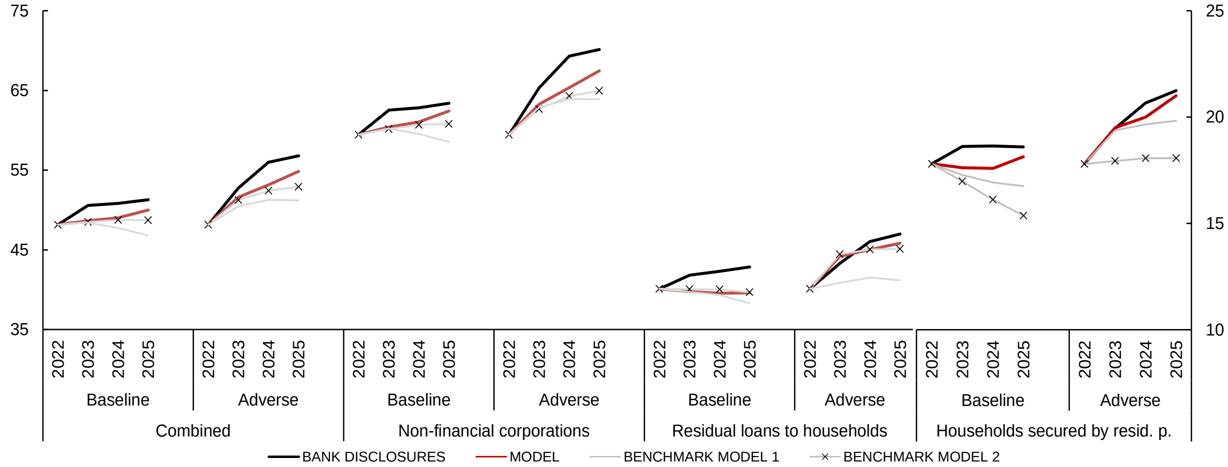
[12] In practical terms, this means we used the satellite models of the participating banks rather than those of the Czech National Bank (CNB). This approach aligns with our primary objective of assessing the efficacy of the proposed granular RWA modelling method, rather than testing the performance of the CNB's established satellite models. Furthermore, consistent with the bottom-up supervisory exercise, a static balance sheet was assumed.

Similarly to our approach, these benchmarks combine the average PiT values from the disclosures with historical the PiT time series to construct a satellite through-the-cycle (TTC) time series of PDs and corresponding downturn LGDs. These time series were then employed as inputs to calculate benchmark risk weights using the corresponding IRB formulas and scaled by parameter ϕ on the portfolio level to match the starting point risk weights reported by banks.

Notably, the two benchmark models differ in their approach to the downturn LGD calculations. While Benchmark Model 1 (BM1) follows the methodology for LGD DT suggested in the previous section, Benchmark Model 2 (BM2) adopts the through-the-cycle approach, in line with Article 181 of CRR2, as previously used by the Czech National Bank. The downturn LGD series in this case is calculated from LGD PiT as a 9-year moving average. The results are compared for the IRB non-defaulted portfolios only, as the risk weights stay constant in other cases.

Figure 4 illustrates the starting point risk weights (for 2022) and the estimated risk weight paths (for 2023–2025) for the NFPS portfolios considered. The figure shows bank disclosures, our proposed model and the two benchmarking models. Upon visual examination alone, it is evident that our proposed granular method consistently offers more reliable outcomes in terms of the overall risk weight level. Combined, the bank disclosures suggest an increase in risk weights of 6.5 pp in the baseline scenario and 17.9 pp in the adverse scenario. The corresponding outcomes for the baseline and adverse scenarios respectively are 3.9 pp and 13.9 pp for the proposed model, 1.2 pp and 9.9 pp for BM1 and -2.8 pp and 6.3 pp for BM2. This represents a reduction in the overall estimation error for the adverse scenario at the end of the stress test horizon – commonly the most scrutinized value in stress testing exercises – of 50.4% compared to BM1 and of 65.5% compared to BM2 (with BM2 reflecting the methodology originally used by the CNB).

Figure 4: Evolution of Risk Weights Combined and by NFPS Portfolios (in percent)



Note: The figure presents the risk weights of the IRB non-defaulted portfolio for sub-groups of loans to non-financial private sector. The "Bank disclosures" series were reported by banks in the 2023 supervisory stress test exercise. They represent the evolution of risk weights based on the baseline and adverse macroeconomic scenarios. The "Model" series represent our model, and "Benchmark Model 1" and "Benchmark Model 2" are the alternative approaches. Optimally, the values should be close to the bank disclosures. The right-hand scale shows the risk weights for loans to households secured by residential property.

In addition, we look at the root mean square error (RMSE) statistics, calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=0}^{N}\left(RW_{T_i}^{BANK} - RW_{T_i}^{MODEL}\right)^2}{N+1}} \tag{17}$$

Although the RMSE may not be directly interpretable, larger forecasting errors across the time horizon will yield higher RMSE values. Thus, it is more convenient to compare the RMSE values of our model in relative terms against the alternatives introduced. In combined terms, the reduction in the RMSE for the adverse scenario stands at 34.1% relative to BM1 and 52.8% relative to BM2. When averaged across portfolios and scenarios, it amounts to 30.5% compared to BM1 and 56.3% compared to BM2. The biggest improvements are observed for loans to households secured by residential property, while the smallest are seen for residual loans to households.

Furthermore, to provide a clearer insight into the distributional characteristics across the bank sample, we present box plots of the end-of-period (2025) distributions of risk weights for the individual NFPS portfolios (see Figure 5). These distributions align reasonably well, underscoring the validity of our granular approach to RW estimation.

However, while we observe the significant improvements demonstrated above, we still notice systematic underestimation of the modelled risk weights against those reported by banks. The Pearson and Spearman correlation coefficients between the bank disclosures and our model outputs are both very high, standing at 99.8% and 98.8% respectively. However, the slope coefficient of the OLS regression of our model outputs on bank disclosures without an intercept is significantly below 1, at 0.973, with the upper bound of the 99% confidence interval at 0.983. This can be seen visually in Figure 6, where we observe that the majority of the model outputs lie below the first quadrant axis.

Figure 5: Terminal Risk Weight Distribution by NFPS Portfolios (in percent)

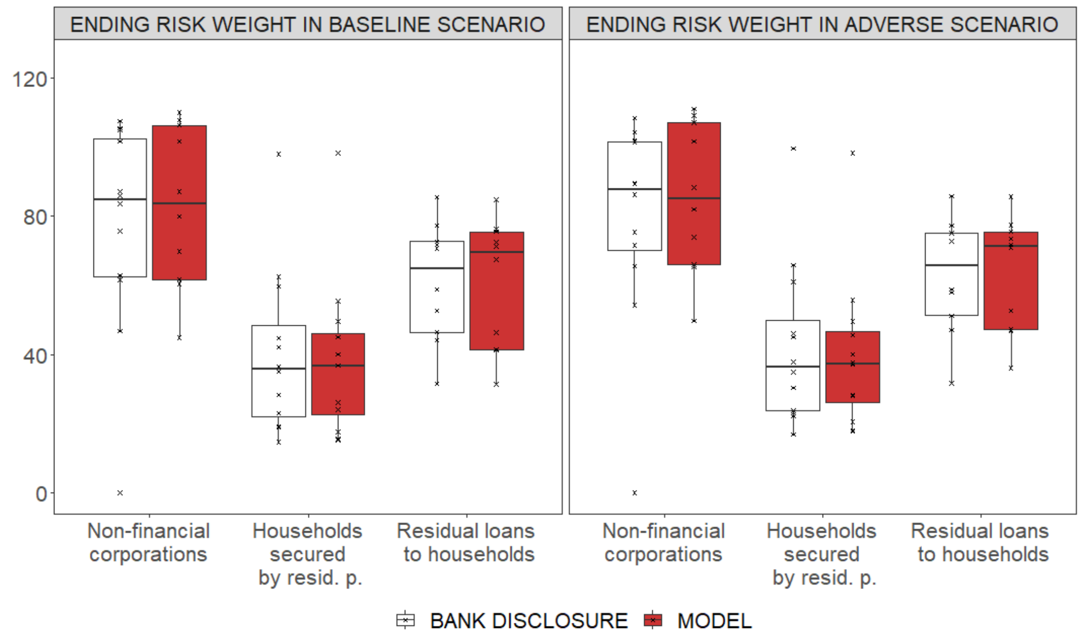
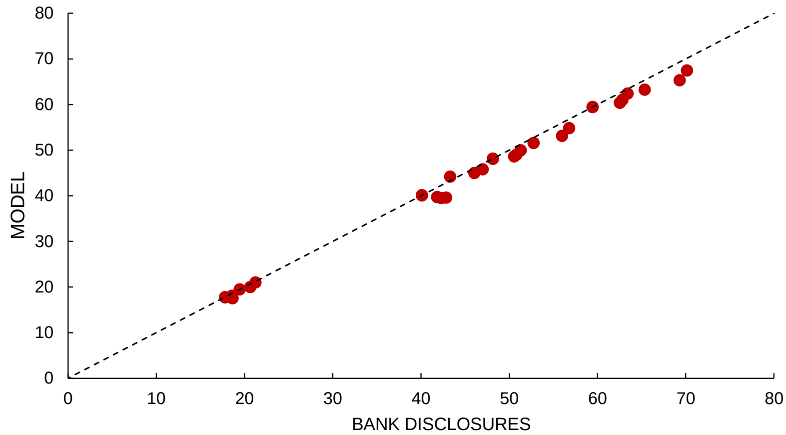


Figure 6: Bank Disclosures Compared with Model Values (in percent)



Several factors could account for this observed underestimation. First, the remaining non-linearities and exceptional cases outlined in the previous section might not be entirely captured even by the granular model. Second, our model may not perfectly represent the relationship between the point-in-time risk parameters and the PDs and LGDs used in the RWA calculations, as the general approach may not be entirely accurate for certain banks. Third, the dynamics of the risk parameters and exposure values at the internal obligor grade level are ultimately driven by the underlying portfolio level satellite models, which might limit the ability to capture different dynamics across the individual obligor grades within a single portfolio. In addition, our approach inherently assumes a static internal structure for each portfolio. While we consider dynamic exposure values, the changes are proportionally allocated across the obligor grades, preserving the portfolio's internal structure, with no allowance for migration between obligor grades. This contrasts with real-world scenarios, where the portfolio structure can evolve due to creditworthiness shifts, leading to obligor migrations between grades during economic downturns. However, integrating a robust approach for transitions between obligor grades would be extremely challenging given the lack of suitable data. In any case, additional comprehensive testing and research will be necessary to understand the precise nature of this systematic underestimation. Such insights will be invaluable in further enhancing and refining our modelling framework.

