

# Assessing the Procyclicality of Expected Credit Loss Provisions\*

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## Abstract

The Great Recession has pushed loan loss provisioning to shift from an incurred loss approach to an expected credit loss approach. IFRS 9 and the incoming update of US GAAP imply a more timely recognition of credit losses but also greater responsiveness to changes in aggregate conditions, which raises procyclicality concerns. This paper develops a recursive ratings-migration model to assess the impact of different provisioning approaches on the cyclicity of banks' profits and regulatory capital. Its application to a portfolio of European corporate loans allows us to quantify the importance of the procyclical effects.

*Keywords:* credit loss allowances, expected credit losses, incurred losses, rating migrations, procyclicality.

*JEL codes:* G21, G28, M41

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# 1 Introduction

The delayed recognition of credit losses under the incurred loss (IL) approach to loan loss provisioning was argued to have contributed to the severity of the Global Financial Crisis (Financial Stability Forum, 2009). By provisioning “too little, too late,” it might have prevented banks from being more cautious in good times and reduced the pressure for prompt corrective action in bad times. Based on this diagnosis, the G-20 called for a more forward-looking approach. As a result, the International Accounting Standards Board (IASB) and the US Financial Accounting Standards Board (FASB) developed reforms, namely IFRS 9 (entered into force in 2018) and an update of US GAAP (scheduled for 2021), which, with some differences, coincide in adopting an expected credit loss (ECL) approach to provisioning.<sup>1</sup>

Under the new approach, provisions are intended to represent best unbiased estimates of the discounted credit losses expected to emerge over some specified horizons. In the case of IFRS 9, the horizon varies from one year (for stage 1 exposures) to the residual lifetime of the credit instruments (for stage 2 and 3 exposures), depending on whether their credit quality has not or has deteriorated relative to the point at which the instrument was initially recognized. In contrast, the so-called current expected credit loss (CECL) model envisaged by US GAAP opts for using the residual lifetime horizon for all exposures. The general perception is that the ECL approach will increase the reliability of bank capital as a measure of solvency and facilitate prompt corrective action (European Systemic Risk Board 2017).

There are concerns, however, that, absent the capacity of banks to anticipate adverse shifts in aggregate conditions sufficiently in advance, the point-in-time nature of the estimates of ECLs might imply a more abrupt deterioration of profits and capital when the economy enters recession or a crisis starts, as it will be then and not before when the bulk of the implied future credit losses will be recognized (Barclays, 2017). The fear is that banks’ or markets’ reactions to such an increase (or to its impact on profits and regulatory capital) cause or amplify asset sales or a credit crunch, and end up producing negative feedback

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<sup>1</sup>See IASB (2014) and FASB (2016) for details.

effects on the evolution of the economy, making the contraction more severe.

This paper develops a recursive model with which to compare the impact on profits and capital of the new ECL approaches (IFRS 9 and CECL) relative to their less forward-looking alternatives (IL and the one-year expected loss approach behind the internal-ratings based approach to capital regulation). The model contains the minimal ingredients needed to assess the average levels and the dynamics of the allowances associated with a given loan portfolio and their implications for the profit or loss (P/L) and the common equity Tier 1 (CET1) of the bank holding such portfolio. The model is calibrated to capture the evolution of credit risk in a typical portfolio of European corporate loans over the business cycle and to compare the cyclical behavior of impairment allowances, P/L, and CET1 across the various impairment measurement approaches.

We address the modeling of ECLs in the context of a ratings-migration model with a compact description of credit risk categories, the economic cycle represented as a Markov chain, and loan maturity modeled as random. Each of these modeling strategies has a well-established tradition in economics and finance and their combination prevents us from having to keep track of loan vintages, producing a model which is overall highly tractable.<sup>2</sup> The model allows us to examine how the composition across credit risk categories of a bank's loan portfolio varies in response to changes in the cyclical position of the economy. From there, the model allows us to measure the provisions associated with the portfolio under the alternative approaches and their implication for the evolution of P/L and CET1.

To calibrate the model, we match the characteristics of a typical portfolio of corporate loans issued by European banks.<sup>3</sup> We use evidence on the sensitivity of rating migration matrices and credit loss parameters to business cycles, as in Bangia et al. (2002). We

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<sup>2</sup>Ratings-migration models are extensively used in credit risk modeling (see Trueck and Rachev, 2009, for an overview) and Gruenberger (2012) provides an early application of them to the analysis of IFRS 9. Hamilton (1989) showed the possibility of representing the cyclical phases and turning points identified in business cycle dating (e.g. by the NBER) using a binary Markov chain, and Bangia et al. (2002) and Repullo and Suarez (2013), among others, have used such representation in applications regarding fluctuations in credit risk. The modeling of debt maturity as random started with Leland and Toft (1996) and has been recently applied in a banking context by He and Xiong (2012), He and Milbradt (2014), and Segura and Suarez (2017), among others.

<sup>3</sup>The case of a bank fully specialized in European corporate loans must be interpreted as a “laboratory case” with which to run “controlled experiments” about the performance of the different provisioning methods.

find that the more forward-looking methods of IFRS 9 and CECL imply significantly larger impairment allowances, sharper on-impact responses to negative shocks than the old IL and one-year expected loss approaches, and the quicker return to normality of P/L and CET1 in the remaining years after a shock.

Under the baseline calibration of the model, the arrival of a typical recession implies on-impact increases in IFRS 9 and CECL provisions equivalent to about a third of a bank's fully loaded capital conservation buffer (CCB) or, equivalently, about twice as large as those implied by the IL approach.<sup>4</sup> This suggests that the differential impact under the new approaches is sizeable but still suitably absorbable if banks' CCB is sufficiently loaded when the shock hits. As we show, the results depend very highly on the degree to which turning points imply bigger or smaller surprises relative to what banks have anticipated in advance. We show that the sudden arrival of a contraction that is anticipated to be more severe or longer than average will tend to produce sharper responses, while forecasting a recession one or several years in advance would allow to significantly smooth away its impact on P/L and capital.

We are aware of just a few papers trying to assess the cyclical behavior of impairment allowances under the new provisioning approaches. Cohen and Edwards (2017) develop such analysis from a top-down perspective and relying on the historical evolution of aggregate bank credit losses in a number of countries. Chae et al. (2017) use a more bottom-up approach based on credit loss data for first-lien mortgages originated in California between years 2002 and 2015. Krüger, Rösch, and Scheule (2018) use historical simulation methods on portfolios constructed using bonds from Moody's Default and Recovery Database. The first two papers posit the conclusion that if banks are capable to perfectly foresee the incoming credit losses several years in advance, the new approaches will show smaller spikes in impairment allowances than the incurred loss approach when the economy situation deteriorates, which is consistent with what we obtain in the extension in which banks can anticipate the turning points in the evolution of the economy several periods in advance.<sup>5</sup> The results

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<sup>4</sup>Under Basel III, banks' reporting earnings must retain them until reaching a CCB (or buffer of capital on top of the regulatory minimum) equivalent to 2.5% of their risk-weighted assets.

<sup>5</sup>Chae et al. (2017) also show that, if instead the inputs of the credit loss model are predicted using a high-order autoregressive (AR) model based on information available at the time of producing the ECL estimate, the implied provisions (ALLL) spike only once the housing crisis starts. In their words, the "AR

in Krüger, Rösch, and Scheule (2018) are closer to our baseline results and leads the authors to conclude that the new provisioning rules “will further increase the procyclicality of bank capital requirements.”

According to our analysis, if banks fail to anticipate turning points well in advance or to adopt additional precautions during good times, the more forward-looking provisioning methods may paradoxically mean that banks experience more sudden falls in regulatory capital right at the beginning of contractionary phases of the business cycle.<sup>6</sup> Banks might accommodate these effects by consuming the capital buffers accumulated during good times, by cutting dividends or by issuing new equity. However, when confronted with these choices, banks often undertake at least part of the adjustment by reducing their risk-weighted assets (RWAs), for example by cutting the origination of new loans, selling some assets or rebalancing towards safer ones.<sup>7</sup>

Even in light of that evidence, our results do not necessarily imply that credit supply or asset sales will be more procyclical under the new provisioning standards and do not imply a negative overall assessment of the implications of IFRS 9 or CECL provisions for financial stability. First, because the final impact on credit supply or asset sales will depend on endogenous reactions by banks and other agents (e.g. in terms of precautionary buffers, lending policies, and investment policies), as well as general equilibrium effects, which our analysis abstracts from. Second, because the potential disadvantages of a sharper contraction of credit or larger asset sales at the beginning of a recession should be weighed against the advantages of having financial statements that reflect the weakness or strength of the reporting institutions in a more timely and reliable way, as there is evidence suggesting that this helps resolve bank crises in a prompter, safer, and more effective manner.<sup>8</sup> In this sense,

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forecast is not able to forecast the inflection point of home prices which leads to large increases in ALLL in early 2009.”

<sup>6</sup>In Appendix B, we document the difficulties faced by econometricians and professional forecasters to predict sufficiently in advance turning points in the business cycle.

<sup>7</sup>See, for example, Mésonnier and Monks (2015), Aiyar, Calomiris, and Wieladek (2016), Behn, Haselmann and Wachtel (2016), Gropp et al. (2016), and the references therein. The evidence in these papers is consistent with average bank responses to the ESRB Questionnaire on Assessing Second Round Effects that accompanied the EBA stress test in 2016. The questionnaire examined the way in which banks would expect to reestablish their desired levels of capitalization after exiting the adverse scenario.

<sup>8</sup>Laeven and Majnoni (2003) and Huizinga and Laeven (2012) document bank provisioning practices during economic slowdowns and their implications for financial stability. Beatty and Liao (2011) document that banks recognizing loan losses in a timelier manner experience lower reductions in lending during con-

the paper is a first step towards an assessment that will require further modeling, empirical and policy evaluation efforts as we accumulate evidence on the working of the new ECL provisioning methods and their impact on bank behavior.

The paper is organized as follows. Section 2 describes the model, develops formulas for measuring impairment losses under the various provisioning approaches and for assessing their effects on P/L and CET1. Section 3 calibrates the model and uses it to analyze the response to the arrival of a typical recession under the various measures. Having looked at banks operating under the internal ratings-based (IRB) approach to capital requirements as a benchmark, Section 4 analyzes the results in the case of a bank operating under the standardized approach. Section 5 describes several extensions. Section 6 discusses the implications of the results. Section 7 concludes the paper. Appendices A and B contain further details about the formulas of the version of the model with aggregate risk and its calibration, respectively.

## 2 The model

For expositional clarity, we first present the main assumptions and formulas of the model in a version without aggregate risk. Then we comment on the way in which the complete model incorporates aggregate risk by allowing all the credit risk parameters to vary with a variable describing the aggregate state of the economy. The notationally more intensive equations for the complete model are presented in Appendix A.

### 2.1 Main model assumptions

Consider a bank operating in an infinite-horizon discrete-time economy in which dates are denoted by  $t$ . The bank's assets consist solely of a portfolio of loans whose individual credit risk, in the absence of aggregate risk, is fully described by a rating category  $j$ . The dynamics of loan origination, rating migration, default, maturity, and pricing at origination of the loans that make up the bank's loan portfolio are contained in the ten assumptions described below.

The tree in Figure 1 summarizes the contingencies over the life of a loan.

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tractionary periods. Bushman and Williams (2012, 2015) document the link between a timely and decisive recognition of loan losses and banks' risk profiles. For a review of the literature on loan loss provisions and their interaction with bank regulation, see BSBC (2015).

Assumptions:

1. In each date  $t$ , the bank's existing loans belong to one of three credit rating categories: standard ( $j=1$ ), substandard ( $j=2$ ) or non-performing ( $j=3$ ). We denote the measure of loans of each category as  $x_{jt}$ .
2. In each date  $t$ , the bank originates a continuum of standard loans of measure  $e_{1t} > 0$ , with a principal normalized to one and a constant interest payment per period equal to  $c$  (whose endogenous determination is described below). In the language of IFRS 9,  $c$  is the effective contractual interest rate at which future ECLs must be discounted. Throughout the analysis, we will further assume an exogenous steady flow of entry of new loans  $e_{1t} = e_1$  at each date  $t$ .
3. Each loan's exposure at default (EAD) is constant and equal to one up to maturity.
4. Performing loans mature randomly and independently. Specifically, loans rated  $j=1, 2$  mature at the end of each period with a constant probability  $\delta_j$ .<sup>9</sup> This implies that, conditional on remaining in rating  $j$ , a loan's expected life span is of  $1/\delta_j$  periods. By the law of large numbers, the fraction of loans of a given rating  $j$  that mature at the end of each period is  $\delta_j$ . In steady state, this produces a stream of maturity cash flows very similar to those that would emerge with a portfolio of perfectly-staggered loans with identical deterministic maturities at origination.
5. Non-performing loans (NPLs, identified by  $j=3$ ) are resolved randomly and independently. For this loan category,  $\delta_j$  represents the independent per period probability of a loan being resolved. Resolution means that the loan pays back a fraction  $1 - \lambda$  of its principal and exits the portfolio. So  $\lambda$  is the loss rate at resolution, which in the absence of aggregate risk (or if  $\lambda$  is not affected by aggregate state of the economy

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<sup>9</sup>Allowing for  $\delta_1 \neq \delta_2$  may help capture the possibility that longer maturity loans get early redeemed with different probabilities depending on their credit quality.

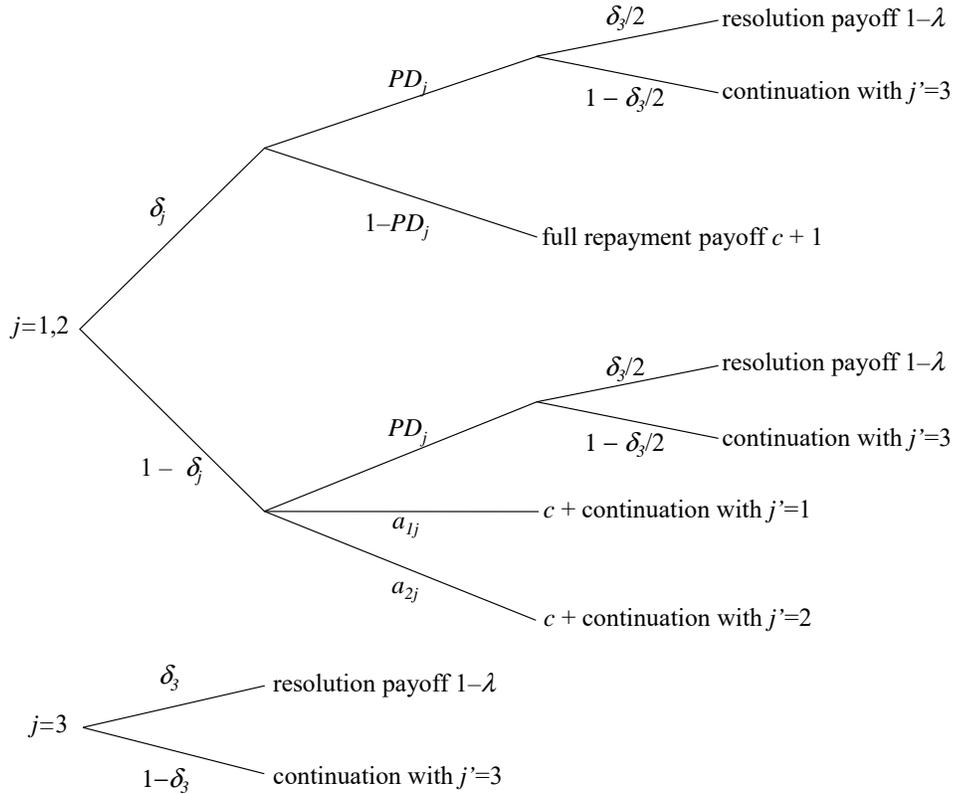
when resolution occurs) coincides with the expected loss given default (LGD) of the loan.

