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Petr Polák, Jiří Panoš

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Jan Sobotka (Czech National Bank)

Project Coordinator: Simona Malovaná

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Petr Polák, Jiří Panoš

The Impact of Expectations on IFRS 9 Loan Loss Provisions

Petr Polák and Jiří Panoš *

Abstract

This paper describes the implementation of the IFRS 9 accounting standard into a macroprudential (top-down) stress-testing framework. It sets out to present a possible way of overcoming data issues and discusses key assumptions which have an effect on the end results and which stress testers should be aware of. According to the results, macroeconomic expectations play a crucial role in the pass-through of impairment. The paper also presents evidence about the pro-cyclicality of the IFRS 9 approach.

Abstrakt

Tato práce popisuje implementaci účetního standardu IFRS 9 do makroobezřetnostních (top-down) zátěžových testů. Jejím cílem je prezentovat možný způsob překonání datových problémů. Zabývá se klíčovými předpoklady, které mají vliv na konečné výsledky a kterých by si testující měli být vědomi. Výsledky ukazují, že při transmisi znehodnocení hrají zásadní roli makroekonomická očekávání. Práce rovněž přináší poznatky o procykličnosti přístupu IFRS 9.

JEL Codes: E44, E62, G01, G21.
Keywords: IFRS 9, impairments, loan loss provisions, macroprudential policy, stress testing.

* Petr Polák, Czech National Bank and Charles University, Prague, petr.polak@cnb.cz
Jiří Panoš, European Central Bank and Czech National Bank and University of Economics, Prague, jiri.panos@cnb.cz
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1. Introduction

International Financial Reporting Standard 9 – Financial Instruments (IFRS 9) was prepared by the International Accounting Standards Board (IASB) and issued in July 2014. It came into force in January 2018 and has been the mandatory accounting framework for a significant number of EU banks since then. This new accounting standard for loan loss provisioning represented a significant change for the whole banking sector. It was created to replace the previous International Accounting Standard 39 (IAS 39) in the wake of the global financial crisis (GFC) with the aim to improve loan loss provisioning. Barth and Landsman (2010) argue that IAS 39 was one of the factors which contributed to the GFC, as it lacked forward-looking credit loss recognition. Bellotti and Crook (2012) explain that the underestimated credit risk present in the portfolio at that time was caused by the mechanism of IAS 39, in which credit losses were recognised right after the impairment took place. This contributed to provisioning pro-cyclicality and underestimation of credit losses and related provisions, which in turn reduced banks' resilience to shocks. IFRS 9, on the other hand, requires banks to base their credit losses on forecasts of the macroeconomic situation.

The motivation for the transition to IFRS 9 stems from the GFC. Pre-crisis IAS 39 loan loss provisioning was based on the incurred loss model, which caused delays in the recognition of credit losses, widely labelled as "too little, too late", such as in Laeven and Majnoni (2003). During the crisis, a significant increase in fair value and impairment losses was observed. The recognition of these losses was perceived to have pro-cyclical features – banks did not have large enough buffers to cover the losses they made during the crisis, and had to form loan loss provisions from their diminished profits in the subsequent downturn. Therefore, in 2009, the G20 called on the accounting standard setters to "strengthen accounting recognition of loan-loss provisions by incorporating a broader range of credit information" and "improve accounting standards for provisioning" (OECD, 2009).

In response to the G20, the Financial Stability Board (FSB) produced advice regarding the interaction between accounting issues and pro-cyclicality based on the argument that recognising loan losses at an earlier stage in the credit cycle might reduce pro-cyclicality. This included a recommendation to "reconsider the incurred loss model by analysing alternative approaches for recognising and measuring loan losses that incorporate a broader range of available credit information" (FSB, 2009). The new IFRS 9 standard is based on the expected credit losses (ECL) framework and aims to be more forward-looking than its predecessor. Thus, according to IASB (2011), IFRS 9 should be more transparent and less pro-cyclical. Optimally, banks would form provisions in good times when they have sufficient profits, so that they can cover losses when an economic downturn comes. This should smooth the impacts of credit losses over the cycle.

It is expected that IFRS 9, if implemented properly, will help banks to recognise credit losses in advance and thus avoid the kind of delays observed during the GFC. The idea of reducing pro-cyclicality is especially important for financial stability – banks are expected to provision appropriately at times of economic growth and should thus be more stable during crises. In addition, the higher provisioning requirements should provide banks with an incentive to behave more cautiously and not to lend excessively during booms, since doing so should be more costly for them. In theory, banks should be able to calculate appropriate risk parameters with high precision given the detailed information they collect about their portfolios. On the other hand, they might have incentives to underestimate the severity of adverse shocks in order to reduce the need to provision. Moreover, given the forward-looking nature of the ECL framework, expectations about future macroeconomic conditions play a crucial role in the new standard and might substantially affect loan loss provisioning.

Stress tests have become an integral part of financial stability analysis since the last crisis. Borio et al. (2014) state that "given current (modelling) methodology, macro stress tests are ill-suited as early warning devices". The argument for this statement comes from the GFC, which was neither predicted nor indicated by the regularly conducted stress tests. We also agree with another assertion made by Borio et al. (2014) that "improvements in the performance of stress tests depend on a change in mindset". To do the stress tests right, one has to revise the methodology regularly, incorporate advances in knowledge, and promptly adjust to new accounting and reporting rules. IFRS 9 is connected to one of the key risks in the banking sector – credit risk, so the change in the accounting standard is being accompanied by gradual changes in regulatory reporting. There is no doubt that supervisory authorities themselves have to adapt in time and modify their existing stress-testing methodologies by integrating the new accounting rules properly, despite very often still lacking sufficient data.

This paper presents the IFRS 9 methodology implemented in the Czech National Bank's top-down macroprudential stress test framework. As we discussed earlier, expectations about future economic conditions are one of the key drivers of loan loss provisioning under IFRS 9, so this paper also uses this framework to show how different expectations might affect the timing of provisioning and analyses whether IFRS 9 differs in terms of pro-cyclicality from its predecessor IAS 39. To conduct our analysis, we decided to employ the CNB's workhorse top-down stress-testing framework augmented by an expectations layer, because this framework is directly tailored to testing the stability of the system as a whole and has all the necessary components already integrated into its structure.

The discussion about the pro-cyclicality of IFRS 9 is not new, but the academic evidence is scarce (see, for example, Gaffney and McCann, 2019; Abad and Suarez, 2017; Reitgruber, 2015). There have also been attempts to quantify the difference between the two standards; for instance, Krüger et al. (2018) simulate the bond portfolio. Domikowsky et al. (2014) analyse loan loss provisioning using a sample of German banks and find counter-cyclical behaviour for specific provisions and no explicit cyclical effects for general provisioning. Taking into account that at the time, German banks were allowed to take a forward-looking approach to provisioning, this seems to be an important finding in support of the new IFRS 9 standard.

Cohen and Edwards (2017) describe the new provisioning approach from a more theoretical perspective and conclude that it represents a step in the right direction. However, it is argued that the burden of the new standard might be substantial, especially for smaller institutions, given the complexity of the data which have to be maintained. From the supervisory perspective, new models have to be verified and well understood. The costs involved are significant and may raise concerns that the new standard might be too demanding. Closer to our analysis is Seitz et al. (2018), who simulate the expected credit loss model (IFRS 9) and compare the results with the incurred loss model (IAS 39). They suggest that ECL provisions tend to exceed IAS 39 provisions during times of crisis and that there will not be a significant increase in counter-cyclical loan loss provisioning.

For our analysis, we decided to use a simplified banking sector model and to focus mainly on loans, since they usually represent the largest part of the banking sector's balance-sheet exposure. The results calculated using the new IFRS 9 model will also be compared with the previous stress-testing framework using the incurred loss model described by Geršl et al. (2012). The first results under the new methodology were presented in the Czech National Bank's 2017/2018 Financial Stability Report (CNB, 2018). However, this paper describes the methodology in more detail and emphasises the challenges stemming from different expectations about future economic conditions. To the best of our knowledge, this paper is the first attempt to analyse the effects of different expectations on loan loss provisioning.

The paper is structured as follows: Section 2 focuses on the key features of IFRS 9, Section 3 describes the credit risk models used in stress testing, Section 4 discusses the effect of expectations and Section 5 gives conclusions.

2. Key Features of IFRS 9 for Loan Loss Provisions

The IFRS 9 accounting standard is primarily concerned with the classification and measurement of financial assets and liabilities and contains three significant building blocks: (a) recognition and measurement of financial assets and liabilities, (b) impairment and (c) hedge accounting. For top-down macroprudential stress testing, the first two are key.

Recognition and measurement deals with the problem of the classification and measurement of financial assets for the balance sheet and profit & loss statement. The previous accounting standard IAS 39 is a rule-based approach with four classification categories of financial assets (loans and receivables, FVPL, available for sale and held to maturity). The new accounting standard IFRS 9 is a principle-based approach with three classification and measurement categories of financial assets (amortised cost, FVPL and FVOCI). Expected credit losses are supposed to be recognised for all assets not measured at FVPL. For financial liabilities there are very few changes. Overall, the new approach should be more robust regarding manipulation, more informative and, thanks to a short set of guidelines, also simpler. However, the real situation is more complicated, since the same assets can be classified for similar firms differently (e.g. bonds) and the standard's generality may lead to heterogeneous implementation across the industry.

Expected credit loss (ECL). The new approach to the classification of financial assets and liabilities also directly affects loan loss provisioning. IAS 39 used the incurred loss framework, which required banks to recognise credit losses only when evidence of a loss was apparent (BIS, 2017). This means that provisions were mainly created only after there were already known troubles with the financial asset. IFRS 9 has introduced the ECL framework for the recognition of asset impairment, which means that banks have to determine the ECL at all times as from the initial recognition and hold a proper amount of provisions. To determine the ECL, banks should not only use the available information about past events, but also predict and forecast future developments. Because virtually every loan has a certain probability of default (even if possibly very small), an appropriate ECL should be associated with every loan since the time it was originated or acquired. If this probability or other factors change, the ECL should be adjusted accordingly, as this new approach aims to be much more forward-looking in order to ensure timely recognition of credit losses.

Impairment stages. Generally, there are three stages under IFRS 9 intended to reflect the deterioration in the credit quality of a financial asset. It should be noted that the actual underlying probability of default does not directly determine whether the loan should be categorised as Stage 1 or Stage 2. In order to classify the loan as Stage 2, the probability of default has to increase significantly in comparison with the initial recognition. See subsection 2.1 for more details.