4. Model Application – Calibrating the Countercyclical Capital Buffer

Our proposed approach, as shown in the previous section, is suited to a range of stress testing applications within the banking sector. In addition, regulators can tailor it to their needs, as it is founded on the reporting standards used across the EU. We see two potential uses for our proposed approach. First, it can clearly serve as an effective building block for stress testing toolkits. Second, the model also offers utility for macroprudential policy objectives, for instance to counter the pro-cyclicality of capital requirements due to the cyclical nature of risk weights. Mechanisms such as the countercyclical capital buffer (CCyB) can be calibrated to offset these fluctuations to ensure a stable capital requirement through the financial cycle. We begin by providing the reasoning for such actions. Next, we detail the data used, and, finally, we conclude with a summary and a potential recalibration of the CCyB. As we are dealing with confidential data, we only provide aggregate data.

Countercyclical Capital Buffer and Risk-Weighted Assets

The main goal of the CCyB is to reduce pro-cyclicality in the banking sector and improve the resilience of banks across financial cycles. International authorities recommend using the CCyB to protect the banking sector from system-wide risks built up in periods of excessive credit growth in the non-financial private sector (see, for example, BCBS, 2010, and ESRB, 2018). Such risks can lead to significant credit losses during downturns. In other words, the CCyB should be raised during the expansion phase of the financial cycle, when risks accumulate, and released during turmoil, when risks materialize. This will help maintain the supply of credit to the real economy and reduce the downswing of the financial cycle.

In a broader view, there are various manifestations of the financial cycle other than credit growth that affect banks' resilience, including the evolution of risk weights. When modelling risk-weighted assets, special attention is typically given to the calculation of internal ratings-based (IRB) risk weights. As demonstrated in the previous sections, the value of IRB risk weights is determined primarily by the probability of default (PD) and loss given default (LGD) risk parameters. These risk parameters can be strongly correlated with financial cycles and the risk weights are thus inherently pro-cyclical, as also evidenced, for example, by banks' adverse scenario disclosures in Figure 4.

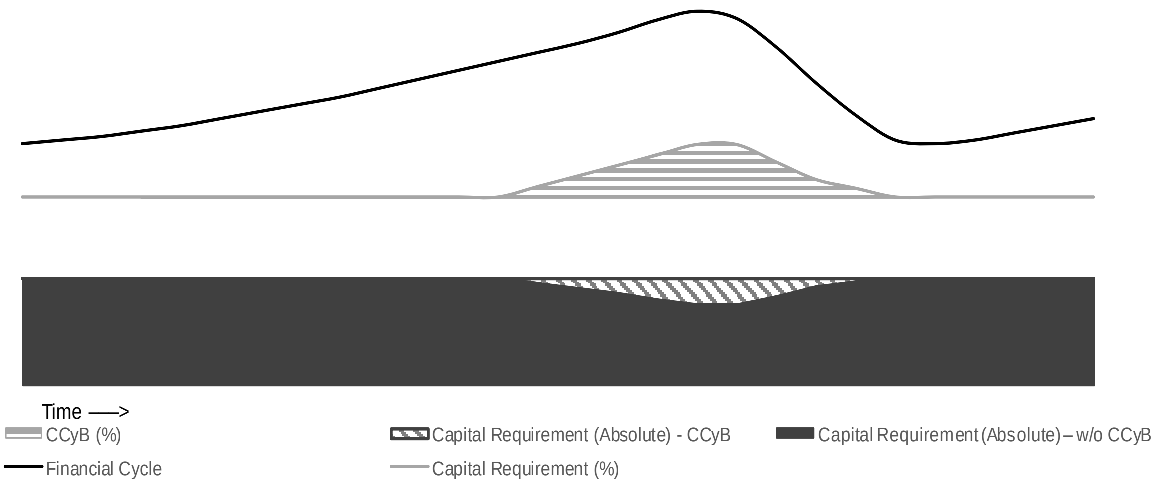
The pro-cyclicality of risk weights has been confirmed by other research studies, including EBA (2016), Montagnoli et al. (2018) and ECB (2009), and, in the case of the Czech banking sector, Malovana (2018) and Broz and Pfeiffer (2019). While the regulations attempt to reduce the pro-cyclical behaviour of risk parameters by using through-the-cycle and downturn parameters (Articles 180 and 181 of CRR2) instead of the point-in-time (PiT) parameters used for IFRS9 provisioning, some cyclicality usually persists.[13] To counter the persisting pro-cyclicality, the current debate in Europe is focused on the possible application of output floors relative to STA portfolios (BCBS, 2015). However, such amendments only solve the long-term decrease in IRB risk weights relative to the STA requirements, not the cyclical dynamics themselves. Moreover, since 2021, the EBA has required the inclusion of a mixture of both "good" and "bad" economic periods in estimating risk parameters for calculating risk weights (EBA, 2017). Nevertheless, the definition of "bad" periods and how they should be mixed with "good" ones in the estimation sample remains rather vague. In this section, we will show an alternative yet effective way of countering the pro-cyclicality of risk weights using the outputs from our model.

During the expansion phase of the financial cycle, credit risks accumulate not only as a result of extensive credit growth, but also due to undesired changes in risk weights and a resulting decrease in the capital requirements (caused by a reduction in the denominator of the capital ratio; see Equation 1), which might further reduce the resilience of banking sector. A downswing in the financial cycle is then likely to be accompanied by elevated credit risk losses. If loan loss provisions are not sufficient to cover the losses (i.e. if the realized losses exceed the expected losses), they must be absorbed by the available capital, which will have a direct negative effect on the capital position (by reducing the numerator of the capital ratio). At the same time, large credit losses (manifested by increased PD PiT and LGD PiT) will correspondingly result in a gradual increase

[13] For example, the data window for deriving PD TTC may be shorter than the expansion phase of the financial cycle, characterized by low PD PiT.

in PD TTC and potentially also LGD DT. This will lead to an increase in risk weights, affecting the capital ratio denominator and further diminishing banks' solvency. Therefore, calibrating the CCyB based solely on the evolution of credit and potential credit losses on loans to the non-financial private sector (NFPS) may not sufficiently reduce the pro-cyclical behaviour of the capital requirement and capital ratios in the banking sector, as it ignores the denominator.

Figure 7: Conceptual Framework of the CCyB Covering Cyclical Movements in Risk Weights

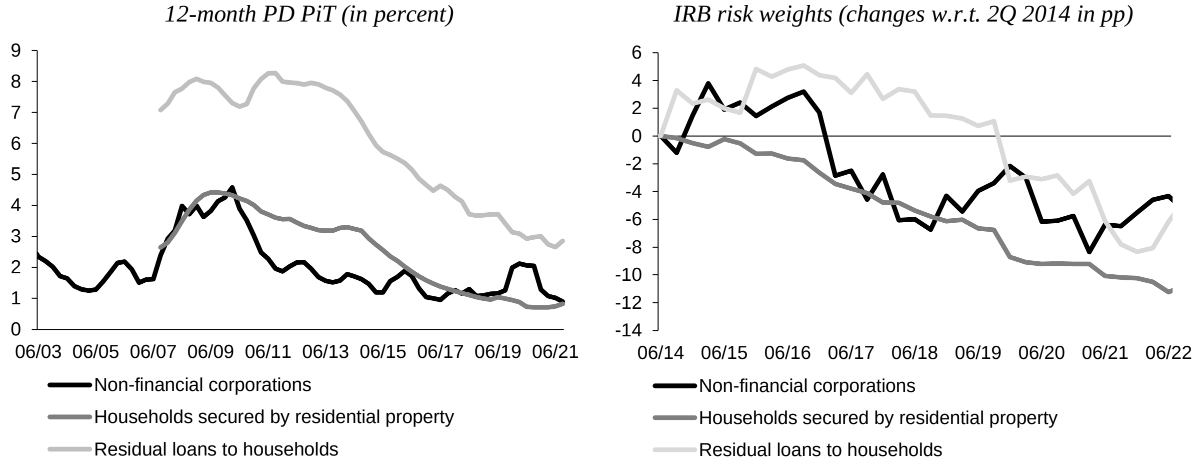


Note: The illustration shows the stylized logic of the CCyB covering cyclical movements in risk weights. Risk accumulation during the expansion phase of the financial cycle increases the probability of a large deterioration in risk parameters. The risk weights start to decrease, which drives down the absolute capital requirement. The CCyB should be raised during this time period. In a downswing of the financial cycle, the CCyB should be released once the risk weights start to rise and their upward shift potential weakens.

The approach presented in Section 2 can be used to estimate the evolution of aggregate risk weights based on the forecasted paths of key risk parameters. It can thus be used to derive the amount of nominal capital required to mitigate the cyclical movement of risk weights, with an emphasis on possibly increasing the CCyB once the financial cycle moves into the contraction phase and risk parameters deteriorate. The underlying logic of the CCyB calibration remains unchanged: the CCyB should be raised during times of expansion, when the perceived risks are likely to be underestimated, and released during downswings, when these risks materialize. Nevertheless, the proposed methodology should be viewed only as a supplement to the existing practices, as credit losses remain one of the key factors in the CCyB calibration. The conceptual framework for the proposed methodology for the CCyB covering cyclical fluctuations in risk weights is illustrated in Figure 7.

We shall support the pro-cyclicality argument using data from the Czech banking sector. Starting in 2014, a prolonged period of favourable economic conditions caused PD PiT on loans to the NFPS to improve gradually (Figure 8, left panel). At the same time, the aggregate IRB risk weights decreased substantially (Figure 8, right panel). We acknowledge that the decrease in IRB risk weights might also have been driven by non-cyclical factors such as structural changes in the portfolios, improvements in internal risk procedures and models, and regulatory changes. However, it is reasonable to assume that it was at least partially driven by cyclical developments. Malovana (2018) supports this assumption by studying these fluctuations using panel data.