6. Each loan rated  $j=1, 2$  at  $t$  that matures at  $t+1$  defaults independently with probability  $PD_j$ . Maturing loans that do not default pay back their principal of one plus interest  $c$ . Each defaulted loan is resolved within the same period with an independent probability  $\delta_3/2$ .<sup>10</sup> Otherwise, it enters the stock of NPLs ( $j=3$ ).
7. Each loan rated  $j=1, 2$  at  $t$  that does not mature at  $t + 1$  goes through one of the following exhaustive possibilities:
  - (a) Default, which occurs independently with probability  $PD_j$ . As in the case when a maturing loan defaults, a non-maturing loan that defaults is resolved within the same period with probability  $\delta_3/2$ , yielding  $1 - \lambda$ . Otherwise, it enters the stock of non-performing loans ( $j=3$ ).
  - (b) Migration to rating  $i \neq j$  ( $i=1,2$ ), which occurs independently with probability  $a_{ij}$ . In this case the loan pays interest  $c$  and continues for one more period with its new rating.
  - (c) Staying in rating  $j$ , which occurs independently with probability  $a_{jj} = 1 - a_{ij} - PD_j$ . In this case the loan pays interest  $c$  and continues for one more period with its previous rating.
8. NPLs ( $j=3$ ) pay no interest and never return to the performing categories, so they accumulate in category  $j=3$  up to their resolution.<sup>11</sup>

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<sup>10</sup>We divide  $\delta_3$  by two to reflect the fact that, if loans default uniformly during the period between  $t$  and  $t+1$ , they will, on average, have just half a period to be resolved. Given that the calibration relies on one-year periods and the resolution rate is large, this refinement is important to realistically describe NPL dynamics. The model could easily accommodate alternative assumptions on same-period resolutions.

<sup>11</sup>For calibration purposes, it is possible to account for potential gains from the unmodelled interest accrued while in default or from returning to performing categories by adjusting the loss rate  $\lambda$ .



**Figure 1. Possible transitions of a loan rated  $j$ .** Possible contingencies between two dates and their implications for payoffs and continuation value. Variables on each branch describe marginal conditional probabilities.

9. The contractual interest rate  $c$  is established at origination as in a perfectly competitive environment with risk-neutral fully-solvent banks that face an opportunity cost of funds between any two periods equal to a constant  $r$ . The originating bank is assumed to hold the loans up to their maturity.<sup>12</sup>

10. Finally, one period corresponds to a calendar year, and dates  $t, t + 1, t + 2$ , etc. denote year-end accounting reporting dates (so “period  $t$ ” ends at “date  $t$ ”).

As further described in Section 2.6, we will add aggregate risk to this structure by allowing all the parameters in the tree depicted in Figure 1 to potentially vary with a variable

<sup>12</sup>In the language of IFRS 9, this implies that the loans satisfy the “business model” condition required for basic lending assets to be measured at amortized cost.

representing the aggregate state of the economy.

## 2.2 Portfolio dynamics

By the law of large numbers, the evolution of the loans in each rating can be represented by the following difference equation:

$$x_t = Mx_{t-1} + e_t \quad (1)$$

where

$$x_t = \begin{pmatrix} x_{1t} \\ x_{2t} \\ x_{3t} \end{pmatrix} \quad (2)$$

is the vector that describes the loans in each rating category  $j=1,2,3$ ;

$$M = \begin{pmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{pmatrix} = \begin{pmatrix} (1 - \delta_1)a_{11} & (1 - \delta_2)a_{12} & 0 \\ (1 - \delta_1)a_{21} & (1 - \delta_2)a_{22} & 0 \\ (1 - \delta_3/2)PD_1 & (1 - \delta_3/2)PD_2 & (1 - \delta_3) \end{pmatrix} \quad (3)$$

is the matrix that accounts for the migrations across categories of the non-matured, non-resolved loans, and

$$e_t = \begin{pmatrix} e_{1t} \\ 0 \\ 0 \end{pmatrix} \quad (4)$$

accounts for the new loans originated at each date, which we write reflecting the fact that, as previously assumed, all loans have rating  $j=1$  at origination.

When computing some moments relevant for the calibration of the model, we will weight each rating category by its share in the steady-state portfolio  $x^*$  that would asymptotically be reached, in the absence of aggregate risk, if the amount of newly originated loans is equal at all dates ( $e_t = e$  for all  $t$ ). Such steady-state portfolio can be obtained as the vector that solves:

$$x = Mx + e \Leftrightarrow (I - M)x = e, \quad (5)$$

that is,

$$x^* = (I - M)^{-1}e. \quad (6)$$

## 2.3 Measuring impairment losses

In the following subsections we provide formulas for impairment allowances under the four different approaches that we are interested in comparing.

### 2.3.1 Incurred losses

Under the narrowest interpretation, allowances measured on an incurred loss basis (that is, upon clear evidence of impairment) are restricted to the losses associated with existing NPLs. With this criterion, provisions at year  $t$  under the IL approach would be

$$IL_t = \lambda x_{3t}, \quad (7)$$

since the loss rate  $\lambda$  is the expected LGD of the bank's NPLs at date  $t$ . Note that, under our assumptions, the losses associated with loans defaulted between dates  $t - 1$  and  $t$  which are resolved within such period,  $\lambda(\delta_3/2)(PD_1x_{1t-1} + PD_2x_{2t-1})$ , do not enter  $IL_t$  and therefore will be directly recorded in the P/L of year  $t$ .

### 2.3.2 Discounted one-year expected losses

For consistency with the measure of expected losses applied to stage 1 exposures under IFRS 9, we define the one-year discounted expected losses as

$$EL_t^{1Y} = \lambda [\beta(PD_1x_{1t} + PD_2x_{2t}) + x_{3t}] \quad (8)$$

where  $\beta = 1/(1 + c)$  is the discount factor based on the contractual interest rate of the loan,  $c$ . Accordingly, for loans performing at  $t$  (rated  $j=1, 2$ ), impairment allowances are computed as the discounted expected losses due to default events expected to occur within the immediately incoming year. They are therefore forward-looking, but the forecasting horizon is limited to one year. Instead, for NPLs ( $j=3$ ), the default event has already happened and the allowances equal the expected LGD of the loans, exactly as in  $IL_t$ .

Roughly speaking,  $EL_t^{1Y}$  coincides with the notion of expected losses prescribed for regulatory purposes for banks following the IRB approach to capital requirements.<sup>13</sup> In matrix notation, which will be useful when comparing the different impairment allowance measures later on,  $EL_t^{1Y}$  can also be expressed as

$$EL_t^{1Y} = \lambda (\beta b x_t + x_{3t}), \quad (9)$$

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<sup>13</sup>Differences between the BCBS prescriptions on expected losses for IRB banks and our definition of  $EL_t^{1Y}$  include the absence of discounting ( $\beta = 1$ ) and the preference for using through-the-cycle (rather than point-in-time) PDs, as well as the use LGD parameters that reflect a distressed liquidation scenario rather than a central scenario. To simplify the analysis, we abstract from all these differences when taking  $EL_t^{1Y}$  as a proxy of IRB banks' regulatory provisions.

where

$$b = (PD_1, PD_2, 0). \quad (10)$$

### 2.3.3 Discounted lifetime expected losses

The definition for discounted lifetime expected losses arises if, instead of considering the discounted expected losses due to default events expected to occur within the immediately incoming year, we consider default events expected to occur over the whole residual lifetime of the loans:

$$EL_t^{LT} = \lambda b (\beta x_t + \beta^2 M x_t + \beta^3 M^2 x_t + \beta^4 M^3 x_t + \dots) + \lambda x_{3t}, \quad (11)$$

This measure reflects the fact that the losses expected from currently performing loans at any future year  $t + \tau$ , with  $\tau = 1, 2, 3, \dots$  can be found as  $\lambda b M^{\tau-1} x_t$ , where  $b$  contains the relevant one-year-ahead PDs (see (10)) and  $M^{\tau-1} x_t$  gives the projected composition of the portfolio at each future year  $t + \tau - 1$ . It also reflects that the allowance for NPLs again equals the expected LGD of the affected loans.

Roughly speaking,  $EL_t^{LT}$  coincides with the notion of CECL adopted by FASB for the incoming update of US GAAP.<sup>14</sup> Equation (11) can also be expressed as

$$EL_t^{LT} = \beta \lambda b (I + \beta M + \beta^2 M^2 + \beta^3 M^3 + \dots) x_t + \lambda x_{3t}, \quad (12)$$

where the parenthesis is the infinite sum of a geometric series of matrices, which can be found as

$$B = (I - \beta M)^{-1}. \quad (13)$$

Thus, using matrix notation, we can write  $EL_t^{LT}$  as

$$EL_t^{LT} = \lambda (\beta b B x_t + x_{3t}), \quad (14)$$

Since obviously  $B \geq I$ , we have  $EL_t^{LT} \geq EL_t^{1Y}$ .

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<sup>14</sup>Opposite to IFRS 9, under the update of US GAAP, the discount factor  $\beta$  will not be based on the effective contractual interest rate of the loan, but on a reference risk-free rate. However, to limit the number of features producing differences between the various compared approaches, we will use the same value of  $\beta$  (the one prescribed by IFRS 9) throughout the analysis.

### 2.3.4 Impairment allowances under IFRS 9

As already mentioned, IFRS 9 adopts, for performing loans, a mixed-horizon approach that combines the one-year and lifetime expected loss approaches described above. Specifically, the allowances for loans that have not suffered a significant increase in credit risk since origination (“stage 1” loans or, in our model, the loans in  $x_{1t}$ ) must equal their one-year expected losses, while the allowances for performing loans with deteriorated credit quality (“stage 2” loans or, in our model, the loans in  $x_{2t}$ ) must equal their lifetime expected losses. Finally, for NPLs (“stage 3” loans or, in our model, the loans in  $x_{3t}$ ), the allowance simply equals the (non-discounted) expected LGD, as under any of the other approaches.

Combining the formulas obtained in (9) and (14), the impairment allowances under IFRS 9 can be described as

$$EL_t^{IFRS9} = \lambda\beta b \begin{pmatrix} x_{1t} \\ 0 \\ 0 \end{pmatrix} + \lambda\beta b B \begin{pmatrix} 0 \\ x_{2t} \\ 0 \end{pmatrix} + \lambda x_{3t}, \quad (15)$$

which, together with  $EL_t^{LT} \geq EL_t^{1Y}$ , implies  $EL_t^{1Y} \leq EL_t^{IFRS9} \leq EL_t^{LT}$ .

## 2.4 Loan rates under competitive pricing

Taking advantage of the recursivity of the model, we can obtain the bank’s ex-coupon value of loans rated  $j$  at any given date,  $v_j$ , by solving the following system of Bellman-type equations:

$$v_j = \mu [(1 - PD_j)c + (1 - PD_j)\delta_j + PD_j(\delta_3/2)(1 - \lambda) + m_{1j}v_1 + m_{2j}v_2 + m_{3j}v_3], \quad (16)$$

for  $j=1, 2$ , and

$$v_3 = \mu [\delta_3(1 - \lambda) + (1 - \delta_3)v_3], \quad (17)$$

where  $\mu = 1/(1 + r)$  is the discount factor of the risk neutral bank. Intuitively, the square brackets in (16) and (17) contain the payoffs and continuation value that a loan rated  $j=1, 2$  or  $j=3$ , respectively, will produce in the contingencies that, in each case, can occur one period ahead (weighted by the corresponding probabilities).<sup>15</sup>

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<sup>15</sup>For calibration purposes, the discount rate  $r$  does not need to equal the risk-free rate. One might adjust the value of  $r$  to reflect the marginal weighted average costs of funds of the bank or even an extra element capturing (in reduced form) a mark-up applied on that cost if the bank is not perfectly competitive.

In (16), contingencies producing payoffs are, in order of appearance, the payment of interest on non-defaulted loans, the repayment of principal by the non-defaulted loans that mature, and the recovery of terminal value on defaulted loans resolved within the period. The last three terms contain continuation value under the three rating categories that can be reached one period ahead. Similarly, (17) reflects the terminal value recovered if an NPL is resolved within the period and the continuation value kept otherwise.

Under perfect competition, the value of extending a unit-size loan of standard quality ( $j=1$ ) must equal the value of its principal,  $v_1 = 1$ , so that the bank obtains zero net present value from its origination. Thus we obtain the endogenous contractual interest rate of the loan,  $c$ , as the one that solves this equation.<sup>16</sup>

## 2.5 Implications for P/L and CET1

To explore the implications of impairment measurement for the dynamics of the P/L account and for CET1, we need to make further assumptions regarding the bank's capital structure. To simplify, we abstract from bank failure and assume that the bank's only assets at the end of any period  $t$  are the loans described by vector  $x_t$  and that its liabilities consist exclusively of (i) one-period risk-free debt  $d_t$  that promises to pay interest  $r$  per period, (ii) the loan loss allowances  $LL_t$  computed under one of the measurement approaches described above (so  $LL_t = IL_t, EL_t^{1Y}, EL_t^{LT}, EL_t^{IFRS9}$ ), and (iii) CET1 denoted by  $k_t$ . This means that the bank's balance sheet at the end of any period  $t$  can be described as

$$\begin{array}{c|c} x_{1t} & d_t \\ x_{2t} & LL_t \\ x_{3t} & k_t \end{array} \quad (18)$$

with the law of motion of  $x_t$  described by (1) and the law of motion of  $k_t$  given by

$$k_t = k_{t-1} + PL_t - \text{div}_t + \text{recap}_t, \quad (19)$$

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<sup>16</sup>The model could easily accommodate departures from perfect competition or the presence of some loan origination costs by modifying the equations presented in this section. In our calibration of the model, we will take the simpler (reduced form) route of calibrating the discount factor  $\mu$  so as to match the average observed loan rates among the loans to which we apply the model.

where  $PL_t$  is the result of the P/L account at the end of period  $t$ ,  $\text{div}_t \geq 0$  are cash dividends paid at the end of period  $t$ , and  $\text{recap}_t \geq 0$  are injections of CET1 at the end of period  $t$ . Under these assumptions, the dynamics of  $d_t$  can be recovered residually from the balance sheet identity,  $d_t = \sum_{j=1,2,3} x_{jt} - LL_t - k_t$ .

The result of the P/L account can in turn be written as

$$PL_t = \left\{ \sum_{j=1,2} \left[ c(1-PD_j) - \frac{\delta_3}{2} PD_j \lambda \right] x_{jt-1} - \delta_3 \lambda x_{3t-1} \right\} - r \left( \sum_{j=1,2,3} x_{jt-1} - LL_{t-1} - k_{t-1} \right) - \Delta LL_t, \quad (20)$$

where the first term contains the income from performing loans net of realized losses on defaulted loans resolved during period  $t$ , the second term is the interest paid on  $d_{t-1}$ , and the third term is the variation in credit loss allowances between periods  $t-1$  and  $t$ .

To model dividends,  $\text{div}_t$ , and equity injections,  $\text{recap}_t$ , in a simple manner, we assume that the bank manages the evolution of its CET1 using a simple *sS*-rule based entirely on existing capital regulations.<sup>17</sup> Specifically, current Basel III prescriptions include the minimum capital requirements and the so-called capital conservation buffer (CCB). Minimum capital requirements force the bank to operate with a CET1 of at least  $\underline{k}_t$ , while the CCB requires the bank to retain profits, whenever feasible, until reaching a fully loaded buffer equal to 2.5% of its RWAs. This means that a bank with positive profits must accumulate them until its CET1 reaches a level  $\bar{k}_t = 1.3125 \underline{k}_t$ .<sup>18</sup>

Thus, we assume the bank's dividends and equity injections to be determined as

$$\text{div}_t = \max[(k_{t-1} + PL_t) - 1.3125 \underline{k}_t, 0], \quad (21)$$

$$\text{recap}_t = \max[\underline{k}_t - (k_{t-1} + PL_t), 0]. \quad (22)$$

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<sup>17</sup>This rule can be rationalized as the one that minimizes the equity capital committed to support the loan portfolio and is consistent with the view that banks find equity financing more costly than debt financing. However, for simplicity, we effectively consider the limit case where the excess cost of equity financing goes to zero (so that, for instance, the loan pricing equations described above do not depend on the bank's capital structure). Additionally, the working of the *sS* rule proposed here implicitly assumes the absence of fixed costs associated with the raising of new equity. If such costs were to be introduced, the optimal rule would imply, as in Fischer, Heinkel, and Zechner (1989), discrete recapitalizations to an endogenous level within the bands if the lower band were to be otherwise passed.

<sup>18</sup>Under Basel III, RWAs equal 12.5 (or 1/0.08) times the bank's minimal required capital  $\underline{k}_t$ . Thus a fully loaded CCB amounts to a multiple  $0.025 \times 12.5 = 0.3125$  of  $\underline{k}_t$ .