Stage 1 – Stage 1 covers all loans for which the credit quality has not deteriorated significantly since its initial recognition. For these loans, the 12-month ECL is recognised and the interest revenue is calculated on the gross carrying amount.

Stage 2 – If a loan's credit quality has deteriorated significantly since its initiation and the credit risk is not very low, the loan is categorised as Stage 2. For loans in Stage 2, the lifetime ECL is recognised, but the interest revenue is still calculated on the gross carrying amount. Institutions should evaluate regularly whether the credit quality has deteriorated and also determine what change will be considered significant.

Stage 3 – If a loan has objective evidence of impairment, it is categorised as Stage 3. The lifetime ECL is recognised, as in Stage 2, but the interest revenue is calculated on the net carrying amount. It should be noted that from the regulatory perspective, Stage 3 (i.e. credit-impaired) loans are not the same as non-performing loans. However, this approximation is usually quite suitable and does not cause any major distortion of the results. Such simplification can thus be part of stress-testing methodologies, (see, for example, EBA, 2018).

12-month and lifetime losses. The ECL is recognised either for 12 months (Stage 1) or for the lifetime of the loan (Stage 2 and Stage 3). The lifetime ECL is the expected present value of the loss that is incurred if the borrower defaults at any time before the loan's maturity. In general, the lifetime expected credit loss is calculated in four steps: (a) determine all the scenarios in which the loan defaults; (b) estimate the loss incurred in each scenario; (c) multiply the loss by the probability of the associated scenario; (d) discount and sum up all the results. This approach gives us the present value of the probability-of-default weighted average of the credit losses. The 12-month ECL is the portion of the lifetime ECL which is associated with the time horizon of the next 12 months.

2.1 Significant Increase in Credit Risk

The important feature for the classification of financial assets under IFRS 9 is the change in credit risk. A loan is reclassified from Stage 1 to Stage 2 if its credit risk deteriorates significantly (paragraph 5.5.9 of IFRS 9)[1]. The precise definition of significant increase in credit risk (SICR) is left for banks' internal methodologies and might differ from bank to bank. For our top-down modelling perspective, we should understand what the main drivers of SICR are and how they can be modelled effectively.

We identify three main determinants of SICR: (a) **Macroeconomic environment**. If the economic conditions deteriorate, uncertainty increases and an economic slowdown or downturn is expected or even occurs, then the credit quality of assets is generally expected to deteriorate as well. We control for this in our approach.[2] (b) **Idiosyncratic factors**. Banks observe behavioural changes in borrowers. Examples include an absence of regular income for retail and a sudden decrease in turnover for non-financial corporations. These are individual idiosyncratic characteristic stemming from other sources than the macroeconomic environment and we are unable to model them properly on the macro level. However, these effects can reasonably be expected to be diversified away on the macro level and are beyond the scope of the top-down modelling framework. (c) **Change in model estimates**. This point might be valid for institutions without a sufficiently long customer credit history or which employ models that are not sufficiently robust.

It can be concluded that from the top-down perspective, the key driver of SICR is the macroeconomic environment and SICR will tend to be strongly pro-cyclical. This logical conclusion is confirmed by Gaffney and McCann (2019). SICR will cause credit exposures to shift from Stage 1 to Stage 2, hence this ratio will be pro-cyclical too. For Stage 2 assets, lifetime expected credit losses are required, so the loss provisioning will be related to the macroeconomic environment as

[1] Instruments with low credit risk are excluded; see paragraphs 5.5.10 and B5.5.23 of IFRS 9

[2] The approach used, however, does not perfectly grasp the entirety of the impact that macro variables could have through SICR, as the changes in the volume of Stage 2 exposures due to changes in macro variables will be proportional to the changes in the PD. However, the observed transitions to and from Stage 2 might be different in a normal economic situation and in a crisis, and they might not be proportional to the increase in the PD.

well. Thus, the ultimate key factor here is the accuracy of the predictions of future macroeconomic conditions which are then fed into the models. This factor can either promote early creation of provisions or cause later recognition of losses similar to IAS 39.

2.2 Interaction with Basel Requirements

In line with the Basel regulation, banks hold capital for unexpected losses, whereas expected losses should be covered by product pricing and loan loss provisions. Banks are also required to compute the regulatory expected losses. However, the Basel computations of expected losses differ from the accounting perspective of IFRS 9. First, unlike in the case of IFRS 9, the time horizon for the Basel regulation is always 12 months. Second, while the regulatory expected losses should be through-the-cycle (TTC) and therefore rather independent of the macroeconomic cycle, IFRS 9 expected losses should be point-in-time (PiT) and thus explicitly take into account the current economic conditions and forecasts (paragraph 5.5.17).

In general, provisioning affects CET1 capital through the profit & loss statement. Moreover, the Basel regulation specifies additional adjustments for possible shortfalls in provisioning. Paragraph 73 of Basel III states that if the regulatory expected loss exceeds the stock of provisions, the difference must be deducted directly from CET1. In the opposite situation, when the stock of provisions exceeds the regulatory expected loss, the excess may be added back to the Tier 2 capital.[3] Ultimately, both measures affect CET1, and since IFRS 9 is expected to form provisions sooner and in a more sufficient manner compared to IAS 39, the new standard can be expected to be more CET1-demanding than its predecessor at least in certain phases of the cycle.

To calculate IFRS 9 provisions, we need to identify, estimate and forecast an appropriate set of PiT risk parameters and key macroeconomic variables (paragraphs 5.5.17 and BS.5.49 of IFRS 9). The Basel requirements try to avoid pro-cyclicality using TTC risk parameters. The TTC values aim to be more independent of the macroeconomic risk factors. However, banks often use observed historical default rates (DF rates) to calibrate their PD models, and DF rates are naturally driven by the macroeconomic situation. Hence, the TTC risk parameters are still indirectly determined by the macroeconomic factors, and a cyclical component is inherently present in the models, since banks produce their estimates usually based on at least five years of historical observations according to Articles 180 and 181 of the CRR. Consequently, this approach might cause the risk weights to behave pro-cyclically and will thus be replaced by a requirement to use data sets which include a representative mix of good and bad years. For more details, see, for example, Andersen (2011) or Heid (2007).

For IRB banks, which already had regulatory credit risk models in place, the adoption of IFRS 9 was often considerably easier than it was for STA banks. This may raise the question of whether this new accounting standard could partially serve as an incentive for banks to switch from the STA to the IRB approach, which is generally less capital demanding (Behn et al., 2016; Mariathasan and Merrouche, 2014). For more information, see Prorokowski (2018), who contributes to the debate on the suitability of the bank models used to meet the Basel requirement to calculate IFRS 9 expected loss provisioning.

[3] There is a limit of 0.6% of RWA; see paragraph 61 of Basel III.

3. Credit Risk Models in the Macro Stress-testing Framework

The majority of EU banks have adopted the new IFRS 9 accounting standard, which directly influences the accounting recognition of credit risk, the most significant risk in the European banking sector. Various approaches to credit risk stress testing are well described, for example, in Daniëls et al. (2017), Breuer and Summer (2017), Drehmann et al. (2010) and Buncic and Melecky (2013). However, in order to present the effects of expectations on the cyclicality of the IFRS 9 accounting standard, we use the adjusted top-down macroprudential stress-testing framework of the CNB. Our approach to IFRS 9 modelling is originally based on the methodology developed at the ECB by Gross et al. (2018) for applications within the EBA EU-wide stress-testing exercise. However, our model is different in several important aspects. We assume the dynamic balance sheet approach, while employing our own data and satellite models for credit growth and risk parameters such as PD and LGD. Moreover, we have significantly re-worked the crucial loss rate estimation module of the model in order to efficiently utilise the full information contained in the transition probability matrix (TPM). We see our main contribution, however, in adding an expectations layer to the model, which allows us to analyse different expectations about future developments and to assess their impact on loan loss provisioning and capital (see Section 4).

3.1 Credit Risk Framework under IAS 39

The previous framework for credit risk stress testing based on the IAS 39 principles was similar across all central banks, so we use this approach as a benchmark measurement. Usually, the model splits the loan portfolio into segments (such as loans to non-financial corporations, households, governments, financial institutions etc.), and for every segment different growth rate, default rate and loss given default parameters are estimated. For the modelling purposes of this paper, we will use just one theoretical segment, but the idea can be simply replicated for the other segments using appropriately estimated parameters. For the regular top-down stress-testing exercise, we model several portfolios for each bank in the system and then aggregate the results. However, for the purposes of this paper it suffices to model just one fictitious bank holding a theoretical, well-diversified, homogeneous[4] portfolio of retail consumer loans.

To model the credit losses, we apply the dynamic balance sheet approach – the volume of gross loans (performing and non-performing together) over the period modelled is determined by a satellite model for the loan growth rate. To get the volume of performing loans, we subtract the non-performing loans volume from the gross loans volume. For each quarter, the volume of NPLs is generated according to the following set of equations:

$$GL_{t+1} = g \cdot GL_t \tag{1}$$

$$NPL_{t+1} = NPL_t + PD_{t+1} \cdot (GL_t - NPL_t) - a \cdot NPL_t \tag{2}$$

$$PL_t = GL_t - NPL_t \tag{3}$$

$$\Delta LLP_{t+1} = PD_{t+1} \cdot (GL_t - NPL_t) \cdot LGD_{t+1} - a \cdot LLP_t + (PL_{t+1} - PL_t) \cdot PLcoverage \tag{4}$$

where g is the gross loan growth parameter, NPL is the volume of non-performing loans, PL is the volume of performing loans, GL is the volume of gross loans, PD is the probability of default, ΔLLP is the change in the volume of loan loss provisions, a is the NPL outflow parameter (write-offs) and $PLcoverage$ is the average performing loans coverage ratio.

[4] The top-down modelling approach presented here implicitly assumes that the portfolios modelled are reasonably diversified and homogeneous. Although this might not always be fulfilled in practice (especially when dealing with corporate or institutional portfolios), it allows us to abstract from idiosyncratic factors and justifies the Markov approach to the modelling of transitions.