Figure 8: Impact of the Financial Cycle on Selected Credit Risk Indicators by NFPS Portfolios



Scenario

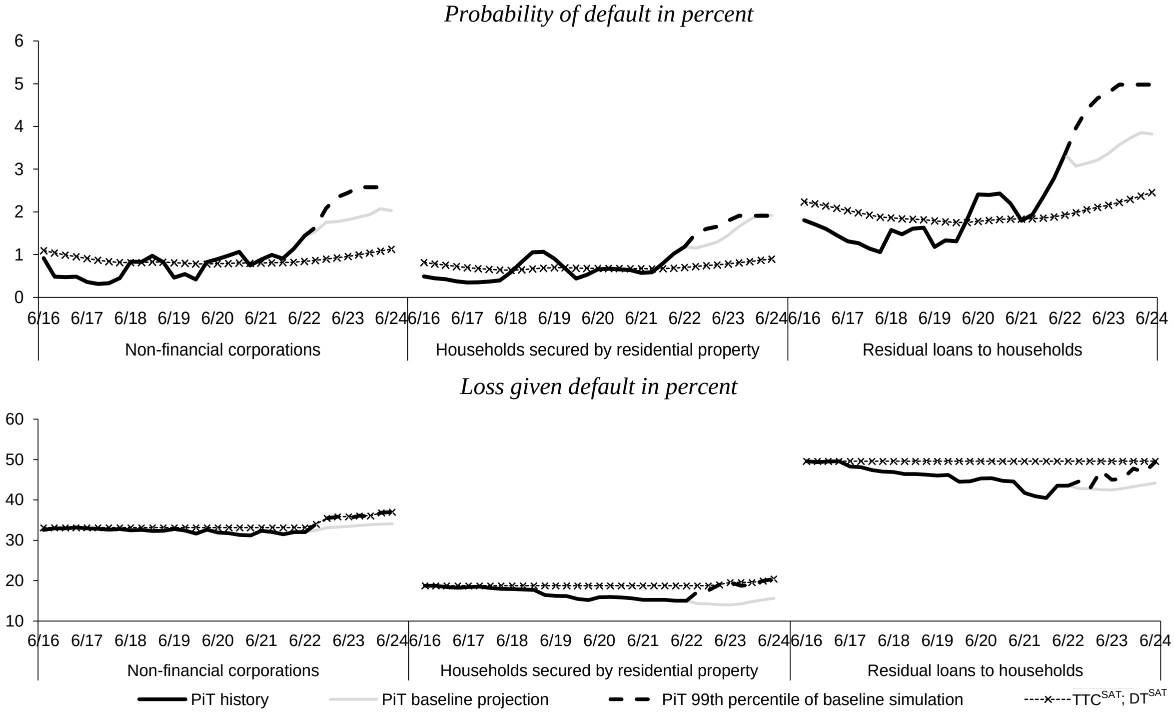
To measure the potential increase in risk weights due to cyclical behaviour, leading to additional requirements for capital, we first need to estimate the potential deterioration in the credit risk parameters. It is reasonable to assume that the level of deterioration depends on the position of the economy in the financial cycle. The potential for a significant increase in point-in-time risk parameters (PD PiT and LGD PiT) is higher in periods of strong financial and credit expansion than in periods of downturn. To quantify the potential deterioration, we estimate a conditional distribution – simulated with the maximum entropy bootstrap method proposed by Vinod (2006) – around the baseline scenario. The shape of the distribution of the parameters is driven by the current phase of the financial cycle, which, in the case of the Czech banking sector, is measured by the financial cycle indicator (FCI; see Plasil et al., 2016). The growing difference between newer and older observations of the FCI also increases the width of the simulated PD PiT and LGD PiT distributions.[14] The simulation of the stressed risk parameters is done on an 8-quarter window starting in the second quarter of 2022. It contains the initial PD PiT[15] and LGD PiT[16] for the three main NFPS portfolios: (i) loans to non-financial corporations, (ii) loans to households secured by residential property and (iii) residual loans to households. The simulation also employs the last 8 quarters of the FCI. The stressed parameters are represented by the 99th quantile of the distribution values. The history and predictions of 12-month PD PiT and LGD PiT, together with the corresponding TTC and DT parameters, are shown in Figure 9.

[14] Note that the ultimate goal of this exercise is to set the CCyB for the evolution of risk weights. Therefore, the potential worsening of the risk parameters is driven solely by cyclical features and not by structural, regulatory and other factors.

[15] The PDs for non-financial corporations are obtained from the Central Credit Register of the Czech Republic managed by the Czech National Bank. The PDs for households are obtained from the Czech Banking Credit Bureau – Client Register of Bank Information.

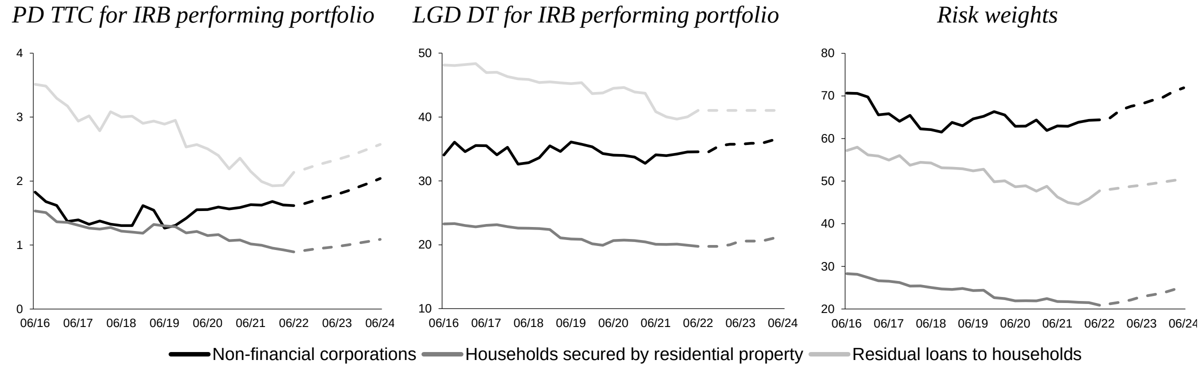
[16] The LGDs are based on data obtained from individual bank submissions reported in the CNB's bottom-up supervisory stress tests.

Figure 9: Estimated Point-in-Time Credit Risk Parameters by NFPS Portfolios (in percent)



With the projections of the risk parameters at hand, it is possible first to estimate the transitions between performing and non-performing status[17] using the procedure outlined in Panos and Polak (2019b) and also the paths of $PD\ TTC^{SAT}$ and $LGD\ DT^{SAT}$ (see Figure 10), which are applied as in Equation 13 and Equation 14. The evolution of the TTC and DT credit risk parameters and the corresponding dynamics of the aggregate risk weights in the NFPS portfolios are illustrated in Figure 10. These dynamics are then translated into a general increase in risk-weighted assets (RWA) observed in Figure 11.

Figure 10: Estimated Through-the-Cycle and Downturn Credit Risk Parameters and Risk Weights by NFPS Portfolios (in percent)



Note: Solid line indicates observed data, dashed line indicates simulation.

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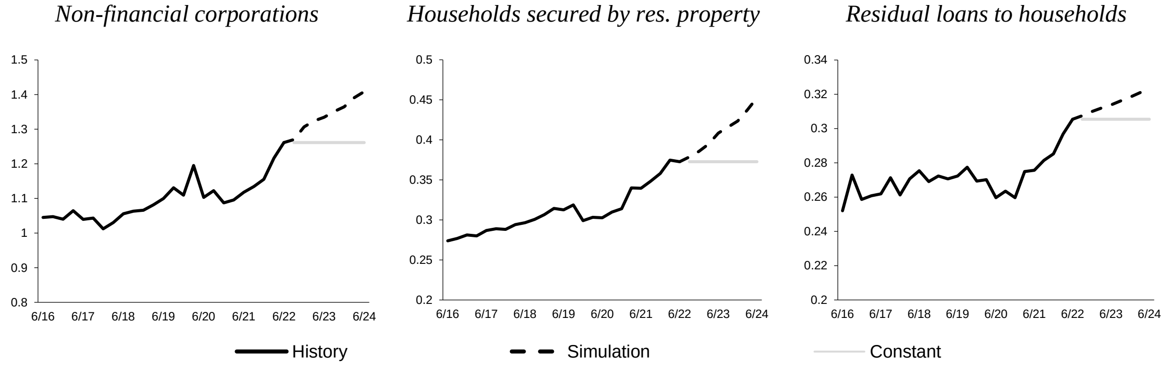
[17] Note that for CCyB calibration purposes, we did not work with credit growth, as the CCyB should be set on the existing portfolio only. We also slightly modified the methodology presented in Section 2 and the Appendix. Instead of credit growth for performing and non-performing exposures, we used the absolute changes to capture transitions between performing and non-performing status. With this approach, we reduce the inflation of the off-balance sheet exposure value to a minimum.

Figure 11: Evolution of Risk-Weighted Assets by NFPS Portfolios (in CZK trillion)



Note: Solid line indicates observed data, dashed line indicates simulation.

In our simulation, the risk-weighted assets increased from an initial CZK 1.94 trillion to CZK 2.18 trillion in 8 quarters purely due to the cyclical behaviour of risk weights.[18] As the capital requirements are prescribed in percentages (currently approximately 14.3% of the TREA without the CCyB for banks regulated by the Czech National Bank), this rise will inherently lead to an increase in the capital requirement in absolute terms. The capital requirement for the portfolios considered would rise from CZK 277.34 billion (CZK 1,940 billion x 14.3%) at the start of our simulation to CZK 312.37 billion (Figure 12). The difference of CZK 35.03 billion represents the absolute increase in capital requirements due to the cyclical behaviour of risk weights, which, in our view, should be covered by the CCyB, as it is a clear manifestation of the financial cycle.[19] In practice, we need to convert the calculated difference to a percentage of the total risk exposure amount (TREA), as the CCyB is prescribed in the regulations as a percentage of the TREA. As of 2Q 2022, the TREA for the Czech banking sector stood at CZK 2.84 trillion. Consequently, our experiment suggests that the hypothetical additional CCyB rate required to cover the cyclical increase in risk weights would be 1.14%.[20]

[18] To obtain relevant results, the size and structure of the portfolio remains unchanged (i.e. credit growth equals zero in this simulation).
[19] The NFPS portfolios considered consist almost entirely of loans to Czech residents.
[20] Note that the final value of the CCyB would be higher, because the estimated additional 1.14% only covers the cyclical increase in risk weights and not the potential unexpected credit losses caused by developments in the financial cycle.