**Minimum capital requirement under the IRB approach** For portfolios operated under the IRB approach, the IRB formula specified in BCBS (2004, paragraph 272) establishes that the regulatory capital requirement must be

$$\underline{k}_t^{IRB} = \sum_{j=1,2} \gamma_j x_{jt}, \quad (23)$$

with

$$\gamma_j = \lambda \frac{1 + [(1/\delta_j) - 2.5]m_j}{1 - 1.5m_j} \left[ \Phi \left( \frac{\Phi^{-1}(PD_j) + \text{cor}_j^{0.5} \Phi^{-1}(0.999)}{(1 - \text{cor}_j)^{0.5}} \right) - PD_j \right], \quad (24)$$

where  $m_j = [0.11852 - 0.05478 \ln(PD_j)]^2$  is a maturity adjustment coefficient,  $\Phi(\cdot)$  denotes the cumulative distribution function of a standard normal distribution, and  $\text{cor}_j$  is a correlation coefficient fixed as  $\text{cor}_j = 0.24 - 0.12(1 - \exp(-50PD_j))/(1 - \exp(-50))$ .<sup>19</sup>

**Minimum capital requirement under the standardized (SA) approach** For banks or portfolios operated under the SA approach, the regulatory minimum capital requirement applicable to loans to corporations without an external rating is just 8% of the exposure net of its “specific provisions,” a regulatory concept related to impairment allowances (BCBS, 2004, paragraphs 52, 66 and 75). Assuming that all the loans in  $x_t$  correspond to unrated borrowers and that all the loan loss allowances  $LL_t$  qualify as specific provisions, this implies that

$$\underline{k}_t^{SA} = 0.08 \left( \sum_{j=1,2,3} x_{jt} - LL_t \right). \quad (25)$$

Formulas (23) and (25) will allow us to assess the impact of different impairment measurement methods on the dynamics of  $PL_t$ ,  $k_t$ ,  $\text{div}_t$ , and  $\text{recap}_t$  under each of the approaches to capital requirements.

It is important to notice that, as a first approximation, our analysis abstracts from the existence of “regulatory filters” dealing with the implications of possible discrepancies between “accounting” and “regulatory” provisions and their effects on “regulatory capital.” In this sense, our assessment can be seen as an evaluation of the impact of accounting rules on bank capital dynamics in the extreme event that bank capital regulators accept the new

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<sup>19</sup>In (24) we measure the maturity of performing loans as the expected residual maturity  $1/\delta_j$  implied by our formulation.

accounting provisions (and the resulting accounting capital) as provisions (and available capital) for regulatory purposes as well.<sup>20</sup>

## 2.6 Adding aggregate risk

As anticipated above, we introduce aggregate risk in the model by considering an aggregate state variable  $s_t$  whose evolution affects the key parameters governing portfolio dynamics and credit losses in the structure described above. To keep things simple, we assume that  $s_t$  follows a Markov chain with two states  $s=1,2$  and time-invariant transition probabilities  $p_{s's} = \text{Prob}(s_{t+1} = s' | s_t = s)$ . In this representation,  $s=1$  could identify expansion or quiet periods, while  $s=2$  could identify contraction or crisis periods.

In Appendix A we present the model equations and the formulae for the calculation of impairment allowances for the case in which the parameters determining the (expected) maturity of the loans, default probabilities, rates of migration across ratings, probabilities of being resolved when in default, loss rates upon resolution, and the origination of new loans between any dates  $t$  and  $t + 1$  may vary with the arrival state  $s_{t+1}$ .

In short, the approach that allows us to keep the analysis recursive as in the baseline model is to expand the vectors describing loan portfolios so that components describe “loans originated in state  $z$ , currently in state  $s$  and rated  $j$ ”, for each possible  $(z, s, j)$  combination, instead of just “loans rated  $j$ ”. In parallel, we expand the transition matrices describing the dynamics of these portfolios to reflect the possible transitions of the aggregate state and their impact on all the relevant parameters. The need to keep track of the state at origination  $z$  comes from the IFRS 9 prescription that future credit losses of each loan must be discounted using the effective contractual interest rate, which now varies with the aggregate state at origination and is denoted  $c_z$ .

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<sup>20</sup>In the case of banks operating under the IRB approach, the current regulatory regime (which might be revised to accommodate the expected credit loss approaches in accounting) relies on a notion of one-year expected losses similar to  $EL_t^{1Y}$ , say  $REL_t^{1Y}$ . If  $REL_t^{1Y}$  exceeds the accounting allowances,  $LL_t$ , the difference,  $REL_t^{1Y} - LL_t$ , must be subtracted from CET1. By contrast, if  $REL_t^{1Y} - LL_t < 0$ , the difference can be added back as Tier 2 capital up to a maximum of 0.6% of the bank’s credit RWAs. In the case of SA banks, there is a filter for general provisions (which, for simplicity, we assume to be zero in our analysis), which can be added back as Tier 2 capital up to a maximum of 1.25% of credit RWAs.

## 3 Baseline quantitative results

### 3.1 Calibration

Table 1 describes the calibration of the baseline model under a parameterization intended to represent a typical portfolio of corporate loans issued by EU banks. Given the absence of detailed publicly available microeconomic information on such a portfolio, the calibration relies on matching aggregate variables taken from recent European Banking Authority (EBA) reports and European Central Bank (ECB) statistics using rating migration and default probabilities consistent with the Global Corporate Default reports produced by Standard & Poor’s (S&P) over the period 1981-2015.<sup>21</sup> The probabilities of default (PDs) and yearly probabilities of migration across our standard and substandard categories are extracted from S&P rating migration data using the procedure described in Appendix B. These probabilities are consistent with the alignment of our standard category ( $j=1$ ) with ratings AAA to BB in the S&P classification and our substandard category ( $j=2$ ) with ratings B to C.

In a nutshell, to reduce the  $7 \times 7$  rating-migration probabilities and the seven PDs extracted from S&P data to the  $2 \times 2$  migration probabilities and two PDs that appear in matrix  $M$  (equation (3)), we calculate weighted averages that take into account the steady-state composition that the loan portfolio would have under its 7-ratings representation in the absence of aggregate risk. To obtain this composition, we assume that loans have an average duration of 5 years (or  $\delta_1=\delta_2=0.2$ ) as reflected in Table 1; that they have a rating BB at origination, and that they then evolve (through improvements or deteriorations in their credit quality before defaulting or maturing) exactly as in our model, but with the seven non-default rating categories in the original S&P data.

As explained further in section B.2 of Appendix B, we allow for state-variation in the probabilities of loans migrating across rating categories and into default in a way consistent with the historical correlation between those variables (as observed in S&P rating-migration data) and the US business cycle as dated by the National Bureau of Economic Research (NBER).<sup>22</sup> The dynamics of the aggregate state as parameterized in Table 1 imply that the

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<sup>21</sup>We use reports equivalent to S&P (2016) published in years 2003 and 2005-2016, which provide the relevant information for each of the years between 1981 and 2015.

<sup>22</sup>See <http://www.nber.org/cycles.html>.

average duration of expansion and contraction periods is 6.75 years and 2 years, respectively, meaning that the system spends about 77% of the time in state  $s=1$ . Expansions are characterized by significantly smaller PDs among both standard and substandard loans than contractions. During a contraction, the probability of standard loans being downgraded (or, under IFRS 9, moved into stage 2) is almost double than during an expansion and the probability of substandard loans recovering standard quality (or returning to stage 1) is reduced by about one-third.

**Table 1**  
**Calibration of the baseline model**

Parameters without variation with the aggregate state			
Banks' discount rate	$r$	1.8%	
Persistence of the expansion state ( $s=1$ )	$p_{11}$	0.852	
Persistence of the contraction state ( $s=2$ )	$p_{22}$	0.5	
		Expansion	Contraction
Parameters that can vary with aggregate arrival state		( $s'=1$ )	( $s'=2$ )
Yearly probability of migration $1 \rightarrow 2$ if not maturing	$a_{21}$	6.16%	11.44%
Yearly probability of migration $2 \rightarrow 1$ if not maturing	$a_{12}$	6.82%	4.47%
Yearly probability of default if rated $j=1$	$PD_1$	0.54%	1.91%
Yearly probability of default if rated $j=2$	$PD_2$	6.05%	11.50%
Loss given default	$\lambda$	36%	36%
Average time to maturity if rated $j=1$	$1/\delta_1$	5 years	5 years
Average time to maturity if rated $j=2$	$1/\delta_2$	5 years	5 years
Yearly probability of resolution of NPLs	$\delta_3$	44.6%	44.6%
Newly originated loans per period (all rated $j=1$ )	$e_1$	1	1

Under this calibration, the unconditional average yearly PDs for our standard and substandard categories are 0.9% and 7.3%, respectively. As shown in Table 2, given the composition of the ergodic portfolio, the unconditional average annual loan default rate equals 1.9%, which is below the average 2.5% PD for non-defaulted corporate exposures that EBA (2013, Figure 12) reports for the period from the first half of 2009 to the second half of 2012 for a sample of EU banks operating under the IRB approach. Conditional on being in an expansion and in a contraction, our calibration implies average annual loan default rates for performing loans of 1.36% and 3.43%, respectively.

To keep the potential sources of cyclical variation under control, we maintain the parameters determining the effective maturity of performing loans, the speed of resolution of NPLs, the LGD, and the flow of entry of new loans as time invariant.

Banks' discount rate  $r$  is fixed at 1.8% so as to obtain an unconditional average of the contractual loan rate  $c$  equal to 2.54%, which is very close to the 2.52% average interest rate of new corporate loans made by Euro Area banks in the period from January 2010 to September 2016.<sup>23</sup>

**Table 2**  
**Endogenous variables under the baseline calibration**  
 (IRB bank, percentage of mean exposures unless indicated)

	Mean	St. Dev.	Conditional means	
			Expansions	Contractions
Yearly contractual loan rate $c$ (%)			2.52	2.62
Share of standard loans (%)	81.35	3.48	82.68	76.85
Share of substandard loans (%)	15.46	1.90	14.59	18.42
Share of NPLs (%)	3.19	1.05	2.73	4.73
Realized default rate (% of performing loans)	1.89	0.90	1.36	3.43
Impairment allowances:				
Incurred losses	1.15	0.38	0.98	1.70
One-year expected losses	1.79	0.50	1.55	2.60
Lifetime expected losses	4.65	0.59	4.36	5.63
IFRS 9 allowances	2.67	0.62	2.38	3.66
Stage 1 allowances	0.24	0.05	0.22	0.33
Stage 2 allowances	1.28	0.21	1.18	1.63
Stage 3 allowances	1.15	0.38	0.98	1.70
IRB minimum capital requirement	8.15	0.07	8.14	8.19
IRB minimum capital requirement + CCB	10.69	0.09	10.68	10.74

The LGD parameter  $\lambda$  is set equal to 36%, which roughly matches the average LGD on corporate exposures that the EBA (2013, Figures 11 and 13) reports for the period from the first half of 2009 to the second half of 2012 for the same sample as above. Regarding the resolution of NPLs, we set  $\delta_3$  equal to 44.6% in order to produce an unconditional average fraction of NPLs consistent with the 5% average PD, including defaulted exposures that the EBA (2013, Figure 10) reports for the earliest period in its study, namely the first half of 2008.<sup>24</sup> This value of  $\delta_3$  implies an average time to resolution for NPLs of 2.24 years, which

<sup>23</sup>We use the Euro area (changing composition), annualised agreed rate/narrowly defined effective rate on euro-denominated loans other than revolving loans and overdrafts, and convenience and extended credit card debt, made by banks to non-financial corporations (see [http://sdw.ecb.europa.eu/quickview.do?SERIES\\_KEY=124.MIR.M.U2.B.A2A.A.R.A.2240.EUR.N](http://sdw.ecb.europa.eu/quickview.do?SERIES_KEY=124.MIR.M.U2.B.A2A.A.R.A.2240.EUR.N)).

<sup>24</sup>We take this observation, right before experiencing the full negative impact of the Global Financial Crisis, as the best proxy in the data for the model's steady state. As shown in Table 2, with this procedure, we obtain an average 3.2% share of defaulted exposures in the ergodic portfolio, right inbetween the 2.5%

is very close to the 2.42-year average duration of corporate insolvency proceedings across EU countries documented by the EBA (2016, Figure 13).

Finally, the assumed size of the flow of newly originated loans,  $e_1=1$ , only provides a normalization and solely affects the average size of the bank’s total exposures. Further, we report most variables as a percentage of the bank’s total mean exposures (assets) making the absolute value of those exposures irrelevant in the analysis.

### 3.2 Size, volatility and cyclicity of the impairment measures

Table 2 reports unconditional means, standard deviations, and means conditional on each aggregate state for a number of endogenous variables. The variation in the aggregate state causes a significant variation in the composition of the bank’s loan portfolio. Not surprisingly, in the contraction state, substandard and non-performing loans represent a larger share of the portfolio, and the overall realized default rate is more than double than in the expansion state.

The mean relative sizes of the various impairment allowances are ranked as predicted above. While for the considered portfolio, impairment allowances under IFRS 9 ( $EL_t^{IFRS9}$ ) more than double those associated with the IL approach ( $IL_t$ ), the incoming CECL approach ( $EL_t^{LT}$ ) almost quadruples them. Note that higher level of allowances associated with IFRS 9 comes mostly from stage 2 loans in spite of the fact that these loans only represent a modest 15.5% in the loan portfolio. Interestingly, impairments measured under IFRS 9 are the most volatile, followed closely by the lifetime CECLs of the new US GAAP rules. The least volatile provisions are those computed under the IL approach.

The decomposition by stage shown for IFRS 9 reveals that allowances associated with NPLs, followed by those associated with substandard loans, are those that contribute most to cross-state variation in impairment allowances. However, NPLs are treated in the same way by all measures, which means that the differing volatilities of the various measures must stem from the treatment of standard loans (which is the same in  $EL^{1Y}$  and  $EL^{IFRS9}$ , but is different in  $IL$  and  $EL^{LT}$ ) and stage 2 loans (which is the same in  $EL^{LT}$  and  $EL^{IFRS9}$ , but

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and 4.4% reported by the EBA (2013, Figure 8) for corporate loans in the second half of 2008 and the first half of 2009, respectively. Conditional on being in an expansion and in a recession, the mean share of defaulted exposures equals 2.73% and 4.73%, respectively.

is different in  $IL$  and  $EL^{1Y}$ ) or from the cyclical shift of loans across stages 1 and 2 (under  $EL^{IFRS9}$ ).

Finally, Table 2 also reports the descriptive statistics of the implied overall minimum capital requirement ( $\underline{k}$ ) and the minimum requirement plus the CCB ( $\bar{k}$ ) that would apply to an IRB bank under our calibration. As noted in the titles of the tables and figures, in this section, we focus the analysis of the implications of the impairment measures for CET1 on the case of an IRB bank, leaving the comparison with the case of an SA bank for Section 4.

### 3.3 Impact on the cyclicity of P/L and CET1

Table 3 summarizes the impact of the various impairment measurement approaches on P/L and CET1 in the case of an IRB bank. The unconditional mean of P/L differs across provisioning methods, reflecting that different levels of provisions imply *de facto* different levels of debt financing for the same portfolio and, hence, different amounts of interest expense. Confirming what one might expect after observing the volatility ranking of the impairment measures in Table 2, P/L is significantly more volatile under the more forward-looking  $EL^{LT}$  and  $EL^{IFRS9}$  than under  $EL^{1Y}$  or  $IL$ .  $EL^{IFRS9}$  ( $IL$ ) is clearly the impairment measure producing the highest (lowest) volatility of P/L across aggregate states.

The more forward-looking impairment measures are the ones that make the bank, on average, more CET1-rich in expansion states and less CET1-rich in contraction states; that is, those that render CET1 more procyclical in this sense. In any case, the reported quantitative differences for this variable are not huge, in part because under our assumptions on the bank's management of its CET1, the range of variation in CET1 under any of the impairment measures is limited by the regulatory-determined bands of the  $sS$ -rule described in equations (21) and (22). As explained above, the bank adjusts its CET1 to remain within those bands by paying dividends or raising new equity.

Thus, a complementary way to assess the potential procyclicality associated with each impairment measure is to look at the frequency and size (conditional on them being strictly positive) of dividends and recapitalizations. Quite intuitively, under all measures we obtain that dividend distributions only occur (if at all) during periods of expansion, while recapitalizations only occur (if at all) during periods of contraction.