Calculating the credit losses is therefore quite straightforward, as we have only one probability of default value determining the amount of newly defaulted loans. In this model, banks create provisions equal to the realised losses. This means that the change in the NPL volume directly affects the profit & loss statement. We assume that all losses from the new NPLs are directly realised, so the loss is equal to the product of LGD and the new NPL volume. The loan losses are then directly recorded in the profit & loss statement and hence directly affect the banks' capital. Moreover, although banks were not required to provision for the expected losses, they usually held a certain amount of them, as reflected by the *PLcoverage* parameter. In general, loan loss provisioning under the incurred loss model tends to be significantly pro-cyclical, as discussed, for example, by Pool et al. (2015).

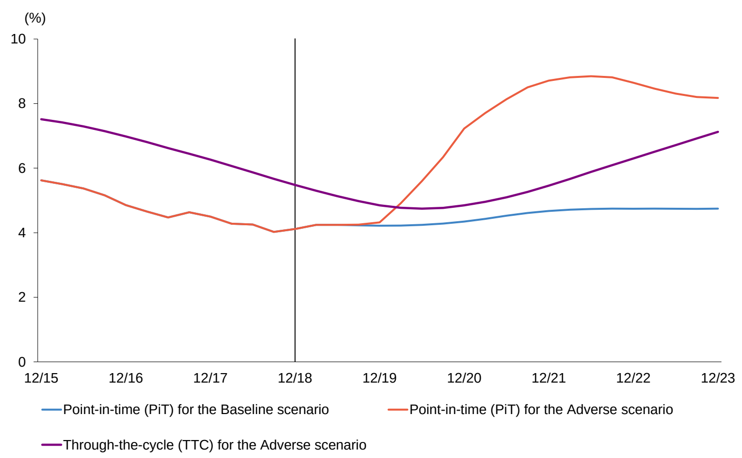
Even under the IAS 39 framework, we distinguish TTC and PiT values. The TTC values are used for the Basel capital requirements and the PiT values for the loan loss calculations.

3.2 Credit Risk Framework under IFRS 9

3.2.1 Probability of Default

For stress-testing purposes, the probability of default trajectory is usually produced by a satellite model. In general, central banks rarely have access to detailed loan-level data, so aggregate values are usually used. We were able to identify three different approaches to modelling the TTC and PiT values: (a) treat the PiT and TTC values completely separately and assume that the TTC values required for the Basel capital requirements are constant at a rating-class level, (b) use the TTC values reported by banks and then add a shock to get the PiT values, as at De Nederlandsche Bank (Daniëls et al., 2017), for example, or (c) take the PiT model values and calculate the TTC values as a long-term average. The last-mentioned approach is currently employed at the CNB (Geršl et al., 2012). This approach allows the TTC values to vary and is also in line with Article 181 of the CRR and the current EBA approach.

Figure 1: Probability of Default and Its Projection



Note: The chart depicts the historical default rates, projected PiT PD values and calculated TTC PD values for the five-year horizon.

CNB (2018) discusses the lowering of IRB risk weights in the banking sector and states that the further we are from the crisis, the more the values from the post-crisis period dominate the input data of banks' internal models. The prolongation of the favourable phase of the business cycle lowers the TTC values and thus also the risk weights. Regulatory authorities (the Basel Committee and the EBA) have responded with guidelines valid as from 2021 which suggest that TTC values should be based on a representative mix of observations from good and bad years (see EBA, 2017, for the full report).

As mentioned above, our current approach goes from the PiT to the TTC values in line with the CRR. To calibrate our PD model, we use historical default rate time series (which are available quarterly and for each of the key loan segments) and a set of macroeconomic variables. This approach is consistent with the implemented top-down macroprudential stress-testing approach. Our PD model is based on the ARDL (autoregressive distributed lag) framework and calibrated using the constrained Bayesian model averaging (constrained BMA) method. This approach, along with a sample calibration, is described in detail in Panoš and Polák (2019), and the PiT and TTC values for the hypothetical retail portfolio are shown in Figure 1.

Our approach has two advantages: (a) the inclusion of macroeconomic variables follows the requirements of the IFRS 9 accounting standard, and (b) the calculation of the TTC values is in line with the Basel approach for regulatory capital. We can therefore easily use one model as the cornerstone for both purposes. Figure 1 shows the cyclicality of the PiT values but also a certain level of cyclicality of the TTC values,[5]) which are calculated as the average of the PiT values. The alternative computation of the TTC values based on a mix of good and bad times should be more stable over time.

The following subsubsection 3.2.2 describes our approach to loan loss provisions modelling under IFRS 9 in detail.

3.2.2 Loan Stages and TPM

As mentioned in Section 2, loan staging is one of the key features of the IFRS 9 accounting standard. Under the previous IAS 39 standard, it was sufficient to have a PD model in place, which was used to estimate the amount of loans defaulting. For IFRS 9 modelling, however, we need to know not only the total amount of loans defaulting, but also the transitions between the individual stages. Our PD model by itself does not estimate how many loans newly classified as Stage 3[6] were previously in Stage 1 and how many were in Stage 2. In addition, we have to account for the fact that loans can be classified as Stage 2 while in the previous period they were classified as Stage 1 and vice versa.

There are basically two possible approaches to stage modelling. The first is to simplify the situation and just model the ratio of Stage 2 to Stage 1 exposures. This means that we can re-use the previous framework to model performing and non-performing loans using the PD model and then split the performing loans between Stage 1 and Stage 2. This simplifying assumption can usually be considered justifiable for the macroeconomic stress-testing exercise and for discussions regarding the pro-cyclicality of IFRS 9 loan loss provisioning. The remaining challenge is to model the Stage 2 to Stage 1 ratio when the relevant historical data are absent. A possible proxy is the historical ratio of watch to standard loans. This approach is very simple, but it also has significant shortcomings.[7] More details on the ratio approach can be found in subsubsection 3.2.3.

[5] Such cyclicality drives the discussion of pro-cyclical behaviour of risk weights (see, for example, ECB, 2009)
[6] We assume that Stage 3 loans correspond to non-performing loans. In reality, these two categories are not necessarily equivalent, but our analyses show that the overall difference is not material.
[7] The difference in the respective volumes in the Czech banking sector can be found in section 3 of CNB (2018).

The second possible approach is to model the whole transition probability matrix (TPM) and the corresponding flows between the individual stages. This approach is more precise and provides additional information as well. The TPM in our approach is a time-variant stochastic matrix of a discrete-time, discrete-state-space inhomogeneous Markov chain, and we use the subscript t to highlight that the TPM elements are not constant over time. $TP_{XY,t}$ represents the transition probability from Stage X to Stage Y at time t. In addition, some methodologies (e.g. EBA, 2018) add the "no-cure from Stage 3" assumption, which means that loans can never recover once classified as Stage 3. This assumption makes the modelling considerably easier, since we are not required to model the transition probabilities from Stage 3 back to Stage 1 and Stage 2 and we do not have to deal with double defaults over the period modelled. Thus, in our approach we too assume no cures (and no repayments) from Stage 3, which consequently becomes an absorbing state of the Markov chain, and the number of parameters which need to be modelled is therefore reduced by two (see Table 1).

Table 1: TPM of Markov Chain

From/To	Stage 1	Stage 2	Stage 3
Stage 1	$TP_{11,t} = 1 - TP_{12,t} - TP_{13,t}$	$TP_{12,t}$	$TP_{13,t}$
Stage 2	$TP_{21,t}$	$TP_{22,t} = 1 - TP_{21,t} - TP_{23,t}$	$TP_{23,t}$
Stage 3	$TP_{31,t} = 0$	$TP_{32,t} = 0$	$TP_{33,t} = 1$

Note: Blue cells represent matrix elements which need to be modelled.

To get the volume of loans in each stage under the constant balance sheet approach, we can simply multiply the vector of current volumes in each stage by the corresponding TPM to get the volumes in each stage at the beginning of the next period, as in equation 5. The general approach under dynamic balance sheets and further details are described in subsubsection 3.2.4.

$$\begin{bmatrix} ExpS_{1,t+1} \\ ExpS_{2,t+1} \\ ExpS_{3,t+1} \end{bmatrix}^T = \begin{bmatrix} ExpS_{1,t} \\ ExpS_{2,t} \\ ExpS_{3,t} \end{bmatrix}^T \cdot \begin{bmatrix} TP_{11,t} & TP_{12,t} & TP_{13,t} \\ TP_{21,t} & TP_{22,t} & TP_{23,t} \\ TP_{31,t} & TP_{32,t} & TP_{33,t} \end{bmatrix} \tag{5}$$

3.2.3 Using S1/S2 Ratio to Model Loan Stages

As the starting point for the modelling under the baseline scenario, we can use the current ratio of Stage 2 to Stage 1 loans that banks report within the regulatory reporting. However, our main aim is to model the path under the adverse scenario. To achieve that, we assume that the ratio of Stage 2 to Stage 1 exposures would double over the stress period. As a benchmark to derive this relative increase, we use the ratio of standard to watch loans during the GFC. The predicted probabilities of default from the current model can be used without changes. In the new context, they represent the total transition from Stage 1 and Stage 2 to Stage 3. Nevertheless, modelling of the whole TPM is necessary, as it allows us to model the transitions between the different stages using the individual transition probabilities, and it is also important for more rigorous modelling of the ECL. Therefore, we reject the S1/S2 ratio approach in favour of the approach detailed in the next subsection, which has the potential to deliver more precise and informative results.