Figure 12: Change in the Capital Requirement due to the Estimated Increase in RWA (in CZK billion)

5. Conclusion

This paper proposes a refined methodology for modelling banks' risk-weighted assets, with a focus on capturing the internal risk structure of their portfolios at the individual obligor grade level. The approach can be applied to estimate future solvency positions in stress testing exercises and to improve the calibration of certain macroprudential instruments, such as the countercyclical capital buffer (CCyB). We have demonstrated that the framework has the potential to surpass the commonly applied portfolio level approaches in terms of estimation accuracy, as it takes advantage of highly granular supervisory data. This should reduce the likelihood of significant misestimation of risk-weighted assets, which can lead to poor estimations of solvency measures and induce false confidence. The methodology is sufficiently easy to replicate, as it is based on the EU-wide CRR2 regulation and the supervisory common reporting (COREP) framework. It is also flexible enough, as various building blocks can be tailored to specific requirements. A hands-on example is provided in the Appendix, including direct links to the COREP row and column identifiers, further enhancing the transparency and replicability of the approach.

Nevertheless, there are several caveats to our methodology. Firstly, the granularity of the COREP data is limited to the individual internal obligor grade level. This level of granularity is suitable for diversified retail portfolios, but it may not be sufficient for lumpy portfolios that contain large financial institutions or non-financial corporates. Secondly, some relevant information, such as the correlation reduction coefficient for companies with total annual sales below EUR 50 million, cannot be derived from the COREP data. Thirdly, the underlying portfolio level satellite models ultimately drive the dynamics of the risk parameters and exposure values at the internal obligor grade level. Therefore, the ability to capture different dynamics across the internal grades within a single portfolio might be limited. In addition, our methodology does not allow for migration between obligor grades, effectively preserving the portfolio's internal structure. Lastly, the satellite models themselves are subject to model risk and other deficiencies common to stress testing satellite models.

The paper also highlights the pro-cyclical behaviour of risk weights in the banking sector, amplifying financial cycles and potentially exacerbating financial instability, and the need for macroprudential policy to counter such behaviour. We propose the use of the CCyB to address this cyclical behaviour of risk weights and its impact on banks' capital position. The proposal is illustrated by an example where we calibrate the CCyB to cover the cyclical movement of risk weights, with an emphasis on possibly increasing the CCyB once the financial cycle moves into the contraction phase and risk parameters deteriorate. The simulation builds on data from the Czech banking sector and applies the proposed granular risk-weighted assets estimation approach. This methodology is used to derive the nominal amount of capital required to keep the capital requirement stable in the event of increasing risk weights during a downturn phase of the cycle.

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Appendix

The aim of this section is to illustrate the methodology proposed for REA_{CR}^{M} in Section 2 with a hands-on example featuring a simplified banking sector consisting of a single bank with three stylized portfolios: (1) Retail – Secured by immovable property non-SME (A-IRB approach), (2) Corporate – SME (F-IRB approach) and (3) Exposures to corporates (STA approach).[21] Portfolios in both the A-IRB and F-IRB approach use only three internal obligor grades. There is no loss of generality caused by these simplifications, as the concepts introduced in this section can be easily generalized for additional obligor grades, portfolios and banks. The bank and satellite model numbers used for this example are, however, purely illustrative and selected to highlight features of the proposed methodology.

The input data are sourced from the EBA Common Reporting (COREP) framework, so they should be commonly available to all EU regulatory bodies. The particular COREP templates and row and column identifiers[22] are shown in Table A.1 (A-IRB), Table A.2 (F-IRB) and Table A.3 (STA) below. Table A.3 is split into two parts, as defaulted exposures are reported in a separate STA exposure class. Data are shown for each of the internal grade systems considered and also as totals.

At the beginning of this appendix, we will show how using the internal obligor grade structure for modelling purposes can deliver better outcomes than relying on the aggregated (row "total") data, as it provides more accurate calculations of the starting point risk weights for each of the portfolios considered. Then we discuss how the projected PDs and LGDs, together with credit growth from satellite models, are used to model the evolution of risk weights at the grade level and how this affects the overall results.

Table A.1: Input Data – A-IRB

IRB exposure class:	Retail – Secured by immovable property non-SME					
Own estimates of LGD and/or conversion factors:	Yes					
Obligor grade (row identifier)	**COREP template / row**	**PD assigned to obligor grade or pool (%)**	**Exposure value (EUR)**	**Exposure weighted average LGD (%)**	**Exposure-weighted average maturity value (days)**	**Risk weighted exposure amount after supporting factors (EUR)**
Column	-	0010	0110	0230	0250	0260
Total exposures	C 08.01 / 0010	4.87	157,000,000	22.36	-	79,915,795
Grade 1	C 08.02 / 0010-0001	0.05	85,000,000	20.00	-	2,494,848
Grade 2	C 08.02 / 0010-0002	8.00	70,000,000	25.00	-	76,670,947
Grade 3	C 08.02 / 0010-0003	100.00	2,000,000	30.00	-	750,000

Note: The numbers in the table are purely fictitious and designed for illustrative purposes.

[21] Please also refer to the mapping in Table 1.
[22] A detailed description of the rows and columns from the COREP Framework is available on the EBA website: https://www.ebaeuropa.eu/risk-analysis-and-data/reporting-frameworks/reporting-framework-3.2

Table A.2: Input Data – F-IRB

IRB exposure class:	Corporate – SME					
Own estimates of LGD and/or conversion factors:	No					
Obligor grade (row identifier)	**COREP template / row**	**PD assigned to obligor grade or pool (%)**	**Exposure value (EUR)**	**Exposure weighted average LGD (%)**	**Exposure-weighted average maturity value (days)**	**Risk weighted exposure amount after supporting factors (EUR)**
Column	-	0010	0110	0230	0250	0260
Total exposures	C 08.01 / 0010	7.49	138,000,000	45.29	753	88,254,898
Grade 1	C 08.02 / 0010-0001	0.15	55,000,000	45.00	730	15,635,057
Grade 2	C 08.02 / 0010-0002	3.00	75,000,000	45.00	770	72,619,841
Grade 3	C 08.02 / 0010-0003	100.00	8,000,000	50.00	750	0

Note: The numbers in the table are purely fictitious and designed for illustrative purposes.

Table A.3: Input Data – STA

STA exposure class:	Corporates		
Row identifier	**COREP template / row**	**Exposure value (EUR)**	**Risk weighted exposure amount after supporting factors (EUR)**
Column	-	0200	0220
Total exposures	C 07.00 / 0010	25,000,000	25,000,000

STA exposure class:	Exposures in default		
Row identifier	**COREP template / row**	**Exposure value (EUR)**	**Risk weighted exposure amount after supporting factors (EUR)**
Column	-	0200	0220
Total exposures	C 07.00 / 0010	1,000,000	1,500,000

Note: The numbers in the table are purely fictitious and designed for illustrative purposes.

A.1 Initial Calculations: Total Level Approach

A-IRB Approach

Table A.4 captures the initial risk weight calculations without using the individual internal obligor grade data for the A-IRB portfolio Retail – Secured by immovable property non-SME. Columns A and B contain total exposure and REA, which are sourced directly from Table A.1.

Table A.4: Initial Calculations (using total data) – A-IRB

Total			
A-IRB exposure class:	Retail – Secured by immovable property non-SME		
Exposure value (EUR)	**REA value (EUR)**	**Implied risk weight (%)**	**Calculated risk weight (%)**

(A) = C 08.01 (R0010 C0110)	(B) = C 08.01 (R0010 C0260)	(C) = B / A	(D), exposure weighted avg. of (H) and (R)
157,000,000	79,915,795	50.90	65.16

Non-defaulted (1/2)				
A-IRB exposure class:	Retail – Secured by immovable property non-SME			
Exposure value (EUR)	**REA value (EUR)**	**Implied risk weight (%)**	**Calculated risk weight (%)**	**Phi coefficient ($\boldsymbol{\phi}$)**
(E), sum of exposure values in non-defaulted grades	(F), sum of REA values in non-defaulted grades	(G) = F / E	(H), see Eq. 5	(I) = G / H
155,000,000	79,165,795	51.07	65.52	0.78

Table continues

Non-defaulted (2/2)					
A-IRB exposure class:	Retail – Secured by immovable property non-SME				
Non-defaulted PD (%)	**Non-defaulted LGD (%)**	**Maturity ($\boldsymbol{M}$) (years)**	**Maturity adjustment ($\boldsymbol{Z(M, PD)}$)**	**Correlation coefficient ($\boldsymbol{R(PD)}$) (%)**	**SME supporting factor**
(J), exposure weighted avg. of PDs in non-defaulted grades	(K), exposure weighted avg. of LGDs in non-defaulted grades	(L), not required for retail portfolios	(M), fixed 1 for retail portfolios	(N), fixed 15% for exposures secured by immovable property	(O), 0.7619 - 0.85 for SME exposures; 1 for non-SME exposures
3.64	22.26	-	1.00	15.00	1.00

Defaulted		
A-IRB exposure class:	Retail – Secured by immovable property non-SME	
Exposure value (EUR)	**REA value (EUR)**	**Implied risk weight (%)**
(P) = C 08.02 (R0010 C0110-0003)	(Q) = C 08.02 (R0010 C0260-0003)	(R) = Q / P
2,000,000	750,000	37.50

Note: The numbers in the table are purely fictitious and designed for illustrative purposes.

