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Navigating Banking Resilience: Bail-ins & Bailouts in the Czech Banking Sector

Josef Švéda *

Abstract

How much capital is truly enough to shield banks from default? Understanding this threshold is critical for designing regulatory frameworks that balance financial stability with economic growth. This paper develops a reverse stress testing framework to assess the resilience of the banking sector under extreme credit shocks. It focuses on the conditions under which banks facing distress transition from bail-ins to government bailouts, using the Czech banking sector as a case study. Our findings indicate that a capital ratio of 23.5% is sufficient to absorb losses comparable to the most severe stress experienced during the Global Financial Crisis (GFC), preventing the need for public intervention. Moreover, we show that regulatory capital buffers are well-calibrated, covering losses up to the second-largest stress event observed in the GFC. Unlike many reverse stress testing approaches, our model explicitly accounts for the dynamic effects of risk-weighted asset (RWA) adjustments, revealing that static RWA assumptions may overestimate capital resilience. These results provide critical insights for policymakers, suggesting that capital adequacy requirements remain well-calibrated but warrant further scrutiny regarding how risk weights evolve under stress conditions.

JEL Codes: E58, G01, G18, G21, G28, G32, G33.

Keywords: Bail-in, bailout, banks, capital adequacy, capital ratio, crisis, resilience, reverse stress test.

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1. Introduction

The ability of banks to withstand financial shocks remains a central concern for regulators, particularly in the aftermath of crises like the Global Financial Crisis (GFC). Despite post-crisis reforms aimed at strengthening bank capitalisation, uncertainties persist regarding whether current capital levels are sufficient to prevent government bailouts under severe stress scenarios. While regulatory capital requirements have increased significantly, the debate continues over the optimal level of bank capitalisation (Dagher et al., 2016; Ambrocio et al., 2020; Feyen and Mare, 2021) and whether it can fully absorb losses without triggering systemic intervention.

Existing research has examined the macroeconomic factors driving banking crises (Grundke and Pliszka, 2018; Baes and Schaanning, 2023; Breuer and Summer, 2020) and the determinants of bank failures (Vallascas and Keasey, 2012; Jabra et al., 2017). Higher capital ratios have been shown to improve bank resilience (Klein and Turk-Ariss, 2022; Cicchiello et al., 2022) and lower the risk of crises (Firestone et al., 2017; Cardot-Martin et al., 2022). However, less attention has been paid to the specific capital thresholds at which banks transition from bail-ins to requiring government bailouts. Reverse stress testing frameworks often do not account for the endogenous growth of risk-weighted assets -RWAs- (Feyen and Mare, 2021; Ambrocio et al., 2020), potentially leading to an overestimation of bank resilience under extreme conditions. This paper addresses this gap by developing a reverse stress testing framework that explicitly models capital depletion, RWA adjustments, and the critical thresholds that trigger external intervention.

This paper seeks to answer three key questions:

- What level of stress drives the banking sector from a bail-in scenario to requiring a government bailout?
- Are current capital levels and regulatory capital requirements well-calibrated to absorb losses comparable to the most severe stress events observed during the GFC?
- How do risk-weighted asset adjustments influence bank resilience?

By addressing these issues, we contribute to the broader international debate on banking regulation and optimal capital ratios from a risk perspective. Our model is inspired by classic stress testing exercises (Daniëls et al., 2017; Budnik et al., 2020; Geršl et al., 2012) and to ensure realistic asset behaviour under stress, we follow the methodologies of Gross et al. (2020); Polak and Panos (2019).

We apply our framework to the Czech banking sector, using end-2021 balance sheet data to assess its resilience to extreme stress scenarios. The Czech banking sector presents a compelling case study due to its strong capital buffers and low historical probability of government bailouts, making it an ideal setting to examine the adequacy of capital requirements under severe stress.

Beyond modelling credit risk that could lead to a government bailout, we examine banking sector resilience in a comparative historical context, using the GFC experience in the EU's hardest-hit countries as a benchmark. While historical crises differ across countries, this approach provides a valuable reference point for assessing the severity of risk materialisation and determining the optimal level of capital ratios. Unlike conventional stress testing approaches that specify the macroeconomic environment in which the distress occurs or attempt to estimate the probability of the extreme events, we admit that such an approach is challenging and introduces additional model risk (Tarashev, 2010; Gross and Población, 2019; Casellina et al., 2023). Instead, we acknowledge the large uncertainties involved, as highlighted in Baes and Schaanning (2023), and assess the resilience of the banking sector in relative terms, comparing it with previous crises rather than making deterministic probability-based models.

Our findings offer several key insights into the ongoing debate. First, a capital ratio of 23.5% is enough to cover losses similar to those seen in the Global Financial Crisis (GFC), meaning banks would not need government support under such conditions.

Second, this ratio also marks the point where financial stress shifts from bail-ins to bailouts, showing the level of losses that would force government intervention. This suggests that a significant increase in capital buffers is unnecessary, i.e. optimal from a risk perspective. While some academic studies suggest support for stricter regulations, especially in terms of leverage requirements (Ambrocio et al., 2020), our results indicate that current capital levels are adequate. Moreover, existing capital requirements provide substantial cover for credit risk materialisation for up to the second largest crisis during the GFC, providing a large buffer against credit risk materialisation.

Third, movements in risk weights play a crucial role in determining the banking sector's resilience. The omission could lead to an overestimation of resilience. Fourth, the introduction of bail-in regulations has significantly enhanced the resilience of the banking sector, reducing the need for public interventions. Fifth, the aggregate results mask considerable variation across individual loan portfolios. Notably, loans to households secured by real estate exhibit lower resilience. This finding supports the need for output floors, as introduced into EU legislation from Basel III.

The rest of the paper is organized as follows: Section 2 reviews the relevant literature. Section 3 outlines the framework for analyzing banking sector resilience, followed by the data used for calibration in Section 4. Section 5 presents the results, while Section 6 offers additional robustness checks. Concluding remarks are provided in Section 7. Detailed descriptions of the credit risk model and the risk-weighted assets model are available in Appendix A and Appendix B, respectively. Appendix C explores the resilience of the banking sector across individual loan portfolios.

2. Related Literature

The fragility of the banking sector poses a significant threat to the broader economy. When banks fail, depositors may face restricted access to their funds, causing the crisis to spread across the economic system. Bank defaults can result from a variety of factors, including regulatory quality, political stability (Jabra et al., 2017), and macroeconomic conditions such as GDP growth and interest rates (Baselga-Pascual et al., 2015; Delis and Kouretas, 2011). Additionally, Vazquez and Federico (2015); Klomp and de Haan (2012); Vallascas and Keasey (2012) highlight the size of banks as an important factor influencing their stability.

A substantial body of literature agrees that the core determinant of banking resilience is the level of capitalisation and profitability (Soenen and Vennet, 2022; Lagasio et al., 2022; Berger and Bouwman, 2013; Firestone et al., 2017; Baselga-Pascual et al., 2015). This resilience is often measured using proxies like Z-scores, which link profitability to risk through variance measures (Lagasio et al., 2022), and CAMEL indicators, which assess risk-weighted capital, liquidity, asset quality, and profitability (Parrado-Martínez et al., 2019).

Cardot-Martin et al. (2022) find that higher capital levels reduce the likelihood of a banking crisis. Capitalisation not only strengthens banks' ability to absorb shocks (Klein and Turk-Ariss, 2022; Cicchiello et al., 2022) but may also introduce new systemic risks (Zhou, 2013). In contrast, Òscar Jordà et al. (2021), using a dataset spanning from 1870, argue that while capital buffers alone do not reduce banking risk, better-capitalised banks tend to recover faster from crises, as credit flows back into the economy more quickly.

Capital requirements, the primary regulatory tool for ensuring sufficient capitalisation, play a critical role in mitigating the negative effects of banking crises. Danisman and Demirel (2019) assert that capital requirements are the most effective regulatory measure, though the optimal level remains unclear.

Several studies explore different thresholds for capital requirements. Dagher et al. (2016) suggest that risk-weighted capital ratios of 15-23% would have prevented creditor losses in past crises for advanced economies, a finding supported by the Financial Stability Board's (FSB) recommendations for globally systemic banks (FSB, 2014) and the US Federal Reserve's total loss-absorbing capacity proposal of more than 18% (Federal Reserve Board, 2015).

Other approaches, such as reverse stress testing, focus on the economic environment that depletes banks' equity. Grundke and Pliszka (2018) demonstrate that a combination of macroeconomic variables threatening banks is plausible. Baes and Schaanning (2023) and Breuer and Summer (2020) explore worst-case scenarios and their implications for banking capitalisation. Baes and Schaanning (2023) highlight that the design of stress scenarios is less critical, as large shocks tend to expose weak banks regardless of scenario specifics, while Breuer and Summer (2020) show that the probability of defaults (PDs) must rise considerably to challenge large banks beyond the levels tested in EU-wide stress exercises.

To overcome the uncertainty in scenario selection, Dagher et al. (2016) and Feyen and Mare (2021) focus on credit losses alone. Feyen and Mare (2021) analyze the PD and loss-given default (LGD) levels that would endanger the financial system and use these findings to develop a country-specific indicator of banking risk. Dagher et al. (2016) further discuss the costs of higher capital requirements, finding that a 1pp increase in capital requirements leads to a minimal increase in lending rates, ranging from 2 to 20bps, in steady-state conditions. This aligns with the review by Birn et al. (2020). However, during transitional periods, higher capital requirements can reduce lending volumes temporarily. Firestone et al. (2017) estimate that a 1pp increase in capital ratios reduces long-term US GDP by 7.4bps, and they derive an optimal capital ratio for US banks ranging from 13 to 26%, depending on specific bank characteristics.

Ambrocio et al. (2020) ask academic researchers to suggest the optimal level of capital requirements. They find that the most preferred risk-weighted capital requirement level is 15% and 10% in terms of leverage ratio. Respondents also approve further strengthening of banks' resilience via hybrid assets and bail-in liabilities, with a weaker consensus. Still, the regulation on bail-in should provide additional cushion to prevent banking bailouts (Dagher et al., 2016). Well-designed convertible bonds can also decrease the risk of default (Hilscher and Raviv, 2014), although Jones et al. (2022) find it not as effective as expected.

The suitable level of capital ratios in the referenced literature reflects the risk profile of banks via risk weighting of the assets. Long-term one-year PDs and LGDs primarily drive the risk weights. There is, however, increasing evidence that risk weights are volatile more than expected (Farkas et al., 2020; Malovaná, 2018), and thus they may not reflect the risk loaded fully (Krebs and Nippel, 2021; Johnston, 2009). Consequently, capital ratios can decrease due to movements in risk weights more than the literature suggests. In turn, optimal capital ratios presented earlier can be underestimated. This effect can play a role as typical stress does not materialize as a one-off shock but throughout longer periods. Ari et al. (2021) conclude that increased defaults stretch around three years on average, and Honohan and Klingebiel (2000) find a five-year period of banking crisis' on a median. In such cases, systematic underestimation of the long-term risk may arise, and we argue that the movements should be considered. In addition, the resiliency of banks' capitalisation may be assessed at the level of individual asset portfolios, which is consistent with the design of capital requirements. The findings from such an analysis offer valuable insights into the undercapitalisation of portfolios. Regulators may change their strategy toward portfolio capital requirements accordingly. Nevertheless, to the best of our knowledge, no literature exists on this specific subject.

3. Methodology

3.1 Introducing Concepts of the Framework

To answer our questions from Introduction, we build a model that evaluates the *resilience* of the banking sector against rising credit risk levels. We use the term resilience in the sense of banks' ability to retain their capital ratios above minimal regulatory requirements. The capital ratio serves us to indicate a bank's capacity to absorb negative shocks and is calculated as the proportion of eligible regulatory capital (Cap) to risk-weighted assets (RWAs)[1]. We present the relationship in Equation 1. Capital here represents banks' own funds available to absorb losses on going concern and the RWAs amount or long-term risk accumulated on banking balance and off-balance sheets. A critical threshold in this context is the total SREP capital requirement (TSCR), set by the regulatory authorities. When a bank's capital ratio falls below this threshold, a bank is legally not allowed to grant new loans and effectively falls into default. Subsequently, a bank needs to undergo recapitalisation to be operational again. To recapitalise the bank, the capital and eligible liabilities available from bail-in[2] is used first, and when all of these available resources are

[1] For clarity, while the accurate term is the Total Risk Exposure Amount (TREA) in the EU, we refer to it as RWAs for consistency with common academic terminology.

[2] The legal basis for the MREL framework in the European Union is laid down by Bank Recovery and Resolution Directive (BRRD) and, to some extent, by Single Resolution Mechanism Regulation (SRM Regulation), the

consumed, the government must bail out the bank. This dynamics is the core of our model, as it defines the key event - a default - and the boundaries between when bail-in and bailout occur.

$$CapitalRatio = \frac{RegulatoryCapital}{RWA} \geq TSCR \tag{1}$$

We characterize credit risk with a combination of two systematic parameters: i) the probability of default (PD) and ii) loss-given default (LGD). The first variable represents a share of bank's assets going to default, and the second is the expected loss incurred when assets default. We iteratively increase the levels of the two parameters and analyse their impact on capital ratios by searching for a point of default in the banking sector.[3]

Capital ratio is influenced by the materialization of credit risk through two distinct channels. First, we account for the standard impact of credit losses on capital (the numerator of the capital ratio). The materialization of credit risk on loans results in credit losses, which in turn reduce the available capital, thereby lowering the overall capital ratio.

However, there exists a second, often overlooked, channel. During periods of significant or prolonged stress,[4] RWAs (denominator of the capital ratio) interact with the elevated credit risk and henceforth increase. This is a known effect in the stress testing community, and many supervisory tests such as EBA (2020) therefore include RWA modelling in their exercises. The growth in RWAs further diminishes the capital ratio and brings the bank closer to the default. We show the impacts of both channels on capital ratio in Equation 2.

$$\downarrow\downarrow CapitalRatio = \frac{\downarrow RegulatoryCapital}{\uparrow RWA} \geq TSCR \tag{2}$$

The interaction between credit risk and RWAs introduces additional complexity to our framework. RWAs are influenced by the historical evolution of credit risk, which means that modelling them requires a time dimension with a specific pre-set length. To capture this, we rely on the findings of Ari et al. (2021), which show that elevated credit risk during crises typically lasts 12 quarters (3 years). Following these findings, we assume a 12-quarter time frame in our model to assess bank resilience.

However, the inclusion of a time dimension introduces another challenge. Banks generate profits over time from the assets they hold and the services they provide to customers. These profits must also be accounted for in our model to ensure a reliable framework for evaluating bank resilience. We label them *returns to cover losses* throughout our analysis. Note that we do not consider them to be affected by the credit risk as potential reductions from increased defaults are implicitly accounted for by the level of LGD.