3.2.4 TPM Modelling Methodology

As mentioned above, the TPM in our framework is a stochastic matrix which is not constant over time and carries information about the probabilities of transition between the IFRS 9 stages. Since we are limited by a lack of historical data availability, we do not model each TP_{xy} separately. Instead, we use the initial value of the TPM, the constrained-BMA PD model (Panoš and Polák, 2019) and a set of bridge equations to infer the values of the matrix in each period. Therefore, to get the transition probabilities we use three different ingredients for each loan segment: (a) the starting point values of the TPM, (b) the projected PiT PD trajectories from the PD satellite model and (c) a pair of linear bridge equations with suitably estimated parameters. First, the starting values of the TPM have to be estimated using either the regulatory reporting data or some other relevant data source, such as the bottom-up supervisory stress testing. Afterwards, the trajectories of TP_{13} and TP_{23} can be estimated using distance-to-default (DD) transformation. Finally, the TP_{12} and TP_{21} trajectories are calculated using the TP_{13} and TP_{23} values acquired in the previous step. To obtain the remaining TP_{11} and TP_{22} values on the main diagonal of the TPM, we can utilise the fact that the TPM is a stochastic matrix and hence these values can be calculated such that the sum of each row is equal to one. We assume Stage 3 to be the absorbing state with no recovery rates, hence TP_{31} and TP_{32} are both equal to zero and TP_{33} equals one. The general DD transformation is mathematically expressed as:

$$DD := -\Phi^{-1}(PD) \tag{6}$$

where Φ^{-1} is the inverse cumulative distribution function (CDF) of the standard normal distribution. This transformation was first defined by Merton (1974). In the context of the original model, it measured how many standard deviations of the asset probability distribution a given firm is distant from bankruptcy. Among market practitioners, it is widely agreed that the distance to default is a useful measure for assessing the credit risk of a non-financial corporation (Chan-Lau and Sy, 2007). From the mathematical perspective, it is virtually equivalent to the probit transformation. The main advantage of this transformation is that we are no longer limited to the [0,1] interval for PD, but we have the whole set of real numbers. In addition, the non-linear nature of the transformation leads to smaller values of PD being stressed more than larger ones. That further promotes the conservative nature of the model, which is fully in line with the spirit of the top-down macroprudential stress test. Naturally, the inverse transformation is used to get the projected values back to the [0,1] interval:

$$\begin{aligned} TP_{13,T_i} &= \Phi\left(\Phi^{-1}\left(TP_{13,T_0}\right) + \Phi^{-1}\left(PD_{T_i}\right) - \Phi^{-1}\left(PD_{T_0}\right)\right) \\ TP_{23,T_i} &= \Phi\left(\Phi^{-1}\left(TP_{23,T_0}\right) + \Phi^{-1}\left(PD_{T_i}\right) - \Phi^{-1}\left(PD_{T_0}\right)\right) \end{aligned} \tag{7}$$

At this point, we are in a position to obtain the TP_{12} and TP_{21} trajectories. Empirical observations made by Gross et al. (2018) suggest that in the DD space, linear relations exist between TP_{12} and TP_{13} and TP_{21} and TP_{23}, which can be expressed as a regression line model:

$$\begin{aligned} \Phi^{-1}\left(TP_{12,t}\right) &= \alpha + \beta\Phi^{-1}\left(TP_{13,t}\right) + \varepsilon_t, \forall t \\ \Phi^{-1}\left(TP_{21,t}\right) &= \gamma + \delta\Phi^{-1}\left(TP_{23,t}\right) + \omega_t, \forall t \end{aligned} \tag{8}$$

We a priori expect a positive correlation between TP_{12} and TP_{13} (i.e. $\beta > 0$) and a negative correlation between TP_{21} and TP_{23} (i.e. $\delta < 0$). Unfortunately, only very limited data series from regulatory reporting are available to estimate the coefficients β and δ at the moment. For the time being, we therefore resort to the values estimated for the Czech Republic in the EBA stress-testing exercise, which we periodically update using Bayesian regression principles. For the purposes of our analysis with only one hypothetical loan segment, we use approximately average values of these coefficients, i.e. $\hat{\beta} = 0.5$ and $\hat{\delta} = -0.5$ The final projections of the TP_{12} and TP_{21} values are then obtained using the starting point values, the estimated coefficients $\hat{\beta}$ and $\hat{\delta}$, the previously obtained trajectories of TP_{13} and TP_{23} and inverse DD transformation:

$$
\begin{aligned}
TP_{12,T_i} &= \Phi\left(\Phi^{-1}\left(TP_{12,T_0}\right) + \hat{\beta}\left(\Phi^{-1}\left(TP_{13,T_i}\right) - \Phi^{-1}\left(TP_{13,T_0}\right)\right)\right) \\
TP_{21,T_i} &= \Phi\left(\Phi^{-1}\left(TP_{21,T_0}\right) + \hat{\delta}\left(\Phi^{-1}\left(TP_{23,T_i}\right) - \Phi^{-1}\left(TP_{23,T_0}\right)\right)\right)
\end{aligned} \tag{9}
$$

As mentioned before, the rest of the TPM is calculated such that it satisfies the definition of a stochastic matrix, i.e. the sum of the row values is equal to one. There is no mechanism in this approach to ensure that the sum of the modelled parameters $TP_{12} + TP_{13}$ and $TP_{21} + TP_{23}$ is less than or equal to one. If the sum is actually greater than one, the transition probability on the main diagonal is then set to zero and the off-diagonal entries are normalised (ECB, 2017).

The initial TPM for the period is shown in Table 2. With the initial TPM and its evolution over time in our hands, we can calculate the loan volumes in each stage for every loan segment and time step, as described in the following part of this paper. The data limitations that prevent us from modelling

Table 2: Sample TPM

From/To	Stage 1	Stage 2	Stage 3	$\sum$
Stage 1	96.8	1.8	1.4	100.0
Stage 2	11.7	78.0	10.3	100.0
Stage 3	0.0	0.0	100.0	100.0

Note: Values are shown in percentages.

the transitions between stages directly will hopefully soon perish. Since the introduction of IFRS 9, banks have been paying more attention to instrument classification, and various pieces of information regarding the stage transitions are reported to supervisory authorities. More detailed data are available to supervisors thanks not only to IFRS 9, but also to projects such as AnaCredit.[8] However, it will take several years (maybe even decades) before sufficient-quality time series from these sources become available, i.e. before the series are long enough to contain a period of economic downturn.

3.2.5 Credit Growth, Loan Volumes and Stages

For each loan segment, the flows between stages have to be modelled for the whole stress-testing period. These flows are governed by the transition probability matrix and its evolution over time (for the derivation of the TPM, see subsubsection 3.2.4).

Determining the loan volumes in the individual stages one time step ahead is divided into two steps. First, the corresponding TPM is applied to the current loan volumes. Then, the new loans are added to Stage 1 and the loans that banks write off are subtracted from Stage 3. Together with the written-off loans, we also remove the appropriate amount of provisions. This approach allows us to use the dynamic balance sheet and produces a more realistic ratio of performing to non-performing loans.[9] Formally, the loan volume in each stage is given by:

[8] AnaCredit is a project to set up a data-set containing detailed information on individual bank loans in the euro area, harmonised across all member states. "AnaCredit" stands for analytical credit datasets. It was set out in Regulation (EU) 2016/867 of May 2016 (ECB/2016/13).

[9] We prudentially assume no repayments from Stage 3, which can be reduced only via write-offs. However, it is also implicitly assumed there are no repayments from Stage 2. This assumption would not hold in reality – unfortunately, our current credit growth satellite model does not allow us to distinguish between new credit (inflow to Stage 1) and repayments (outflow from Stage 1 and Stage 2), hence we consider this to be one of the areas for potential improvement.

$$\begin{bmatrix} ExpS_{1,t+1} \\ ExpS_{2,t+1} \\ ExpS_{3,t+1} \end{bmatrix}^T = \begin{bmatrix} ExpS_{1,t} \\ ExpS_{2,t} \\ ExpS_{3,t} \end{bmatrix}^T \cdot \begin{bmatrix} TP_{11,t} & TP_{12,t} & TP_{13,t} \\ TP_{21,t} & TP_{22,t} & TP_{23,t} \\ 0 & 0 & 1 \end{bmatrix} + \begin{bmatrix} CC_t \cdot Exp_t + WO_t \cdot ExpS_{3,t} \\ 0 \\ -WO_t \cdot ExpS_{3,t} \end{bmatrix}^T \tag{10}$$

where $ExpS_{s,t}$ represents the exposure at time t in Stage s; $TP_{ij,t}$ represents transition from Stage i to Stage j at time t; CC_t is the credit growth of the total gross exposure (Exp_t) at time t; and WO_t is the write-off parameter at time t.[10] It is important to emphasise that the credit growth captured by CC_t is lowered in each period by the outflow of Stage 3 exposures captured by WO_t. However, since we target credit growth at the CC_t level, we have to add the volume that has been written off. This is a rather technical issue based on an understanding of the CC_t parameter, specifically that the growth of the whole stock of exposures is a more relevant financial stability indicator and is also easier to model over time.

3.2.6 Loan Loss Provision Modelling

The next step in IFRS 9 expected loss modelling is to estimate the loss rates for the individual stages. For exposures moving to Stage 3, we use the loss given default (LGD) parameter, as we assume that the losses are realised immediately and that no cure from S3 is possible. It follows that the total amount of Stage 3 provisions depends on the previous LGDs and corresponding exposure amounts transitioning to Stage 3. For exposures in Stage 1 and Stage 2, we need the 12-month loss rate (12M LR) and the lifetime loss rate (LT LR) respectively. Last but not least, we need the average residual maturity for each credit segment. The residual maturity data are taken from regulatory reporting and the bottom-up supervisory stress tests. For the LGD estimation, we use a satellite model and, once again, information from the bottom-up stress tests, where banks provide their LGDs and other risk parameters. The LGD satellite model is defined in detail by Geršl et al. (2012).

IRB banks also report their LGD values within regulatory reporting. Some central banks (see, for example, Daniëls et al., 2017) use these values in their stress-testing frameworks. These values are reported according to the Basel regulation and should be interpreted as "downturn" LGDs, meaning that estimated losses should be appropriate for an economic downturn. The situation is in fact analogous to the PD case discussed earlier, as here again we require PiT values for the computation of credit losses and provisioning and different regulatory values for the capital adequacy calculations. Similarly to PD PiT, the LGD PiT values are expected to be pro-cyclical, as collateral value tends to be negatively affected by recessions (see Figure 2).

12-month and Lifetime Loss Rates It is a well-known property of an inhomogeneous Markov chain that the elements of the product of the chain's N subsequent TPMs represent the probabilities that a chain which originally started in a state given by a specific row is, after N periods, in a state given by a specific column. From the absorbing property of Stage 3, it can be concluded that the element at position (1,3) (respectively (2,3)) of the product of N subsequent TPMs gives us the probability that an exposure which initially started in Stage 1 (Stage 2) moved to Stage 3 from any other stage in the N-th period at the latest. From that, it can be further derived that the difference between the elements at position (1,3) (respectively (2,3)) of the multiples of N and N-1 subsequent TPMs gives the probability of an exposure initially starting in Stage 1 (Stage 2) moving to Stage 3 from any other stage exactly in the N-th period. Let us denote these probabilities as TP^{1-3}_{N,T_i} for

[10] In reality, Stage 3 exposures can also be reduced through loan sales. We abstract from loan sales in our modelling approach.

exposures being in Stage 1 at time T_i and TP^{2-3}_{N,T_i} for exposures being in Stage 2 at time T_i. The 12M LR is then calculated as:

$$LR^{S_1}_{12M,T_i} = \sum_{k=1}^{4} \left[\left(\frac{1}{1+r_{T_i}} \right)^k \cdot EAD_{T_i-1+k} \cdot LGD_{T_i-1+k} \cdot TP^{1-3}_{k,T_i} \right] / EAD_{T_i} \tag{11}$$

where r stands for the interest rate in the specific loan segment and EAD for the exposure size. Thus, $LR^{S_1}_{12M,T_i}$ represents the discounted value of the expected credit losses for exposures in Stage 1 in the next 12 months (four quarters) expressed as a percentage of the original exposure value, which meets the IFRS 9 requirements.