The total implied risk weight in column C represents the actual risk weight reported by the bank. It can be obtained easily as

$$Total\ implied\ RW\ (\mathrm{C}) = \frac{REA\ (\mathrm{B})}{Exposure\ (\mathrm{A})} = \frac{79{,}915{,}795}{157{,}000{,}000} = 50.90\% \tag{A.1}$$

The total calculated risk weight in column D is the exposure-weighted average of the calculated risk weights for non-defaulted exposures (column H) and the implied risk weight for defaulted exposures (column R).

$$\begin{aligned} Total\ calculated\ RW\ (\mathrm{D}) &= \frac{(\mathrm{H}) * (\mathrm{E}) + (\mathrm{R}) * (\mathrm{P})}{(\mathrm{E}) + (\mathrm{P})} \\ &= \frac{65.52\% * 155{,}000{,}000 + 37.50\% * 2{,}000{,}000}{155{,}000{,}000 + 2{,}000{,}000} \\ &= 65.16\% \end{aligned} \tag{A.2}$$

The values in columns E and F represent non-defaulted exposures and REA, which are the sums over the respective exposures and the REA values in non-defaulted grades in Table A.1:

$$Non-def\ exposure\ (\text{E}) = \sum_{i \in \{0001;0002\}} \text{C 08.02 (R0010 – i C0110)}$$
$$= 85{,}000{,}000 + 70{,}000{,}000 = 155{,}000{,}000 \tag{A.3}$$

and

$$Non-def\ REA\ (\text{F}) = \sum_{i \in \{0001;0002\}} \text{C 08.02 (R0010 – i C0260)}$$
$$= 2{,}494{,}848 + 76{,}670{,}947 = 79{,}165{,}795 \tag{A.4}$$

The non-defaulted implied risk weight in column G follows the same logic as the total implied risk weight in column C and thus

$$Non-def\ implied\ RW\ (\text{G}) = \frac{Non-def\ REA\ (\text{F})}{Non-def\ exposure\ (\text{E})} = \frac{79{,}165{,}795}{155{,}000{,}000}$$
$$= 51.07\% \tag{A.5}$$

Column H shows the non-defaulted calculated risk weight, which is derived using the CRR2 regulatory risk weight formula (see Equation 5) employing the reported values of risk parameters as inputs.

$$Non-def\ calculated\ RW\ (\text{H})$$
$$= \left((\text{K}) * N\left\{ \frac{1}{\sqrt{(1-(\text{N}))}} * G((\text{J})) + \sqrt{\frac{(\text{N})}{1-(\text{N})}} * G(0{,}999) \right\} - (\text{K}) * (\text{J}) \right)$$
$$* (\text{M}) * 1.06 * 12.5 * (\text{O}) \tag{A.6}$$
$$= \left(22.26\% * N\left\{ \frac{1}{\sqrt{(1-15\%)}} * G(3.64\%) + \sqrt{\frac{15\%}{1-15\%}} * G(0{,}999) \right\} - 22.26\% * 3.64\% \right)$$
$$* 1.00 * 1.06 * 12.5 * 1.00 = 65.52\%$$

The coefficient ϕ in column I can then be obtained as

$$\phi\ (\text{I}) = \frac{Non-def\ implied\ RW\ (\text{G})}{Non-def\ calculated\ RW\ (\text{H})} = \frac{51.07\%}{65.52\%} = 0.78 \tag{A.7}$$

The value of ϕ well below 1 indicates that in this case the calculated risk weight is significantly higher than the actually reported implied risk weight. The main reason for this large discrepancy is the non-linearity of the risk weight formula.

Columns J to O cover the individual inputs to Equation (A.***6*** above. In particular, columns J and K represent non-defaulted PD and LGD respectively. The values are calculated as exposure-weighted averages of the corresponding parameters in non-defaulted grades:

$$Non-def\ PD\ (J) = \frac{\sum_{i\in\{0001;0002\}} \text{C 08.02 (R0010 – i C0010)} * \text{C 08.02 (R0010 – i C0110)}}{\sum_{i\in\{0001;0002\}} \text{C 08.02 (R0010 – i C0110)}} = \frac{0.05\% * 85{,}000{,}000 + 8.00\% * 70{,}000{,}000}{85{,}000{,}000 + 70{,}000{,}000} = 3.64\% \tag{A.8}$$

and

$$Non-def\ LGD\ (K) = \frac{\sum_{i\in\{0001;0002\}} \text{C 08.02 (R0010 – i C0230)} * \text{C 08.02 (R0010 – i C0110)}}{\sum_{i\in\{0001;0002\}} \text{C 08.02 (R0010 – i C0110)}} = \frac{20.00\% * 85{,}000{,}000 + 25.00\% * 70{,}000{,}000}{85{,}000{,}000 + 70{,}000{,}000} = 22.26\% \tag{A.9}$$

Maturity (column L) is not required for retail exposures, as the maturity adjustment (column M) is always set to 1. Similarly, the correlation coefficient (column N) is always set to 15% for exposures secured by immovable property and the SME supporting factor (column O) is set to 1, as the portfolio analysed is non-SME.

The last part of the table deals with defaulted exposures. These are treated in a simplified manner, as we assume a constant spread between LGD and the expected loss best estimate, which results in constant projections for A-IRB non-performing exposure risk weights, and the fixed value is equal to the implied risk weight. Columns P and Q contain defaulted exposures and REA, which are sourced directly from Table A.1. The defaulted implied risk weight in the last column R is obtained using the familiar equation:

$$Def\ implied\ RW\ (R) = \frac{Def\ REA\ (Q)}{Def\ exposure\ (P)} = \frac{750{,}000}{2{,}000{,}000} = 37.50\% \tag{A.10}$$

F-IRB Approach

Table A.5 has an identical structure to Table A.4 and captures the initial risk weight calculations without using the individual internal obligor grade data for the F-IRB portfolio Corporate – SME. The data are sourced from Table A.2. Columns A to K are essentially equivalent to the corresponding columns in Table A.4, so no further comments are necessary here.

Table A.5: Initial Calculations (using total data) – F-IRB

Total			
F-IRB exposure class:	Corporate – SME		
Exposure value (EUR)	**REA value (EUR)**	**Implied risk weight (%)**	**Calculated risk weight (%)**
(A) = C 08.01 (R0010 C0110)	(B) = C 08.01 (R0010 C0260)	(C) = B / A	(D), exposure weighted avg. of (H) and (R)
138,000,000	88,254,898	63.95	80.47

Non-defaulted (1/2)				
F-IRB exposure class:	Corporate – SME			
Exposure value (EUR)	**REA value (EUR)**	**Implied risk weight (%)**	**Calculated risk weight (%)**	**Phi coefficient (ϕ)**
(E), sum of exposure values in non-defaulted grades	(F), sum of REA values in non-defaulted grades	(G) = F / E	(H), see Eq. 5	(I) = G / H
130,000,000	88,254,898	67.89	85.43	0.79

Table continues

Non-defaulted (2/2)					
F-IRB exposure class:	Corporate – SME				
Non-defaulted PD (%)	**Non-defaulted LGD (%)**	**Maturity (M) (years)**	**Maturity adjustment ($Z(M, PD)$)**	**Correlation coefficient ($R(PD)$) (%)**	**SME supporting factor**
(J), exposure weighted avg. of PDs in non-defaulted grades	(K), exposure weighted avg. of LGDs in non-defaulted grades	(L), exposure weighted avg. of maturity in non-defaulted grades in years	(M), see Eq. 9 and Eq. 10	(N), see Eq. 6	(O), 0.7619 - 0.85 for SME exposures; 1 for non-SME exposures
1.79	45.00	2.06	1.15	16.89	0.7619

Defaulted		
F-IRB exposure class:	Corporate – SME	
Exposure value (EUR)	**REA value (EUR)**	**Implied risk weight (%)**
(P) = C 08.02 (R0010 C0110-0003)	(Q) = C 08.02 (R0010 C0260-0003)	(R) = Q / P; always 0 in F-IRB approach
8,000,000	0	0

Note: The numbers in the table are purely fictitious and designed for illustrative purposes.

Column L captures the exposure-weighted average of the maturities in non-defaulted grades expressed in years:

$$\begin{aligned} &Non-def\ Maturity\ (L) \\ &= \frac{\sum_{i\in\{0001;0002\}} \text{C 08.02 (R0010 – i C0250)} * \text{C 08.02 (R0010 – i C0110)}}{365 * \sum_{i\in\{0001;0002\}} \text{C 08.02 (R0010 – i C0110)}} \\ &= \frac{730 * 55{,}000{,}000 + 770 * 75{,}000{,}000}{365 * (55{,}000{,}000 + 75{,}000{,}000)} = 2.06 \end{aligned} \tag{A.11}$$

The value from Equation (A.***11***, together with the non-defaulted PD, is then used to calculate the maturity adjustment $Z(M, PD)$ in column M using Equation 9 and Equation 10:

$$\begin{aligned} Z(M, PD)\ (\text{M}) &= \frac{1 + \big((L) - 2.5\big) * \big(0.11852 - 0.05478 * \ln\big((\text{J})\big)\big)^2}{1 - 1.5 * \big(0.11852 - 0.05478 * \ln\big((\text{J})\big)\big)^2} \\ &= \frac{1 + (2.06 - 2.5) * (0.11852 - 0.05478 * \ln(1.79\%))^2}{1 - 1.5 * (0.11852 - 0.05478 * \ln(1.79\%))^2} \\ &= 1.15 \end{aligned} \tag{A.12}$$

Also, the correlation coefficient $R(PD)$ in column N is in this case a function of PD according to Equation 6:

$$R(PD)\ (\mathrm{N}) = 0.12 * \frac{1 - e^{-50*(\mathrm{J})}}{1 - e^{-50}} + 0.24 * \left(1 - \frac{1 - e^{-50*(\mathrm{J})}}{1 - e^{-50}}\right)$$
$$= 0.12 * \frac{1 - e^{-50*1.79\%}}{1 - e^{-50}} + 0.24 * \left(1 - \frac{1 - e^{-50*1.79\%}}{1 - e^{-50}}\right) \quad \text{(A.13)}$$
$$= 16.89\%$$

The applied SME supporting factor in column O takes the value of 0.7619 in this case, as we are dealing with an SME portfolio. The last difference stems from the defaulted exposures, which always receive a zero risk weight in the F-IRB approach.