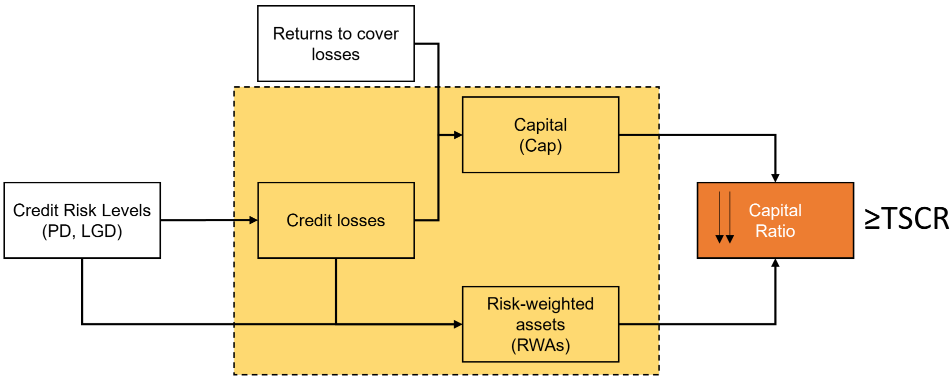
Capital Requirements Regulation (CRR), and Capital Requirements Directive (CRD) (the Banking Package). The MREL requirement is also connected to the global standard for total loss absorption capacity (TLAC) introduced by Financial Stability Board (FSB) for globally systematic important institutions.

[3] Our model, therefore, falls into the area of reverse stress testing frameworks.

[4] This can also arise from increases in long-term risk, as noted by Malovaná (2018).

In sum, we consider three building blocks in our framework: a model for i) credit losses, ii) RWAs, and iii) returns to cover losses. Our general framework is presented in Figure 1. Credit risk levels, characterized by PD and LGD, affect credit losses, which, together with returns to cover losses, change the capital available to the banking sector. Credit risk also affects RWAs. Note that there is an interaction between credit losses and RWAs. We describe this interaction in more detail in subsection 3.3. The resulting capital and RWA form the capital ratio which is evaluated against the minimum requirement, TSCR.

Figure 1: Model Framework Diagram



Note: The diagram presents our modelling framework for evaluation of the resilience of the banking sector. Credit risk levels, characterized by PD and LGD, affect credit losses, which, together with returns to cover losses, change the capital available to the banking sector. Credit risk also affects RWAs. Note that we also connect credit losses with RWAs. In fact, there is interaction between these channels as described in subsection 3.3. The final capital and RWA form the capital ratio, which is evaluated with respect to the minimum requirement, TSCR, and decides whether the banking sector is in default. The orange area covers blocks that are dependent on credit risk in our framework.

Our presented framework is flexible enough to assess the resilience of the entire banking sector or a specific portion of its balance sheet. This is feasible because RWAs are calculated individually for each asset, enabling the evaluation of capital ratios for a more targeted set of assets. The banking sector should demonstrate resilience both at the aggregate level and within individual balance sheet portfolios, as capital allocated in banks should be used for specific types of risk and assets.

Assessing resilience based solely on credit risk across the entire balance sheet would yield overly optimistic results. This is because various parts of the balance sheet are exposed to different risks, each requiring its own capital allocation. For example, consider a building owned by a bank and used for its employees. While the building is exposed to flood risk (a form of climate risk), it is not subject to credit risk. Allocating capital to cover this building for credit risk would overestimate the bank's resilience to credit risk, as it addresses flood risk.

We utilize the feature of RWAs to examine the resilience of the key loan portfolio — loans to the non-financial sector (denoted as L). The portfolio L consists of loans to various counterparties, introducing heterogeneity, as credit risk can propagate unevenly through its sub-portfolios. To account for this, we further divide L into three homogeneous sub-portfolios: i) loans to non-financial corporations (NFC), ii) loans to households secured by real estate (HH-H), and iii) loans to households for consumption (HH-C).

Thus, L can be defined as: $L = \{\text{NFC}, \text{HH-H}, \text{HH-C}\}$.

We assume that the initial capital ratios at time T_0 for all $l \in L$ match[5] the overall capital ratio of the banking sector (Equation 3). The risk-weighted assets (RWAs) of each sub-portfolio l are used to gauge the capital $Cap^l_{T_0}$ available to support it, as shown in Equation 4, while the RWAs from other assets, denoted as O, are excluded from this calculation. This means that the amount of capital ready to absorb credit risk is proportional to the long-term risk calculated by banks. Importantly, the total RWAs of the banking sector at time T_0 (RWA_{T_0}) are the sum of $RWA^l_{T_0}$ and $RWA^O_{T_0}$ (Equation 3).

$$\text{Capital Ratio}_{T_0} = \text{Capital Ratio}^L_{T_0} = \text{Capital Ratio}^l_{T_0}, \quad \forall l \in L \tag{3}$$

$$Cap^l_{T_0} = \frac{RWA^l_{T_0}}{RWA_{T_0}} \cdot Cap_{T_0}, \quad RWA_{T_0} = \sum_{l \in L} RWA^l_{T_0} + RWA^O_{T_0} \tag{4}$$

While gauging the amount of capital for the selected portfolio of the bank balance sheet with RWA is the main strength of our framework, it is also a limitation. In practice, credit risk may concentrate on our selected portfolios, while other parts of the balance sheet may face proportionally less stress. In such cases, banks could use capital from the rest of the balance sheet to cover the losses on the selected portfolios. However, the risk dynamics in the remaining balance sheet are uncertain, and we, therefore, exclude it from our framework. We interpret the banking sector without the rest of the balance sheet as if the stress would proportionally increase across the types of risks.

We start our analysis by evaluating the resilience of loan sub-portfolios (l) individually, and we then combine the results using bridge equations to assess the resilience of the whole loan portfolio L. For each l, we apply a consistent modelling approach as illustrated in Figure 1 and further detailed below.

3.2 Non-technical Summary of Credit Losses Model

We opt to model the credit losses as realistically as possible using a structural approach instead of calibrating the model on historical experience. In turn, we should be able to depict the evolution of credit losses more precisely, even for very rare levels of credit risk that did not even occur. We also respect the IFRS9 Standard[6] requirements in our model, which further boosts the consistency of loan portfolio evolution under stress.

The credit loss model is conceptually based on Gross et al. (2020) and Polak and Panos (2019). In this section, we present a brief description to provide basic intuition of the mechanism, whereas the detailed one is provided in Appendix A. Generally, for each iteration of credit risk level (combination of PD and LGD), we model the credit losses (CLoss) over time. The resulting credit

[5] Note that we later introduce a minor adjustment to this assumption to reflect the specific capital requirement setup. For further details, see subsection 3.5.

[6] IFRS9 Standard is available under the following link: `https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016R2067`. The website was accessed in September 2024.

loss is the difference between loss allowances at the end of the modelling period (after 12 quarters) and its levels at the starting point (Equation 5).

$$CLoss^{l}_{T_{12}} = LA^{l}_{T_{12}} - LA^{l}_{T_0}, \quad \forall l \in L \tag{5}$$

The loss allowance (LA) is the amount of provisions allocated to the assets according to the IFRS9 Standard. They represent the provisions on the balance sheet, i.e., they do not include off-balance sheet items (e.g., commitments to credit lines or mortgages). Assets that receive a loss allowance are typically measured using the amortized cost method[7] and, therefore, do not reflect current market prices. Instead, their levels are mainly driven by PDs and LGDs.

We model LA via two components: i) the evolution of the distribution of assets across the impairment stages in one sufficiently homogeneous sub-portfolio l, and ii) respective loss ratios (LRs). IFRS9 recognizes three impairment stages, each representing a specific state of assets with respect to default risk.

- S_1: Stage 1 (performing assets, low risk of default)
- S_2: Stage 2 (under-performing assets, significant increase in credit risk)
- S_3: Stage 3 (defaulted assets)

The total assets value in sub-portfolio l at time T_i is the sum of assets across all stages:

$$\sum_{S_z \in S} GCA^{l,S_z}_{T_i} = GCA^{l}_{T_i} \tag{6}$$

where $GCA^{l}_{T_i}$ is the gross carrying amount (total gross value) of sub-portfolio l at time T_i.

The loss allowance $LA^{l}_{T_i}$ for sub-portfolio l at time T_i is the sum of the gross carrying amounts $GCA^{l,S_z}_{T_i}$ across all impairment stages, weighted by the loss ratios $LR^{l,S_z}_{T_i}$:

$$LA^{l}_{T_i} = \sum_{S_z \in S} LR^{l,S_z}_{T_i} \cdot GCA^{l,S_z}_{T_i}, \quad \forall l \in L \tag{7}$$

where $LR^{l,S_z}_{T_i}$ is the loss ratio for sub-portfolio l at time T_i in impairment stage S_z.

Here, the loss ratio $LR^{l,S_z}_{T_i}$ is the present value of expected cash shortfalls due to default for each stage. We define it as a function of PD and LGD. The higher the credit risk, the larger the loss ratios get. More assets in higher stages also translate to more weight into larger loss ratios (for more information, see Appendix A).

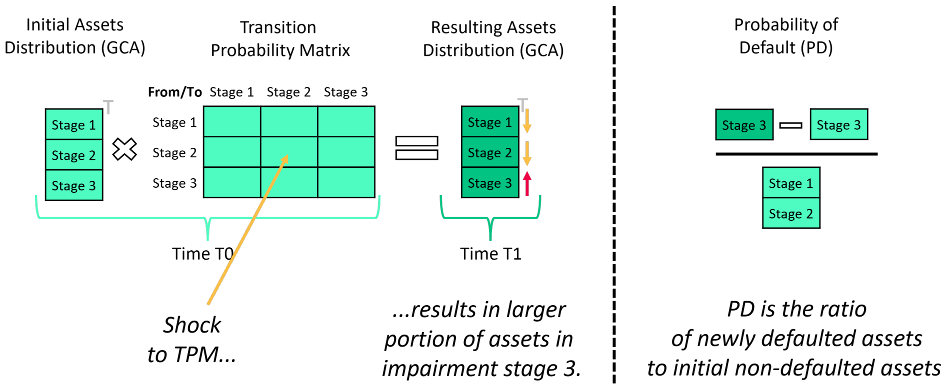
The evolution of loans across impairment stages is modelled using a transition probability matrix (TPM), which governs how loans move between different risk stages S_i over time. Assets in the

[7] For further information on the different methods of measurement, see the IFRS9 Standard here: `https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016R2067`. The website was accessed in September 2024.

third stage are the most important for us because they are recognized to be in default. We stylize the mechanism in Figure 2. Credit risk is implemented as a shock[8] to the TPM that increases the amount of assets in impairment stage S_3. In this mechanism, we also discover the level of PD as a ratio of newly defaulted assets to the amount of non-defaulted assets in the previous period. PD for the whole time period $PD^{3Y,l}$ is then calculated as in Equation 8. We apply a constant shock to the TPM for 12 quarters, after which it quickly fades.

$$PD^{3Y,l} = \frac{GCA_{T_{12}}^{l,S_3} - GCA_{T_0}^{l,S_3}}{GCA_{T_0}^{l,S_1} + GCA_{T_0}^{l,S_2}} \tag{8}$$

Figure 2: Shock Introduction to TPM Increases the Amount of Assets in Stage Three



Note: The figure displays credit risk propagation across the assets. We introduce a shock to the transition probability matrix (TPM) that affects the distribution of assets across the impairment stages. GCA is the gross carrying amount (gross value) of assets. We also show how the probability of default for a given sub-portfolio l (PD^l) is calculated.

3.3 Non-technical Summary of Risk-weighted Assets Model

The modelling methodology for RWAs strictly follows Sveda et al. (2023). We again provide only the summary, and the full version is accessible in Appendix B and Sveda et al. (2023). The Basel Accords and CRR2 regulation[9] define RWAs as the product of i) risk weight (RW) and ii) exposure value (EV), and they are set for each asset a. The sum across all the assets is the resulting $RWA_{T_i}^l$ (as shown in Equation 9). The summation of RWA is very powerful because it allows us to split banking balance sheets into multiple portfolios and evaluate their resilience separately, as we do in this paper.

$$RWA_{T_i}^l = \sum_{a \in A} RW_{T_i,a}^l \cdot EV_{T_i,a}^l \tag{9}$$

[8]Note that banks can fully anticipate the shock. Therefore, we do not have to account for potential discontinuity in credit losses in our model, as our approach is independent of what banks expect at time T_0.

[9]CRR2 is accessible under the following link: `http://data.europa.eu/eli/reg/2013/575/oj`. The website was accessed in September 2024.

The risk weights $RW^{l}_{T_i,a}$ are functions taking different shapes based on regulatory prescriptions. They mainly depend on PD, LGD, regulatory approach applied by banks, asset & counterparty types, and performance state. We let to change the levels of PDs and LGDs in time on granular portfolio level whenever the regulation allows[10] and the other variables are assumed constant. An increase in the individual risk weights increases RWA, which, in turn, reduces the capital ratio and brings the banking sector closer to default. Note that PDs and LGDs from the credit loss model do not step into the risk weights functions directly, but they must be significantly adjusted to reflect the regulatory requirements.

Exposure values are the regulatory-adjusted gross asset values. The exposure values do not change in our model (because of the constant balance sheet assumption). However, they still migrate between non-/defaulting states based on the TPM from the credit loss model. This, as a consequence, changes the resulting RWAs because RWs have different functions prescribed for different non-/defaulting states. Defaulted assets get usually higher risk weight than non-defaulted ones.

3.4 Return to Cover Losses

Banks experiencing materialization of credit risk continue to provide their services: they send funds on behalf of their customers, provide FX exchange, or collect interest from loans and bonds. Those activities generate profits that can be used to counter elevated credit risk. Those profits are not extensively affected by the credit risk directly[11] but rather from the macroeconomic environment surrounding those events. This mainly includes large drops in interest rates and slowing economic growth.

To keep the model parsimonious, we assume a stable level of adjusted returns on assets (RoA_{adj}), adjusted upward to account for taxation and excluding direct credit losses[12] and other risk materializations[13]. Introducing further complexity to capture the full macroeconomic environment would be overly restrictive in our framework and introduce significant model risk. Therefore, we calibrate RoA_{adj} based on historical experiences, such as the banking sector's performance during the GFC and the COVID-19 pandemic—periods that are comparable to environments where elevated credit risk materializes.

Return to cover losses ($RetCovrLoss_{T_{12}}$) account for the amount of RoA_{adj} for 12 quarters multiplied by initial assets of the banking sector (A_{T_0}) as shown in Equation 10.

$$\text{RetCovrLoss}_{T_{12}} = \sum_{t=1}^{12} RoA_{adj} \cdot A_{T_0} \tag{10}$$

[10]Note that regulation allows to calculate risk weights only for the internal-risk-based (IRB) approach, whereas the standard-based approach (STA) gets the risk weights values prescribed from the regulation. Assets in a non-performing state also follow different methods to set the RWs.

[11]However, it should be noted that interest from defaulted assets may decrease or even cease altogether due to individual bank write-off policies. These effects are, in contrast, mitigated by adjustments, such as shortening the time to maturity.

[12]Specifically items for impairment allocation and provisioning.

[13]Items for Gains and losses, including trading.

Similar to capital allocation (see Equation 3), we distribute RetCovrLoss across loan sub-portfolios in proportion to their relative share of RWAs (Equation 11). This ensures that higher-risk portfolios receive a greater share of the profits generated.

$$\text{RetCovrLoss}^{l}_{T_{12}} = \frac{RWA^{l}_{T_0}}{RWA_{T_0}} \cdot \text{RetCovrLoss}_{T_{12}}, \quad \forall l \in L \tag{11}$$

3.5 Capital After Credit Risk Materialisation

Capital Adjustments for Loan Portfolios l

After establishing credit losses $CLoss^{l}_{T_{12}}$ and returns to cover losses $RetCovrLoss^{l}_{T_{12}}$, we are ready to compute the capital ($Cap^{l}_{T_{12}}$) for each loan portfolio l at time T_{12}. However, before finalising this calculation, a small adjustment to the available capital is necessary, to properly account for the resilience of each portfolio.

