

Still “Too Much, Too Late”: Provisioning for Expected Loan Losses*

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The new accounting standards of IFRS 9 and U.S. GAAP adopt the expected loss (EL) approach for loan loss recognition. We investigate the effect of the EL approach on bank loan supply and stability. When a bank is unable to anticipate a downturn in the business cycle, it ends up recognizing the bulk of expected losses *after* the arrival of a contraction. This aggravates lending procyclicality and can potentially worsen bank stability. We develop a dynamic model of a bank to quantitatively assess these effects and show that they are economically significant.

JEL Codes: G21, G28, M41, M48.

1. Introduction

To ensure an accurate assessment of their overall financial positions, banks periodically account for anticipated future loan losses through loan loss provisions. In doing so, they must comply with accounting standards for loan loss recognition. The recent financial crisis spurred

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criticism of the then-existing standards, which were based on the incurred loss (IL) approach. This approach limited loss recognition only to those losses that were factually identified (i.e., incurred) before the balance sheet date. As these standards led to delayed provisioning and insufficient loan loss reserves, they were blamed for contributing to the credit crunch (Financial Stability Forum 2009). The policy response was to adopt a more “forward-looking” provisioning approach based on *expected* rather than incurred credit losses.¹ Under the expected loss (EL) approach, banks’ provisions constitute unbiased estimates of future losses over a specified horizon. The new accounting standards of IFRS 9 and the new U.S. GAAP replace the IL approach with the EL approach.

The objective of this paper is to quantify the long-term effect of the EL approach on the cyclicity of bank lending and stability. As a rationale for the adoption of the EL approach, the Financial Stability Forum (2009) states that “earlier recognition of loan losses could have dampened cyclical moves in the current crisis and is consistent both with financial statement users’ needs for transparency regarding changes in credit trends and with prudential objectives of safety and soundness.” However, there is a shared concern among academics, policymakers, and market participants that the EL approach may actually have a strong procyclical effect (Barclays 2017, European Systemic Risk Board 2017, Abad and Suarez 2018). If banks fail to anticipate a downturn in the business cycle, they recognize the bulk of expected losses *after*, and not before, the arrival of a contraction. This leads to a spike in provisions right at the start of a contraction, which erodes banks’ profit margins and, unless they can swiftly raise fresh equity, reduces their lending capacity. Such a

¹The G-20 summit in London on April 2, 2009 resulted in signing the Declaration on Strengthening the Financial System, which included the following reforms among others: strengthen accounting recognition of loan loss provisions by incorporating a broader range of credit information and improve accounting standards for provisioning. The International Accounting Standards Board (IASB) and the U.S. Financial Accounting Standards Board (FASB) set in motion a joint project to improve accounting standards and, in particular, to develop methods of accounting for credit losses that would give more timely recognition of those losses, thereby helping to reduce lending procyclicality. This effort resulted in the International Financial Reporting Standard (IFRS) 9 and the credit loss standard (ASC 326) under the U.S. GAAP (generally accepted accounting principles), both of which adopt the expected credit loss approach.

sudden front-loading of losses at the dawn of a contraction could not only force banks to cut new loans but also jeopardize their stability.

From a macroprudential point of view, bank procyclicality is widely viewed as undesirable by both academics and policymakers (Hanson, Kashyap, and Stein 2011).² The effort to reduce the procyclical effect of risk-based capital regulation led to the revision of the Basel Accords in the form of the new Basel III regulation, which includes policy instruments designed to reduce lending procyclicality.³ The EL approach can potentially undermine the post-crisis regulatory effort to reduce bank procyclicality and is likely to be inefficient from a macroprudential point of view.

To quantify the effect of the EL approach, we adopt a structural, rather than reduced-form, approach.⁴ We develop a dynamic model of a bank. Our model features endogenous loan origination, distribution, leverage, and default. The bank faces corporate taxes, the cost of issuing external equity, and regulation. The regulatory environment comprises a minimum capital requirement and provisioning standards. The capital structure of the bank consists of fully insured short-term deposits and equity. The asset side is composed of risky long-term loans with stochastic and time-varying default probabilities.

First, we calibrate our model under the benchmark provisioning requirement, which is based on the IL approach of the International Accounting Standards (IAS) 39. Next, we solve our model under two variations of the EL approach, namely the expected credit loss (ECL) of IFRS 9 and the current expected credit loss (CECL) of the

²The literature on *optimal* time-varying capital requirements provides much support in favor of a countercyclical capital regulation (i.e., procyclical capital requirements), which helps to smooth the cyclicity of credit supply (see Kashyap and Stein 2004, Dewatripont and Tirole 2012, Repullo 2013, Gersbach and Rochet 2017, and Malherbe 2020, among others). Empirical evidence further suggests that a countercyclical capital regulation indeed helps to reduce credit crunch (Jiménez et al. 2017).

³Basel III instruments such as the countercyclical capital buffer, the conservation capital buffer, and contingent capital are all meant to reduce lending procyclicality.

⁴An empirical investigation using a reduced-form approach would require data that include a full credit cycle under the EL approach. However, such data are not available, since the accounting standards that adopt the EL approach either have only recently been put in effect (i.e., IFRS 9) or are still planned to be implemented (U.S. GAAP).

new U.S. GAAP.⁵ We compare the solutions of the model under the two versions of the EL approach to the benchmark case.