STA Using Total Data

Table A.6 shows the initial calculations for the STA portfolios Corporates and Exposures in default, which, unlike in the IRB approaches, are reported as a separate exposure class. For both exposure classes, the exposure and REA values are sourced directly from Table A.3 and the total implied risk weight follows the logic introduced earlier in this section. No ϕ ratio is calculated, as we assume a constant risk weight for STA exposure classes equal to the total implied risk weight induced from the regulatory data.

Table A.6: Initial Calculations (using total data) – STA

Total		
STA exposure class:	Corporates	
Exposure value (EUR)	**REA value (EUR)**	**Implied risk weight (%)**
(A) = C 07.00 (R0010 C0200)	(B) = C 07.00 (R0010 C0220)	(C) = B / A
25,000,000	25,000,000	100

Total		
STA exposure class:	Exposures in default	
Exposure value (EUR)	**REA value (EUR)**	**Implied risk weight (%)**
(D) = C 07.00 (R0010 C0200)	(E) = C 07.00 (R0010 C0220)	(F) = B / A
1,000,000	1,500,000	150

Note: The numbers in the table are purely fictitious and designed for illustrative purposes.

A.2 Initial Calculations: Grade Level Approach

Next, we repeat the initial calculations for the A-IRB and F-IRB portfolios, but now with the calculations using the internal obligor grade level data. The procedure is provided in Table A.7 and Table A.8. The STA portfolio is not recalculated, as no higher granularity is available in COREP.

We observe significant convergence of the implied and calculated risk weights on the grade level, so the values of ϕ near 1. For the A-IRB exposure class Retail – Secured by immovable property non-SME, almost a perfect match was achieved, while for the F-IRB exposure class Corporate – SME, some (albeit much smaller than in Table A.5) discrepancies remain. Although some discrepancies might remain for certain portfolios, the granular approach based on the internal obligor grade data seems to be more desirable, as it allows us to match the implied and calculated risk weights in a significantly more precise manner than relying solely on the aggregate values.

In general, the numbers in this example are fictitious. However, the ϕ ratio values were inspired by actual values we were able to obtain in real-world applications.

Table A.7: Initial Calculations (using grade-level data) – A-IRB

Total			
A-IRB exposure class:	Retail – Secured by immovable property non-SME		
Exposure value (EUR)	**REA value (EUR)**	**Implied risk weight (%)**	**Calculated risk weight (%)**
(A) = C 08.01 (R0010 C0110)	(B) = C 08.01 (R0010 C0260)	(C) = B / A	(D), exposure weighted avg. of all (H) rows and (R)
157,000,000	79,915,795	50.90	50.90

Non-defaulted (1/2)					
A-IRB exposure class:	Retail – Secured by immovable property non-SME				
Grade level	**Exposure value (EUR)**	**REA value (EUR)**	**Implied risk weight (%)**	**Calculated risk weight (%)**	**Phi coefficient (ϕ)**
Internal rating grade level as in C 08.02	(E) = C 08.02 (R0010 C0110); only non-defaulted grades	(F) = C 08.02 (R0010 C0260); only non-defaulted grades	(G) = F / E	(H), see Eq. 5	(I) = G / H
Grade 1	85,000,000	2,494,848	2.94	2.94	1.00
Grade 2	70,000,000	76,670,947	109.53	109.53	1.00

Table continues …

Non-defaulted (2/2)						
A-IRB exposure class:	Retail – Secured by immovable property non-SME					
Grade level	**Non-defaulted PD (%)**	**Non-defaulted LGD (%)**	**Maturity (M) (years)**	**Maturity adjustment ($Z(M, PD)$)**	**Correlation coefficient ($R(PD)$) (%)**	**SME supporting factor**
Internal rating grade level as in C 08.02	(J), C 08.02 (R0010 C0010); only non-defaulted grades	(K), C 08.02 (R0010 C0230); only non-defaulted grades	(L), not required for retail portfolios	(M), fixed 1 for retail exposures	(N), fixed 15% for exposures secured by immovable property	(O), 0.7619 - 0.85 for SME exposures; 1 for non-SME exposures
Grade 1	0.05	20.00	-	1.00	15.00	1.00
Grade 2	8.00	25.00	-	1.00	15.00	1.00

Defaulted (Grade 3)		
A-IRB exposure class:	Retail – Secured by immovable property non-SME	
Exposure value (EUR)	**REA value (EUR)**	**Implied risk weight (%)**
(P) = C 08.02 (R0010 C0110-0003)	(Q) = C 08.02 (R0010 C0260-0003)	(R) = Q / P
2,000,000	750,000	37.50

Note: The numbers in the table are purely fictitious and designed for illustrative purposes.

Table A.8: Initial Calculations (using grade-level data) – F-IRB

Total			
F-IRB exposure class:	Corporate – SME		
Exposure value (EUR)	**REA value (EUR)**	**Implied risk weight (%)**	**Calculated risk weight (%)**
(A) = C 08.01 (R0010 C0110)	(B) = C 08.01 (R0010 C0260)	(C) = B / A	(D), exposure weighted avg. of all (H) rows and (R)
138,000,000	88,254,898	63.95	64.94

Non-defaulted (1/2)					
F-IRB exposure class:	Corporate – SME				
Grade level	**Exposure value (EUR)**	**REA value (EUR)**	**Implied risk weight (%)**	**Calculated risk weight (%)**	**Phi coefficient (ϕ)**
Internal rating grade level as in C 08.02	(E) = C 08.02 (R0010 C0110); only non-defaulted grades	(F) = C 08.02 (R0010 C0260); only non-defaulted grades	(G) = F / E	(H), see Eq. 5	(I) = G / H
Grade 1	55,000,000	15,635,057	28.43	26.82	1.06
Grade 2	75,000,000	72,619,841	96.83	99.82	0.97

Table continues …

Non-defaulted (2/2)						
F-IRB exposure class:	Corporate – SME					
Grade level	**Non-defaulted PD (%)**	**Non-defaulted LGD (%)**	**Maturity (M) (years)**	**Maturity adjustment ($Z(M, PD)$)**	**Correlation coefficient ($R(PD)$) (%)**	**SME supporting factor**
Internal rating grade level as in C 08.02	(J), C 08.02 (R0010 C0010); only non-defaulted grades	(K), C 08.02 (R0010 C0230); only non-defaulted grades	(L), C 08.02 (R0010 C0250); only non-defaulted grades in years	(M), see Eq. 9 and Eq. 10	(N), see Eq. 6	(O), 0.7619 - 0.85 for SME exposures; 1 for non-SME exposures
Grade 1	0.15	45.00	2.00	1.34	23.13	0.7619
Grade 2	3.00	45.00	2.11	1.13	14.68	0.7619

Defaulted (Grade 3)		
F-IRB exposure class:	Corporate – SME	
Exposure value (EUR)	**REA value (EUR)**	**Implied risk weight (%)**
(P) = C 08.02 (R0010 C0110-0003)	(Q) = C 08.02 (R0010 C0260-0003)	(R) = Q / P
8,000,000	0	0

Note: The numbers in the table are purely fictitious and designed for illustrative purposes.

A.3 Satellite Models

Section 2 of the paper discusses the use of satellite models to model REA. Table A.9 and Table A.10 present the starting point (T0) and projections (T1, T2 and T3) for PD, LGD and growth rates for both defaulted and non-defaulted exposures. Both the starting point and the projections are again simplified and fictitious and do not represent any scenario or satellite model outputs considered by the Czech National Bank.

Table A.9: Risk Parameters Projections – Retail

Total – Adverse				
Exposure class:	Retail – Secured by immovable property			
Time step	**PD TTC (%)**	**LGD DT (%)**	**Non-defaulted exposure growth (%)**	**Defaulted exposure growth (%)**
Typically quarters or years	(A), estimated by satellite models	(B), estimated by satellite models	(C), estimated by satellite models	(D), estimated by satellite models
T0	3.50	25.00	1.50	2.00
T1	4.00	27.50	0.00	7.50
T2	4.50	30.00	0.50	6.00
T3	3.75	30.00	1.00	3.00

Note: The numbers in the table are purely fictitious and designed for illustrative purposes.

Table A.10: Risk Parameters Projections – Corporates

Total – Adverse				
Exposure class:	Corporates			
Time step	**PD TTC (%)**	**LGD DT (%)**	**Non-defaulted exposure growth (%)**	**Defaulted exposure growth (%)**
Typically quarters or years	(A), estimated by satellite models	(B), estimated by satellite models	(C), estimated by satellite models	(D), estimated by satellite models
T0	2.00	55.00	3.00	4.00
T1	4.00	60.00	-2.00	12.00
T2	3.00	60.00	1.00	7.00
T3	2.50	60.00	2.00	4.50

Note: The numbers in the table are purely fictitious and designed for illustrative purposes.