Relative to  $EL^{1Y}$ , the usage of  $EL^{IFRS9}$  implies an increase from 12% to 15% in the probability that the bank needs to be recapitalized during periods of contraction (mirrored by a more modest increase from 67% to 70% in the probability of dividends being paid during periods of expansion).<sup>25</sup> Instead, the usage of  $EL^{LT}$  reduces both the probability of having to recapitalize the bank in a contraction and the conditional size of the recapitalization needs. This striking difference (despite the similar standard deviation of P/L) is largely due to the higher mean value of P/L implied by the lower leverage kept by the bank under CECL.

**Table 3**  
**Endogenous variables under the baseline calibration**  
 (IRB bank, percentage of mean exposures unless otherwise indicated)

	$IL$	$EL^{1Y}$	$EL^{LT}$	$EL^{IFRS9}$
<hr/>				
P/L				
Unconditional mean	0.16	0.17	0.23	0.19
Conditional mean, expansions	0.35	0.41	0.49	0.46
Conditional mean, contractions	-0.46	-0.61	-0.66	-0.71
Standard deviation	0.34	0.43	0.51	0.50
CET1				
Unconditional mean	10.20	10.19	10.25	10.17
Conditional mean, expansions	10.38	10.43	10.53	10.46
Conditional mean, contractions	9.55	9.32	9.28	9.16
Standard deviation	0.76	0.76	0.71	0.77
Probability of dividends being paid (%)				
Unconditional	49.53	51.79	56.38	53.93
Conditional, expansions	64.20	67.11	73.07	69.89
Conditional, contractions	0	0	0	0
Dividends, if positive				
Conditional mean, expansions	0.35	0.36	0.42	0.38
Conditional mean, contractions	–	–	–	–
Probability of having to recapitalize (%)				
Unconditional	2.34	2.86	2.34	3.41
Conditional, expansions	0	0	0	0
Conditional, contractions	10.26	12.50	10.22	14.94
Recapitalization, if positive				
Conditional mean, expansions	–	–	–	–
Conditional mean, contractions	0.42	0.40	0.34	0.38

<sup>25</sup>However, these effects become counterbalanced by the fact that, when strictly positive, the average size of the recapitalizations needed (and dividends paid) under  $EL^{IFRS9}$  is slightly lower than that under  $EL^{1Y}$ .

### 3.4 Effects of the arrival of a contraction

Figure 2 shows the effects of the arrival of a contraction at  $t=0$  (that is, the realization of  $s_0=2$ ) after having spent a long enough period in the expansion state (that is, having had  $s_t=1$  for sufficiently many dates prior to  $t=0$ ). The results shown in the figure are equivalent to those typical of impulse response functions in macroeconomic analysis. From  $t=1$  onwards the aggregate state follows the Markov chain calibrated in Table 1, thus making the trajectories followed by the variables depicted in the figure stochastic. The figure depicts the average trajectories resulting from simulating 10,000 paths.

The higher amount of loans becoming substandard immediately after a recession arrives makes the effects of the arrival of a recession persistent over time, despite the relatively short duration of the contraction state under our baseline calibration (2 periods on average). This can be seen in Panel A of Figure 2, which depicts the evolution of NPLs.

The results regarding the evolution of the various impairment measures over the same time span appear in Panel B of Figure 2. The average trajectories of the impairment allowances  $IL_t$ ,  $EL_t^{1Y}$ ,  $EL_t^{LT}$ , and  $EL_t^{IFRS9}$  are reported as a percentage of the total initial loans. The levels of the series at  $t=-1$  reflect the different sizes of the impairment allowances obtained after a long expansion phase under each of the compared measurement methods. When the recession arrives at  $t=0$ , all the measures based on expected losses move upwards, on average, for one period before entering a pattern of exponential decay, driven by maturity, defaults, migration of substandard loans back to the standard category, and the continued origination of new standard-quality loans.<sup>26</sup> Because of its backward-looking nature,  $IL_t$  reacts more slowly, peaks on average after two periods, and then also falls gradually.

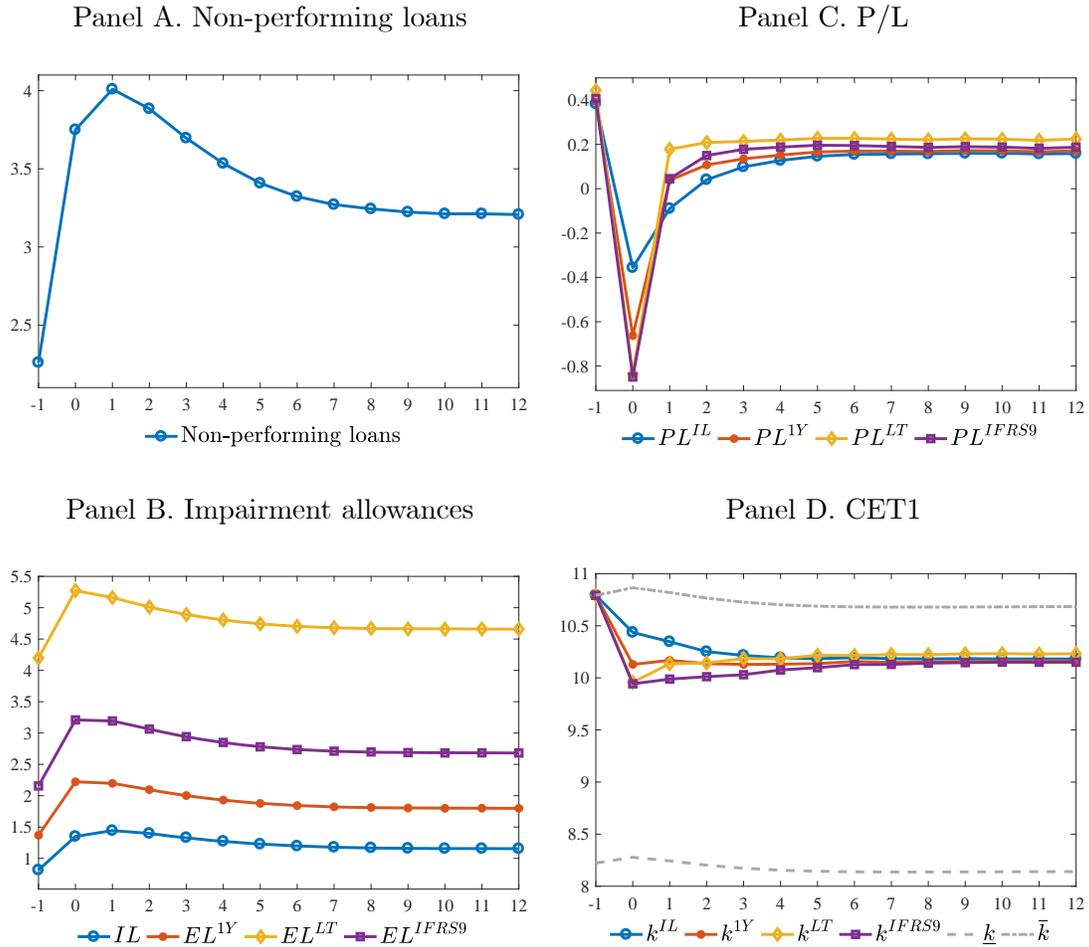
The on-impact responses of  $EL_t^{LT}$  and  $EL_t^{IFRS9}$  are larger than those of  $IL_t$  and  $EL_t^{1Y}$ . The on-impact response of  $EL_t^{IFRS9}$  exceeds slightly that of  $EL_t^{LT}$  because of the so-called “cliff effect” associated with the change in the provisioning horizon when exposures shift from stage 1 to stage 2.

The implications of the various impairment measures for P/L are described in Panel C

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<sup>26</sup>Variations of the experiment that simultaneously shut down or reduce origination of new loans for a number periods can be easily performed without losing consistency. Experiencing lower loan origination after  $t=0$  delays the process of reversion to the steady state but does not qualitatively affect the results.

of Figure 2. Essentially, each measure spreads the (same final average) impact of the shock on P/L over time in a different manner.  $EL_t^{IFRS9}$  and, to a slightly lesser extent,  $EL_t^{LT}$  front-load the impact of the shock to the extent that P/L becomes very negative on impact, but then positive and even above normal for a number of periods afterwards. With  $IL_t$ , P/L is affected much less on impact but remains negative for several periods. Interestingly, the measure which allows P/L to return to normal the soonest on average is  $EL_t^{LT}$ .



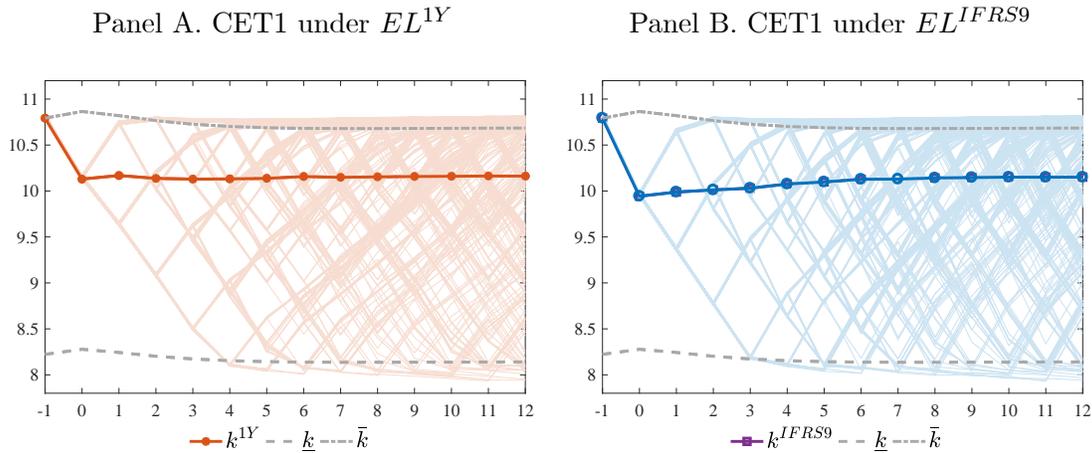
**Figure 2. Effects of the arrival of a contraction**  
Average responses to the arrival of  $s=2$  after a long period in  $s=1$   
(IRB bank, as a percentage of average exposures).

Panel D of Figure 2 shows the implications for an IRB bank's CET1. Before the shock hits, at  $t=-1$ , the bank is assumed to have its fully-loaded CCB, implying a buffer on top of the minimum required capital of more than 2.5% of total assets. The change in the bands  $\underline{k}$  and  $\bar{k}$  reflected in the figure is the result of the change in RWAs following the deterioration

in the composition of the loan portfolio. The differences in the effects of the alternative measures on CET1 are visible, essentially mirroring their impact on P/L.

The fact that the trajectories depicted are average trajectories is important for interpreting Figure 2. For example, in Panel D, the average trajectory of CET1 lies within the average bands of the  $sS$ -rule that determines its management, but this does not mean that the bank does not need to recapitalize (or does not pay dividends) after the initial shock. Actually, many of the actual trajectories are upward and touch the upper band for paying dividends (e.g. if the contraction ends and does not return) and several are downward and force the bank to recapitalize (e.g. if the contraction lasts a long time or another contraction follows soon after an initial recovery).

To illustrate the difference between the average and the realized trajectories, Figure 3 shows 500 simulated trajectories for CET1 under  $EL^{1Y}$  and  $EL^{IFRS9}$ . Under IFRS 9, it takes four consecutive years in the contraction state ( $s=2$ ) for a bank to deplete its CCB and require a recapitalization. By contrast, under the one-year expected loss approach, the CCB would be used up only after five years in the contraction state.



**Figure 3. CET1 after the arrival of a contraction (IRB bank)**  
500 simulated trajectories of CET1 under  $EL^{1Y}$  and  $EL^{IFRS9}$   
in response to the arrival of  $s=2$  after a long period in  $s=1$   
(IRB bank, as a percentage of average exposures)

Intuitively, the closer the average trajectory for CET1 is to the lower band in Panel D of Figure 2, the more likely it is that the bank needs to raise new equity following the arrival of the contraction state. This explains why, as reported in Table 3, the probability of the bank

needing to be recapitalized in the contraction state is higher under  $EL^{IFRS9}$  than under any of the other three approaches.

## 4 Quantitative results for SA banks

Capital requirements for banks following the standardized approach (SA banks) apply to exposures net of specific provisions and, hence, are sensitive to how those provisions are computed. Thus, Table 4 includes the same variables as Table 3 for IRB banks together with details on the minimum capital requirement implied by each of the impairment measurement methods. Except for the minimum capital requirement and the implied size of a fully-loaded CCB, all the other variables in Table 2 are equally valid for IRB and SA banks.

The results in Table 4 are qualitatively very similar to those described for an IRB bank in Table 3, with some quantitative differences that are worth commenting on. It turns out that, in our calibration, an SA bank holding exactly the same loan portfolio as an IRB bank would be able to support it with lower average levels of CET1 (between 48 basis points and 157 basis points lower, depending on the impairment measurement method). Therefore, in a typical year, our SA bank features *de facto* higher leverage levels, and hence higher interest expenses than its IRB counterpart. This explains why its P/L is slightly lower than that of an IRB bank. This difference explains most of the level differences which can be seen in the remaining variables in Table 4.

When comparing impairment measurement methods in the case of an SA bank, the differences are very similar to those observed in Table 3 for IRB banks. The higher state-dependence of the more forward-looking measures explains the higher cross-state differences in CET1, dividends and probabilities of needing capital injections under such measures. As for IRB banks, the differences associated with IFRS 9 relative to either the incurred loss approach or the one-year expected loss approach are significant, but not huge.

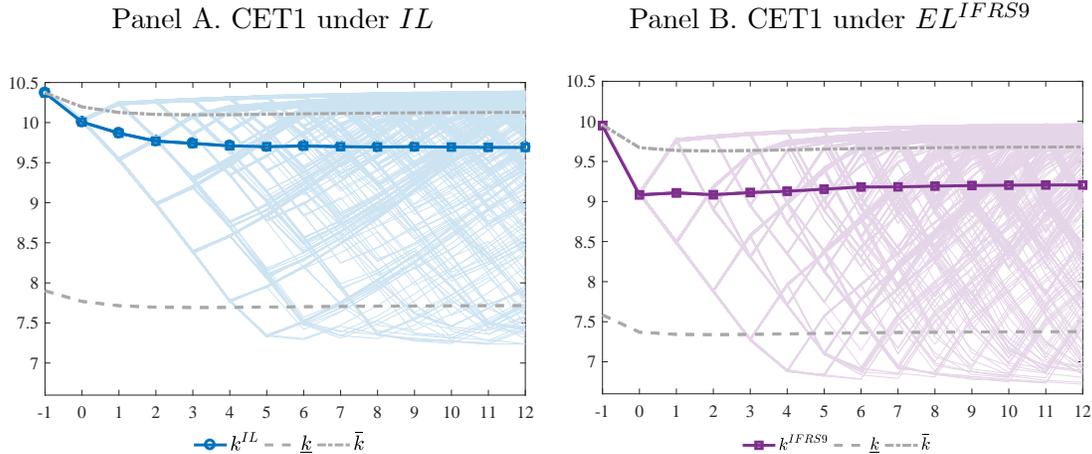
Comparing the results in Tables 3 and 4 leads to the conclusion that the effects on SA banks of IFRS 9 and CECL are quantitatively very similar to those on IRB banks. As for IFRS 9, this is further confirmed by Figure 4, which shows the counterpart of Figure 3 for a bank operating under the SA approach. It depicts 500 simulated trajectories for CET1 under  $IL$  and  $EL^{IFRS9}$ . As in Figure 3, it takes four consecutive years in the contraction

state ( $s=2$ ) for an SA bank under IFRS 9 to use up its CCB and require a recapitalization, while under the incurred loss method, the CCB would be fully depleted only after (roughly) five years in the contraction state.<sup>27</sup>

**Table 4**  
**Endogenous variables under SA capital requirements**  
(SA bank, as a percentage of mean exposures unless otherwise indicated)

	<i>IL</i>	<i>EL</i> <sup>1Y</sup>	<i>EL</i> <sup>LT</sup>	<i>EL</i> <sup>IFRS9</sup>
<hr/>				
P/L				
Unconditional mean	0.15	0.16	0.20	0.17
Conditional mean, expansions	0.34	0.39	0.46	0.44
Conditional mean, contractions	-0.46	-0.62	-0.69	-0.73
Standard deviation	0.34	0.43	0.51	0.50
Minimum capital requirement				
Unconditional mean	7.72	7.57	6.88	7.36
Conditional mean, expansions	7.72	7.56	6.88	7.35
Conditional mean, contractions	7.74	7.58	6.89	7.37
Standard deviation	0.14	0.17	0.18	0.19
CET1				
Unconditional mean	9.70	9.50	8.68	9.23
Conditional mean, expansions	9.88	9.76	8.97	9.54
Conditional mean, contractions	9.04	8.61	7.67	8.19
Standard deviation	0.83	0.83	0.77	0.85
Probability of dividends being paid (%)				
Unconditional	51.32	52.95	59.08	53.20
Conditional, expansions	66.53	68.64	76.59	68.96
Conditional, contractions	0	0	0	0
Dividends, if positive				
Conditional mean, expansions	0.32	0.33	0.35	0.35
Conditional mean, contractions	–	–	–	–
Probability of having to recapitalize (%)				
Unconditional	2.36	2.67	2.67	2.94
Conditional, expansions	0	0	0	0
Conditional, contractions	10.33	11.70	11.68	12.88
Recapitalization, if positive				
Conditional mean, expansions	–	–	–	–
Conditional mean, contractions	0.40	0.30	0.36	0.40

<sup>27</sup>In this case, the dashed lines that delimit the band within which CET1 evolves are averages across simulated trajectories and across provisioning methods, since the sizes of the minimum capital requirement and the minimum capital requirement plus the fully-loaded CCB depend on the size of the corresponding provisions.