Similarly, we model the lifetime LR as:

$$LR^{S_2}_{LT,T_i} = \sum_{k=1}^{M} \left[\left(\frac{1}{1+r_{T_i}} \right)^k \cdot EAD_{T_i-1+k} \cdot LGD_{T_i-1+k} \cdot TP^{2-3}_{k,T_i} \right] / EAD_{T_i} \tag{12}$$

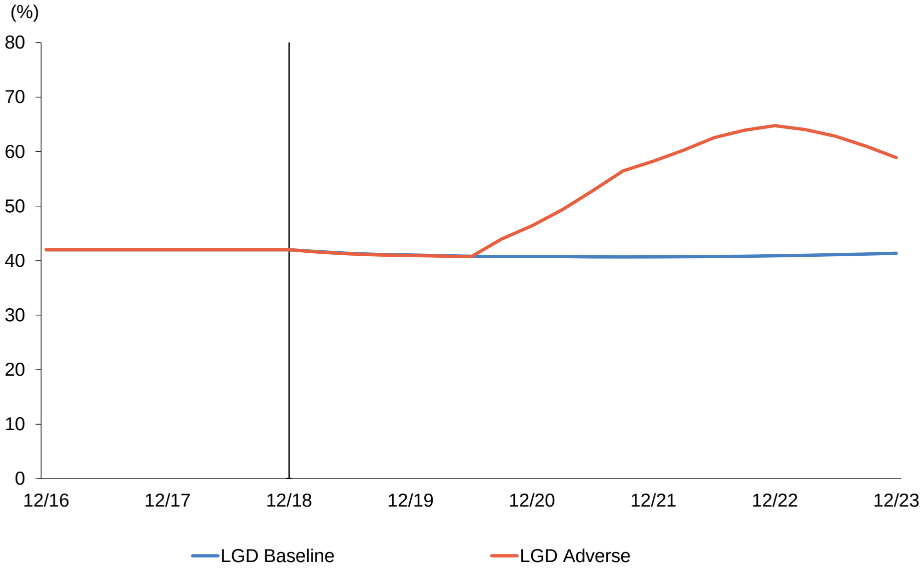
where M represents the residual maturity expressed in quarters in the given loan segment. $LR^{S_2}_{LT,T_i}$ represents the discounted value of the expected credit losses for exposures in Stage 2 from T_i until maturity expressed as a percentage of the original exposure value, which again meets the IFRS 9 requirements.

For simplicity, we assume that the EAD decreases linearly up to maturity. The LGD values also decrease linearly, but cannot fall below a defined threshold representing the costs of litigation and other relevant fixed costs associated with a default event. The transition probabilities TP^{1-3}_{k,T_i} and TP^{2-3}_{k,T_i} are also important drivers of the ECL in formulae 11 and 12. For many loan segments, the maturities stretch beyond the modelling horizon, so we have to determine the long-term averages to which the both the baseline and adverse values of the risk parameters converge after the stress-testing period. These long-term averages can be calculated using historical time series (if available) or as weighted averages of the values from the baseline and adverse scenarios, or can be set by expert judgement. We assume a six-year convergence period, after which the risk parameters stay flat.

Figure 2 shows the LGD path and Figure 3 the loss rate paths for the given scenarios. As mentioned above, we again differentiate between the LGDs used for the capital requirements and the PiT LGDs used for the IFRS 9 ECL provisions.

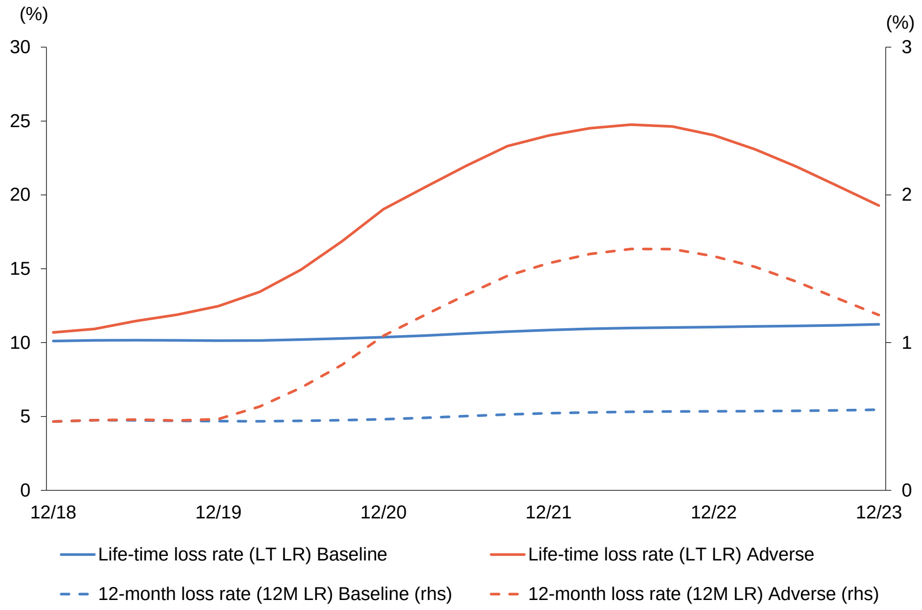
Since we have already discussed all the necessary features required to calculate the ECL and the associated loan loss provisions in the IFRS 9 framework, the next part of this paper forms a stylised portfolio and applies the methods and calculations introduced above to show how different expectations about future macroeconomic conditions might influence provisioning and ultimately affect capital adequacy, which is one of the key measures of banks' stability.

Figure 2: LGD



Note: The chart depicts the LGD path under the baseline and adverse scenarios for the sample portfolio.

Figure 3: Loss Rates



Note: The chart depicts the LR and 12M loss rate paths under the baseline and adverse scenarios for the sample portfolio.

4. Expectations and Impact on Capital

4.1 Stylised Credit Portfolio

This section presents a hypothetical retail loan portfolio and calculates the impact of macroeconomic scenarios under different expectations about future conditions. This allows for a comprehensive comparison of the impact and for a discussion regarding the pro-cyclicality of the IFRS 9 accounting standard. We first make several assumptions that are inherently embodied in the standard macro-stress-testing exercise and add the macroeconomic scenarios for which the impact of the new accounting standard will be calculated. The period modelled is five years, and the evolution of the variables is computed on a quarter-by-quarter basis. We approach the portfolio from the top-down perspective, so homogeneity is assumed and aggregate values are used. We assume the IRB methodology for calculating regulatory capital and consider only one homogeneous retail portfolio of consumer loans.[11]

Regarding the scenario design, our main motivation is the time span in which we want to demonstrate the effects of the accounting framework, while maintaining basic economic principles and applying a severe yet plausible economic downturn. In the adverse scenario, the economy follows a positive trend in the first six quarters and is then hit by a sudden crisis. This crisis lasts for roughly three years, which means that within the five-year horizon we are also able to model the beginning of an economic recovery. The final results are presented for two macroeconomic scenarios (baseline and adverse) and three different types of expectations, and are compared among themselves and with the previous IAS 39 approach. We consider the same starting point values and long-term averages for all calculations to ensure that any differences in the results are solely determined by the different approaches to expectations.

Table 3: Stylised Credit Portfolio

Stage	Volume	Provisions	Coverage ratio (%)	Risk weight
Stage 1	892	4	0.5	47.0
Stage 2	61	6	10.4	47.0
Stage 3	47	34	72.3	50.0

Note: The table provides starting-point information about the stylised portfolio. We assume that loans are retail consumer loans, split into stages, and that the coverage ratios are proportionately equivalent to those of the Czech banking sector. For the risk weight for defaulted exposures, we assume that the difference between LGD and ELBE is 4% and constant over time.

Table 3 summarises the stylised credit portfolio, which has a nominal value of 1,000 units, and we assume that there are no other assets. We use the S1-S2-S3 ratio from the Czech banking sector, resulting in 892 units in Stage 1, 61 units in Stage 2 and 47 units in Stage 3. Based on the evidence from regulatory reporting, we set Stage 3 loans equal to non-performing loans and to loans in default according to CRR.[12] For the coverage ratios' starting values (i.e. the stock of provisions for each stage divided by the associated loan volume), we again use values from the Czech banking sector. The coverage ratios for Stage 1, Stage 2 and Stage 3 loans are 0.5%, 10.4% and 72.3% respectively. The starting-point risk weight (RW) of 47.0% for non-defaulted loans and 50% for defaulted loans implies an initial risk exposure amount (REA) of 474.4 units. We assume a starting capital ratio of

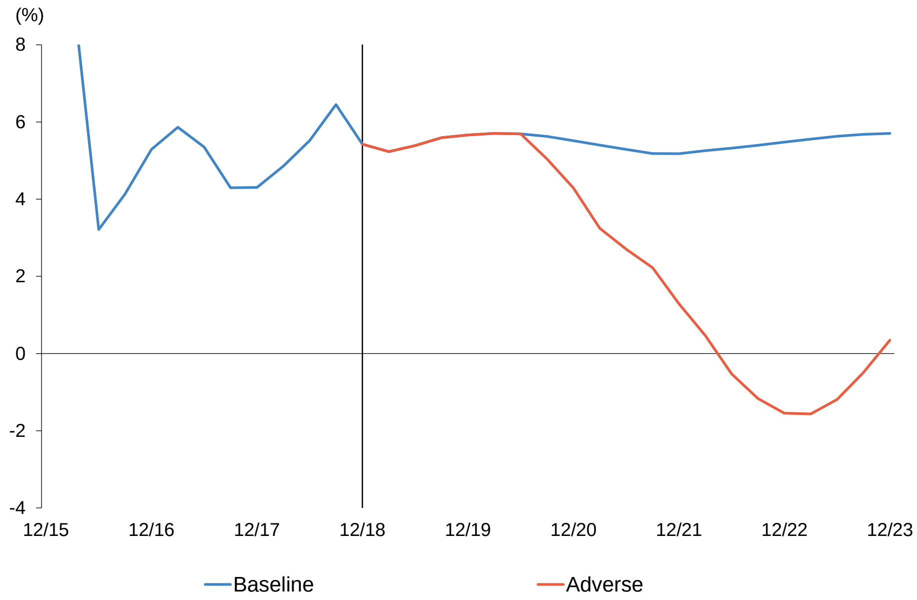
[11] In the actual CNB stress-testing exercise, we distinguish between loan segments with respect to FINREP reporting.