A.4: Projections of Risk-Weighted Assets

A-IRB Approach

Table A.11 presents the risk weight projections based on the individual internal obligor grades for the A-IRB portfolio Retail – Secured by immovable property non-SME. The starting point values are sourced from Table A.7. Column A and column B represent the sum of the exposures (columns D and N) and REA (columns F and P) across all grades in a given time period, such that, for example, for T3:

$$\begin{aligned} &Total\ exposure_{T3}\ \text{(A)} = \sum_{i \in \{1,2,3\}} Grade\ i\ exposure_{T3}\ \text{(D \& N)} \\ &= 86{,}279{,}250 + 71{,}053{,}500 + 2{,}347{,}370 \\ &= 159{,}680{,}120 \end{aligned} \tag{A.14}$$

and

$$Total\ REA_{T3}\ (\mathrm{B}) = \sum_{i\in\{1,2,3\}} Grade\ i\ REA_{T3}\ \ (\mathrm{F\ \&\ P})$$
$$= 3{,}381{,}030 + 95{,}800{,}191 + 880{,}264 \tag{A.15}$$
$$= 100{,}061{,}485$$

Column C then shows the total projected risk weight for the portfolio, given (for T3) as

$$Total\ projected\ RW_{T3}\ (\mathrm{C}) = \frac{Total\ REA_{T3}\ (\mathrm{B})}{Total\ exposure_{T3}\ \ (\mathrm{A})}$$
$$= \frac{100{,}061{,}485}{159{,}680{,}120} = 62.66\% \tag{A.16}$$

The non-defaulted exposure projections are captured in column D. They are calculated using the parameters from column C of Table A.9. Thus, for example, the T3 value of Grade 1 can be obtained as:

$$Non-def\ exposure_{T3}^{Grade\ 1}\ (\mathrm{D})$$
$$= Non-def\ exposure_{T2}^{Grade\ 1}(\mathrm{D}) * (1 + gr_{T3}^{Non-def}) \tag{A.17}$$
$$= 85{,}425{,}000 * (1 + 1\%) = 86{,}279{,}250$$

Column E then shows the risk weight projections based on Equation 15, which for T3 of Grade 1 would go as follows:

$$Non-\mathrm{def}\,calculated\,RW_{T3}^{Grade\ 1}\ (E)$$
$$= \left((I) * N\left\{\frac{1}{\sqrt{(1-(L))}} * G((H)) + \sqrt{\frac{(L)}{1-(L)}} * G(0.999)\right\} - (I) * (H)\right) * (K) * 1.06 * 12.5 * (M) * (G) \tag{A.18}$$
$$= \left(24.46\% * N\left\{\frac{1}{\sqrt{(1-15\%)}} * G(0.06\%) + \sqrt{\frac{15\%}{1-15\%}} * G(0.999)\right\} - 24.46\% * 0.06\%\right) * 1.00 * 1.06 * 12.5 * 1.00 * 1.00 = 3.92\%$$

The REA value for the given grade and time period (column F) can then be simply calculated as follows (again shown for T3 of Grade 1):

$$Non-def\ REA_{T3}^{Grade\ 1}\ \text{(F)}$$
$$= Non-def\ exposure_{T3}^{Grade\ 1}\ \text{(D)} * Non-def\ calculated\ RW_{T3}^{Grade\ 1}\ \text{(E)}$$
$$= 86{,}279{,}250 * 3.92\% = 3{,}381{,}030 \tag{A.19}$$

The coefficient ϕ in column G is sourced from the initial calculations in column I of Table A.7 and is kept constant throughout the projection period. It is a key ingredient in Equation (A.***18***, which ensures that the initial calculated risk weight is always equal to the initial implied risk weight derived from the supervisory templates.

Columns H to M contain the remaining inputs to Equation (A.***18***. In particular, columns H and I show projections of PD and LGD based on columns A and B of Table A.9 and Equation 13 and Equation 14. Thus, for T3 of Grade 1 the equations are applied as follows:

$$Non-def\ PD_{T3}^{Grade\ 1}\ \text{(H)}$$
$$= \Phi\left(\Phi^{-1}\left(PD_{\mathrm{T0}}^{Grade\ 1}\ \text{(H)}\right) + \Phi^{-1}\left(PD\ TTC_{T3}^{SAT}\right) - \Phi^{-1}\left(PD\ TTC_{\mathrm{T0}}^{SAT}\right)\right)$$
$$= \Phi\left(\Phi^{-1}(0.05\%) + \Phi^{-1}(3.75\%) - \Phi^{-1}(3.5\%)\right) = 0.06\% \tag{A.20}$$

and

$$Non-def\ LGD_{T3}^{Grade\ 1}\ \text{(I)}$$
$$= \Phi\left(\Phi^{-1}\left(LGD_{\mathrm{T0}}^{Grade\ 1}\ \text{(I)}\right) + \Phi^{-1}\left(TTC\ LGD_{T3}^{SAT}\right) - \Phi^{-1}\left(TTC\ LGD_{\mathrm{T0}}^{SAT}\right)\right)$$
$$= \Phi\left(\Phi^{-1}(20.00\%) + \Phi^{-1}(30.00\%) - \Phi^{-1}(25.00\%)\right) = 24.46\% \tag{A.21}$$

As mentioned earlier, maturity (column J) is not required for retail exposures, as the maturity adjustment (column K) is always set to 1. Similarly, the correlation coefficient (column L) is always set to 15% for exposures secured by immovable property and the SME supporting factor (column M) is set to 1, as the projected portfolio is non-SME.

The last part of Table A.11 covers the simplified approach to the risk weight projections of defaulted exposures. The defaulted exposure projections are captured by column N and are calculated using the parameters from column D of Table A.9. Thus, for T3 we get:

$$Def\ exposure_{T3}\ \text{(N)}$$
$$= Def\ exposure_{T2}\ \text{(N)} * (1 + gr_{T3}^{Def})$$
$$= 2{,}279{,}000 * (1 + 3\%) = 2{,}347{,}370 \tag{A.22}$$

The projected risk weight values for defaulted exposures (column O) are fixed across time periods and equal to the implied risk weight from the initial calculations in Table A.7. Finally, the defaulted REA projections (column P) are obtained by simple multiplication, as shown below for T3:

$$\begin{aligned} &Def\ REA_{T3}\ (\mathrm{N}) \\ &= Def\ exposure_{T3}\ (\mathrm{N}) * Def\ calculated\ RW_{T3}\ (\mathrm{O}) \\ &= 2{,}347{,}370 * 37.50\% = 880{,}264 \end{aligned} \tag{A.23}$$

Table A.11: Projection Calculations (using grade-level data) – A-IRB

Total			
A-IRB exposure class:	Retail – Secured by immovable property non-SME		
Time step	**Exposure value (EUR)**	**REA value (EUR)**	**Projected risk weight (%)**
Typically quarters or years	(A), sum of exposure values in all grades	(B), sum of REA values in all grades	(C) = B / A
T0	157,000,000	79,915,795	50.90
T1	157,150,000	92,637,119	58.95
T2	158,054,000	106,193,990	67.19
T3	159,680,120	100,061,485	62.66

Non-defaulted (1/2) – Adverse					
A-IRB exposure class:	Retail – Secured by immovable property non-SME				
Grade level	**Time step**	**Exposure value (EUR)**	**Projected risk weight (%)**	**REA value (EUR)**	**Phi coefficient (ϕ)**
Internal rating grade level as in C 08.02	Typically quarters or years	(D), projected using column (C) of Table A.9	(E), see Eq. 15	(F) = D * E	(G), fixed value calculated in column (I) of Table A.7
Grade 1	**T0**	85,000,000	2.94	2,494,848	1.00
	T1	85,000,000	3.86	3,283,767	1.00
	T2	85,425,000	4.94	4,220,398	1.00
	T3	86,279,250	3.92	3,381,030	1.00
Grade 2	**T0**	70,000,000	109.53	76,670,947	1.00
	T1	70,000,000	126.50	88,547,102	1.00
	T2	70,350,000	143.74	101,118,967	1.00
	T3	71,053,500	134.83	95,800,191	1.00

Table continues

Non-defaulted (2/2)							
A-IRB exposure class:	Retail – Secured by immovable property non-SME						
Grade level	**Time step**	**Non-defaulted PD (%)**	**Non-defaulted LGD (%)**	**Maturity (M) (years)**	**Maturity adjustment ($Z(M, PD)$)**	**Correlation coefficient ($R(PD)$) (%)**	**SME supporting factor**
Internal rating grade level as in C 08.02	Typically quarters or years	(H), projected using column (A) of Table A.9 and Eq. 13	(I), projected using column (B) of Table A.9 and Eq. 14	(J), not required for retail portfolios	(K), fixed 1 for all retail exposures	(L), fixed 15% for exposures secured by immovable property	(M), 0.7619 - 0.85 for SME exposures; 1 for non-SME exposures
Grade 1	**T0**	0.05	20.00	-	1.00	15.00	1.00
	T1	0.06	22.22	-	1.00	15.00	1.00
	T2	0.08	24.46	-	1.00	15.00	1.00
	T3	0.06	24.46	-	1.00	15.00	1.00
Grade 2	**T0**	8.00	25.00	-	1.00	15.00	1.00
	T1	8.95	27.50	-	1.00	15.00	1.00
	T2	9.88	30.00	-	1.00	15.00	1.00
	T3	8.48	30.00	-	1.00	15.00	1.00

Defaulted (Grade 3) - Adverse			
A-IRB exposure class:	Retail – Secured by immovable property non-SME		
Time step	**Exposure value (EUR)**	**Projected risk weight (%)**	**REA value (EUR)**
Typically quarters or years	(N), projected using column (D) of Table A.9	(O), fixed value calculated in column (R) of Table A.7	(P) = N * O
T0	2,000,000	37.50	750,000
T1	2,150,000	37.50	806,250
T2	2,279,000	37.50	854,625
T3	2,347,370	37.50	880,264

Note: The numbers in the table are purely fictitious and designed for illustrative purposes.

F-IRB Approach

Table A.12 has an identical structure to Table A.11 and captures the risk weight projections using the individual internal obligor grade data for the F-IRB portfolio Corporate – SME. The starting point values are sourced from Table A.8 and the risk parameter projections from Table A.10. Columns A to H are essentially equivalent to the corresponding columns in Table A.11, so no further comments are necessary here.

Column I contains LGD projections, which, according to the regulation, are fixed at 45% for senior exposures without eligible collateral under the F-IRB approach, so no calculations are required (which also means that the LGD DT projections in column B of Table A.10 are effectively unused in our example). We also assume that maturity (column J) remains fixed at the initial value during the projection period. The maturity adjustment, however, evolves over time, as it also depends on PD, which is not fixed (see Equation (A.***12***). Analogously, the correlation coefficient is also dependent on PD (see Equation (A.***13***) and hence evolves throughout the projection period.

The applied SME supporting factor in column M takes the value of 0.7619 in this case, as we are projecting an SME portfolio. Another major difference is caused by the defaulted exposures, which always receive a zero risk weight in the F-IRB approach, and thus, while the exposure amount itself evolves (analogously to Equation (A.***22***), the projected REA for defaulted exposures is always 0.