**Figure 4. CET1 after the arrival of a contraction (SA bank)**  
500 simulated trajectories of CET1 under  $IL$  and  $EL^{IFRS9}$   
in response to the arrival of  $s=2$  after a long period in  $s=1$   
(SA bank, as a percentage of average exposures)

## 5 Sensitivity analysis

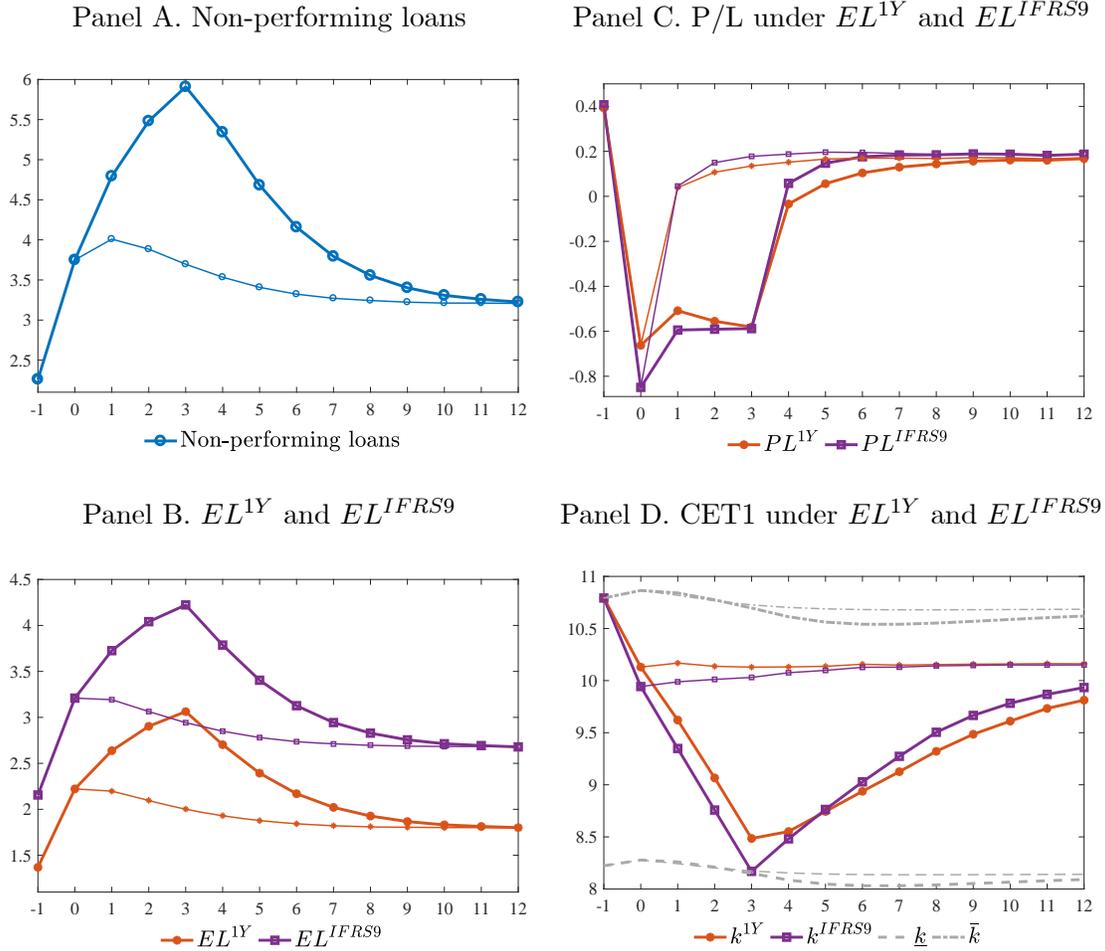
### 5.1 Especially severe crises

In this section, we explore whether the severity of crises and the potential anticipation of a particularly severe crisis make a difference in terms of our assessment of the cyclicity of the new more forward-looking provisioning methods (IFRS 9 and CECL) vis-a-vis the prior less forward-looking measures (incurred losses and one-year expected losses). For brevity, we again focus on IRB banks and on the comparison of one of the more forward looking approaches. IFRS 9, with just one of the alternatives, namely the one-year expected loss approach (the one so far prescribed by regulation for IRB banks).

#### 5.1.1 Unanticipatedly long crises

We first explore what happens with the dynamic responses analyzed in the benchmark calibration with aggregate risk when we condition them on the realization of the contraction state  $s=2$  for four consecutive periods starting from  $t=0$ . So, as in the analysis shown in Figure 4, we assume that the bank starts at  $t=-1$  with the portfolio and impairment allowances

resulting from having been in the expansion state ( $s=1$ ) for a long enough period, and that at  $t=0$  the aggregate state switches to contraction ( $s=2$ ).



**Figure 5. Unanticipatedly long crises**

Average responses to the arrival of  $s=2$  when the contraction is unanticipatedly “long” (thick lines) rather than “average” (thin lines) (IRB bank, as a percentage of average exposures)

In Figure 5, we compare the average response trajectories already shown in Figure 2 (where, from  $t=1$  onwards, the aggregate state evolves stochastically according to the Markov chain calibrated in Table 1) with trajectories conditional on remaining in state  $s=2$  for at least up to date  $t=3$  (four years).<sup>28</sup>

<sup>28</sup>In the conditional trajectories, the aggregate state is again assumed to evolve according to the calibrated Markov chain from  $t=4$  onwards.

When a crisis is longer than expected, the largest differential impact of  $EL^{IFRS9}$  relative to  $EL^{1Y}$  still happens in the first year of the crisis ( $t=0$ ), since  $EL^{IFRS9}$  front-loads the expected beyond-one-year losses of the stage 2 loans. In years two to four of the crisis ( $t=1,2,3$ ) the differential impact of IFRS 9 (compared to one-year) expected losses on P/L lessens before it switches sign (after  $t=5$ ). In the first years of the crisis,  $EL^{IFRS9}$  leaves CET1 closer to the recapitalization band and, in the fourth year ( $t=3$ ), the duration of the crisis forces the bank to recapitalize only under  $EL^{IFRS9}$ . However,  $EL^{IFRS9}$  supports a quicker recovery of profitability and, hence, CET1 after  $t=5$ .

### 5.1.2 Anticipatedly long crises

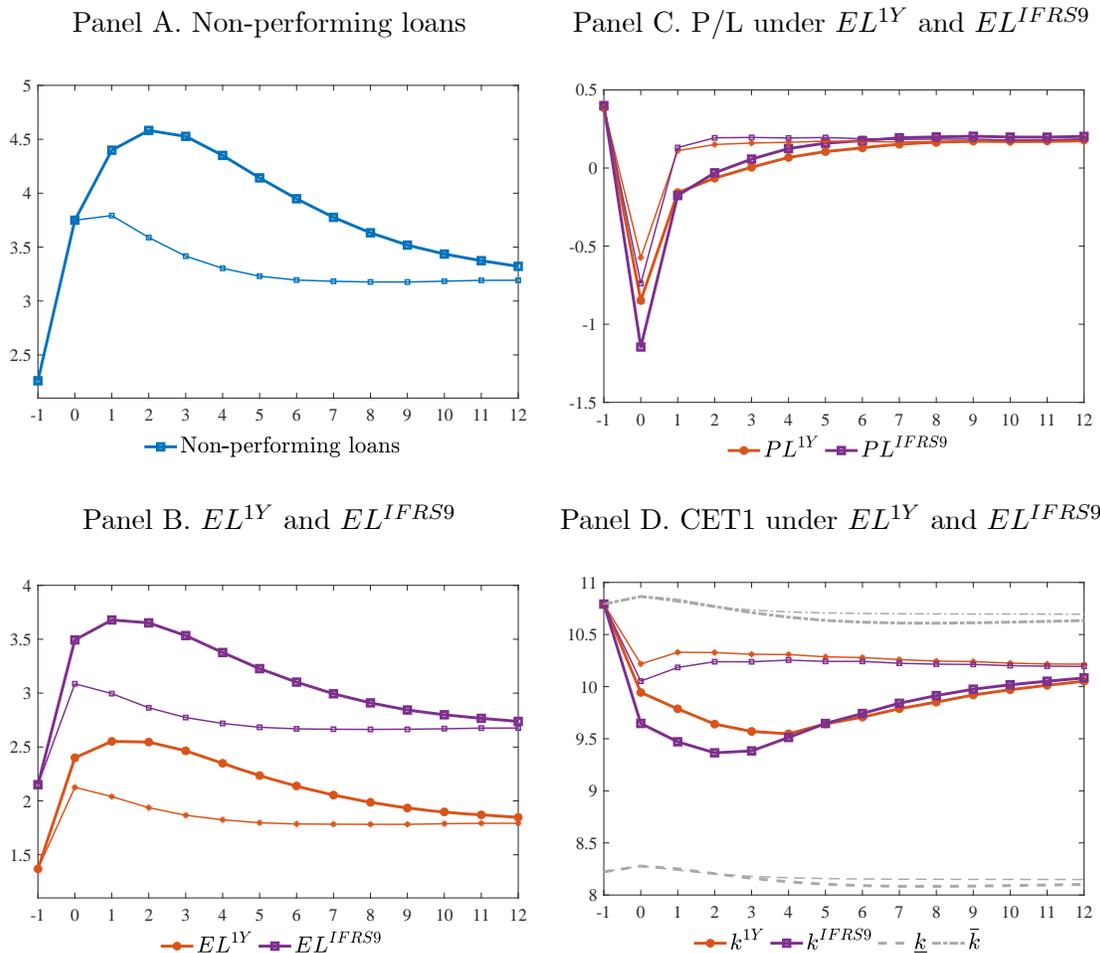
We now turn to the case in which crises can be anticipated to be long from their outset. To study this case, we extend the model to add a third aggregate state that describes “long crises” ( $s=3$ ) as opposed to “short crises” ( $s=2$ ) or “expansions” ( $s=1$ ). To streamline the analysis, we make  $s=2$  and  $s=3$  have exactly the same impact on credit risk parameters as prior  $s=2$  in Table 2, and keep the impact of  $s=1$  on credit risk parameters also exactly the same as in Table 2. The only difference between states  $s=2$  and  $s=3$  is their persistence, which determines the average time it takes for a crisis period to come to an end. Specifically, we consider the following transition probability matrix for the aggregate state:

$$\begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{pmatrix} = \begin{pmatrix} 0.8520 & 0.6348 & 0.250 \\ 0.1221 & 0.3652 & 0 \\ 0.0259 & 0 & 0.750 \end{pmatrix}, \quad (26)$$

which implies an average duration of four years for long crises ( $s=3$ ), 1.6 years for short crises ( $s=2$ ), and the same duration as in our benchmark calibration for periods of expansion ( $s=1$ ). The parameters in (26) are calibrated to make  $s=3$  to occur with an unconditional frequency of 8% (equivalent to suffering an average of two long crises per century) and to keep the unconditional frequency of  $s=1$  at the same 77% as in our benchmark calibration.

In Figure 6 we compare the average response trajectories that follow the entry in state  $s=2$  (thin lines) or state  $s=3$  (thick lines) after having spent a sufficiently long period in state  $s=1$ . Therefore, the figure illustrates the average differences between entering a “normal” short crisis or a “less frequent” long crisis at  $t=0$ . Both  $EL^{1Y}$  and  $EL^{IFRS9}$  behave differently across short and long crises from the very first period, since even the one-year ahead loss

projections behind  $EL^{1Y}$  factor in the lower probability of a recovery at  $t=1$  under  $s=3$  than under  $s=2$ . However,  $EL^{IFRS9}$  additionally takes into account the losses further into the future associated with the stage 2 loans. Hence, the differential rise on impact experienced by  $EL^{IFRS9}$  is higher than that experienced by  $EL^{1Y}$ .



**Figure 6. Anticipated long crises**

Average responses to the arrival of a contraction at  $t=0$  when it is anticipated to be “long” ( $s'=3$ , thick lines) rather than “normal” ( $s'=2$ , thin lines) (IRB bank, as a percentage of average exposures)

This difference also explains the larger initial impact of IFRS 9 on P/L and CET1. As a result, at the onset of an anticipated long crisis,  $EL^{IFRS9}$  pushes CET1 closer to the recapitalization band and the difference with respect to  $EL^{1Y}$  increases. Quantitatively, however, the effect on CET1 is still moderate, using up on impact less than half of the fully

loaded CCB. Of course, later on in the long crisis,  $EL^{IFRS9}$  results, on average, in a quicker recovery of profitability and CET1 than  $EL^{1Y}$ .

As a quantitative summary of the implications of an anticipatedly long crisis, the following table reports the unconditional yearly probabilities of the bank needing equity injections, under each of the impairment measures compared, in the baseline model with aggregate risk and in the current extension:

	$IL$	$EL^{1Y}$	$EL^{LT}$	$EL^{IFRS9}$
Baseline model	2.34%	2.86%	2.34%	3.41%
Model with anticipatedly long crises	3.28%	3.78%	4.23%	4.52%

Note that the anticipatedly long crises significantly increase the probability of having to recapitalize banks under the CECL approach ( $EL^{LT}$ ), making it closer to the one obtained under IFRS 9.