[12] These three sets are generally not identical, but the difference tends to be sufficiently small.

20%, which implies 94.9 units of regulatory capital, and we further assume that banks will earn 7.5 units quarterly.[13] If banks' capital ratio is higher than the initial level of 20% in any given period, the rest is paid out as dividends. This assumption should lead to higher resilience for banks that use the forward-looking IFRS 9 approach and thus conserve their capital in good times in comparison to those which do not take expected future developments into account.

We employ the dynamic balance sheet approach with the credit growth path shown in Figure 4. Moreover, we work under the assumption that banks reduce their lending volume during the crisis, but the riskiness of new loans is the same as that of the current stock, so the homogeneity of the portfolio is maintained. In reality, however, banks tend to loosen their lending standards during periods of economic growth and tighten them during downturns (Hromadkova et al., 2018). Rigorous modelling of such behaviour is quite complex and therefore we leave aside this phenomenon and instead prefer to work with conservative values of the risk parameters.

Figure 4: Credit Growth in the Scenario



Note: The chart depicts the credit growth path under the baseline and adverse scenarios. The scenario-conditional trajectories are produced by a dedicated CNB satellite model.

In the stress-testing exercise, the scenarios are the key drivers of the final results. Since IFRS 9 aims to be forward-looking and we need to calculate the lifetime expected losses for Stage 2 loans, we have to make assumptions about the evolution of key variables beyond the stress-testing horizon. Furthermore, we need data regarding the residual maturity of the loan portfolio. Both of these issues were discussed earlier in this paper.

Credit losses are driven by loan defaults. Under the IAS 39 modelling approach, the projected PD is the only variable needed to determine the volume of newly defaulted loans. For simplicity, we assume that provisions are created in the same amount as the actual loan losses (defined as the volume of newly defaulted loans times the loss given default). Under the IFRS 9 modelling approach, provisions equal to the ECL should be created even for performing loans, which means

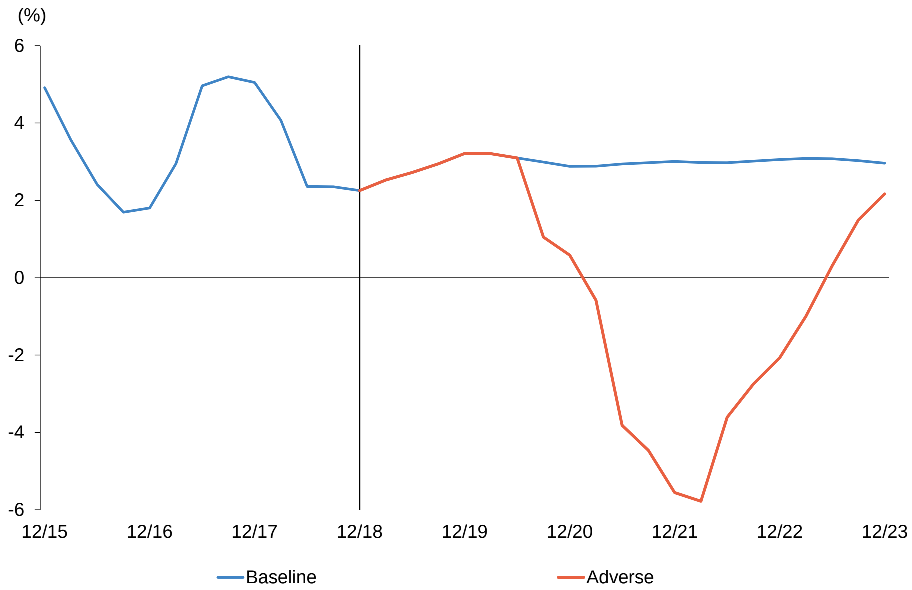
[13] This assumption is based on an ROA equal to 3%.

that the stock of provisions has to be modelled for each stage and each time period. The expected losses differ between the individual stages, so the associated stocks of provisions differ as well. In the IAS 39 framework, there are only performing loans and NPLs. For IFRS 9, however, we have to split performing loans into Stage 1 and Stage 2. This split is crucial, and the possible ways of doing so were discussed in subsubsection 3.2.2. In the following part, we will use both approaches and compare them.

4.2 Expectations about Future Developments

According to IFRS 9, current and expected macroeconomic conditions should be taken into account when determining the ECL. Estimates of current economic indicators are usually available, but forecasting future developments is often problematic. Not only are the models used to predict the future imperfect, but the magnitude of crises is often underestimated, as shown by An et al. (2018). The following analysis compares different types of expectations about macroeconomic conditions and their impact on provisioning.

Figure 5: Real GDP Growth Forecast and Possible Crisis Timing



Note: The chart shows the assumed path of real GDP growth. The blue line represents the baseline scenario, while the red line shows the path of the economic downturn in the adverse scenario.

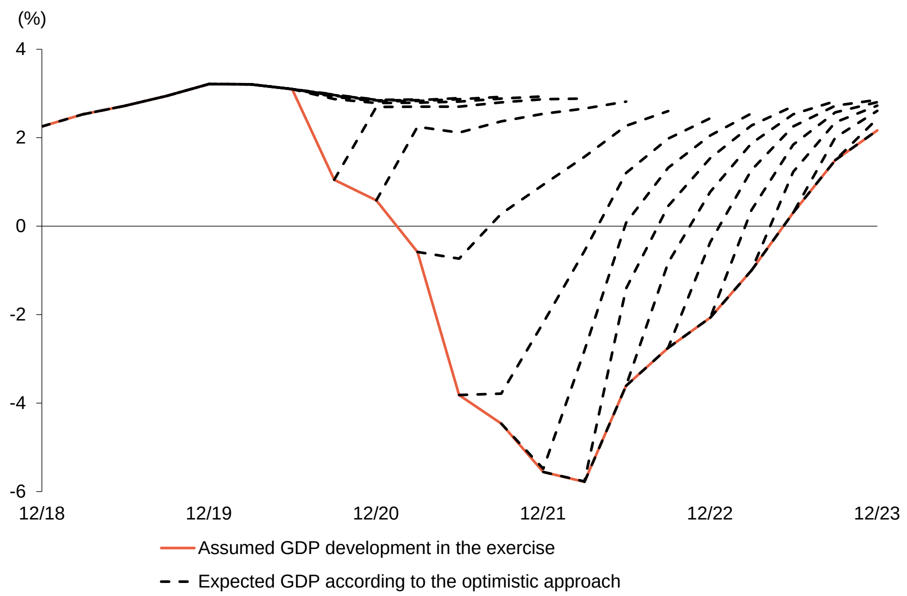
We have already shown how 12-month and lifetime loss rates are calculated in our model, but the key driver in these calculations is expectations about future developments. One possible approach is perfect foresight. Perfect foresight means that all the information is available at any time, and entities know precisely when the next crisis will arise and how long and severe it will be. On the one hand, this assumption is obviously very strong and rather unrealistic. On the other hand, for the top-down stress-testing exercise it makes the situation easier, because the stress-testing scenarios are transferred directly into the estimated risk parameters from the beginning of the test. This was one of the reasons behind the emergence of IFRS 9 accounting – banks are supposed to create loan loss provisions in good times, before a crisis hits them. However, if we want to achieve and analyse closer-to-reality behaviour, we can relax this assumption and try to model how different expectations and applications of the IFRS 9 principles can affect banks. For the purposes of this paper, we assume a crisis (negative GDP growth) that comes a year and a half after the beginning of the modelling period and lasts approximately three years (see Figure 5 for a graphical representation).

For the crisis given by our scenario, we test three types of expectations (a) the perfect foresight approach, where all the information is known from the beginning, (b) the optimistic approach, where banks always believe that the situation will start to revert to the baseline scenario in the next period and (c) the Bayesian approach, where banks' expectations are gradually adjusted to reflect the inflow of new information.

The perfect foresight approach assumes that the exact path of the crisis is known to all entities at the beginning of the stress test. Under perfect foresight, provisioning tends to be smoother. Therefore, banks are better able to manage the crisis, since they have enough provisions on their balance sheets before the crisis, as they conserve revenues in good times to cover their losses in bad times. However, in a real stress situation, no bank will have perfect knowledge of the future, which means IFRS 9 provisions might behave differently than under the perfect foresight approach.

The optimistic approach is our label for the second type of expectations under consideration. It assumes that at each time step of the downturn period, banks expect the situation to start converging towards the baseline path in the next period. Figure 6 shows the optimistic approach to expectations about the path of real GDP over time.

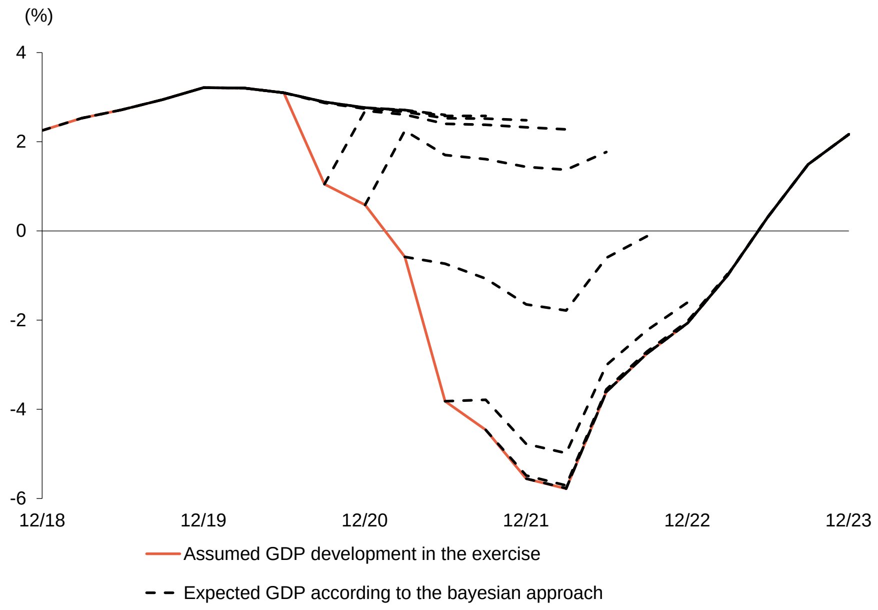
Figure 6: Real GDP Growth Rate Forecast Based on Optimistic Expectations about Future Developments



Note: The dashed lines represent expectations about the real GDP growth path at any given time. It is always assumed that the economic situation will start improving in the next period and quickly converge towards the baseline scenario.