This adjustment is required due to regulatory constraints that link the countercyclical buffer (CCyB) exclusively to loan portfolios l.[14] The full capacity of the CCyB must be distributed across loan portfolios L. Since part of this capital has already been accounted for in Equation 4, we add the remaining CCyB amount for each portfolio l, denoted as $\Delta Cap^{l}_{CCyB,T_0}$. This adjustment is given by Equation 12, where $\Delta Cap^{l}_{CCyB,T_0}$ represents the additional capital allocated to portfolio l.

$$\Delta Cap^{l}_{CCyB,T_0} = \left(\frac{RWA^{l}_{T_0}}{RWA^{L}_{T_0}} - \frac{RWA^{l}_{T_0}}{RWA_{T_0}} \right) \cdot \text{CCyB requirement} \cdot RWA_{T_0}, \quad \forall l \in L \tag{12}$$

Capital & Capital Ratio After Credit Risk Materialisation

Once this adjustment is made, the capital available at time T_{12} ($Cap^{l}_{T_{12}}$) for each portfolio l is calculated as follows[15]:

$$Cap^{l}_{T_{12}} = Cap^{l}_{T_0} + \Delta Cap^{l}_{CCyB,T_0} + RetCovrLoss^{l}_{T_{12}} - CLoss^{l}_{T_{12}} \tag{13}$$

where $Cap^{l}_{T_0}$ is the initial capital endowment, $\Delta Cap^{l}_{CCyB,T_0}$ the adjustment for CCyB capital $RetCovrLoss^{l}_{T_{12}}$ return to cover losses after 12 quarters, and $CLoss^{l}_{T_{12}}$ the credit loss after 12 quarters. The capital $Cap^{l}_{T_{12}}$ is then used to compute the capital ratio for each portfolio l, based on the model's updated risk-weighted assets ($RWA^{l}_{T_{12}}$) (Equation 14).[16]

[14] The CCyB is part of the Combined Buffer Requirement (CBR), which also includes the Capital Conservation Buffer (CCoB), for systemically important institutions, the Systemic Risk Buffer (SRB), and for other systematically important institutions buffer (OSIIB), designed to strengthen banks' resilience.

[15] Note that we could also account for changes of capital due to excess or shortfall of loss allowances compared to expected losses. However, banks in our framework know the future path of the credit risk (perfect foresight), which consequently makes these regulatory adjustments of capital obsolete.

[16] This calculation allows for an assessment of the resilience of individual loan portfolios. The results are presented in Appendix C.

$$\text{Capital ratio}^{l}_{T_{12}} = \frac{Cap^{l}_{T_{12}}}{RWA^{l}_{T_{12}}}, \quad \forall l \in L \tag{14}$$

3.6 Merging Sub-Portfolios with Bridge Equations

The resulting capital ratios of the loan sub-portfolios l to the non-financial sector L are combined together with bridge equations. Since we evaluate the credit risk with combinations of PDs and LGDs, we construct the bridge equations based on those two variables. Our aim is to set the level of PD and LGD on the sub-portfolio to NFC and find corresponding PDs and LGDs for the remaining sub-portfolios.

We construct two bridge equations for PD that define the long-term connection between pairs of PDs[17] on the loan sub-portfolios. First, we estimate the relationship of PDs between households secured by real estate (HH-H) and loans to non-financial corporations (NFC) where the first is used as a dependent variable. Second, we do the same between the pair of loans to households for consumption (HH-C) and loans to non-financial corporations (NFC).

We base our regressions on data from the Czech Banking Credit Bureau[18] and Central Credit Register[19] in the period between 2007 and 2021. We estimate the relationship on three-year PD, which allows us to use the regression to match the individual sub-portfolios. The registers have provided us PDs with a quarterly frequency, which we transformed to 3-year cumulative PD $PD^{3Y,l}_{T_i}$ via the following equation:

$$PD^{3Y,l}_{T_i} = 1 - \prod_{z=0}^{11} (1 - PD^{Q,l}_{T_i+z}) \tag{15}$$

where T_i represents time at quarterly intervals, and Q denotes the initial quarterly frequency. The quarterly frequency is appropriate for our framework, as we model credit losses at the same frequency. The relationships between PDs are shown in Figure 3 and the estimated regression equations used as bridge equations in Equation 16. Specifically, the relationship between loans to NFC and HH-H is not linear[20].

$$\begin{aligned} PD^{3Y}_{HH-H} &= 7.0843 \cdot \ln(PD^{3Y}_{NFC}) + 4.2069 \\ PD^{3Y}_{HH-C} &= 1.2426 \cdot PD^{3Y}_{HH-H} + 7.9956 \end{aligned} \tag{16}$$

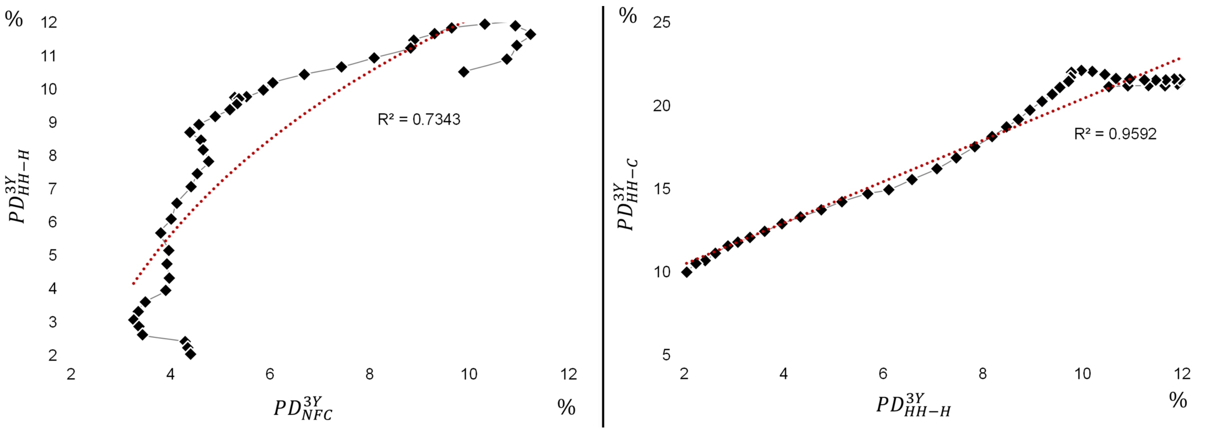
[17] Note that those should be labelled rather as default rates, but since there are no conventions on an exact formula to calculate default rates, we stick to PD.

[18] `https://cbcb.cz`. The website was accessed in September 2024.

[19] `https://www.cnb.cz/en/supervision-financial-market/central-credit-register/`. The website was accessed in September 2024.

[20] This has interesting implications. As the stress on the NFC portfolio increases, the PD marginal increase on the HH-H portfolio decreases, and thus, to some extent, the amplification effect of systematic risk is exhausted.

Figure 3: Estimation of PD Levels Between Pairs of Loan Portfolios



Note: The figure illustrates the relationship between the 12-quarter (3Y) PD^{3Y}_{l} for two pairs of loan portfolios. The left panel shows the relationship between the PD of loans to households secured by real estate (PD^{3Y}_{HH-H}) on the y-axis and loans to non-financial corporations (PD^{3Y}_{NFC}) on the x-axis. The right panel depicts the relationship between the PD of loans to households for consumption ((PD^{3Y}_{HH-C})) and (PD^{3Y}_{HH-H}).

For LGDs, we apply a simpler approach, as they tend to be more stable over time, with a consistent gap between portfolio pairs. We base this on historical experience. For the HH-H and NFC loan portfolios, we maintain an LGD difference of 15pps, and for the HH-C and NFC pair, the difference is 10pps. The LGD bridge equations are shown in Equation 17.

$$\begin{aligned} LGD^{HH-H} &= LGD^{NFC} - 15 \\ LGD^{HH-C} &= LGD^{NFC} + 10 \end{aligned} \tag{17}$$

The resulting $PD^{3Y,L}$ and LGD^{L} for portfolio L are calculated as follows:

$$PD^{3Y,L} = \frac{\sum_{l \in L} \sum_{S_z=1}^{2} GCA_{T_0}^{l,S_z} \cdot PD^{3Y,l}}{\sum_{l \in L} \sum_{S_z=1}^{2} GCA_{T_0}^{l,S_z}} \tag{18}$$

$$LGD^{L} = \frac{\sum_{l \in L} GCA_{T_0}^{l} \cdot LGD^{l}}{\sum_{l \in L} GCA_{T_0}^{l}} \tag{19}$$

3.7 Capital Ratio of L at T_{12}

Using the established relationships between $PD^{3Y,l}$ and LGD^{l}, we combine the sub-portfolios l as follows:

1. We pre-set the PD^{3Y}_{NFC} and LGD_{NFC} levels for the NFC loan portfolio and determine the corresponding values for HH-H and HH-C portfolios using Equation 16 and Equation 17.
2. Once the PDs and LGDs are known, we find appropriate credit losses $CLoss^{l}_{T_{12}}$ and RWAs $RWA^{l}_{T_{12}}$ for the credit risk level, and calculate $Cap^{l}_{T_{12}}$ for each sub-portfolio l separately.
3. We sum across l which yields $Cap^{L}_{T_{12}}$ and $RWA^{L}_{T_{12}}$.
4. By dividing $Cap^{L}_{T_{12}}$ and $RWA^{L}_{T_{12}}$, we gain the final capital ratio Capital ratio$^{L}_{T_{12}}$ (Equation 20), which we evaluate compared to the TSCR.

$$\text{Capital ratio}^{L}_{T_{12}} = \frac{\sum_{l\in L} Cap^{l}_{T_{12}}}{\sum_{l\in L} RWA^{l}_{T_{12}}} \geq TSCR \tag{20}$$

3.8 Granular Approach to Banking Resilience

Having the capital ratios after the credit risk materialisation enables us to determine whether there is a default or not. We show this in Figure 4A. Here, credit risk depletes capital and increases RWA, which, in turn, reduces the portfolio capital ratio of the banking sector. The banking sector falls into portfolio default (the portfolio capital ratio is below TSCR) and must be bailed out.

Our framework enables us to investigate how different levels of credit risk can lead to a bailout, offering insights into the resilience of the banking sector. By dividing capital ratios into finer resilience segments RS^{L}_{o}, each representing a key threshold, we can gain further detail. This more granular approach further improves the understanding of the sector's vulnerabilities and also enhances policy measures more effectively.

At lower levels of credit risk, banks can cover losses with their returns (*RetCovrLoss*), maintaining profitability, paying dividends, and strengthening their capital ratios. However, as credit risk increases, these returns may be fully consumed, forcing banks to draw on their voluntary capital excess (VCE), which is the capital ratio above regulator requirements of the whole banking sector at time T_0 (Equation 21). This reduces capital ratios below their initial levels, signalling stress within the banking sector.

$$VCE = \text{Capital ratio}_{T_0} - \text{TSCR} - \text{CBR} \tag{21}$$

As credit risk intensifies, banks may need to dip into the capital reserved for regulatory requirements. Initially, the combined buffer requirement (CBR) is consumed. Regulatory restrictions, such as limits on dividend payouts, are triggered when the CBR is depleted, signalling increased risk to the market. If credit risk continues to escalate, the sector reaches the threshold of the TSCR representing default.

At this stage, bailinable funds from the MREL are used to recapitalise portfolios and bring them back to TSCR. These funds come from recently established regulation for bail-in that aims to further reduce the need for government interventions (Hilscher and Raviv, 2014). However, if these funds are also exhausted, a government bailout becomes necessary to restore stability. We calculate this by adjusting capital ratios for bail-in capacity. Bail-in is used to recapitalise banks only up to the level of TSCR as shown in Equation 22. When Capital ratio$_{T_{12}}^{L,BAIL}$ starts to fall below TSCR again, the portfolio requires a bailout.

$$\text{Capital ratio}_{T_{12}}^{L,\text{BAIL}} = \min\left(\text{Capital ratio}_{T_{12}}^{L} + \text{MREL}; \text{TSCR}\right) \tag{22}$$

We formalize this process using resilience segments RS_o^L, identified through the following steps. First, we classify the resilience segments (RS_o^L) by comparing the capital ratio against predefined lower and upper bounds, L_o and U_o. This classification can be expressed as:

$$RS_o^L : L_o < \text{Capital ratio}_{T_{12}}^{L} \leq U_o$$

If the Capital ratio$_{T_{12}}^{L}$ exceeds TSCR, the resilience segments are the following:

If Capital ratio$_{T_{12}}^{L} \geq TSCR$: (23)

RS_o^L	Lower Limit L_o	Capital ratio$_{T_{12}}^{L}$	Upper Limit U_o
$RS_{\text{RetCovrLoss}}^L$	U_{VCE}	$<$ Capital ratio$_{T_{12}}^{L}$	
RS_{VCE}^L	U_{CBR}	$<$ Capital ratio$_{T_{12}}^{L}$	$\leq U_{\text{CBR}} + \text{VCE}$
RS_{CBR}^L	TSCR	$<$ Capital ratio$_{T_{12}}^{L}$	$\leq \text{TSCR} + \text{CBR}$

When the Capital ratio$_{T_{12}}^{L}$ falls below TSCR, the resilience segments for bail-in and bailouts are the following:

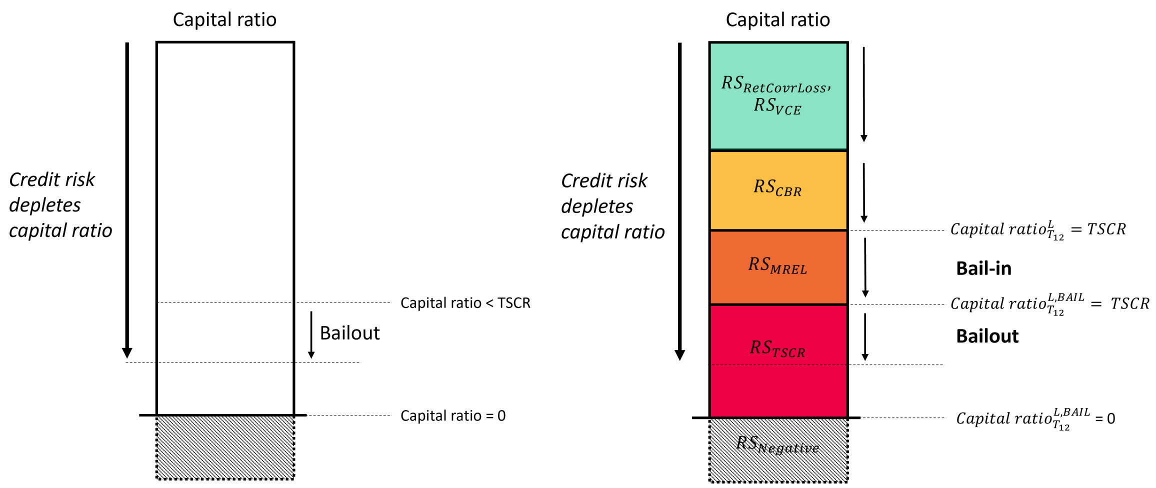
If Capital ratio$_{T_{12}}^{L} < TSCR$: (24)

RS_o^L	Lower Limit L_o	Capital ratio$_{T_{12}}^{L,BAIL}$	Upper Limit U_o
RS_{MREL}^L	$TSCR$	$<$ Capital ratio$_{T_{12}}^{L,BAIL}$	
RS_{TSCR}^L	0	$<$ Capital ratio$_{T_{12}}^{L,BAIL}$	$\leq TSCR$
RS_{Negative}^L		Capital ratio$_{T_{12}}^{L,BAIL}$	≤ 0

Figure 4B illustrates this process, showing how the capital ratio segments are progressively consumed as credit risk intensifies. By modelling this progression, we can identify when the banking sector transitions from managing risks internally to requiring external intervention.