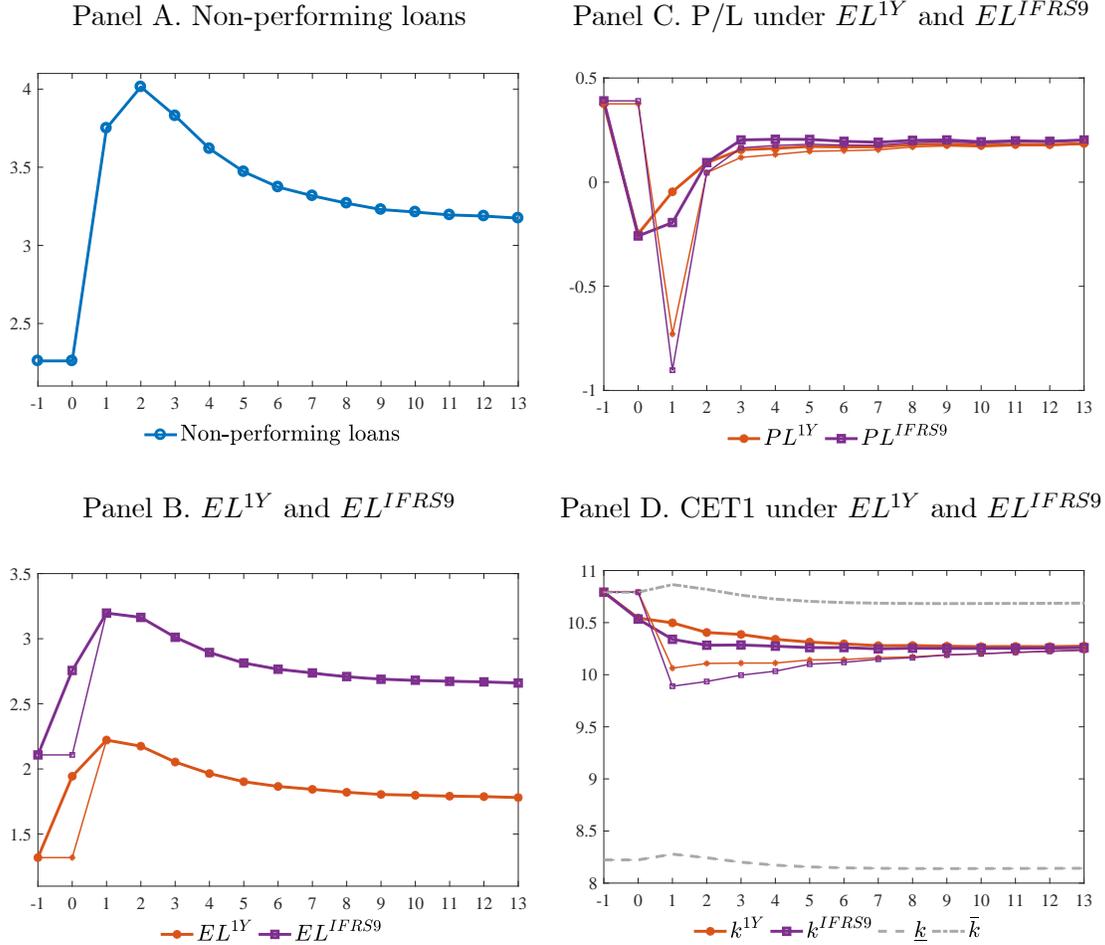
## 5.2 Better foreseeable crises

We now consider the case in which some crises can be foreseen one year in advance. Similar to the treatment of long crises in the previous subsection, we formalize this by introducing a third aggregate state,  $s=3$ , which describes normal or expansion states in which a crisis (transition to state  $s'=2$ ) is expected in the next year with a larger than usual probability. So we make  $s=3$  identical to  $s=1$  in all respects (that is, the way it affects the PDs, rating migration probabilities, and LGDs of the loans, et cetera) except in the probability of switching to aggregate state  $s' = 2$  in the next year.

To streamline the analysis, we look at the case in which  $s=3$  is followed by  $s'=1$  with probability one and assume that half of the crisis are preceded by  $s = 3$  (while the other half are preceded, as before, by  $s = 1$ , which means that they are not seen as coming). Adjusting the transition probabilities to imply the same relative frequencies and expected durations of non-crisis versus crisis periods as the baseline calibration in Table 1, the matrix of state transition probabilities used for this exercise is

$$\begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{pmatrix} = \begin{pmatrix} 0.8391 & 0.5 & 0 \\ 0.0740 & 0.5 & 1 \\ 0.0869 & 0 & 0 \end{pmatrix}.$$

The thick lines in Figure 7 show the average response trajectories to the arrival of the pre-crisis state  $s'=3$  at  $t=-1$  after having spent a long time in the normal state  $s=1$ . We compare  $EL^{1Y}$  and  $EL^{IFRS9}$  and include, using thin lines, the results of the baseline model (regarding the arrival of  $s'=2$  at  $t=0$  having been in  $s=1$  for a long period). The results confirm the notion that being able to better anticipate the arrival of a crisis helps to considerably soften its impact on impairment allowances, P/L, and CET1.



**Figure 7. Better foreseeable crises**

Average responses to the arrival of pre-crisis state at  $t=-1$  after long in  $s=1$  (thick lines). Thin lines describe the arrival of  $s=2$  at  $t=0$  in the baseline model (IRB bank, as a percentage of average exposures)

Finally, as in the previous extension, the following table reports the unconditional yearly probabilities of the bank needing equity injections under each of the impairment measures

compared, in the baseline model with aggregate risk and in the current extension. Indeed, crises that are better anticipated imply a lower yearly probability that the bank needs an equity injection. Yet, the ranking of the various approaches in terms of this variable remains the same as in the baseline model, with IFRS 9 performing the worst:

	$IL$	$EL^{1Y}$	$EL^{LT}$	$EL^{IFRS9}$
Baseline model	2.34%	2.86%	2.34%	3.41%
Model with better foreseeable crises	1.84%	1.99%	1.54%	2.66%

### 5.3 Other possible extensions

In this section, we briefly describe additional extensions that the model could accommodate at some cost in terms of notational, computational, and calibration complexity.

**Multiple standard and substandard ratings** Adding more rating categories within the broader standard and substandard categories would essentially imply expanding the dimensionality of the vectors and matrices described in the baseline model and in the aggregate-risk extension. If loans were assumed to be originated in more than just one category, the need to keep track of the (various) contractual interest rates for discounting purposes means we would need to expand the dimensionality of the model further. Alternatively, an equivalent and potentially less notationally cumbersome possibility would be to consider the same number of portfolios as different-at-origination loans and to aggregate across them the impairment allowances and the implications for P/L and CET1.

**Relative criterion for credit quality deterioration** This extension would be a natural further development of the previous one and only relevant for the assessment of IFRS 9. Under IFRS 9, the shift to the lifetime approach (“stage 2”) for a given loan is supposed to be applied not when an absolute substandard rating is attained, but when the deterioration in terms of the rating at origination is significant in relative terms, for example because the rating has fallen by more than two or three notches. This distinction is relevant if operating under a ratings scale that is finer than the one we have used in our analysis. As in the case with the above-mentioned multiple standard and substandard ratings, keeping the analysis recursive under the relative criterion for treating loans as “stage 1” or “stage 2” loans in

IFRS 9 would require considering as many portfolios as different-at-origination loan ratings and writing expressions for impairment allowances that impute lifetime expected losses to the components of each portfolio for which the current rating is significantly lower than the initial rating.

## 6 Implications of the results

The results in prior sections assess quantitatively the cyclical performance of various loan loss provisioning methods, showing that the new ECL approach of IFRS 9 and, to a lower extent, US GAAP will imply a more upfront recognition of impairment losses upon the arrival of a recession. As shown, the timing and importance of such loss recognition and its impact on P/L and CET1 depends on the extent to which cyclical turning points can be anticipated in advance and the size of the surprises regarding the severity or duration of the recession. While these mechanical impacts of provisioning on P/L and CET1 are little controversial, their implications for the cyclical performance of loan supply or asset sales would be much harder to estimate. Our analysis has focused on capturing the subtle differences between the different provisioning methods, abstracting from the more controversial modeling of loan demand, the frictions that might lead to potential changes in credit supply, and any relevant feedback effects. While waiting for the modeling, empirical and policy evaluation efforts needed for a fuller assessment of the broader implications, this section elaborates on the conditions that might lead the time profile of IFRS 9 and CECL provisions to have a procyclical impact on loan supply or asset sales.

A fall in CET1 that reduces a bank's CCB (and hence forces it to cancel its dividends) or even produces the need for raising new equity in order to continue complying with the minimum capital requirement, does not necessarily imply that credit supply or bank assets will contract. This will depend on the extent to which the bank dislikes cancelling dividends and on how quickly or cheaply the bank can raise new capital. Our quantitative results are produced as if there were no concerns or imperfections on these two fronts so that the bank represented in the model is able to maintain its normal flow of loan origination (which in the calibration, to keep things simple, is taken as constant over time). In the presence of imperfections leading banks to experience pressure to show up good capital ratios or a stable

dividend flow or that introduce frictions in the raising of new capital (as in, e.g., Bolton and Freixas, 2006, Allen and Carletti, 2008, or Plantin, Sapra and Shin, 2008), the bank may opt for reducing its assets.

Similar to discussions on the potential procyclical effects of Basel capital requirements (Kashyap and Stein, 2004, and Repullo and Suarez, 2013), there are multiple factors that will determine whether the cyclical performance of provisions under the new ECL methods will add procyclicality to the system. First, banks may react to IFRS 9 and CECL by choosing to have larger voluntary capital buffers or undertaking less cyclical investments. Second, even if the new provisions cause a larger contraction in credit supply when a negative shock hits the economy, such a contraction may be lower than the contraction in credit demand, which may also be negatively affected by the shock. Third, the negative effects of an additional contraction in credit supply right at the beginning of a recession may be counterbalanced by the advantages of an earlier recognition of loan losses (e.g. by precluding forbearance or the continuation of dividend payments during the initial stages of a crisis), including the possibility that they could enable banks to return to sound financial health more quickly.

Despite all these considerations, recent evidence (including Mésonnier and Monks, 2015, Aiyar, Calomiris, and Wieladek, 2016, Behn, Haselmann, and Wachtel, 2016, Gropp et al., 2016, Jiménez et al., 2017) suggests that banks tend to accommodate sudden increases in capital requirements or other regulatory buffers (or, similarly, falls in available regulatory capital) by reducing risk-weighted assets, most typically bank lending, which has significant impact on the real economy.<sup>29</sup> If this process occurs at an economy-wide level (e.g. in response to an aggregate shock), the contractionary effects on aggregate credit supply might be significant, potentially causing negative second-round effects on the system (as in, e.g., Gertler and Kiyotaki, 2010, or Brunnermeier and Sannikov, 2014) by weakening aggregate demand, depressing asset prices, damaging inter-firm credit chains or causing larger default rates among the surviving loans.

These feedback effects –although theoretically and empirically difficult to assess– are at the heart of the motivation for the macroprudential approach to financial regulation and

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<sup>29</sup> Jiménez et al (2017) document the countercyclicality associated with the Spanish statistical provisions, with results suggesting that the effects of changes in capital pressure on credit are significantly more pronounced in recessions than in expansions.

for macroprudential policies.<sup>30</sup> Fortunately, in case the procyclicality concerns raised by this line of reasoning became material, there is a broad range of policies that might help to address the procyclical effects of IFRS 9 and CECL if deemed necessary. One possibility is to rely on the existing regulatory buffers and, specifically, on the countercyclical capital buffer (CCyB), possibly after a suitable revision of the guidance on its expected use by the authorities. Specifically, the national macroprudential authorities could broaden the focus and aim to not just preventing excessive credit growth but also offsetting undesirable contractions in credit supply. This would involve setting the CCyB at a level above zero in expansionary or normal times, so as to have the capacity to partly or fully release it if, and when, the change in aggregate conditions leads to a sudden increase in provisioning needs and a potential contraction in credit. Another possibility would be to influence the impact of accounting provisions on regulatory capital by revising the regulatory definition of expected losses, and the adjustments in regulatory capital that apply when there are discrepancies between accounting provisions and regulatory expected losses (see BCBS, 2015, 2016). This option is typically regarded undesirable in that large discrepancies between accounting and regulatory capital may erode investors' confidence in the reliability of both numbers.

## 7 Conclusions

We have described a simple recursive model for the assessment of the level and cyclical implications of the new ECL approaches to impairment allowances under IFRS 9 and the incoming update of US GAAP. We have calibrated the model to represent a portfolio of corporate loans of an EU bank. We have compared the old incurred loss approach, the one-year expected loss approach (used to establish the regulatory provisions of IRB banks), the lifetime expected loss approach behind the CECL of US GAAP, and the mixed-horizon expected loss approach of IFRS 9.

Our results suggest that the loan loss provisions implied by IFRS 9 and the CECL approach will rise more suddenly than their predecessors when the cyclical position of the

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<sup>30</sup>As put by Hanson, Kashyap and Stein (2011, p. 5), “in the simplest terms, one can characterize the macroprudential approach to financial regulation as an effort to control the social costs associated with excessive balance sheet shrinkage on the part of multiple financial institutions hit with a common shock.”

economy switches from expansion to contraction (or if banks experience a shock that sizably damages the credit quality of their loan portfolios). This implies that P/L and, without the application of regulatory filters, CET1 will decline more severely at the start of those episodes. The baseline quantitative results of the paper suggest that the arrival of an average recession might imply on-impact losses of CET1 twice as large as those under the incurred loss approach and equivalent to about one third of the fully-loaded CCB of the analyzed bank. This loss is significantly smaller than the amount that would deplete a fully-loaded CCB and thus presumably manageable in most circumstances.

While the early and decisive recognition of forthcoming losses may have significant advantages (e.g. in terms of transparency, market discipline, inducing prompt supervisory intervention, etc.), it may also imply, via its effects on regulatory capital, a loss of lending capacity for banks at the very beginning of a contraction (or in the direct aftermath of a negative credit-quality shock), potentially contributing, through feedback effects, to its severity. With this concern in mind, it would be advisable for macroprudential authorities to monitor the cyclical evolution of provisions under the new accounting standards (e.g. through stress testing) and to stand ready to take compensatory measures (e.g. the preventive uploading and subsequent release of the CCyB), if the potential negative impact on credit supply makes it necessary.

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# Appendices

## A The model with aggregate risk

In this appendix we extend the equations of the benchmark model presented in the main text to the case in which aggregate risk affects the key parameters governing credit risk and, potentially, loan origination. We capture aggregate risk by introducing an aggregate state variable that can take two values  $s_t \in \{1, 2\}$  at each date  $t$  and follows a Markov chain with time-invariant transition probabilities  $p_{s's} = \text{Prob}(s_{t+1} = s' | s_t = s)$ . The approach can be trivially generalized to deal with a larger number of aggregate states.

In order to measure expected losses corresponding to default events in any future date  $t$ , we have to keep track of the aggregate state in which the loans existing at  $t$  were originated,  $z=1,2$ , the aggregate state at time  $t$ ,  $s=1,2$ , and the credit quality or rating of the loan at  $t$ ,  $j=1,2,3$ . Thus, it is convenient to describe (stochastic) loan portfolios held at any date  $t$  as vectors of the form

$$y_t = \begin{pmatrix} x_t(1, 1, 1) \\ x_t(1, 1, 2) \\ x_t(1, 1, 3) \\ x_t(1, 2, 1) \\ x_t(1, 2, 2) \\ x_t(1, 2, 3) \\ x_t(2, 1, 1) \\ x_t(2, 1, 2) \\ x_t(2, 1, 3) \\ x_t(2, 2, 1) \\ x_t(2, 2, 2) \\ x_t(2, 2, 3) \end{pmatrix}, \quad (\text{A.1})$$

where component  $x_t(z, s, j)$  denotes the measure of loans at  $t$  that were originated in aggregate state  $z$ , are in aggregate state  $s$  and have rating  $j$ .<sup>31</sup>

Our assumptions regarding the evolution and payoffs of the loans between any date  $t$  and  $t + 1$  are as follows. Loans rated  $j=1, 2$  at  $t$  mature at  $t + 1$  with probability  $\delta_j(s')$ , where  $s'$  denotes the aggregate state at  $t + 1$  (unknown at date  $t$ ). In the case of NPLs ( $j=3$ ),  $\delta_3(s')$  represents the independent probability of a loan being resolved, in which case it pays back a fraction  $1 - \tilde{\lambda}(s')$  of its unit principal and exits the portfolio. Conditional on  $s'$ , each loan rated  $j=1, 2$  at  $t$  which matures at  $t + 1$  defaults independently with probability  $PD_j(s')$ , being resolved within the period with probability  $\delta_3(s')/2$  or entering the stock of NPLs ( $j=3$ ) with probability  $1 - \delta_3(s')/2$ . Maturing loans that do not default pay back their

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<sup>31</sup>Along a specific history (or sequence of aggregate states), for any  $z$  and  $j$ , the value of  $x_t(z, s, j)$  will equal 0 whenever  $s_t \neq s$ .

principal of one plus the contractual interest  $c_z$ , established at origination.