Table A.12: Projection Calculations (using grade-level data) – F-IRB

Total			
F-IRB exposure class:	Corporate – SME		
Time step	**Exposure value (EUR)**	**REA value (EUR)**	**Projected risk weight (%)**
Typically quarters or years	(A), sum of exposure values in all grades	(B), sum of REA values in all grades	(C) = B / A
T0	138,000,000	88,254,898	63.95
T1	136,360,000	113,627,594	83.33
T2	138,261,200	101,958,984	73.74
T3	141,266,104	96,850,878	68.56

Non-defaulted (1/2)					
F-IRB exposure class:	Corporate – SME				
Grade level	**Time step**	**Exposure value (EUR)**	**Projected risk weight (%)**	**REA value (EUR)**	**Phi coefficient (ϕ)**
Internal rating grade level as in C 08.02	Typically quarters or years	(D), projected using column (C) of Table A.10	(E), see Eq. 15	(F) = D * E	(G), fixed value calculated in column (I) of Table A.8
Grade 1	**T0**	55,000,000	28.43	15,635,057	1.06
	T1	53,900,000	48.01	25,878,542	1.06
	T2	54,439,000	38.93	21,194,862	1.06
	T3	55,527,780	33.88	18,810,964	1.06
Grade 2	**T0**	75,000,000	96.83	72,619,841	0.97
	T1	73,500,000	119.39	87,749,052	0.97
	T2	74,235,000	108.80	80,764,121	0.97
	T3	75,719,700	103.06	78,039,914	0.97

Table continues

Non-defaulted (2/2)							
F-IRB exposure class:	Corporate – SME						
Grade level	**Time step**	**Non-defaulted PD (%)**	**Non-defaulted LGD (%)**	**Maturity (M) (years)**	**Maturity adjustment ($Z(M, PD)$)**	**Correlation coefficient ($R(PD)$) (%)**	**SME supporting factor**
Internal rating grade level as in C 08.02	Typically quarters or years	(H), projected using column (A) of Table A.10 and Eq. 13	(I), fixed 45% for senior exposures without eligible collateral	(J), fixed values given by column (L) of Table A.8	(K), see Eq. 9 and Eq. 10	(L), see Eq. 6	(M), 0.7619 - 0.85 for SME exp.; 1 for non-SME exp.
Grade 1	**T0**	0.15	45.00	2.00	1.34	23.13	0.7619
	T1	0.39	45.00	2.00	1.24	21.90	0.7619
	T2	0.26	45.00	2.00	1.28	22.54	0.7619
	T3	0.20	45.00	2.00	1.31	22.84	0.7619
Grade 2	**T0**	3.00	45.00	2.11	1.13	14.68	0.7619
	T1	5.73	45.00	2.11	1.09	12.68	0.7619
	T2	4.38	45.00	2.11	1.11	13.34	0.7619
	T3	3.70	45.00	2.11	1.11	13.89	0.7619

Defaulted (Grade 3)			
F-IRB exposure class:	Corporate – SME		
Time step	**Exposure value (EUR)**	**Projected risk weight (%)**	**REA value (EUR)**
Typically quarters or years	(N), projected using column (D) of Table A.10	(O), fixed 0% for all F-IRB exposures	(P) = N * O
T0	8,000,000	0	0
T1	8,960,000	0	0
T2	9,587,200	0	0
T3	10,018,624	0	0

Note: The numbers in the table are purely fictitious and designed for illustrative purposes.

STA Approach

The STA portfolios in Table A.13 receive a simplified treatment regarding their projections. The starting point values are sourced from Table A.6 and the exposure growth projections from Table A.10**,** as we are dealing with a corporate portfolio. The logic of the STA projections is straightforward. The amount of non-defaulted and defaulted exposures evolves in line with Equation (A.***17*** and Equation (A.***22***. The projected risk weights are fixed and equal to the initial implied risk weight induced from the regulatory data. The total projected risk weight, however, evolves over time as the ratio of non-defaulted to defaulted exposures changes due to different growth rates.

Table A.13: Projection Calculations – STA

Total			
STA exposure class:	Corporates, including exposures in default		
Time step	**Exposure value (EUR)**	**REA value (EUR)**	**Projected risk weight (%)**
Typically quarters or years	(A), sum of exposure values in all STA classes	(B), sum of REA values in all grades	(C) = B / A
T0	26,000,000	26,500,000	101.92
T1	25,620,000	26,180,000	102.19
T2	25,943,400	26,542,600	102.31
T3	26,492,228	27,118,392	102.36

Total			
STA exposure class:	Corporates		
Time step	**Exposure value (EUR)**	**Projected risk weight (%)**	**REA value (EUR)**
Typically quarters or years	(A), projected using column (C) of Table A.10	(B), fixed value based on column (C) of Table A.6	(C) = N * O
T0	25,000,000	100	25,000,000
T1	24,500,000	100	24,500,000
T2	24,745,000	100	24,745,000
T3	25,239,900	100	25,239,900

Total			
STA exposure class:	Exposures in default		
Time step	**Exposure value (EUR)**	**Projected risk weight (%)**	**REA value (EUR)**
Typically quarters or years	(D), projected using column (D) of Table A.10	(E), fixed value based on column (F) of Table A.6	(F) = N * O
T0	1,000,000	150	1,500,000
T1	1,120,000	150	1,680,000
T2	1,198,400	150	1,797,600
T3	1,252,328	150	1,878,492

Note: The numbers in the table are purely fictitious and designed for illustrative purposes.

A.5 Projection Calculations – Total

Table A.14 illustrates the final step, where the projections under the A-IRB (Table A.11), F-IRB (Table A.12) and STA (Table A.13) approaches are aggregated together. The aggregation logic is very straightforward. Columns A and B contain the total exposure and REA values across all defaulted and non-defaulted portfolios. See the example for T3:

$$\begin{aligned} &Total\ exposure_{T3}\ \text{(A)} \\ &= Total\ non-def\ exposure_{T3}\ \text{(D)} + Total\ def\ exposure_{T3}\ \text{(G)} \\ &= 313{,}820{,}130 + 13{,}618{,}322 = 327{,}438{,}452 \end{aligned} \tag{A.24}$$

and

$$\begin{aligned} &Total\ REA_{T3}\ \text{(B)} \\ &= Total\ non-def\ REA_{T3}\ \text{(E)} + Total\ def\ REA_{T3}\ \text{(H)} \\ &= 221{,}271{,}999 + 2{,}758{,}756 = 224{,}030{,}755 \end{aligned} \tag{A.25}$$

The total projected risk weight (column C) for time period T3 can then be simply calculated as:

$$\begin{aligned} &Total\ projected\ RW_{T3}\ \text{(C)} \\ &= \frac{Total\ REA_{T3}\ \text{(B)}}{Total\ exposure_{T3}\ \text{(A)}} = \frac{224{,}030{,}755}{327{,}438{,}452} = 68.42\% \end{aligned} \tag{A.26}$$

Columns D and E show the total exposure and REA evolution for non-defaulted exposures. For T3, the calculations would be:

$$\begin{aligned} &Non-def\ exposure_{T3}\ \text{(D)} \\ &\quad = AIRB\ non-def\ exposure_{T3} + FIRB\ non-def\ exposure_{T3} \\ &\qquad + SA\ non-def\ exposure_{T3} \\ &= (86{,}279{,}250 + 71{,}053{,}500) + (55{,}527{,}780 + 75{,}719{,}700) + 25{,}239{,}900 \\ &= 313{,}820{,}130 \end{aligned} \tag{A.27}$$

and

$$\begin{aligned} &Non-def\ REA_{T3}\ \text{(E)} \\ &\quad = AIRB\ non-def\ REA_{T3} + FIRB\ non-def\ REA_{T3} + SA\ non-def\ REA_{T3} \\ &= (3{,}381{,}030 + 95{,}800{,}191) + (18{,}810{,}964 + 78{,}039{,}914) + 25{,}239{,}900 \\ &= 221{,}271{,}999 \end{aligned} \tag{A.28}$$

The non-defaulted projected risk weight (column F) for time period T3 can then be calculated using the familiar formula:

$$\begin{aligned} &Non-\text{def}\,projected\ RW_{T3}\ \text{(F)} \\ &= \frac{Non-def\ REA_{T3}\ \text{(E)}}{Non-def\ exposure_{T3}\ \text{(D)}} = \frac{221{,}271{,}999}{313{,}820{,}130} = 70.51\% \end{aligned} \tag{A.29}$$

Finally, the calculations for defaulted exposures in columns G to I follow the same logic as presented for the non-defaulted exposures above.

Table A.14: Projection Calculations – Total CR REA

Total			
Exposure class:	All defaulted and non-defaulted exposure classes across approaches		
Time step	**Exposure value (EUR)**	**REA value (EUR)**	**Projected risk weight (%)**
Typically quarters or years	(A), sum of all exposure values	(B), sum of all REA values	(C) = B / A
T0	321,000,000	194,670,694	60.65
T1	319,130,000	232,444,713	72.84
T2	322,258,600	234,695,574	72.83
T3	327,438,452	224,030,755	68.42

Total non-defaulted			
Exposure class:	All non-defaulted exposure classes across approaches		
Time step	**Exposure value (EUR)**	**REA value (EUR)**	**Projected risk weight (%)**
Typically quarters or years	(D), sum of all non-defaulted exposure values	(E), sum of all non-defaulted REA values	(F) = E / D
T0	310,000,000	192,420,694	62.07
T1	306,900,000	229,958,463	74.93
T2	309,194,000	232,043,349	75.05
T3	313,820,130	221,271,999	70.51

Total defaulted			
Exposure class:	All defaulted exposure classes across approaches		
Time step	**Exposure value (EUR)**	**REA value (EUR)**	**Projected risk weight (%)**
Typically quarters or years	(G), sum of all non-defaulted exposure values	(H), sum of all non-defaulted REA values	(I) = H / G
T0	11,000,000	2,250,000	20.45
T1	12,230,000	2,486,250	20.33
T2	13,064,600	2,652,225	20.30
T3	13,618,322	2,758,756	20.26

Note: The numbers in the table are purely fictitious and designed for illustrative purposes.

This step concludes the calculation of REA_{CR}^{M}. The last step for obtaining $TREA$ would entail adding the constant terms for REA_{CR}^{NON-M} and REA_{Other} according to Equation 16.

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ISSN 1803-7070