Figure 4: Capital Ratio Depletion and Resilience Thresholds

(A) Credit Risk Depletes the Capital Ratio to Bailout ***(B) Credit Risk Breaches Multiple Resilience Segments***



Note: Left panel: The figure illustrates the depletion of the capital ratio due to credit risk materialization. The capital ratio is depleted under TSCR, and a bailout is required to top up the banking sector to be operational back to TSCR.
Right panel: The figure illustrates the same setup as in the left panel but reveals each component of the capital ratio based on its purpose and order of depletion. Initially, capital above regulatory requirements is exhausted (green box) (returns to cover losses and voluntary capital excess VCE), followed by the combined buffer requirement (CBR, yellow box). Once depleted, the capital ratio reaches the total SREP capital requirement (TSCR), signalling the banking sector's default on its portfolio. Banks then use MREL funds (orange box) to recapitalise up to the TSCR. The funds are, however, fully consumed, and a government bailout on the chosen portfolio becomes necessary. The red box corresponds to the capital ratio available from TSCR requirements that need to be fully capitalised before banks can continue their activities on the portfolio level.

4. Data

The data for our analysis reflect the Czech banking sector regulated by the Czech National Bank as of the end of 2021,[21] including capital levels, capital requirements, balance sheet structure, and calibration parameters. These data were sourced from FINREP and COREP reports stored in the Czech National Bank's internal repositories. Given our structural approach, the results are sufficiently robust to the choice of test start date, as the calibrated parameters exhibit insignificant variation over time, ensuring consistency in the analysis.

The balance sheet structure is illustrated in the left panel of Figure 5A. Loans to the non-financial sector L account for 41% of the balance sheet. While this might suggest that a significant portion is excluded in our analysis, another 39% consists of central bank reserves (27%) and Czech government bonds (12%), both of which carry minimal risk for banks. In practice, therefore, we capture a substantial portion of the banking sector's riskier activities. This becomes more evident when examining the structure of risk-weighted assets (RWA) in Figure 5B. Loan portfolio L accounts for 59% of all RWA, with the largest share coming from loans to non-financial

[21] Excluding two state-owned banks: the National Development Bank and Czech Export Bank due to their specific business model.

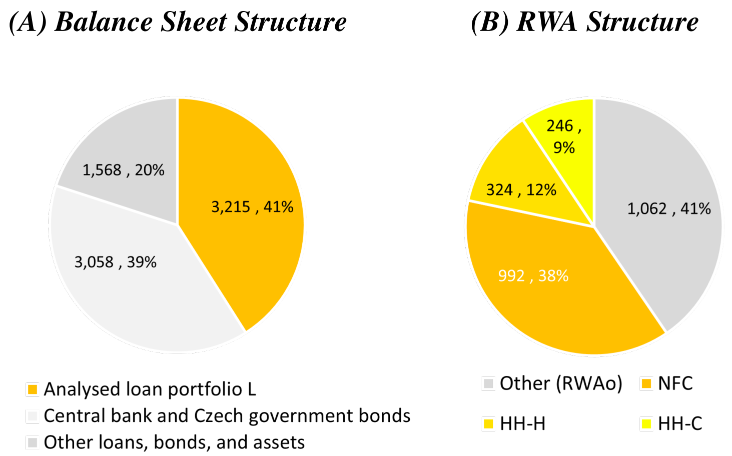
corporations (NFC), representing 38%. Loans secured by real estate to households (HH-H) account for 12%, and consumer loans (HH-C) make up 9%.

Table 1 provides more detailed overview of the initial loan portfolios of L_{T_0}. The gross carrying amount $GCA^L_{T_0}$ reached CZK 3.2 tn., with an accumulated loss allowance $LA^L_{T_0}$ of CZK 65 bn. The ratio of the loss allowance $LA^L_{T_0}$ and gross carrying amount $GCA^L_{T_0}$ is the loss rate $LR^L_{T_0}$ and it amounts 2%. The largest sub-portfolio is the loans to households secured with real estate HH-H) followed by loans to non-financial corporations (NFC).

The initial capital ratio of the entire banking sector is 23.5% as shown in Table 2 (Total column). This consists of capital allocated to TSCR (9.5%)[22], CBR (6.3%)[23], and voluntary capital excess VCE (7.7%). Additionally, the banking sector is ready to allocate 8.8% of bailinable funds from MREL[24], while returns raised to cover losses $RetCovrLoss_{T_{12}}$ amount to 7.9% of RWA_{T_0}.

Overall, the banking sector has a total of 40.2% of capital and funds available to mitigate the credit risk materialisation before reaching negative capital ratios in terms of RWA_{T_0}. Furthermore, we present the allocated resources to individual loan portfolios l in Table 2.[25] The largest portion of capital is allocated to the NFC portfolio.

Figure 5: Balance Sheet and RWA Structure of the Czech Banking Sector at T_0 in CZK bn.



Note: The left-panel figure illustrates the composition of the balance sheet of the Czech banking sector at the end of 2021. Loans to non-financial sector (L) share is 41%, central bank and Czech government bonds is 39% and Other loans, bonds, and assets cover 20% of the balance sheet.
The right-panel figure illustrates the composition of RWA. The loan portfolio to the non-financial corporations (NFC) amounts 38% (CZK 992 bn.), to households secured by real estate (HH-H) 12% (CZK 324 bn.), and to households for consumption (HH-C) 9% (CZK 246 bn.). The rest is composed of RWAs to other loans and risks and amounts 41% (CZK 1,062bn.). The total RWA amounts to CZK 2,623 bn.

[22] Pillar 1 requires 8% and Pillar 2 adds 1.5%.
[23] The CCyB and CCoB require 2.5%, and the OSIIB adds 1.3%.
[24] We assume banks have bailinable funds in the amount of MREL requirement.
[25] Note that $\Delta Cap^l_{CCyB,T_0}$ has already been included in the CBR.

Table 1: Initial Loan Sub-Portfolios l_{T_0} in CZK bn.

Category	Impairment stage S_z	NFC	HH-H	HH-C	L
$GCA_{T_0}^{l,S_z}$	S_1	1024	1457	362	2843
	S_2	178	126	55	358
	S_3	48	13	18	79
	Sum	1250	1595	435	3280
$LA_{T_0}^{l,S_z}$	S_1	4	1	3	8
	S_2	7	3	5	15
	S_3	26	4	12	42
	Sum	37	8	20	65
$LR_{T_0}^{l,S_z}$	S_1	0.4%	0.1%	0.8%	0.3%
	S_2	4.1%	2.4%	9.3%	4.3%
	S_3	53.8%	30.3%	68.0%	53.2%
	Average	3.0%	0.5%	4.6%	2.0%

Note: The table presents the initial loan sub-portfolios l_{T_0} and overall loan portfolio to non-financial sector L. NFC represents the portfolio to non-financial corporations, HH-H to households secured with real estate, and HH-C to households for consumption. $GCA_{T_0}^{l,S_z}$ is the gross carrying amount of loans, $LA_{T_0}^{l,S_z}$ loss allowance (accumulated provisions), and $LR_{T_0}^{l,S_z}$ the loss ratios. L is the sum of l portfolios.

Table 2: Capital Ratios and Funds Available at Time T_0

	Total	NFC	HH-H	HH-C	L
Resilience segments RS_o	**% of RWA_{T_0} (Capital in CZK bn.)**				
Return to Cover Losses $RetCovrLoss_{T_{12}}$	7.9% (208)	3.0% (78.7)	1.0% (25.7)	0.7% (19.5)	4.7% (123.9)
Voluntary Capital Excess (VCE)	7.7% (200.6)	2.9% (75.9)	0.9% (24.8)	0.7% (18.8)	4.5% (119.5)
Combined buffer requirement (CBR)	6.3% (166.1)	3.0% (79.7)	1.0% (26.0)	0.7% (19.7)	4.7% (125.4)
MREL capacity (MREL)	8.8% (232)	3.4% (87.8)	1.1% (28.6)	0.8% (21.7)	5.3% (138.1)
TSCR	9.5% (250.1)	3.6% (94.6)	1.2% (30.9)	0.9% (23.4)	5.7% (148.9)
Sum	**40.2% (1056.8)**	**15.9% (416.7)**	**5.2% (136)**	**3.8% (103.1)**	**24.9% (655.8)**

Note: Return to cover losses, voluntary capital excess (VCE), combined buffer requirement (CBR), bail-in capacity from MREL, and TSCR were distributed to portfolios l using the approach as in Equation 11. $RWA_{T_0}^{l}$ served as a weight against total RWA_{T_0}. Combined buffer requirement (CBR) for l also accounts for additional capital allocated to the $\Delta Cap_{CCyB,T_0}^{l}$.

5. Results

We present the results in tables that display terminating the capital ratios (Capital ratio$_{T_{12}}^{L}$) at time T_{12} for portfolio L following the application of credit risk. Credit risk is characterised by $PD^{3Y,L}$ in rows and LGD^{L} in columns.

We use colour coding to indicate which resiliency segments RS_o^L for capital ratios absorb the credit risk: ■ indicates when banks use returns to cover losses to absorb elevated credit risk ($RS_{RetCovrLoss}^{L}$). ■ highlights the use of voluntary capital excess (RS_{VCE}^{L}). ■ shows when the CBR is used to absorb credit risk (RS_{CBR}^{L}). ■ signals the activation of bail-in and its capacity to absorb losses (RS_{MREL}^{L}). ■ marks the breach of TSCR, triggering a government bailout (RS_{TSCR}^{L}). Finally,

■ indicates when the capital ratio turns negative, suggesting a more extensive bailout is imminent ($RS^L_{Negative}$).

In addition, we provide guidance for the maximum plausible credit risk levels by incorporating data from the highest credit risk observed during the GFC in the five most affected EU countries.[26] These are marked with turquoise ellipses ⬭, with labels indicating the specific countries where the credit risk was recorded.

A key feature of our model is that it allows the reader to explore the entire range of credit risk levels and assess the plausibility of each scenario independently. This flexibility is a major strength, as it avoids introducing additional model risk by, for example, tying credit risk levels directly to macroeconomic variables (Baes and Schaanning, 2023). However, this approach also requires the reader to apply their own experience and judgment in interpreting the severity of these credit risk levels, making it both a strength and a limitation of the framework.

5.1 Baseline Results

Figure 6 shows the progressive deterioration of portfolio capital ratios as credit risk increases. We see immediately that credit risk does not affect banks in a linear manner. There are concave upper limits for each of the resilience segments RS^L_o. The resilience segments also vary in the area to cover credit risk: while the voluntary capital excess RS^L_{VCE} has much more capital available at time T_0 (4.5% of $RWA^L_{T_0}$, Table 2), it manages to cover only an area of 5.0pp of $PD^{3Y,L}$ on average. In contrast, the RS^L_{CBR}, with the initial capacity of 4.7% (Table 2), manages to cover 10pp of $PD^{3Y,L}$. As a result, we observe that each RS^L_o capability to absorb risk depends not only on the amount of initial capital available to the segment but also on the point when the capital is used to absorb credit risk.

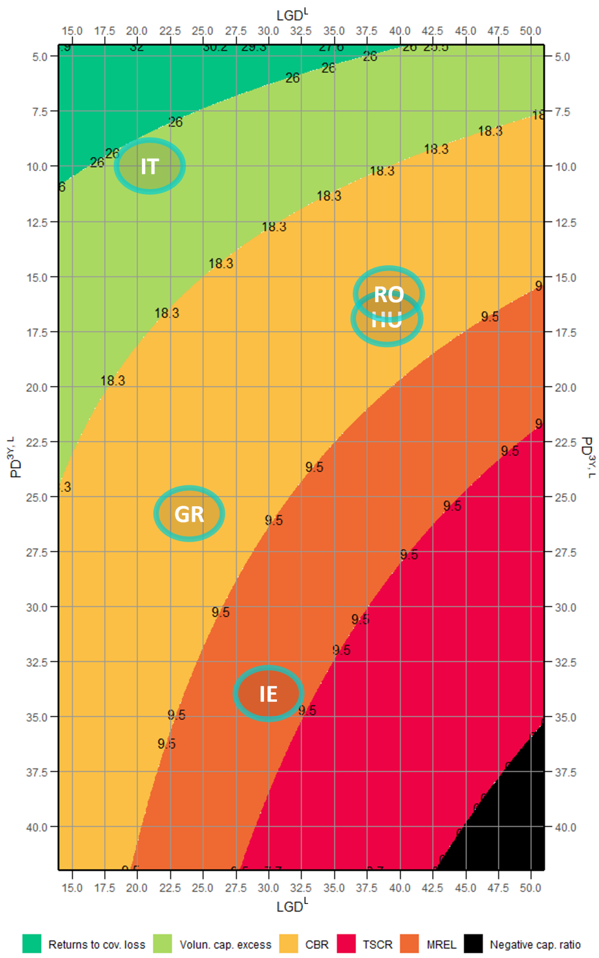
Next, we use the table to find the lowest combination of $PD^{3Y,L}$ and LGD^L that lead to bail-in and bailout. We label such combination as the efficient upper limit eU^L_o[27]. For bail-in eU^L_{MREL} occurs when $PD^{3Y,L}$ reaches 15.7% and LGD^L is 50%. A bailout becomes inevitable when 22.1% of the portfolio defaults, with the same 50% LGD^L.

While these levels may seem extreme, comparing them to the highest credit risk observed during the Global Financial Crisis in the most affected EU countries offers another perspective. For instance, the crisis in Ireland would have still led to a portfolio bail-in, while other severely impacted countries would not have required recapitalisation. Thus, we conclude that maintaining an initial capital ratio of 23.5% is sufficient. Considering the improvements in micro- and macroprudential regulation and supervision, further reductions in the capital ratio may be feasible.

[26] PDs and LGDs for each portfolio l were obtained from the EBA Risk Dashboard (EBA, 2014) and aggregated using $GCA^l_{T_0}$ as the weighting factor.

[27] We identify the lowest combination of $PD^{3Y,L}$ and LGD^L that reaches the upper limit U^L_o for the resiliency segments RS^L_o.

Figure 6: Capital Ratios and Resilience Segments under Credit Risk



Note: The figure illustrates the impact of credit risk on the capital ratios of loan portfolio L (Capital ratio$^L_{T_{12}}$). Credit risk is defined by a combination of $PD^{3Y,L}$ in rows and LGD^L in columns. The capital ratios are split into multiple resilience segments RS^L_o that provide a granular view of what type of capital and funds are enough to absorb materialising risk. indicates when returns are sufficient to cover losses and absorb credit risk ($RS^L_{RetCovrLoss}$). highlights the use of voluntary capital excess (RS^L_{VCE}). shows when the CBR is used to absorb credit risk (RS^L_{CBR}). signals the activation of bail-in and its capacity to absorb losses (RS^L_{MREL}). marks the breach of TSCR, triggering a government bailout (RS^L_{TSCR}). Finally, indicates when the capital ratio turns negative, suggesting a more extensive bailout is imminent ($RS^L_{Negative}$). Additionally, turquoise ellipses ( ) highlight the PD-LGD combinations observed in specific EU countries during the Global Financial Crisis, based on EBA (2014) data.