Conditional on  $s'$ , each loan rated  $j=1, 2$  at  $t$  which does not mature at  $t+1$  goes through one of the following exhaustive possibilities:

1. Default, which occurs independently with probability  $PD_j(s')$ , and in which case one of two things can happen: (i) it is resolved within the period with probability  $\delta_3(s')/2$ ; or (ii) it enters the stock of NPLs ( $j=3$ ) with probability  $1 - \delta_3(s')/2$ .
2. Migration to rating  $i \neq j$  ( $i=1,2$ ), in which case it pays interest  $c_z$  and continues for one more period; this occurs independently with probability  $a_{ij}(s')$ .
3. Continuation in rating  $j$ , in which case it pays interest  $c_z$  and continues for one more period; this occurs independently with probability

$$a_{jj}(s') = 1 - a_{ij}(s') - PD_j(s').$$

## A.1 Portfolio dynamics under aggregate risk

Under aggregate risk, the dynamics of the loan portfolio between any dates  $t$  and  $t+1$  is no longer deterministic, but driven by the realization of the aggregate state variable at  $t+1$ ,  $s_{t+1}$ . To describe the dynamics of the system compactly, let the binary variable  $\xi_{t+1} = 1$  if  $s_{t+1} = 1$  and  $\xi_{t+1} = 0$  if  $s_{t+1} = 2$ . The dynamics of the system can be described as

$$y_{t+1} = G(\xi_{t+1})y_t + g(\xi_{t+1}),$$

where

$$G(\xi_{t+1}) = \begin{pmatrix} \begin{pmatrix} \xi_{t+1}M(1) & \xi_{t+1}M(1) \\ (1-\xi_{t+1})M(2) & (1-\xi_{t+1})M(2) \end{pmatrix} & 0_{6 \times 6} \\ 0_{6 \times 6} & \begin{pmatrix} \xi_{t+1}M(1) & \xi_{t+1}M(1) \\ (1-\xi_{t+1})M(2) & (1-\xi_{t+1})M(2) \end{pmatrix} \end{pmatrix},$$

$$g(\xi_{t+1})^T = (\xi_{t+1}e_1(1), 0, 0, 0, 0, 0, 0, 0, 0, (1-\xi_{t+1})e_1(2), 0, 0),$$

$$\xi_{t+1} = \begin{cases} 1 & \text{if } u_{t+1} \in [0, p_{1s_t}], \\ 0 & \text{otherwise,} \end{cases}$$

$$s_{t+1} = \xi_{t+1} + 2(1 - \xi_{t+1}),$$

$u_{t+1}$  is an independently and identically distributed uniform random variable with support  $[0, 1]$ ,  $e_1(s')$  is the (potentially different across states  $s'$ ) measure of new loans originated at  $t+1$ , and  $0_{6 \times 6}$  denotes a  $6 \times 6$  matrix full of zeros.

## A.2 Incurred losses

Incurred losses measured at date  $t$  would be those associated with NPLs that are part of the bank's portfolio at date  $t$ . Thus, the incurred losses reported at  $t$  would be given by

$$IL_t = \sum_{z=1,2} \sum_{s=1,2} \lambda(s)x_t(z, s, 3),$$

where  $\lambda(s)$  is the expected LGD on an NPL conditional on being at state  $s$  in date  $t$ . This can be more compactly expressed as

$$IL_t = \widehat{b}y_t, \tag{A.2}$$

where  $\widehat{b} = (0, 0, \lambda(1), 0, 0, \lambda(2), 0, 0, \lambda(1), 0, 0, \lambda(2))$ .

The expected LGD conditional on each current state  $s$  can be found as functions of the previously specified primitives of the model (state-transition probabilities, probabilities of resolution of the defaulted loans in subsequent periods, and loss rates  $\widetilde{\lambda}(s')$  suffered if resolution happens in each of the possible future states  $s'$ ) by solving the following system of recursive equations:

$$\lambda(s) = \sum_{s'=1,2} p_{s's} \left[ \delta_3(s')\widetilde{\lambda}(s') + (1 - \delta_3(s'))\lambda(s') \right], \tag{A.3}$$

for  $s=1, 2$ .

## A.3 Discounted one-year expected losses

Based on the loan portfolio held by the bank at  $t$ , provisions computed on the basis of the discounted one-year expected losses add to the incurred losses written above the losses stemming from default events expected to occur within the year immediately following. Since a period in the model is one year, the corresponding allowances are given by

$$EL_t^{1Y} = (b_\beta + \widehat{b})y_t, \tag{A.4}$$

where  $b_\beta = (\beta_1 b, \beta_2 b)$ ,  $\beta_z = 1/(1 + c_z)$ , and  $b = (b_{11}, b_{12}, 0, b_{21}, b_{22}, 0)$ , with

$$b_{sj} = \sum_{s'=1,2} p_{s's} PD_j(s') \left\{ [\delta_3(s')/2] \widetilde{\lambda}(s') + [1 - \delta_3(s')/2] \lambda(s') \right\}, \tag{A.5}$$

for  $j=1, 2$ . The coefficients defined in (A.5) attribute one-year expected losses to loans rated  $j=1, 2$  in state  $s$  by taking into account their PD and LGD over each of the possible states  $s'$  that can be reached at  $t + 1$ , where the corresponding  $s'$  are weighted by their probability of occurring given  $s$ . The losses associated these one-year ahead defaults are discounted using

the contractual interest rate of the loans,  $c_z$ , as set at their origination. In Section A.6, we derive an expression for the endogenous value of such rate under our assumptions on loan pricing. As for the loans that are already non-performing ( $j=3$ ) at date  $t$ , the term  $\widehat{b}y_t$  in (A.4) implies attributing their conditional-on- $s$  LGD to them, exactly as in (A.2).

#### A.4 Discounted lifetime expected losses

Impairment allowances computed on an lifetime-expected basis imply taking into account not just the default events that may affect the currently performing loans in the next year, but also those occurring in any subsequent period. Building on prior notation and the same approach explained for the model without aggregate risk, these provisions can be computed as

$$\begin{aligned}
EL_t^{LT} &= b_\beta y_t + b_\beta M_\beta y_t + b_\beta M_\beta^2 y_t + b_\beta M_\beta^3 y_t + \dots + \widehat{b}y_t \\
&= b_\beta (I + M_\beta + M_\beta^2 + M_\beta^3 + \dots) y_t + \widehat{b}y_t \\
&= b_\beta (I - M_\beta)^{-1} y_t + \widehat{b}y_t = (b_\beta B_\beta + \widehat{b}) y_t,
\end{aligned} \tag{A.6}$$

with

$$\begin{aligned}
M_\beta &= \begin{pmatrix} \beta_1 M_p & 0_{6 \times 6} \\ 0_{6 \times 6} & \beta_2 M_p \end{pmatrix}, \\
M_p &= \begin{pmatrix} p_{11} M(1) & p_{12} M(1) \\ p_{21} M(2) & p_{22} M(2) \end{pmatrix}, \\
M(s') &= \begin{pmatrix} m_{11}(s') & m_{12}(s') & 0 \\ m_{21}(s') & m_{22}(s') & 0 \\ (1 - \delta_3(s')/2) PD_1(s') & (1 - \delta_3(s')/2) PD_2(s') & (1 - \delta_3(s')) \end{pmatrix},
\end{aligned}$$

and  $m_{ij}(s') = (1 - \delta_j(s')) a_{ij}(s')$ .

#### A.5 Discounted expected losses under IFRS 9

As already mentioned, IFRS 9 adopts a hybrid approach that combines the one-year-ahead and lifetime approaches described above. Specifically, it applies the one-year-ahead measurement to loans whose credit quality has not increased significantly since origination. For us, these are the loans with  $j=1$ , namely those in the components  $x_t(z, s, 1)$  of  $y_t$ . By contrast, it considers the lifetime expected losses for loans whose credit risk has significantly increased since origination. For us, these are the loans with  $j=2$ , namely those in the components  $x_t(z, s, 2)$  of  $y_t$ .

As in the case without aggregate risk, it is convenient to split vector  $y_t$  into a new auxiliary vector

$$\hat{y}_t = \begin{pmatrix} x_t(1, 1, 1) \\ 0 \\ 0 \\ x_t(1, 2, 1) \\ 0 \\ 0 \\ x_t(2, 1, 1) \\ 0 \\ 0 \\ x_t(2, 2, 1) \\ 0 \\ 0 \end{pmatrix},$$

which contains the loans with  $j=1$ , and the difference

$$\tilde{y}_t = y_t - \hat{y}_t,$$

which contains the rest.

Combining the formulas obtained in (A.4) and (A.6), loan loss provisions under IFRS 9 can be compactly described as follows:<sup>32</sup>

$$EL_t^{IFRS9} = b_\beta \hat{y}_t + b_\beta B_\beta \tilde{y}_t + \hat{b} y_t. \quad (\text{A.7})$$

## A.6 Determining the initial loan rate

Taking advantage of the recursivity of the model, for given values of the contractual interest rates  $c_z$  of the loans originated in each of the aggregate states  $z=1,2$ , one can obtain the ex-coupon value of a loan originated in state  $z$ , when the current aggregate state is  $s$  and their current rating is  $j$ ,  $v_j(z, s)$ , by solving the system of Bellman-type equations given by:

$$v_j(z, s) = \mu \sum_{s'=1,2} p_{s's} \left[ (1 - PD_j(s'))c_z + (1 - PD_j(s'))\delta_j(s') + PD_j(s')(\delta_3(s')/2)(1 - \tilde{\lambda}(s')) \right. \\ \left. + m_{1j}(s')v_1(z, s') + m_{2j}(s')v_2(z, s') + m_{3j}(s')v_3(z, s') \right], \quad (\text{A.8})$$

for  $j \in \{1, 2\}$  and  $(z, s) \in \{1, 2\} \times \{1, 2\}$ , and

$$v_j(z, s) = \mu \sum_{s'=1,2} p_{s's} [\delta_3(s')(1 - \tilde{\lambda}(s')) + (1 - \delta_3(s'))v_3(z, s')],$$

for  $j=3$  and  $(z, s) \in \{1, 2\} \times \{1, 2\}$ .

Under perfect competition and using the fact that all loans are assumed to be of credit quality  $j=1$  at origination, the interest rates  $c_z$  can be found as those that make  $v_1(z, z) = 1$  for  $z=1,2$ , respectively.

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<sup>32</sup>These definitions clearly imply  $EL_t^{IFRS9} = EL_t^{LT} - b_\beta(B_\beta - I)\hat{y}_t \leq EL_t^{LT}$  and  $EL_t^{IFRS9} = EL_t^{1Y} + b_\beta(B_\beta - I)\hat{y}_t \geq EL_t^{1Y}$ .

## A.7 Implications for P/L and CET1

By trivially extending the formula derived for the case without aggregate risk, the result of the P/L account with aggregate risk can be written as

$$\begin{aligned}
 PL_t = & \sum_{z=1,2} \left\{ \sum_{j=1,2} \left[ c_z(1-PD_j(s_t)) - \frac{\delta_3(s_t)}{2} PD_j(s_t) \tilde{\lambda}(s_t) \right] x_{t-1}(z, s_t, j) - \delta_3(s_t) \tilde{\lambda}(s_t) x_{t-1}(z, s_t, 3) \right\} \\
 & - r \left( \sum_{z=1,2} \sum_{j=1,2,3} x_{t-1}(z, s_t, j) - LL_{t-1} - k_{t-1} \right) - \Delta LL_t, \tag{A.9}
 \end{aligned}$$

which differs from (20) in the dependence on the aggregate state at the end of period  $t$ ,  $s_t$ , of a number of the relevant parameters affecting the default, resolution, and loss upon resolution of the loans.

With the same logic as in the baseline model, dividends and equity injections are now determined by

$$\text{div}_t = \max[(k_{t-1} + PL_t) - 1.3125 \underline{k}_t, 0] \tag{A.10}$$

and

$$\text{recap}_t = \max[\underline{k}_t - (k_{t-1} + PL_t), 0]. \tag{A.11}$$

Finally, for IRB banks, the minimum capital requirement is now given by<sup>33</sup>

$$\underline{k}_t^{IRB} = \sum_{j=1,2} \gamma_j(s_t) x_{jt}, \tag{A.12}$$

and

$$\gamma_j(s_t) = \lambda(s_t) \frac{1 + \left[ \left( \sum_{s'} p_{s's_t} \frac{1}{\delta_j(s')} \right) - 2.5 \right] \bar{m}_j}{1 - 1.5 \bar{m}_j} \left[ \Phi \left( \frac{\Phi^{-1}(\overline{PD}_j) + \text{cor}_j^{0.5} \Phi^{-1}(0.999)}{(1 - \text{cor}_j)^{0.5}} \right) - \overline{PD}_j \right], \tag{A.13}$$

where  $\bar{m}_j = [0.11852 - 0.05478 \ln(\overline{PD}_j)]^2$  is a maturity adjustment coefficient,  $\overline{\text{cor}}_j$  is a correlation coefficient fixed as  $\overline{\text{cor}}_j = 0.24 - 0.12(1 - \exp(-50\overline{PD}_j))/(1 - \exp(-50))$ , and

$$\overline{PD}_j = \sum_{i=1,2} \pi_i PD_j(s_i) \tag{A.14}$$

is the through-the-cycle PD for loans rated  $j$  (with  $\pi_i$  denoting the unconditional probability of aggregate state  $i$ ). Equation (A.14) implies assuming that the bank follows a strict through-the-cycle approach to the calculation of capital requirements (which avoids adding cyclicity to the system through this channel).<sup>34</sup>

<sup>33</sup>For SA banks, the equation for the minimum capital requirements in (25) remains valid.

<sup>34</sup>A point-in-time approach would imply setting  $\overline{PD}_j(s_t) = \sum_{s'} p_{s's_t} PD_j(s')$  instead of  $\overline{PD}_j$  in (A.13).

## B Calibration details

### B.1 Migration and default rates for our two non-default states

We calibrate the migration and default probabilities of our two non-default loan categories using S&P rating migration data based on a finer rating partition. To map the S&P partition into our partition, we start considering the  $7 \times 7$  matrix  $\tilde{A}$  obtained by averaging the yearly matrices provided by S&P global corporate default studies covering the period from 1981 to 2015. This matrix describes the average yearly migrations across the seven non-default ratings in the main S&P classification, namely AAA, AA, A, BBB, BB, B and CCC/C.<sup>35</sup> Under our convention, each element  $\tilde{a}_{ij}$  of this matrix denotes a loan’s probability of migrating to S&P rating  $i$  from S&P rating  $j$ , and the yearly probability of default corresponding to S&P rating  $j$  can be found as  $\widetilde{PD}_j = 1 - \sum_{i=1}^7 \tilde{a}_{ij}$ . With the referred data, we obtain  $\tilde{A}$ :

$$\tilde{A} = \begin{pmatrix} 0.8960 & 0.0054 & 0.0005 & 0.0002 & 0.0002 & 0.0000 & 0.0007 \\ 0.0967 & 0.9073 & 0.0209 & 0.0022 & 0.0008 & 0.0006 & 0.0000 \\ 0.0048 & 0.0798 & 0.9161 & 0.0463 & 0.0034 & 0.0026 & 0.0022 \\ 0.0010 & 0.0056 & 0.0557 & 0.8930 & 0.0626 & 0.0034 & 0.0039 \\ 0.0005 & 0.0007 & 0.0044 & 0.0465 & 0.8343 & 0.0618 & 0.0112 \\ 0.0003 & 0.0009 & 0.0017 & 0.0082 & 0.0809 & 0.8392 & 0.1390 \\ 0.0006 & 0.0002 & 0.0002 & 0.0013 & 0.0079 & 0.0432 & 0.5752 \end{pmatrix}, \quad (\text{B.1})$$

which implies

$$\widetilde{PD}^T = (0.0000, 0.0002, 0.0005, 0.0023, 0.0100, 0.0493, 0.2678).$$

To calibrate our model, we want to first collapse the above seven-state Markov process into the two-state one specified in our benchmark model without aggregate risk. We want to obtain its  $2 \times 2$  transition probability matrix, which we denote  $A$ , and the implied probabilities of default in each state,  $PD_j = 1 - \sum_{i=1}^2 a_{ij}$  for  $j=1,2$ . To collapse the seven-state process into the two-state process, we assume that the S&P states 1 to 5 (AAA, AA, A, BBB, BB) correspond to our state 1 and S&P states 6 to 7 (B, CCC/C) to our state 2. We also assume that all the loans originated by the bank belong to the BB category, so that the vector representing the entry of new loans in steady state under the S&P classification is  $\tilde{e}^T = (0, 0, 0, 0, 1, 0, 0)$ . Under these assumptions, we produce an average PD for the steady state portfolio of the model without aggregate risk of 1.88%, slightly below the 2.5% average PD on non-defaulted exposures of reported by the EBA (2013, Figure 12) for the period from the first half of 2009 to the second half of 2012 for a sample of EU banks using the IRB approach.

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<sup>35</sup>We have reweighted the original migration rates in S&P matrices to avoid having “non-rated” as an eighth possible non-default category to which to migrate.