The Bayesian approach is our label for the third type of expectations about future developments. In this case, banks can see as far as two periods ahead and evaluate the currently available information about economic developments. We start in good times, so banks' prior beliefs incline towards the baseline scenario and then gradually switch to the adverse one as new information arrives. The expectations about real GDP in the Bayesian approach are depicted in Figure 7.

Figure 7: Real GDP Growth Rate Forecast Based on Bayesian Expectations about Future Developments



Note: The dashed lines represent expectations about the GDP growth path at any given time. Banks use the available information up to two periods ahead to gradually update their beliefs regarding the scenario.

From our perspective, the alternative approaches to expectations are closer to reality than the perfect foresight approach, as banks do not possess crystal balls and in general might be tempted to postpone provisioning to the future in the hope that a more serious downturn will never come.

4.3 Impairment Creation

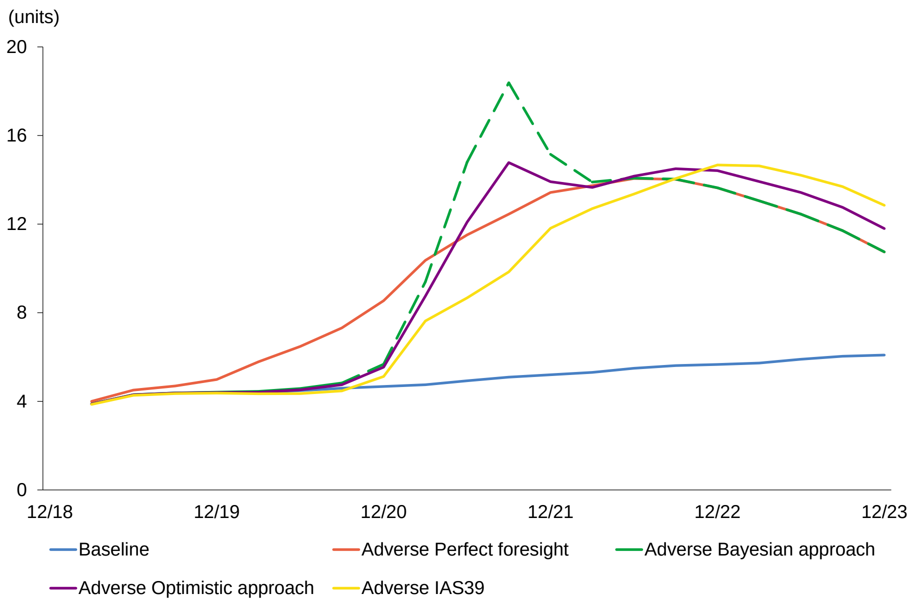
Different paths of the loss rate parameters and the stock of provisions are calculated for each of the selected approaches to expectations. The techniques described in subsubsection 3.2.6 are used to simulate the projected paths conditional on the presented scenarios and approaches to expectations. One of the key results is the path of provisions, as shown in Figure 8. The following paragraphs aim to highlight the differences between the presented approaches.

The provisions created according to **IAS 39** depict the losses suffered by banks under the previous accounting framework and also serve as a benchmark for all the IFRS 9 framework results. The path is based on the losses already incurred and is therefore strongly connected to the way the crisis unfolds in the hypothetical retail credit portfolio. No substantial buffers are created prior to the crisis in this approach.

Under the **perfect foresight approach**, one can easily observe the gradual increase in provisioning ahead of the crisis, as banks know with certainty that the crisis is approaching. The perfect foresight ensures that there are more provisions at the dawn of the crisis, and the provisions created to cover performing loans (Stage 1 and Stage 2) can be used in later stages to cover the losses arising from loans that become non-performing (Stage 3) in the course of the crisis.

In the case of the **optimistic approach**, banks provision much less for performing loans (especially prior to the crisis), as the economic situation perceived by banks is always more optimistic than the actual situation prescribed by the scenario at each time step. Since the macroeconomic path is ultimately the same in all the approaches, this leads to banks postponing the creation of provisions. This causes the provisioning to be more pro-cyclical and, in the later stages, similar to IAS 39, as banks need to provision for the new non-performing loans, for which the ECL and the associated provisions were previously underestimated.

Figure 8: Loan Loss Provisions Creation



Note: The figure shows the quarterly creation of loan loss provisions for each expectation type for the same underlying scenario. PF stands for perfect foresight.

One of the potential pitfalls of IFRS 9 is captured by the **Bayesian approach**. In this case, banks realise the true depth and length of the crisis too late and so are forced (either internally or by supervisors, auditors or other authorities) to create a vast amount of additional provisions during the downturn, when their revenues are diminished. This leads to a severe “cliff effect” with a large impact on banks’ overall capital position. This potentially causes a credit crunch with spillovers to the real economy, and threatens the stability of the system.

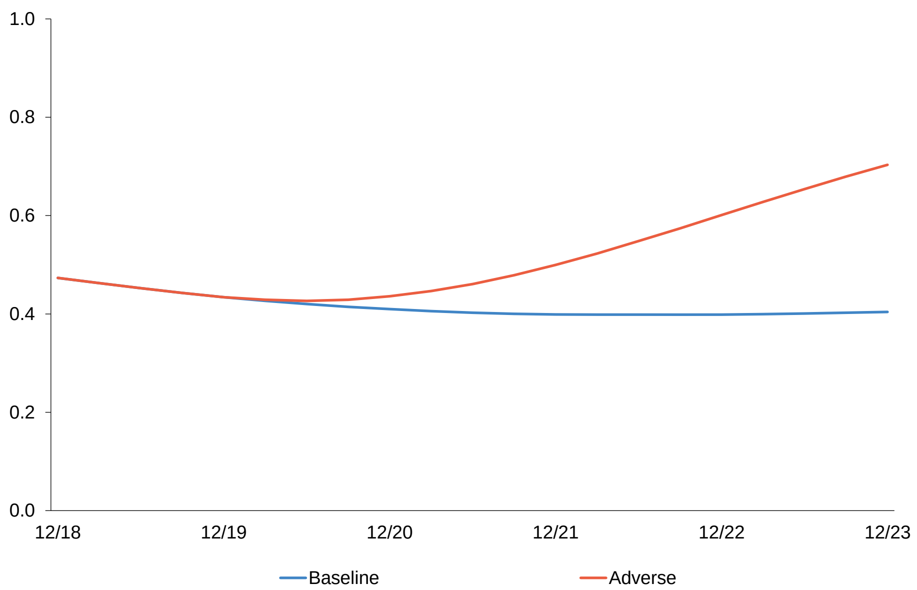
Hence, based on an examination of Figure 8, it seems that perfect foresight is the key ingredient of IFRS 9, one which can truly reduce the need to form loan loss provisions during recessions. If banks knew about the crisis in advance and behaved accordingly, IFRS 9 would without doubt be less pro-cyclical than the previous standard.

The pre-crisis period and recovery period actually highlight the biggest differences between the perfect foresight IFRS 9 and IAS 39. We observe that at the end of the crisis, banks can start to release provisions created for performing loans and use them to cover the losses caused by the increased inflow of non-performing loans. Such behaviour, where the creation of provisions is higher before the start than at the end of the crisis, is desirably counter-cyclical. In addition, banks pay the least dividends, as they use their profits in good times to create a cushion for bad times (this is discussed in more detail in the following section). However, the assumption of perfect foresight can effectively only be applied in stress-testing exercises. In reality, banks do not have a precise knowledge of either the timing or length and depth of the crisis. In addition, the majority of macroeconomic forecasts and equilibrium models rarely predict deep or prolonged crises. We therefore expect banks' real-world behaviour to resemble our alternative approaches to expectations rather than the perfect foresight approach.

4.4 Basel Requirements and CET1 Capital Impact

Once we have calculated the volume of loans in each stage, we can compute not only the corresponding amount of provisions according to IFRS 9, but also the capital requirements according to the Basel regulation. Here, we remind the reader that for the IFRS 9 calculations we use the PiT models, while the regulatory capital computations depend on the TTC/downturn models for the regulatory PD and LGD (see Section 3). The final path of the risk weights under the two scenarios is shown in Figure 9.

Figure 9: Risk-Weight Path



Note: The blue line represents the baseline scenario and the red line the adverse scenario.

Having both the volumes of loans and provisions and the associated risk weights at hand, we can investigate the ultimate impact on banks' CET1 capital, which is one of the key indicators of their solvency and resilience. Loan loss provisions lower the capital via the profit & loss statement. However, this effect is partially covered by profits. For the purposes of this paper, we assume that profits stay unchanged over time in both scenarios. The change in risk weights also affects the capital ratio – in the adverse scenario, the risk weights rise, causing the capital ratio to decrease and putting additional pressure on banks' capital adequacy ratios and thus their solvency. Since the risk weights are calculated according to the CRR and the regulatory parameters are driven by the same underlying models, we obtain the same paths for IAS 39 and IFRS 9.

Table 4 provides a summary of the results, including the impact on the capital adequacy ratio. The starting point is identical for all the expectation types and both accounting standards. The table shows that the new standard enforces higher provisioning in all cases. However, it also conserves more capital, since the payout of dividends is highest under IAS 39. These observations favour IFRS 9, as the higher amount of provisions and increased capital conservation should strengthen banks' stability during a downturn. However, clearly only the perfect foresight approach ensures a significant improvement in terms of conservation, as it retains almost six units of capital more in comparison with the other approaches based on IFRS 9 and almost seven units of capital more in comparison with IAS 39.