5.2 Regulatory Perspective on Loan Resilience

A significant portion of the available capital consists of voluntary capital excess (VCE), which is not required by regulators to remain on the banking balance sheet. Banks have discretion over how to allocate this capital, and they can distribute it among shareholders at any time. Consequently, it may not be available when credit risk materializes. Policymakers, therefore, cannot be certain that the capital is truly available for the banking sector.

We thus continue our analysis by exploring the limits of resilience without VCE, which we define as a regulatory perspective on banking resilience. To account for this, we reduce $Cap^L_{T_{12}}$ by the amount of VCE assigned to portfolio L as shown in Equation 25, and consistently apply our original methodology thereafter.

$$Cap_{T_{12}}^{L,regulatory} = Cap_{T_{12}}^{L} - RWA_{T_0}^{L} \cdot VCE \tag{25}$$

Figure 7 presents the results excluding the voluntary capital excess. Without VCE, portfolio resilience is significantly diminished. A portfolio bail-in (in terms of eU_{MREL}^{L}) is required when $PD^{3Y,L}$ reaches 10.6% and LGD^{L} is 50%, representing a 5.1pp resilience reduction in terms of $PD^{3Y,L}$. Similarly, a bailout (eU_{TSCR}^{L}) occurs when $PD^{3Y,L}$ reaches 16.5%, a reduction of 5.6pp from the banking perspective. On average, bail-ins occur 8.4pp earlier in terms of $PD^{3Y,L}$, and bailouts are triggered 7.9pp earlier. This outcome pinpoints the crucial role of voluntary capital excess in risk absorption.

This diminished resilience is further underscored when compared to credit risk levels observed during the Global Financial Crisis. In Greece (GR), Romania (RO), and Hungary (HU), portfolio bail-ins would have been triggered under these risk conditions, while in Ireland (IE), the crisis severity would have necessitated a portfolio bailout. These findings emphasize the importance of voluntary capital excess in maintaining financial stability under extreme stress scenarios.

Fiscal Costs of a Bailout

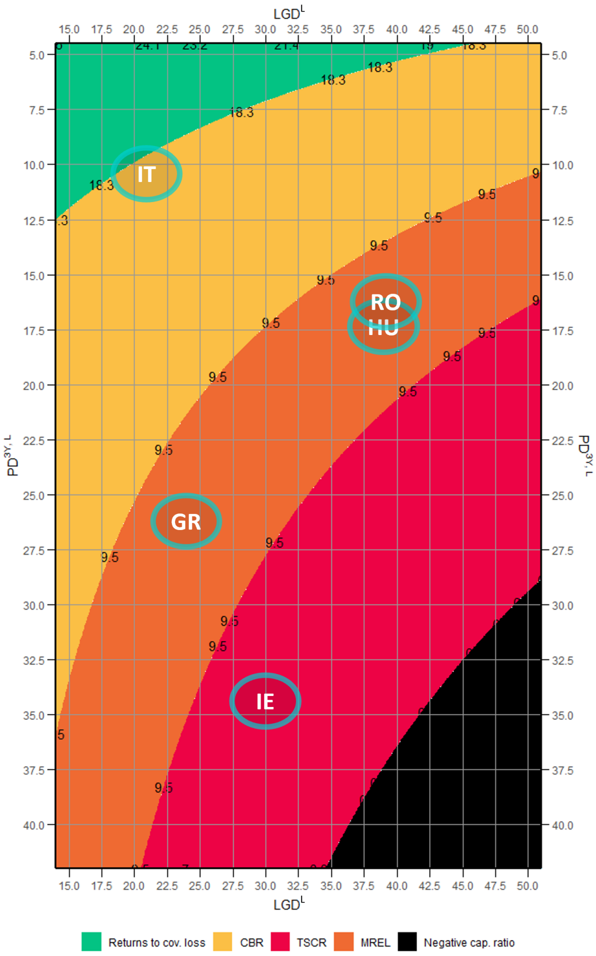
We can also use our figures to measure the direct fiscal costs of a bailout if Ireland's credit risk levels were applied to our case study. We define fiscal costs as the funds required to recapitalise the portfolio and bring it back to the TSCR. We calculate the direct fiscal costs as the difference between the U_{TSCR} and the Capital ratio$_{T_{12}}^{L,BAIL}$ multiplied by $RWA_{T_{12}}^{L}$. For convenience, we present the costs in terms of national GDP. In this case, the direct fiscal cost would amount to 1.7% of GDP.[28] By comparison, the fiscal cost of the Irish banking crisis was estimated at 41% of GDP (Laeven and Valencia, 2012),[29] underscoring the relatively low fiscal burden for the case study government. This would not be critical for the Czech government, whose debt-to-GDP ratio stood at 42.0% in 2021.

It is important to recognize, however, that the Irish banking crisis was largely attributed to inadequate risk management and supervisory failures (O'Sullivan and Kennedy, 2010). This underscores the uncertainty in estimating whether similar levels of credit risk could materialize in the current banking environment. Improvements in macroprudential regulation and supervisory capabilities, along with the introduction of output floors for mortgage portfolios, further mitigate such risks. Output floors, introduced in the finalisation of Basel Accords III and transposed into EU legislation via CRR3, lead to an increase in $RWA_{T_0}^{HH-H}$, making more of the voluntary capital excess binding to regulatory capital requirements and thereby enhancing the banking sector's resilience from a regulatory perspective. The results for individual loan portfolio HH-H are provided in Appendix C.

[28] If a bail-in were not feasible, the fiscal cost would increase to 5.2%.

[29] The capital adequacy ratio of Irish banks was 12.0% in 2008, with fiscal costs ranking among the ten highest globally since 1970.

Figure 7: Capital Ratios and Resilience Segments from Regulatory Perspective



Note: The figure illustrates the impact of credit risk on the capital ratios of loan portfolio L (Capital ratio$^{L,regulatory}_{T_{12}}$). Credit risk is defined by a combination of $PD^{3Y,L}$ in rows and LGD^{L} in columns. The capital ratios are split into multiple resilience segments $RS^{L,regulatory}_{o}$ that provide a granular view of what type of capital and funds are enough to absorb materialising risk. indicates when returns are sufficient to cover losses and absorb credit risk ($RS^{L,regulatory}_{RetCovrLoss}$). highlights the use of voluntary capital excess ($RS^{L,regulatory}_{VCE}$). shows when the CBR is used to absorb credit risk ($RS^{L,regulatory}_{CBR}$). signals the activation of bail-in and its capacity to absorb losses ($RS^{L,regulatory}_{MREL}$). marks the breach of TSCR, triggering a government bailout ($RS^{L,regulatory}_{TSCR}$). Finally, indicates when the capital ratio turns negative, suggesting a more extensive bailout is imminent ($RS^{L,regulatory}_{Negative}$). Additionally, turquoise ellipses ( ) highlight the PD-LGD combinations observed in specific EU countries during the Global Financial Crisis, based on EBA (2014) data.

6. Robustness Tests

We now turn our attention to how the results change when applying more commonly used modelling approaches. First, we assess how resilience is affected by using a simpler model for credit losses. Second, we explore how resilience changes if we assume static RWAs.

6.1 Capital Ratios with a Reduced Credit Losses Model

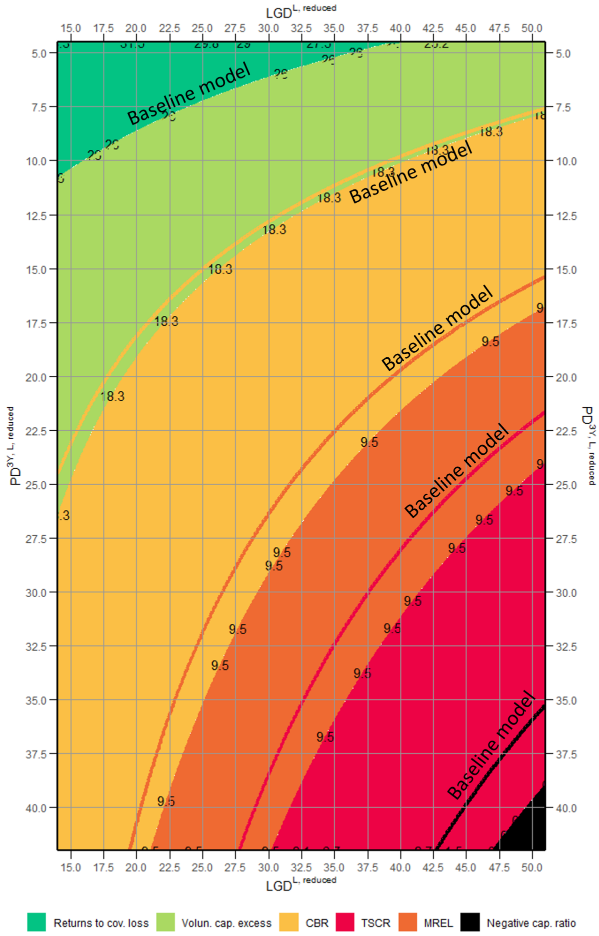
The first robustness test focuses on the credit losses model, $CLoss^{l}_{T_{12}}$. In the baseline simulations, credit losses are calculated using a comprehensive framework that closely tracks the evolution of portfolio distribution ($GCA^{l,S_z}_{T_i}$) across impairment stages S_z and reflects the provisions of the IFRS9 Standard. However, the complexity of this model often limits its extensive application in research, leading many to adopt simpler approaches. A commonly used alternative is to multiply PD and LGD by the initial gross value of non-defaulted assets. This reduced approach requires minimal information about the portfolio, making it both powerful and popular.

To test this alternative, we calculate credit losses as $\text{CLoss}^{l,reduced}_{T_i}$, as shown in Equation 26, and apply it to derive Capital $\text{ratio}^{L,reduced}_{T_{12}}$. The results are presented in Figure 8 with $PD^{3Y,L,reduced}$ in rows and $LGD^{L,reduced}$ in columns. Figure 8 also provides for comparison the upper limits for all RS^{L}_{o} from the baseline model.

$$\text{CLoss}^{l,reduced}_{T_i} = \sum_{S_z \in \{1,2\}} GCA^{l,S_z}_{T_0} \cdot PD^{3Y,l,reduced} \cdot LGD^{l,reduced}, \quad \forall l \in L \tag{26}$$

The results indicate that the reduced approach yields a similar resilience compared to the baseline model at lower levels of credit risk. The upper limits $U^{L,reduced}_{VCE}$ for voluntary capital excess and CBR $U^{L,reduced}_{CBR}$ differ by less than 1pp of $PD^{3Y,L,reduced}$ on average. However, as credit risk increases, the resilience upper limits start to diverge, making the banking sector appear more resilient under the reduced model than in the baseline. On average, bail-ins occur at a higher $PD^{3Y,L,reduced}$ by 2.3pp, and bailouts by 3.1pp. The capital ratios under the reduced approach are, on average, 3.7pp more resilient in terms of $PD^{3Y,L,reduced}$ compared to the baseline results. We conclude that the simpler multiplication of PDs and LGDs is a reasonable approximation for credit losses at lower and middle-risk levels but less accurate for very high-risk scenarios.

Figure 8: Capital Ratios and Resilience Segments with Reduced Credit Losses Model



Note: The figure illustrates the impact of credit risk on the capital ratios of loan portfolio L (Capital ratio$_{T_{12}}^{L,reduced}$). Credit risk is defined by a combination of $PD^{3Y,L,reduced}$ in rows and $LGD^{L,reduced}$ in columns. The capital ratios are split into multiple resilience segments RS_o^L that provide a granular view of what type of capital and funds are enough to absorb materialising risk. ■ indicates when returns are sufficient to cover losses and absorb credit risk ($RS_{RetCovrLoss}^L$). ■ highlights the use of voluntary capital excess ($RS_{VCE}^{L,reduced}$). ■ shows when the CBR is used to absorb credit risk ($RS_{CBR}^{L,reduced}$). ■ signals the activation of bail-in and its capacity to absorb losses ($RS_{MREL}^{L,reduced}$). ■ marks the breach of TSCR, triggering a government bailout ($RS_{TSCR}^{L,reduced}$). Finally, ■ indicates when the capital ratio turns negative, suggesting a more extensive bailout is imminent ($RS_{Negative}^{L,reduced}$). Lines depicted present the upper limits U_o^L for resilience segments RS_o^L from the baseline results.

6.2 Capital Ratios with Static RWAs

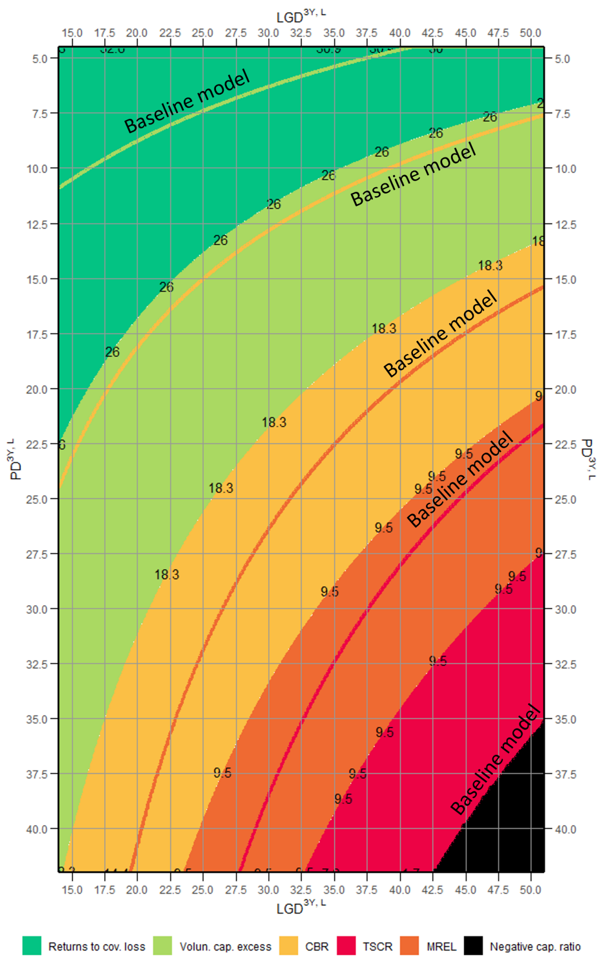
Next, we explore the effect of assuming constant RWAs $RWA^{l,const}$, a simplification commonly adopted due to the extensive data requirements for modelling dynamic RWAs. For each portfolio l we assume that the RWA^l remains the same as $RWA_{T_0}^l$ (Equation 27). Again, we compare the resulting segmented Capital ratio$_{T_{12}}^{L,const}$ with the frontiers from the baseline model.

$$RWA^{l,const} = RWA_{T_{12}}^l = RWA_{T_0}^l \tag{27}$$

The results, summarized in the Figure 9, show that constant RWAs lead to a notable increase in the banking sector's resilience across all the risk levels. The average resilience increased by 7.0pp in $PD^{3Y,L}$. On average, the bail-in ($U^{L,const}_{MREL}$) occurs 6.2pp later in $PD^{3Y,L}$, while the bailout ($U^{L,const}_{TSCR}$) is delayed by 6.4pp. This suggests that constant RWAs give an overly optimistic view of portfolio resilience, as banks appear able to absorb more risk before breaching the critical capital thresholds.

Therefore, the constant RWA assumption significantly underestimates the speed at which the banking sector would need to resort to bail-in or bailout mechanisms in a more realistic, dynamic environment.