The steady state portfolio under the S&P classification can be found as  $z^* = [I_{7 \times 7} - \widetilde{M}]^{-1} \widetilde{e}$ , where the matrix  $\widetilde{M}$  has elements  $\widetilde{m}_{ij} = (1 - \delta_j) \widetilde{a}_{ij}$  and  $\delta_j$  is the independent probability of a loan rated  $j$  maturing at the end of period  $t$ . For the calibration we set  $\delta_j=0.20$  across all categories, so that loans have an average maturity of five years. The “collapsed” steady state portfolio  $x^*$  associated with  $z^*$  has  $x_1^* = \sum_{j=1}^5 z_j^*$  and  $x_2^* = \sum_{j=6}^7 z_j^*$ .

For the collapsed portfolio, we construct the  $2 \times 2$  transition matrix  $M$  (that accounts for loan maturity) as

$$M = \begin{pmatrix} \frac{\sum_{j=1}^5 \sum_{i=1}^5 \widetilde{m}_{ij} z_j^*}{x_1^*} & \frac{\sum_{j=6}^7 \sum_{i=1}^5 \widetilde{m}_{ij} z_j^*}{x_2^*} & 0 \\ \frac{\sum_{j=1}^5 \sum_{i=6}^7 \widetilde{m}_{ij} z_j^*}{x_1^*} & \frac{\sum_{j=6}^7 \sum_{i=6}^7 \widetilde{m}_{ij} z_j^*}{x_2^*} & 0 \\ (1 - \delta_3/2)PD_1 & (1 - \delta_3/2)PD_2 & (1 - \delta_3) \end{pmatrix}, \quad (\text{B.2})$$

where the probabilities of default for the collapsed categories are found as

$$PD_1 = \frac{\sum_{j=1}^5 \widetilde{PD}_j z_j^*}{x_1^*}, \quad (\text{B.3})$$

and

$$PD_2 = \frac{\sum_{j=6}^7 \widetilde{PD}_j z_j^*}{x_2^*}. \quad (\text{B.4})$$

Putting it in words, we find the moments describing the dynamics of the collapsed portfolio as weighted averages of those of the original distribution, with the weights determined by the steady state composition of the collapsed categories in terms of the initial categories.

## B.2 State contingent migration matrices

Calibrating the full model with aggregate risk on which we base our quantitative analysis requires calibrating state contingent versions of the matrix  $M$  found in (B.2), namely the matrices  $M(s)$  for aggregate states  $s = 1, 2$  that appear in the formulas derived in Appendix A. We find  $M(1)$  and  $M(2)$  following a procedure analogous to that used to obtain  $M$  in (B.2) but starting from state-contingent versions,  $\widetilde{A}(1)$  and  $\widetilde{A}(2)$ , of the  $7 \times 7$  migration matrix  $\widetilde{A}$  in (B.1). As described in B.1, we can go from each  $\widetilde{A}(s)$  to the maturity adjusted matrix  $\widetilde{M}(s)$  with elements  $\widetilde{m}_{ij}(s) = (1 - \delta_j) \widetilde{a}_{ij}$  and then find the elements of  $M(s)$  as weighted averages of the elements of  $\widetilde{M}(s)$ . To keep things simple, we use the same unconditional weights as in (B.2), implying

$$M(s) = \begin{pmatrix} \frac{\sum_{j=1}^5 \sum_{i=1}^5 \widetilde{m}_{ij}(s) z_j^*}{x_1^*} & \frac{\sum_{j=6}^7 \sum_{i=1}^5 \widetilde{m}_{ij}(s) z_j^*}{x_2^*} & 0 \\ \frac{\sum_{j=1}^5 \sum_{i=6}^7 \widetilde{m}_{ij}(s) z_j^*}{x_1^*} & \frac{\sum_{j=6}^7 \sum_{i=6}^7 \widetilde{m}_{ij}(s) z_j^*}{x_2^*} & 0 \\ (1 - \delta_3(s)/2)PD_1(s) & (1 - \delta_3(s)/2)PD_2(s) & (1 - \delta_3(s)) \end{pmatrix}$$

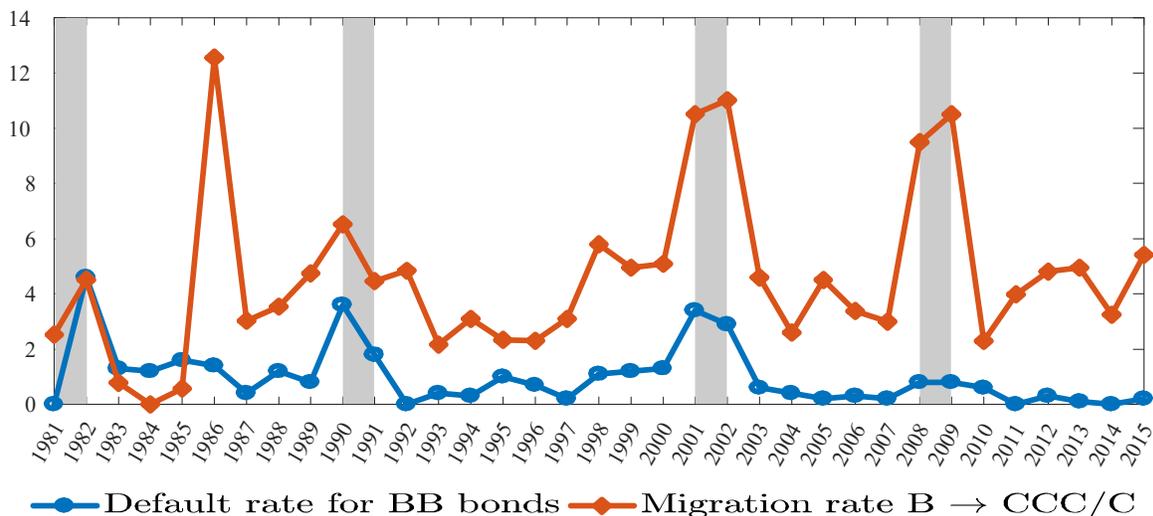
where

$$PD_1(s) = \frac{\sum_{j=1}^5 \widetilde{PD}_j(s) z_j^*}{x_1^*},$$

$$PD_2(s) = \frac{\sum_{j=6}^7 \widetilde{PD}_j(s) z_j^*}{x_2^*},$$

with  $\widetilde{PD}_j(s) = 1 - \sum_{i=1}^7 \tilde{a}_{ij}(s)$ .

We calibrate  $\tilde{A}(1)$  and  $\tilde{A}(2)$  exploring the business cycle sensitivity of S&P yearly migration matrices previously averaged to find  $\tilde{A}$ . We identify state  $s=1$  with expansion years and  $s=2$  with contraction years. We use the years identified by the NBER as the start of the recession to identify the entry in state  $s=2$  and assume that each of the contractions observed in the period from 1981 to 2015 lasted exactly two years. This is consistent with the NBER dating of US recessions except for the recession started in 2001, to which the NBER attributes a duration of less than one year. However, the behavior of corporate ratings migrations and defaults around such recession does not suggest it was shorter for our purposes than the other three. To illustrate this, Figure B.1 depicts the time series of two of the elements of the yearly default rates  $\widetilde{PD}_j$  and migration matrices  $\tilde{A}$  whose cyclical behavior is more evident: (i) the default rate among BB exposures ( $\widetilde{PD}_5$ ) and (ii) the migration rate from a B rating to a CCC/C rating ( $\tilde{a}_{7,6}$ ). Year 2002 emerges clearly as a year of marked deterioration in credit quality among exposures rated BB and B.



**Figure B.1. Sensitivity of default and migrations rates to aggregate states**  
 Selected yearly S&P default and downgrading rates. Grey bars identify  
 2-year periods following the start of NBER recessions

In light of this, we estimate  $\tilde{A}(2)$  by averaging the yearly counterparts of  $\tilde{A}$  extracted

from S&P data for years 1981, 1982, 1990, 1991, 2001, 2002, 2008 and 2009, and  $\tilde{A}(1)$  by averaging those corresponding to all the remaining years. This leads to

$$\tilde{A}(1) = \begin{pmatrix} 0.8923 & 0.0057 & 0.0005 & 0.0002 & 0.0002 & 0.0000 & 0.0000 \\ 0.1012 & 0.9203 & 0.0209 & 0.0023 & 0.0007 & 0.0003 & 0.0000 \\ 0.0039 & 0.0668 & 0.9228 & 0.0500 & 0.0036 & 0.0025 & 0.0027 \\ 0.0010 & 0.0058 & 0.0495 & 0.8939 & 0.0668 & 0.0036 & 0.0043 \\ 0.0007 & 0.0002 & 0.0040 & 0.0429 & 0.8484 & 0.0679 & 0.0117 \\ 0.0000 & 0.0009 & 0.0020 & 0.0084 & 0.0680 & 0.8511 & 0.1548 \\ 0.0000 & 0.0002 & 0.0001 & 0.0009 & 0.0059 & 0.0360 & 0.5860 \end{pmatrix},$$

implying

$$\widetilde{PD}(1)^T = (0.0000, 0.0001, 0.0002, 0.0014, 0.0063, 0.0386, 0.2405),$$

and

$$\tilde{A}(2) = \begin{pmatrix} 0.9087 & 0.0044 & 0.0003 & 0.0005 & 0.0002 & 0.0000 & 0.0030 \\ 0.0786 & 0.8632 & 0.0209 & 0.0014 & 0.0013 & 0.0017 & 0.0000 \\ 0.0077 & 0.1237 & 0.8936 & 0.0340 & 0.0026 & 0.0027 & 0.0009 \\ 0.0010 & 0.0050 & 0.0767 & 0.8899 & 0.0482 & 0.0028 & 0.0024 \\ 0.0000 & 0.0022 & 0.0057 & 0.0587 & 0.7865 & 0.0411 & 0.0095 \\ 0.0013 & 0.0007 & 0.0008 & 0.0076 & 0.1245 & 0.7988 & 0.0858 \\ 0.0027 & 0.0002 & 0.0006 & 0.0025 & 0.0143 & 0.0676 & 0.5389 \end{pmatrix},$$

implying

$$\widetilde{PD}(2)^T = (0.0000, 0.0005, 0.0014, 0.0054, 0.0224, 0.0853, 0.3596).$$

Finally, we set  $p_{12} = \text{Prob}(s_{t+1} = 1 | s_t = 2)$  equal to 0.5 so that contractions have an expected duration of two years, and  $p_{21} = \text{Prob}(s_{t+1} = 2 | s_t = 1)$  equal to 0.148 so that expansion periods have the same average duration as the ones observed in our sample period,  $(35-8)/4=6.75$  years.

### B.3 Calibrating defaulted loans' resolution rate

The yearly probability of resolution of NPLs,  $\delta_3$ , is calibrated so that the model without aggregate risk fed with unconditional means of the credit risk parameters matches the 5% average probability of default including defaulted exposures (*PDID*) that the EBA (2013, Figure 10) reports for the second half of 2008, right before the stock of NPLs in Europe got inflated by the impact of the Global Financial Crisis. The value of *PDID* for the steady state portfolio obtained in the absence of aggregate risk can be computed as

$$PDID = \frac{PD_1 x_1^* + PD_2 x_2^* + x_3^*}{\sum_{j=1}^3 x_j^*}, \quad (\text{B.5})$$

where  $PD_1$  and  $PD_2$  are the unconditional mean probabilities of default for standard and substandard loans obtainable from S&P data using (B.3) and (B.4), respectively (and the procedure explained around those equations). Solving for  $x_3^*$  in (B.5) allows us to set a target for  $x_3^*$  consistent with the target for  $PDID$ :

$$x_3^* = \frac{PD_1x_1^* + PD_2x_2^* - (x_1^* + x_2^*)PDID}{PDID - 1}. \quad (\text{B.6})$$

The law of motion of NPLs evaluated at the steady state implies

$$x_3^* = (1 - \delta_3/2)PD_1x_1^* + (1 - \delta_3/2)PD_2x_2^* + (1 - \delta_3)x_3^*, \quad (\text{B.7})$$

where it should be noted that the dynamic system in (1) allows us to compute  $x_1^*$  and  $x_2^*$  independently from the value of  $\delta_3$ . But, then, solving for  $\delta_3$  in (B.7) yields

$$\delta_3 = \frac{2(PD_1x_1^* + PD_2x_2^*)}{PD_1x_1^* + PD_2x_2^* + 2x_3^*}, \quad (\text{B.8})$$

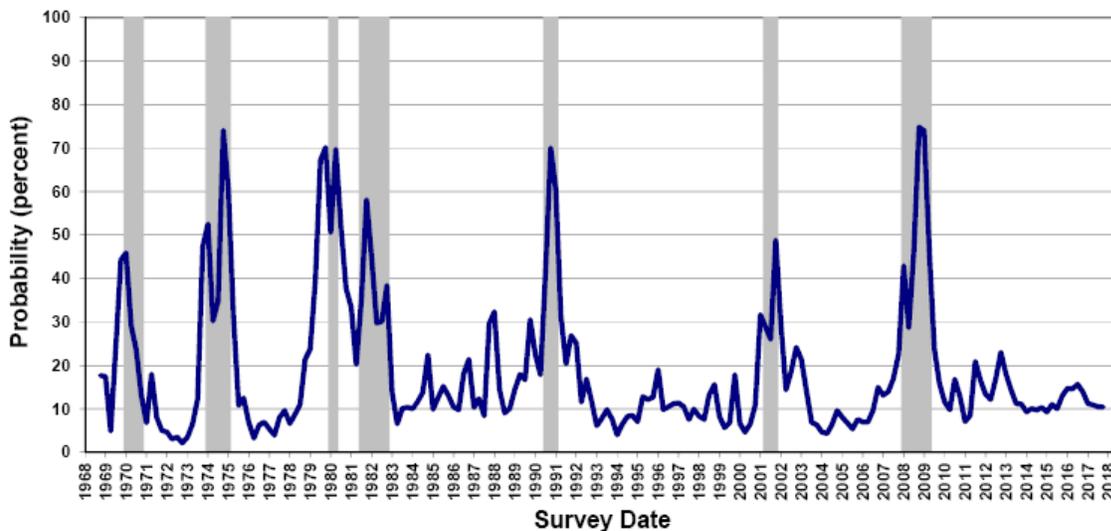
which allows us to calibrate  $\delta_3$  using  $x_1^*$ ,  $x_2^*$ , and the target for  $x_3^*$  found in (B.6).

## B.4 Can professional forecasters predict recessions?

The baseline quantitative results of the model are based on the assumption that changes in the aggregate state  $s_t \in \{1, 2\}$  cannot be predicted beyond what the knowledge of the time-invariant state transition probabilities of the Markov chain followed by  $s_t$  allows (that is, attributing some probability to the continuation in the prior state and a complementary one to switching to the other state). At the other side of the spectrum, several papers assess the cyclical properties of the new ECL approach to provisions using historical data and the assumption of perfect foresight or that banks can perfectly foresee the losses coming in some specified horizon (e.g. two years in Cohen and Edwards, 2017, or two quarters in Chae et al., 2017). In Section 5.2 of the main text, we explore how our own results get modified if banks can foresee the arrival of a recession one year in advance. However, banks' capacity to anticipate turning points in the business cycle, and especially switches from expansion to recession, can be contended. There is a long research tradition in econometrics trying to predict turning points but the state of the question can be summarized by saying that there are a variety of indicators which allow to "nowcast" recessions (that is, to state that the

economy has just entered a recession) but have little or no capacity to “forecast” recessions (see Harding and Pagan, 2010).

The same disappointing conclusion arises from the observation of the so-called *Anxious Index* published by the Federal Reserve Bank of Philadelphia (at <https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/anxious-index>). Such index reflects professional forecasters’ median estimate of the probability of experiencing negative GDP growth in the quarter following the one in which the forecasters’ views are surveyed. The index, which can be traced back to mid 1968 thanks to the data maintained by the Federal Reserve Bank of Philadelphia, is reproduced in Figure B.1. As one can see, it does not systematically rise above good-times levels in the proximity of U.S. recessions (marked as grey shaded areas), with the main exception of the second oil crisis in 1980.



Source: <https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/anxious-index>

**Figure B.2. The Anxious Index**

Professional forecasters’ median probability of decline in Real GDP in the following quarter. Grey bars identify NBER recessions.