Table 4: Summary of Results

Expectations	LLP created	LLP released	LLP created total	Dividends	End CAR (%)
Perfect	206.3	-8.7	197.7	16.0	4.2
Optimistic	198.3	-4.1	194.1	21.9	3.9
Bayes	206.6	-8.9	197.7	21.5	3.4
IAS 39	183.3	0.0	183.3	22.7	5.2

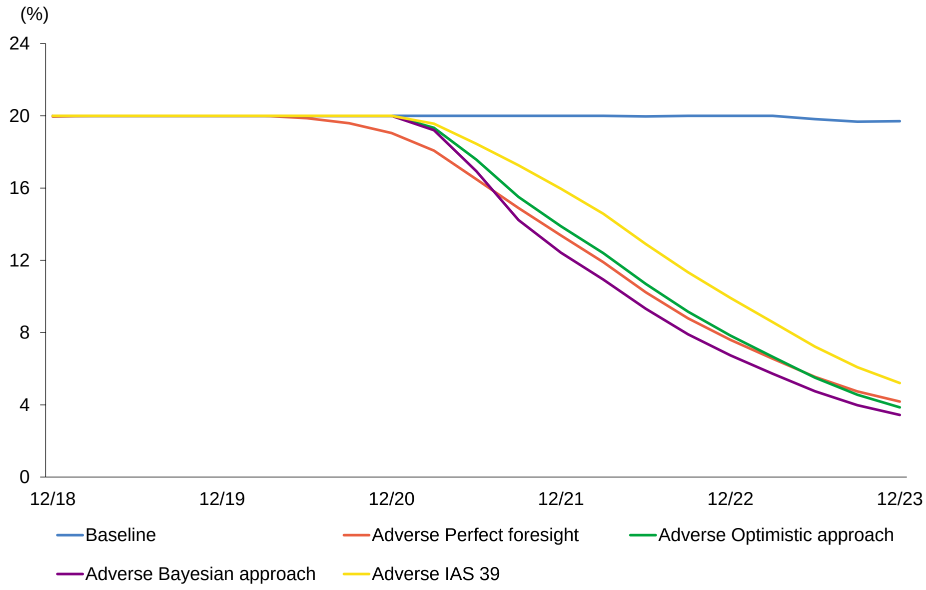
Note: The table provides a summary of selected results, such as the creation of loan loss provisions (LLP) and the effect on the capital adequacy ratio (CAR). All the provisions and dividend values are in units and represent cumulative values for the five years of the scenario. The CAR values are in percentages and represent the values at the end of the scenario.

In addition, as we demonstrated earlier it is not just the sheer amount, but also the timing of provisioning that is important as regards assessing the new standard. And the timing can be highly dependent on banks' expectations. Under the non-perfect foresight IFRS 9 approaches, banks are required to form a substantial amount of provisions during times of high stress, as can be seen in Figure 8. So, once again it seems that the crucial assumption in making IFRS 9 conclusively more appealing than IAS 39 is perfect foresight. If the assumptions of the perfect foresight approach held in reality, the amount of provisions created could even serve as an early-warning device, as the provisions would be formed earlier than under IAS 39 and ahead of the actual crisis. However, if these assumptions do not hold (which we expect to usually be the case in the real world), the new IFRS 9 accounting standard might actually behave in an even more pro-cyclical manner and thus might be even less desirable from the financial stability perspective than the preceding IAS 39 standard.

Figure 10 shows the path of the capital adequacy ratio under the presented scenarios and accounting standards/approaches to expectations. IFRS 9 causes banks to finish the simulation with a lower capital adequacy ratio by comparison with IAS 39 at the end of the five-year simulated horizon. But Figure 8 shows that the required flows of provisions are higher under IAS 39 than under IFRS 9 during the last year of the scenario. This demonstrates that IFRS 9 is actually less capital demanding during that period, and banks should also be better equipped with loss-absorbing capacity in the long term (especially under the perfect foresight and Bayesian approaches).

The model outputs can also be exploited to assess the potential underestimation of credit risk during the period modelled. A simple way to express this potential underestimation is to quantify it as the gap between the provisions required in order to fully cover the true level of the expected credit losses induced by the scenario (as captured by the perfect foresight approach, under which complete information about the macroeconomic path is available and fully utilised by banks at all times) and those which banks actually create under the selected approach at each time step.

Figure 10: CET1 Impact



Note: The figure shows the path of the CET1 capital adequacy ratio for each expectation type for the same underlying scenario. PF stands for perfect foresight.

The abrupt closure of this gap, which peaks at 11.1 units,[14] causes the cliff effect in the Bayesian approach observed in Figure 8 to be much stronger than that in the optimistic approach. On the other hand, this gap never completely closes in the optimistic approach during the period modelled and is 6.3 units on average, with a peak value of 12.2 units.[15] On first inspection, this appears to indicate that it might be more beneficial for banks to stay optimistic in their predictions than to fully admit the deterioration in macroeconomic conditions. Yet this would be offset in the longer term by different recovery paths, as the actual risks materialise in the same manner in each approach regardless of the expectations selected. This means the actual credit losses are ultimately the same for all the approaches. Hence, provisions and retained earnings matter in the long term, and we can conclude that any implementation of IFRS 9 provides a better cushion for further losses and allows for an easier recovery than IAS 39. Unfortunately, the recovery period beyond the five-year scenario modelled is not fully captured by the simulation. However, the consequences discussed above are already starting to become apparent in the last year of the simulated period (see Figure 8 and Figure 10).[16]

Comparing the results under the new IFRS 9 framework only, the perfect foresight approach ensures the strongest capital position among the approaches considered, due to its ability to conserve more capital through the early recognition of loan losses. However, as discussed earlier, the perfect foresight approach is probably not feasible in reality. In general, stress tests should be conducted according to the precautionary principle, meaning that all the relevant risks should be captured well and estimated in a prudential manner, as it is safer to cautiously overestimate uncertain risks in order to be confident they are not underestimated. Bearing that in mind, our results suggest that

[14] At that point this accounts for 12.5% of CET1.
[15] This accounts for 8.4% of CET1 on average and for 13.6% at the peak.
[16] The simulation exercise assumes 3% ROA, which is 7.5 units of income. This does not cover the necessary impairments at the end of the test, which means that the capital ratio would decrease further in all the approaches.

the perfect foresight approach might not be the optimal macroprudential stress-testing assumption, as the simulated solvency position might appear stronger than it would have been in reality, where non-perfect foresight generally applies and loan loss provisioning is driven by the expectations of individual banks.

5. Conclusion

Since 2018, the majority of EU banks have been following the new accounting rules set out in the IFRS 9 standard, which replaced IAS 39. This new approach was created with the clear aim to be less pro-cyclical and to support the resilience of the banking sector by improving loan loss provisioning. While the previous standard was based on the incurred loss framework, the new standard is designed to be more forward-looking and to take into account the current and expected macroeconomic environment. This paper uses an augmented version of the Czech National Bank's macroprudential stress-testing framework to simulate different types of expectations and their impact on timely provisioning and ultimately to assess their influence on the solvency position.

The paper starts with an overview of the key features of IFRS 9 and presents a possible way of implementing these features into a top-down stress-testing framework. The new standard requires the calculation of expected credit losses, which strongly depend on expectations about future macroeconomic conditions. We present and compare three different types of expectations under IFRS 9 with the previous IAS 39 standard using a theoretical portfolio of retail consumer loans over a five-year horizon.

IFRS 9 behaves as intended for the examined portfolio, but largely under the perfect foresight approach only. However, this assumption is not expected to be met in reality, and real expectations might tend to underestimate the length and/or severity of a crisis. Such behaviour would lead to significantly pro-cyclical provisioning, with a potential cliff effect in the midst of a crisis as diminishing profits put banks' capital adequacy ratios under pressure. This has potential implications for the financial stability of the system. Our results suggest that under these assumptions, IFRS 9 might be even more pro-cyclical than its predecessor IAS 39.

The paper argues that the commonly employed perfect foresight approach, though theoretically appealing, might not be the optimal assumption in terms of the precautionary principle of stress testing, as it can potentially underestimate the risks in the banking system. These risks stem from inherent uncertainties about future economic developments limiting the forward-looking features of the new standard. In the real world, neither banks nor their supervisors and auditors are gifted with perfect foresight, and their expectations might differ substantially from the future macroeconomic reality. Thus, expectations might often turn out to be overly optimistic in terms of both the length and severity of the economic downturn (as has happened many times in the past). This would reduce capital conservation and loss-absorbing capacity during a crisis. In addition, the cliff effect caused by late recognition of the actual severity of a downturn could severely affect banks' capital adequacy ratios and exacerbate the vulnerabilities in the financial system.

Comparing our results with the evidence presented in the academic literature, we agree with the conclusions of Novotny-Farkas (2016) that the benefits of the new standard for financial stability will crucially depend on its application in practice. Similarly to Krüger et al. (2018), this paper shows that the aim of reducing the cyclicality of provisions might not be fully met, as the new standard might be even more pro-cyclical depending on expectations and how those expectations differ from the future reality. On the other hand, our exercise suggests that the new accounting standard forces banks to create higher total provisions than IAS 39, which contradicts the conclusion of Krüger et al. (2018).

Abad and Suarez (2017) investigated possible cyclical effects of IFRS 9 using perfect foresight on the corporate loans portfolio. They concluded that IFRS 9 might imply more sudden rises in loan loss provisions when the cyclical position of the economy switches from expansion to contraction, and that CET1 capital might decline more sharply at the start of these episodes. This is fully in line with our findings. For the financial stability of the system, it is therefore important not to ignore the potential warning signals and use capital buffers in a proper and sufficiently prudential manner.

Last but not least, we feel it is important to emphasise the growing need for enhanced disclosure of the approaches to macroeconomic modelling which banks use in their IFRS 9 ECL models. Stress tests conducted by supervisors are an important tool for assessing the banking sector's resilience and for revealing hidden risks and vulnerabilities. Enhanced disclosure would be an important step towards understanding how the approaches employed by banks differ from those currently implemented in the stress-testing frameworks of their supervisors and should thus help those supervisors understand what data and modelling techniques they need to make future improvements to those frameworks.

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Na Příkopě 28, 115 03 Praha 1
Czech Republic
phone: +420 2 244 12 321
fax: +420 2 244 12 329
http://www.cnb.cz
e-mail: research@cnb.cz
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