Figure 9: Capital Ratios and Resilience Segments with Static RWAs



Note: The figure illustrates the impact of credit risk on the capital ratios of loan portfolio L (Capital ratio$^{L,const}_{T_{12}}$). Credit risk is defined by a combination of $PD^{3Y,L}$ in rows and LGD^{L} in columns. The capital ratios are split into multiple resilience segments $RS^{L,const}_{o}$ that provide a granular view of what type of capital and funds are enough to absorb materialising risk. ■ indicates when returns are sufficient to cover losses and absorb credit risk ($RS^{L,const}_{RetCovrLoss}$). ■ highlights the use of voluntary capital excess ($RS^{L,const}_{VCE}$). ■ shows when the CBR is used to absorb credit risk ($RS^{L,const}_{CBR}$). ■ signals the activation of bail-in and its capacity to absorb losses ($RS^{L,const}_{MREL}$). ■ marks the breach of TSCR, triggering a government bailout ($RS^{L,const}_{TSCR}$). Finally, ■ indicates when the capital ratio turns negative, suggesting a more extensive bailout is imminent ($RS^{L,const}_{Negative}$). Lines depicted present the upper limits U^{L}_{o} for resilience segments RS^{L}_{o} from the baseline results.

7. Conclusions

This paper examines the conditions under which a banking sector requires a bailout from the government and what levels of credit risk lead to bail-in. We also assess whether current capitalisation levels are sufficient to absorb extreme financial stress. We find that a capital ratio of 23.5% is sufficient to absorb credit risk losses comparable to the most severe stress observed during the GFC. This suggests that, from a risk perspective, current capital ratios can be perceived as optimal.

Our findings provide insights into the effectiveness of post-crisis regulatory frameworks, particularly the role of capital adequacy requirements and bail-in mechanisms in reducing the need for government intervention. The results indicate that existing capitalisation rules provide a substantial buffer against credit risk materialisation, ensuring financial stability under severe stress. The introduction of bail-in mechanisms further enhances banking sector resilience, reducing reliance on government bailouts and reinforcing market discipline. These findings support the prudential design of current regulatory frameworks, though they also highlight areas where refinements may be warranted.

While our study focuses on credit risk absorption, it is important to acknowledge that banking sector stability depends on a broader set of risk factors, including market risk, liquidity risk, and macroeconomic conditions. These factors are beyond the scope of our framework, which is designed to assess resilience specifically to credit losses. Our framework also relies on granular data, potentially limiting its application in other banking sectors where such data are harder to obtain. Additionally, while our model assumes a static banking sector balance sheet, this assumption is justified in a crisis context, where lending typically contracts rather than expands.

Our model provides a comprehensive framework to assess the full range of credit risk effects on capital ratios, not only at the aggregate banking sector level but also across specific loan portfolios and banks. In particular, we highlight the heightened vulnerability of real estate-backed loans, which can deteriorate sharply under economic stress. Our framework is useful for policymakers and regulators to better target requirements in forms of additional capital requirements of risk weight floors for specific types of assets.

In conclusion, our results suggest that the Czech banking sector is well-positioned to withstand severe credit risk shocks, with existing capital buffers sufficiently calibrated to mitigate systemic vulnerabilities. However, the role of risk-weighted asset adjustments remains critical; static assumptions may lead to an overestimation of resilience in a crisis scenario. Future research could extend this analysis by incorporating liquidity constraints, dynamic macro-financial linkages, and alternative stress-testing methodologies.

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Appendix A: Credit Loss Modelling Approach

The model for credit losses for each loan portfolio is conceptually based on Gross et al. (2020) and Polak and Panos (2019). We assume a static balance sheet without write-offs or derecognition. A similar approach is used in several stress tests (Federal Reserve Board, 2020; EBA, 2020; DNB, 2020). The model is operationally divided into three parts: the first estimates the distribution of loans into individual stages of impairment; the second models the amount of Expected Credit Loss (ECL); and the third combines the two previous parts. This produces the final impact of credit risk on provisioning, which depends on the risk parameters Probability of Default (PD) and Loss Given Default (LGD).

The change in the impairment stage structure of the loan portfolio is modeled using a Probability Transition Matrix (TPM), similar to Gross et al. (2020). The TPM is a time-varying stochastic matrix in discrete time, i.e., a non-homogeneous Markov chain with discrete time and discrete state space. IFRS 9 defines three stages of impairment: Stage 1 (S1) represents assets without a significant increase in credit risk (SICR); Stage 2 (S2) represents assets where SICR has occurred; and Stage 3 (S3) represents assets in default. Since we do not anticipate loan write-offs or portfolio growth, the transition matrix is regular and takes the following form:

Table A1: Probability Transition Matrix

From/To	**Stage 1**	**Stage 2**	**Stage 3**
Stage 1	$1-\sum_{x=2,3} TP_{T_i}^{1\to x}$	$TP_{T_i}^{1\to 2} \in [0,1]$	$TP_{T_i}^{1\to 3} \in [0,1]$
Stage 2	$TP_{T_i}^{2\to 1} \in [0,1]$	$1-\sum_{x=1,3} TP_{T_i}^{2\to x}$	$TP_{T_i}^{2\to 3} \in [0,1]$
Stage 3	0	0	1

Here, the rows represent the initial stage of the asset, and the columns represent the final stage. The individual elements of the matrix are denoted as $TP_{T_i}^{X\to Y}$, where the superscript indicates a transition from Stage X to Stage Y, and the subscript T_i denotes the time period ($T_i; i \in \{0,\ldots,12\}$). In our approach, we apply the no-cure assumption, meaning the elements $TP_{T_i}^{3\to 1}$ and $TP_{T_i}^{3\to 2}$ are set to zero. Therefore, Stage 3 is the absorbing state of the Markov chain. Additionally, because the rows of the transition matrix must sum to one, the elements $TP_{T_i}^{1\to 1}$ and $TP_{T_i}^{2\to 2}$ can be calculated from the other elements in their respective rows. Consequently, only the four elements highlighted in blue need to be modeled.

Their evolution is driven, as in Gross et al. (2020), by the development of systematic risk, which in our case is characterized by a constant shock specific to each model iteration. Due to limitations in historical data and our aim to keep the scenario's dimensionality low, we do not calibrate the development of modeled elements separately. Instead, we use the initial state of the transition matrix at T_0, derived from FINREP supervisory statistics. The TPM elements marked in blue are then modeled through a distance-to-default transformation (first used by Merton (1974)) of the shock into the PD. The distance-to-default approach is a central tool in credit risk modeling (Chan-Lau and Sy, 2007). In our case, we characterize the shift using the inverse cumulative distribution function (CDF), similar to what is used in regulatory risk weight settings in Basel Accords. The development of $TP_{T_i}^{1\to 3}$ and $TP_{T_i}^{2\to 3}$ at time T_i for $i > 0$ is thus modeled as follows:

$$TP_{T_i}^{1\to 3} = \phi\left(\phi^{-1}\left(TP_{T_0}^{1\to 3}\right) + \phi^{-1}\left(\text{Const PD Shock}\right)\right)$$

$$TP_{T_i}^{2\to 3} = \phi\left(\phi^{-1}\left(TP_{T_0}^{2\to 3}\right) + \phi^{-1}\left(\text{Const PD Shock}\right)\right)$$

Here, $TP_{T_0}^{1\to 3}$ and $TP_{T_0}^{2\to 3}$ are the initial values obtained from FINREP supervisory statistics. The term Const PD Shock represents a constant shock to the probability of transition within one model iteration. The function ϕ is the cumulative distribution function (CDF), and ϕ^{-1} is its inverse. It can be seen that the systematic risk factor PD is implicitly calculated using the equation:

$$PD_{T_i} = \frac{TP_{T_i}^{1\to 3} \cdot GCA_{T_i}^{S1} + TP_{T_i}^{2\to 3} \cdot GCA_{T_i}^{S2}}{GCA_{T_i}^{S1} + GCA_{T_i}^{S2}}$$

where $GCA_{T_i}^{S1}$ is the gross carrying amount of assets in impairment stage 1 (S1) at time T_i.

For the development of $TP_{T_i}^{1\to 2}$ and $TP_{T_i}^{2\to 1}$, Gross et al. (2020) and Polak and Panos (2019) propose a bridge-equations approach. This method reduces the number of scenario dimensions, which is a fundamental advantage. However, it requires estimating the parameters $\widehat{\beta}$ and $\widehat{\delta}$. Typically, $\widehat{\beta}$ is positive and $\widehat{\delta}$ is negative. We use parameter values corresponding to those in the Czech National Bank stress testing, based on the ECB's empirical estimates for supervisory stress tests. The bridge equations are as follows:

$$TP_{T_i}^{1\to 2} = \phi\left(\phi^{-1}\left(TP_{T_0}^{1\to 2}\right) + \widehat{\beta}\left(\phi^{-1}\left(TP_{T_i}^{1\to 3}\right) - \phi^{-1}\left(TP_{T_0}^{1\to 3}\right)\right)\right)$$

$$TP_{T_i}^{2\to 1} = \phi\left(\phi^{-1}\left(TP_{T_0}^{2\to 1}\right) + \widehat{\delta}\left(\phi^{-1}\left(TP_{T_i}^{2\to 3}\right) - \phi^{-1}\left(TP_{T_0}^{2\to 3}\right)\right)\right)$$

To obtain the development of the portfolio structure by impairment stages, we also need the initial distribution of loans across these stages, in addition to the initial TPM and the predetermined shock. We use the FINREP supervisory statistics for this initial distribution, as shown in Table 1. The evolution of the portfolio structure by impairment stages is then driven by the following multiplication:

$$\begin{bmatrix} GCA_{T_{i+1}}^{S1} \\ GCA_{T_{i+1}}^{S2} \\ GCA_{T_{i+1}}^{S3} \end{bmatrix}^{\mathrm{T}} = \begin{bmatrix} GCA_{T_i}^{S1} \\ GCA_{T_i}^{S2} \\ GCA_{T_i}^{S3} \end{bmatrix}^{\mathrm{T}} \cdot \begin{bmatrix} TP_{T_i}^{1\to 1} & TP_{T_i}^{1\to 2} & TP_{T_i}^{1\to 3} \\ TP_{T_i}^{2\to 1} & TP_{T_i}^{2\to 2} & TP_{T_i}^{2\to 3} \\ 0 & 0 & 1 \end{bmatrix}$$

This equation allows us to generate the portfolio structure by impairment stage for each time T_i. The evolution depends primarily on the initial portfolio structure and the development of Const PD Shock that changes TPM structure.

The second part of the model estimates the impact of credit risk by modeling the Expected Credit Loss (ECL), which corresponds to the amount of loan allowances (LA) created. In our model, LA is the central variable of interest, as changes in LA are reflected in profit and loss, thereby affecting capital. To model LA, we first model the loss rate (LR), which represents the proportion of LA relative to the GCA. When modeling LR, we must consider the requirements of the IFRS 9 Standard. It specifies different lengths of LR depending on the impairment stage of the asset.[30] Thus, a 12-month LR (denoted as LR^{S1}_{12M,T_i}) is used for assets in Stage 1, and a lifetime LR (denoted as LR^{S2}_{LT,T_i}) is used for assets in Stage 2. For Stage 3, we use an LGD value for newly defaulted loans which is pre-set for each iteration of our model.

To estimate LR^{S1}_{12M,T_i} and LR^{S2}_{LT,T_i}, we need to determine the expected credit loss over the next 12 months or over the entire life of the portfolio, respectively. This involves summing the expected losses in case of default over the next four quarters (for LR^{S1}_{12M,T_i}) or over the entire life of the portfolio (for LR^{S2}_{LT,T_i}), taking into account the probability of default in each individual quarter. Additionally, the exposure size is discounted, and a linear repayment is assumed,[31] leading to the following equations:

$$LR^{S1}_{12M,T_i} = \sum_{k=1}^{4}\left(\left(\frac{1}{1+r}\right)^k \cdot EAD_{T_i-1+k} \cdot LGD_{T_i-1+k} \cdot TP.UNC^{1\to 3}_{T_i,k}\right)$$

$$LR^{S2}_{LT,T_i} = \sum_{k=1}^{M}\left(\left(\frac{1}{1+r}\right)^k \cdot EAD_{T_i-1+k} \cdot LGD_{T_i-1+k} \cdot TP.UNC^{2\to 3}_{T_i,k}\right)$$

Here, M is the number of quarters until the portfolio matures, r is the interest rate, EAD is the exposure at default in a given quarter (assumed to start at 1 and decrease linearly to 0 at maturity), and LGD is the loss given default, which is driven by a systematic LGD and decreases linearly due to debt amortization. However, LGD cannot fall below a pre-specified floor, which accounts for administrative and litigation costs and other potential recovery costs. This floor is calibrated based on historical recovery rates of defaulted loans in the Czech banking sector.

The final parameter for the calculation is $TP.UNC$, which denotes the unconditional probability of a transition from Stage 1 or Stage 2 to Stage 3 for each future quarter k. To calculate $TP.UNC^{1\to 3}_{T_i,k}$ and $TP.UNC^{2\to 3}_{T_i,k}$, we use the property of the TPM as a non-homogeneous Markov chain with an absorbing state at Stage 3. The kth power of the TPM represents the cumulative probability of being in a given impairment stage at time $T_i + k$, starting from the initial stage at time T_i. However, for the calculation of LR^{S1}_{12M,T_i} and LR^{S2}_{LT,T_i}, we need the unconditional probability of default, which represents the probability of default from time T_i only during period $T_i + k$. Thanks to the absorbing state at Stage 3, $TP.UNC^{1\to 3}_{T_i,k}$ and $TP.UNC^{2\to 3}_{T_i,k}$ can be calculated as the difference of the elements at position $1 \to 3$ or $2 \to 3$ of the TPM raised to the power of $(T_i + k)$ and $(T_i + k - 1)$.

[30] This is a key difference between the European (IFRS 9) and American (US GAAP) implementations of the global accounting standard. US GAAP always requires a lifetime LR.

[31] In our approach, we work with counterparty credit sectors where the exact evolution of the maturity structure of loans is not known. Therefore, we assume linear repayment, which simplifies the estimation without significantly impacting the results.

We have described how to obtain the loss rate (LR) for each impairment stage and each period T_i. However, we need to specify what happens to the portfolio after the 3-year stress horizon (12 quarters) of our model. Some portfolios have longer maturities ($M > 12$), such as mortgage portfolios and for those it is required to establish the future path. Unlike Gross et al. (2020) and Polak and Panos (2019), we anticipate an exponential decrease in systematic PDs and LGDs after the end of the scenario period. For PDs, we assume a decline over six quarters, corresponding to the decrease in default rates observed during the financial crisis for loans to non-financial corporations in the Czech banking sector. In contrast, due to the high persistence of LGD, we assume an exponential decline over six years. Note that these assumptions do not significantly impact the results from a macroeconomic perspective, as the credit losses do not change significantly.

Subsequently, the credit risk parameters shift to their long-term values. These are determined as weighted means of the starting values at T_0 (90% weight) and the ending values after 12 quarters (10% weight). This approach characterizes the trajectory of the financial cycle, where the starting values represent its peak and the ending values represent the trough. The rate of convergence to long-term values for systematic LGDs and PDs is given by the equation:

$$LGD_{T_i} = LGD_{LT} + \frac{1}{\text{Conv.speed}^{T_i - \text{Conv.Dur}}} \left(LGD_{T_{12}} - LGD_{LT} \right)$$

Here, Conv.speed is the convergence speed parameter (equal to 1.5), and Conv.Dur is the duration of convergence (6 years for LGD and 6 quarters for PDs). The development of systematic risk parameters PD (in the form of $TP_{T_i}^{1\to 3}$ and $TP_{T_i}^{2\to 3}$) and LGD can thus appear as in Figure 2 within one iteration. It shows the initial state, followed by 12 periods of elevated systematic risk factors, and the subsequent decline to long-term values.

The third part of the credit risk estimation model combines the estimation of the distribution of loans into different impairment stages with the modeling of the LR amount. It determines the impairment amount affecting capital. First, we calculate the amount of loan allowances (LA_{T_i}) generated at each time T_i, which is computed as the product of GCA and LR for each stage. For Stage 3, only newly defaulted loans are affected by the LGD at time T_i. Thus, LA_{T_i} is calculated as follows:

$$LA_{T_i} = LR_{12M,T_i}^{S1} \cdot GCA_{T_i}^{S1} + LR_{LT,T_i}^{S2} \cdot GCA_{T_i}^{S2} + LA_{T_{i-1}}^{S3} + LGD_{T_i} \cdot \left(TP_{T_i}^{1\to 3} \cdot GCA_{T_i}^{S1} + TP_{T_i}^{2\to 3} \cdot GCA_{T_i}^{S2} \right)$$

Now, we know the value of the allowance at each time T_i. The change in LA_{T_i} represents the credit loss ($CLoss$) that enters the profit and loss statement, thus affecting capital. The impairment loss amount for each time T_{i+1} ($CLoss_{T_{i+1}}$) is calculated as follows. Note that the sum of $CLoss$ across the 12 periods constitutes the total credit loss used in the model.

$$CLoss_{T_{i+1}} = LA_{T_{i+1}} - LA_{T_i}$$

Appendix B: Risk-Weighted Assets Modelling Approach

The second model employed is based on Sveda et al. (2023). Our goal is to reflect materialisation of credit risk to risk-weighted assets (RWA) which in turn reduce capital ratios. We approach the modelling in two steps. First, we shift the through-the-cycle (TTC) PD and LGD[32] parameters (labeled as TTC PD and TTC LGD) used in the IRB risk weight formula based on the systematic risk parameters, and second we move the exposure values (see following paragraphs) between performing and non-performing states of IRB and STA exposures utilizing information from the first model (dealing with credit losses). From the operational point of view, we can separate the model for RWA development into several steps, indicating the modeling procedure.

First, we set up the initial portfolio based on regulatory reporting COREP and calculate the initial risk weights with available data. The effects of elevated systematic risk factors (PD and LGD) on TTC PD and TTC LGD are estimated in the second step. It is worth noting that the systematic risk parameters can be viewed as point-in-time (PiT) parameters which are used for computing the though-the-cycle ones. In the last third step, acquired TTC risk parameters are used to calculate new risk weights on IRB portfolios and we also model the portfolio's structure from the performance perspective. We argue that such an approach is highly useful as the prescribed risk weights differ whether the asset is performing or not. After that, we combine information produced to get the final value of RWA which reflects the elevated systematic risk parameters of one particular scenario. The following paragraphs describe these steps in more detail.

B.1 Initial Portfolio

First, we set up the initial regulatory portfolio which is basically the equivalent of the accounting portfolio used in the previous model. To do so, we utilize data obtained from the COREP supervisory reporting, which provide granular information on the internal obligor grades level within each exposure class in the IRB portfolio and on exposure class level in the STA portfolio.

Since exposure classes used in COREP database structuring data to segments do not exclusively match the counterparty sector segmentation used in the first model (which deals with credit losses), we need to define the linkage between the two methodologies. We remind that only non-financial corporations, households collateralised by immovable property, and other household loans are of our interest. Thus, to link both methodologies, we used the segmentation provided in Table B1.

Although we admit that the processing is not without some minor misspecifications, it provides satisfactory and reliable match between both methodologies on the level of the banking sector.

Next, we utilize detailed data provided in the COREP database to set up the initial regulatory riskiness of our portfolios. Our aim is to recalculate the reported risk weight at the start of our modelling to create the deviation measurement between our calculation and the one simply obtained as a ratio of reported risk-weighted exposure amount and reported exposure value after the credit risk mitigation techniques and conversion factors (denoted in this paper as exposure value). The deviation (labeled as ϕ) captures non-linearities of the risk weight stemming in particular from aggregation of individual obligors within a given grade (for further detail, see Sveda et al. (2023)). For start, we re-calculate the risk weights for each internal obligor grade and bank within each IRB considered exposure class. The calculation of risk weights for performing

[32] For the sake of simplicity, we call the LGD used for the risk weight calculation as through-the-cycle, although it should be labeled as downturn LGD in reality.

Table B1: Linkage Between FINREP and COREP Database

Counterparty sector used in FINREP	**Assigned exposure class from COREP**
Non-financial corporations	- Corporate – SME (IRB Approach), - Corporate – Specialised lending (IRB Approach), - Corporate – Other (IRB Approach) - Claims on institutions and corporates with a short-term credit assessment (ST Approach) - Exposures to corporates (ST Approach) - Items associated with particular high risk (ST Approach) - Exposures to institutions and corporates with a short-term credit assessment (ST Approach)
Households collateralized by immovable 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 (ST Approach)
Other household loans	- Retail – Qualifying revolving (IRB Approach) - Retail – Other SME (IRB Approach) - Retail – Other non – SME (IRB Approach) - Retail exposures (ST Approach)

internal obligor grades within IRB portfolios is based on the following formula[33] prescribed by CRR2 (Article 153 and 154):

$$RW = (\text{TTC LGD} \cdot \Psi(\text{TTC PD}) - \text{TTC LGD} \cdot \text{TTC PD}) \cdot Z(\text{M}, \text{TTC PD}) \cdot 1.06 \cdot 12.5 \cdot \text{SME SP}$$

$$\Psi(\text{TTC PD}) = N\left\{\frac{1}{\sqrt{1-R(\text{TTC PD})}} \cdot G(\text{TTC PD}) + \sqrt{\frac{R(\text{TTC PD})}{1-R(\text{TTC PD})}} \cdot G(0.999)\right\}$$

where RW is the risk weight, $N()$ cumulative distribution function for a standard normal random variable, $G()$ inverse of $N()$, $TTC\ LGD$ is the stressed loss given default, $R(TTC\ PD)$ coefficient of correlation dependent on the $TTC\ PD$ (which is the thorough-the-cycle probability of default), $Z(M,\ PD)$ maturity adjustment dependent on average maturity length (M) and $TTC\ PD$, and $SME\ SP$ SME supporting factor. The inputs are either available in the COREP database, or prescribed by the CRR2 (see Sveda et al. (2023)).

[33]The formula is conceptually based on Merton's model application by Vasicek (2002). It was originally introduced within Basel II and the concept is presented by Basel Committee (BCBS, 2005).

Moreover, a particular form of $R(TTC\ PD)$ equation depends on a given exposure class. For exposures to corporates, the formula takes the following form:

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

For retail exposures, $R\,(TTC\ PD)$ it gets the following form:

$$R\,(TTC\ PD) = 0.03 * \frac{1-e^{-35*TTC\ PD}}{1-e^{-35}} + 0.16 * \left(1 - \frac{1-e^{-35*TTC\ PD}}{1-e^{-35}}\right).$$

The exceptions are qualified revolving where $R = 0.04$ and exposures secured by immovable property collateral where $R = 0.15$.

The maturity adjustment $Z\,(M,\ TTC\ PD)$ is simply equal to 1 for all retail exposures. For corporates, it takes the following form:

$$Z\,(M,\ TTC\ PD) = \frac{1+(M-2.5)*b(TTC\ PD)}{1-1.5*b(TTC\ PD)},$$

where b is the maturity adjustment factor calculated as follows:

$$b\,(TTC\ PD) = (0.11852\ -\ 0.05478\ ln\ \ (TTC\ PD)\ )^2.$$

Moreover, a different methodology is prescribed for IRB approach non-performing exposures. In the foundation IRB (F-IRB) approach, the risk weight for non-performing exposures is equal to 0. In the advanced IRB (AIRB) approach, the formula takes the form

$$RW = max\ (EL_{BE} - TTC\ LGD; 0)\ ,$$

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 A-IRB non-performing exposures risk weights. Thus, the risk weight for non-performing exposures in A-IRB stays constant.

Based on the methodology described above, we re-calculated the RW. Now, we can define the deviation parameter ϕ, which is simply the ratio between the re-calculated RW and RW obtained as the ratio of reported risk-weighted amount and exposure value. If no deviation between the RWs occurs, $\phi = 1$. The parameter ϕ will be later used during the modelling of our portfolios.

Having all these steps done, our re-calculated RWs (after taking into account ϕ) fully reflect the initial riskiness of the IRB portfolio. In our model, we can thus change the values of TTC PD and TTC LGD based on movements of systematic risk factors and adjust the RW accordingly. Next, IRB approach is not the only one used by banks. ST approach is commonly used by smaller institutions as it does not require long history of data and strengthened IT infrastructure. In our modelling approach, we account for the application of ST approach in a way that respects the regulation requirements: we assume that there are no changes in the RW, so the risk weight is constant from the beginning of the modeling throughout the whole time. The RW for the STA approach is thus determined at the exposure class level as a proportion of risk exposure amount and exposure value obtained from the COREP database.

B.2 Linking the Systematic Risk Factors and TTC Parameters

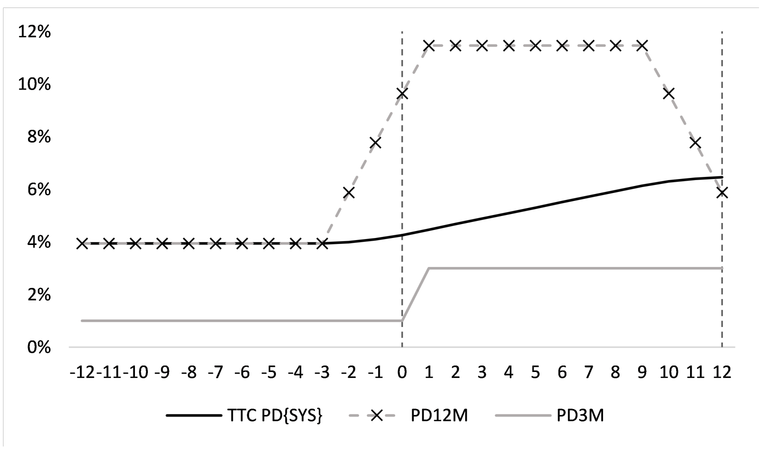
The second step of the model's procedure is to setup the link between systematic risk factors (PD and LGD) and TTC PD and TTC LGD on IRB portfolios. The regulation requires to estimate the TTC PDs as moving averages with minimum of five years length of historical one-year PDs[34]. We argue, that our systematic risk parameters are eligible for the estimation. Moreover, we decided that the moving average with a length of nine-years is the best suitable for the Czech banking sector. The decision is based on the correlation analysis and reaffirmed with the Czech national bank experts. The systematic risk parameters are thus used as part of the moving average series where for the historical values, the forward-looking default rates from COREP database were used for each counterparty sector accordingly. Moreover, we transformed the systematic PD values to one year variant using following transformation,

$$PD12M = 1 - \prod_{j=1}^{4} (1 - PD3M_j)$$

where $PD12M$ is the one-year probability of default and $PD3M_j$ the three month probability of default. The index j represents the time dimension. For LGD, similar approach (without the transformation to one year version) is used. With this method, we obtained an augmented version of systematic risk parameters (labeled as $TTC\ PD^{SYS}$ and $TTC\ LGD^{SYS}$) which serve to shift the TTC PD and TTC LGD values available in the starting portfolio.

To be clear, we present the dynamics of transformation on following example. Suppose a portfolio, with historical PD3M equal to 1%. In the stress scenario, the systematic PD increases to 3% and after 12 quarters, it decreases to initial value. Thus the $PD12M$ was historically equal to almost 4% and during the stress, it rises up to 11.5%. $TTC\ PD^{SYS}$ is calculated as a moving average, so it starts on the level of almost 4% and rises to 6.5% in the end of the stress scenario. The whole situation is depicted in Figure B1.

Figure B1: Example of Transformation Mechanics from $PD3M_j$ to $TTC\ PD^{SYS}$



Note: $PD3M$ is the probability of default on next 3 months. $PD12M$ is the transformed version of $PD3M$. It corresponds to the 12-month probability of default. $TTC\ PD^{SYS}$ is the augmented version of 12-month PD which serves to shift TTC PD. Start of the modelling period is at time 0 and the end at time 12.

[34] Although there are more comprehensive requirements on TTC PDs (see EBA (2017)), it represents the main one.

B.3 Risk Weights and Portfolio Performance Modelling Dependent on Systematic Risk Parameters

The variables $TTC\ PD^{SYS}$ and $TTC\ LGD^{SYS}$ are used to shift the TTC PD and TTC LGD of each of the internal obligor performing grade level within each exposure class assigned to sector counterparty in the IRB portfolio. They are generated via the distance-to-default used already in the first model. We present the methodology only for PD as the methodology for LGD is analogical in the A-IRB approach. In the F-IRB approach, LGD stays constant.

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

$$TTC\ PD_{T_i} = \Phi\left(\Phi^{-1}\left(TTC\ PD_{T_0}\right) + \Phi^{-1}\left(TTC\ PD_{T_i}^{SYS}\right) - \Phi^{-1}\left(PD_{T_0}^{SYS}\right)\right)$$

Resulting $TTC\ PD$ and $TTC\ LGD$ for each internal obligor grade is plugged into regulatory *RW* formula with the additional grade specific characteristics stated previously (for $R(TTC\ PD)$ and $Z(M,\ TTC\ PD)$) which is then multiplied by ϕ to obtain the development of the *RW* in a given internal obligor grade. The final *RW* at time T_i for each internal obligor grade thus gets the following form:

$$RW_{T_i} = (\text{TTC LGD}_{T_i} \cdot \Psi(\text{TTC PD}_{T_i}) - \text{TTC LGD}_{T_i} \cdot \text{TTC PD}_{T_i}) \cdot Z(M, \text{TTC PD}_{T_i}) \cdot 1.06 \cdot 12.5 \cdot \text{SME SP} \cdot \phi$$

$$\Psi(\text{TTC PD}_{T_i}) = N\left\{\frac{1}{\sqrt{1-R(\text{TTC PD}_{T_i})}} \cdot G(\text{TTC PD}_{T_i}) + \sqrt{\frac{R(\text{TTC PD}_{T_i})}{1-R(\text{TTC PD}_{T_i})}} \cdot G(0.999)\right\}$$

where $TTC\ PD_{T_i}$ and $TTC\ LGD_{T_i}$ are shifted based on $TTC\ PD^{SYS}$ and $TTC\ LGD^{SYS}$.

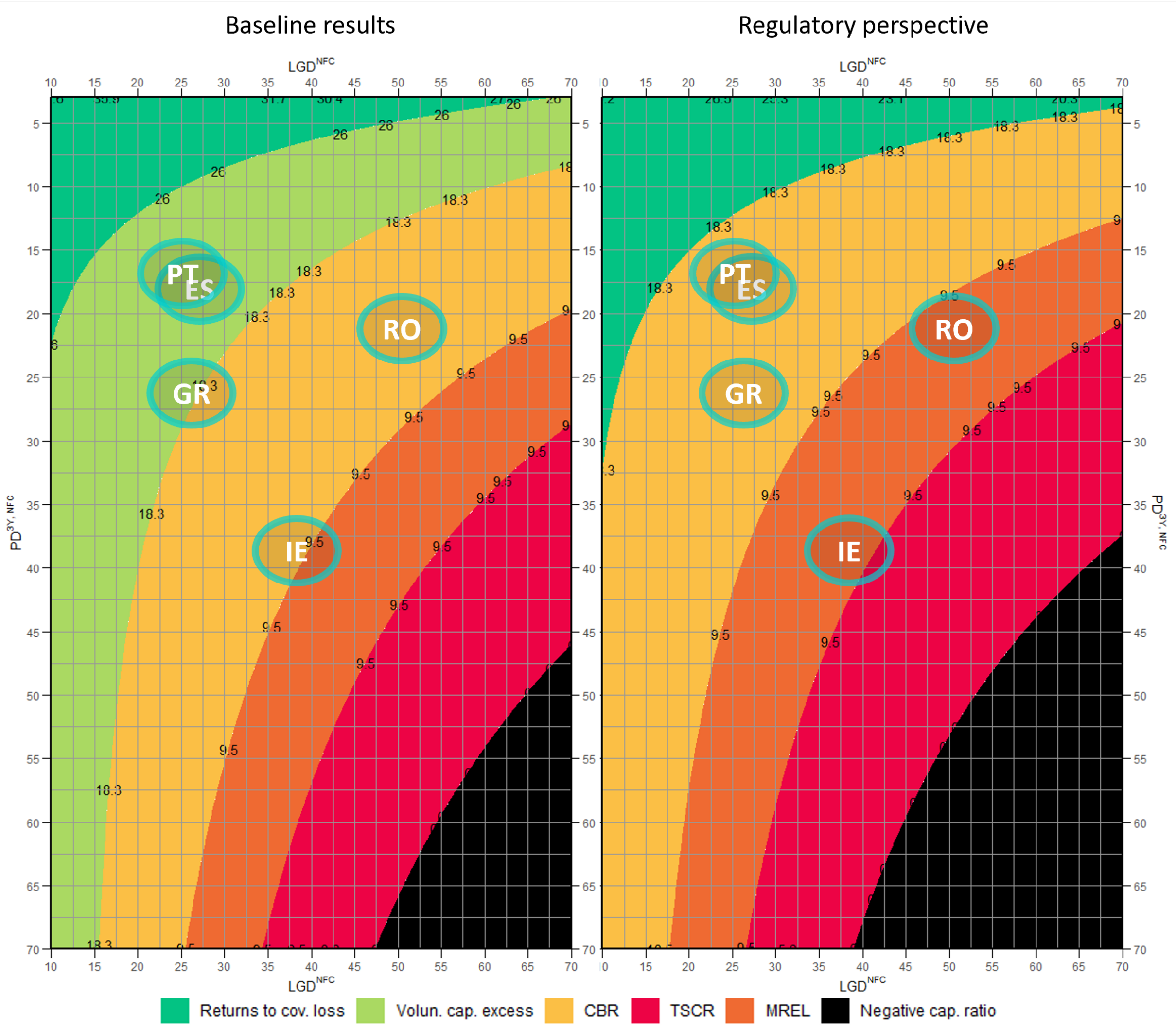
The risk weights are kept constant throughout the scenario period for the non-performing IRB internal obligor grades and for the ST approach exposure classes. Finally, the risk weights are aggregated across the performing and non-performing internal obligor grades to produce exposure class level risk weight.

Besides the risk weights, we also need to model the movements between performing and non-performing states throughout the scenario period. Since the overall development of the loan portfolio from the accounting perspective (the first model) is already known, we can leverage upon the established link between the accounting and regulatory perspectives. For each scenario time, an absolute change for the starting point of an accounting portfolio exposure volume is assigned to a corresponding regulatory exposure class assigned to the counterparty sector. Since the regulatory exposure classes share the same accounting portfolio, the absolute change is weighted by the relative significance of the exposure class of the assigned portfolio. Note that we project the developments of performing and non-performing volumes separately.

In the steps above, we calculated the scenario developments for risk weights and exposure values. We multiply both values at each time and sum the resulting risk exposure amounts across the exposure classes within all regulatory approaches to obtain REA for each scenario time of a given scenario.

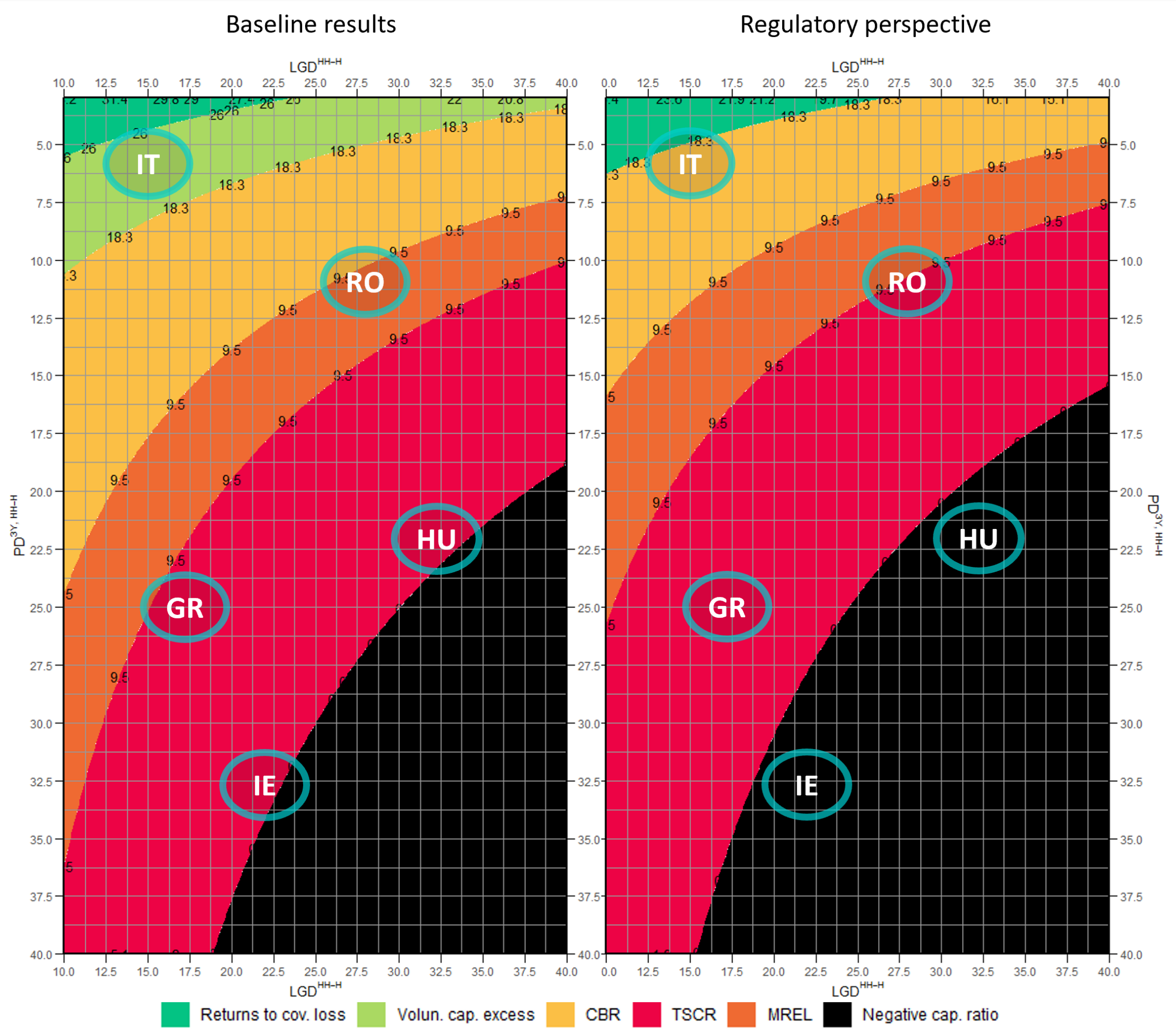
Appendix C: Results for Individual Loan Portfolios l

Figure C1: Capital Ratios and Resilience Segments of Loans to Non-Financial Corporations



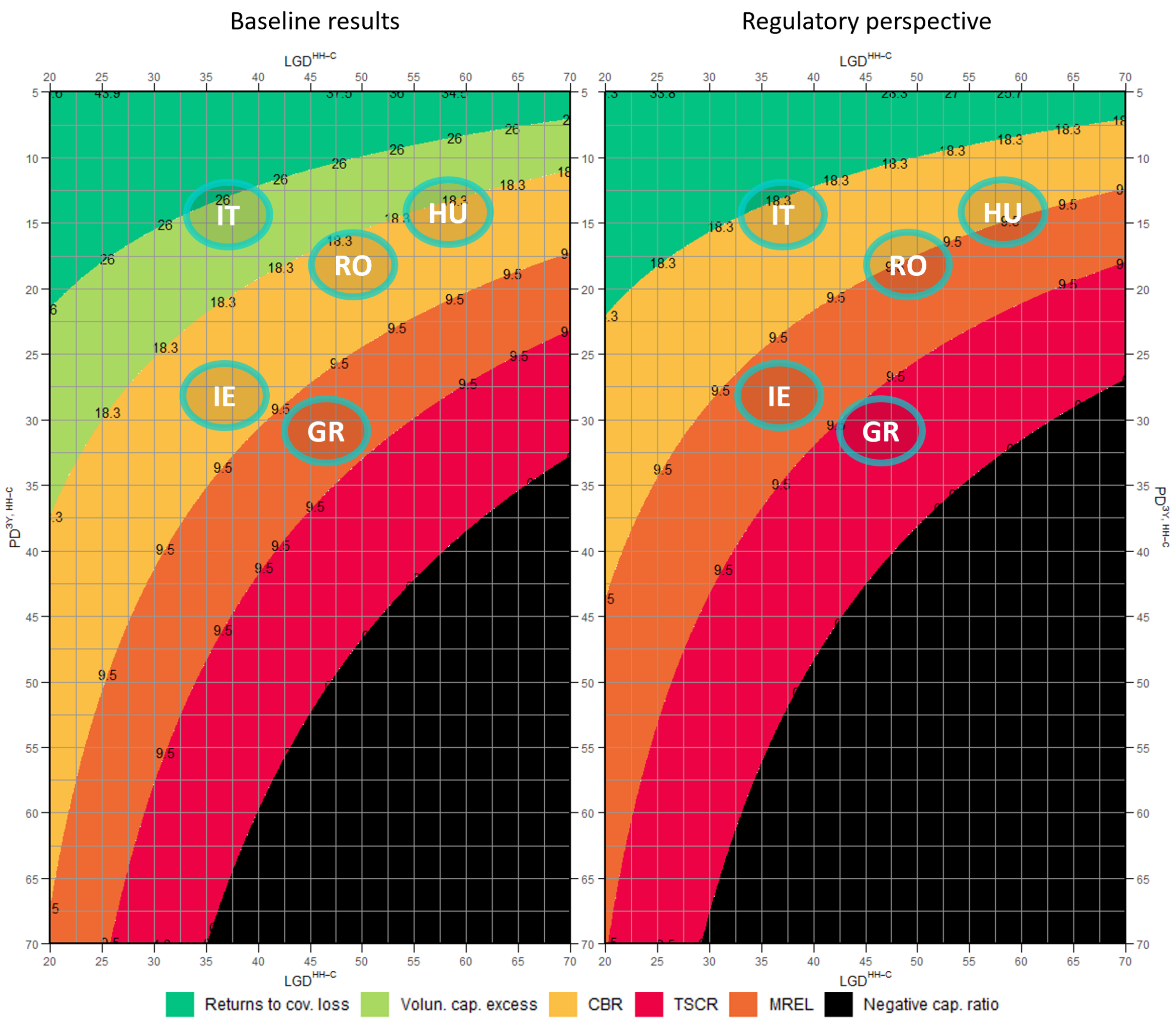
Note: The figure illustrates the impact of credit risk on the capital ratios of loan portfolio NFC (Capital ratio$^{NFC}_{T_{12}}$). Credit risk is defined by a combination of $PD^{3Y,NFC}$ in rows and LGD^{NFC} in columns. The capital ratios are split into multiple resilience segments $RS^{NFC,o}$ that provide a granular view of what type of capital and funds are enough to absorb materialising risk. indicates when returns are sufficient to cover losses and absorb credit risk ($RS^L_{RetCovrLoss}$). highlights the use of voluntary capital excess (RS^L_{VCE}). shows when the CBR is used to absorb credit risk (RS^L_{CBR}). signals the activation of bail-in and its capacity to absorb losses (RS^L_{MREL}). marks the breach of TSCR, triggering a government bailout (RS^L_{TSCR}). Finally, indicates when the capital ratio turns negative, suggesting a more extensive bailout is imminent ($RS^L_{Negative}$). Additionally, turquoise ellipses () highlight the PD-LGD combinations observed in specific EU countries during the Global Financial Crisis, based on EBA (2014) data.

Figure C2: Capital Ratios and Resilience Segments of Loans to Households Secured by Real Estate



Note: The figure illustrates the impact of credit risk on the capital ratios of loan portfolio $HH-H$ (Capital ratio$^{HH-H}_{T_{12}}$). Credit risk is defined by a combination of $PD^{3Y,HH-H}$ in rows and LGD^{HH-H} in columns. The capital ratios are split into multiple resilience segments $RS^{HH-H,o}$ that provide a granular view of what type of capital and funds are enough to absorb materialising risk. ■ indicates when returns are sufficient to cover losses and absorb credit risk ($RS^{L}_{RetCovrLoss}$). ■ highlights the use of voluntary capital excess (RS^{L}_{VCE}). ■ shows when the CBR is used to absorb credit risk (RS^{L}_{CBR}). ■ signals the activation of bail-in and its capacity to absorb losses (RS^{L}_{MREL}). ■ marks the breach of TSCR, triggering a government bailout (RS^{L}_{TSCR}). Finally, ■ indicates when the capital ratio turns negative, suggesting a more extensive bailout is imminent ($RS^{L}_{Negative}$). Additionally, turquoise ellipses () highlight the PD-LGD combinations observed in most affected EU countries during the Global Financial Crisis, based on EBA (2014) data.

Figure C3: Capital Ratios and Resilience Segments of Loans to Household for Consumption



Note: The figure illustrates the impact of credit risk on the capital ratios of loan portfolio $HH-C$ (Capital ratio$_{T_{12}}^{HH-C}$). Credit risk is defined by a combination of $PD^{3Y,HH-C}$ in rows and LGD^{HH-C} in columns. The capital ratios are split into multiple resilience segments $RS^{HH-C,o}$ that provide a granular view of what type of capital and funds are enough to absorb materialising risk. ■ indicates when returns are sufficient to cover losses and absorb credit risk ($RS^{L}_{RetCovrLoss}$). ■ highlights the use of voluntary capital excess (RS^{L}_{VCE}). ■ shows when the CBR is used to absorb credit risk (RS^{L}_{CBR}). ■ signals the activation of bail-in and its capacity to absorb losses (RS^{L}_{MREL}). ■ marks the breach of TSCR, triggering a government bailout (RS^{L}_{TSCR}). Finally, ■ indicates when the capital ratio turns negative, suggesting a more extensive bailout is imminent ($RS^{L}_{Negative}$). Additionally, turquoise ellipses ( ) highlight the PD-LGD combinations observed in specific EU countries during the Global Financial Crisis, based on EBA (2014) data.

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