Our quantitative results indicate that the adoption of either version of the EL approach results in a profound aggravation of lending procyclicality in the long run. Our model predicts that, on average, in a contraction, a bank originates about 6–7 percent fewer new loans under the EL than the IL approach. At the same time, unconditional on the aggregate state, the bank's lending is only about 2–3 percent lower under the EL approach. This highlights the strong procyclicality of the EL approach, as it disproportionately reduces lending in a contraction.

We further examine the procyclicality of the EL approach when a bank is subject to the countercyclical capital buffer (CCyB), which is a new Basel III policy that explicitly aims at reducing procyclicality. We find that the CCyB is unable to fully offset the procyclical effect of the EL approach—that is, the simultaneous adoption of the EL approach and CCyB also results in more procyclical lending than under the benchmark. The magnitudes, however, are attenuated. Furthermore, even when we allow the bank's profits to respond with a one-period delay to the arrival of a contraction, which effectively allows the bank to anticipate the deterioration of its balance sheet, the procyclical effect of the EL approach still persists.

Next, we show that when it comes to the effect of the EL approach on banks' stability there are two effects in play. On the one hand, under the EL approach, a bank holds larger loan loss reserves since on top of the incurred losses it must also recognize expected losses. Larger reserves provide better loss-absorption capacity, thus improving stability. On the other hand, the procyclicality of the EL approach effectively increases the volatility of the bank's profits. This, in turn, increases the bank failure rate. The overall effect of the EL approach on stability will depend on the relative strength of these two effects. Our quantitative model suggests that IFRS 9 is more likely to increase bank failure rate than U.S. GAAP. While their

⁵The primary difference between these models is that they adopt different horizons over which expected losses must be recognized. IFRS 9 is based on a mixed-horizon approach such that, depending on the loan's risk category, the bank recognizes either one-year or lifetime discounted expected losses. The new U.S. GAAP, on the other hand, requires banks to recognize lifetime discounted expected losses on all loans.

procyclical effect on lending is similar, IFRS 9 produces smaller loan loss reserves than U.S. GAAP, due to its mixed-horizon approach.

Our analysis indicates that earlier recognition of losses does not per se help to smooth lending cyclicalities. It matters how early in advance future losses are recognized. If future losses were to be recognized before the arrival of a contraction, this would result in a precautionary capital buffer, which would then help to smooth lending in a downturn. For example, the Spanish dynamic loan loss provisioning approach, which prescribed higher provisions in expansions relative to contractions, allowed the banks to effectively build up a capital buffer during good times and consequently smooth lending when the contraction arrived (Jiménez et al. 2017).⁶ In contrast, under the EL approach, banks will recognize the bulk of expected losses *after* the arrival of a contraction, provided they cannot anticipate the change in the aggregate state well in advance. Thus, forcing banks to recognize their future losses based on the EL approach is equivalent to imposing a more *countercyclical* capital requirement. It is well understood that a countercyclical capital requirement results in more procyclical lending (Kashyap and Stein 2004; Repullo, Saurina, and Trucharte 2010).

Our paper contributes to several strands of the literature. First, our paper relates to a large literature on the cyclical implications of bank regulation. Kashyap and Stein (2004) provide a formal analysis of the procyclical effect of capital regulation on bank lending and advocate for more procyclical capital requirements than those of Basel II. Similarly, in a dynamic model of banking, Repullo and Suarez (2013) show that procyclical adjustment to the Basel II capital requirements are welfare-improving. In general, the theoretical literature provides a vast support in favor of procyclical capital requirements (Dewatripont and Tirole 2012; Repullo 2013; Gersbach and Rochet 2017; Malherbe 2020). Empirical evidence further indicates that more procyclical capital requirements indeed help to smooth bank lending better (Behn, Haselmann, and Wachtel 2016; Jiménez et al. 2017). While this literature examines the cyclical effect of capital regulation, we focus on the cyclical effect of loan loss provisioning requirements. We show that adopting the EL approach for

⁶This approach is very similar to a countercyclical capital buffer policies such as CCyB.

loan loss recognition is similar to imposing a more countercyclical capital requirement.

Second, our paper contributes to the literature on bank loan loss provisioning. While the empirical literature on loan loss provisioning is relatively large (Ahmed, Takeda, and Thomas 1999; Laeven and Majnoni 2003; Beatty and Liao 2011; Bushman and Williams 2015; Huizinga and Laeven 2018), the theoretical literature is rather scarce. To the best of our knowledge, our paper is the first one to formally examine the effect of the provisioning requirement for future losses on bank loan supply and stability.

Third, our paper contributes to the literature that studies the cyclical impact of the expected credit loss approach of the new accounting standards. Early concerns about the potential procyclicality of the expected loss approach can be found in Laux (2012), Barclays (2017), and European Systemic Risk Board (2017). A few papers provide a quantitative assessment of the cyclical implications of the EL approach on capital and provisions. Krüger, Rösch, and Scheule (2018) show that had the banks followed the EL approach, they would have had lower levels of capital, especially during the 2007–08 crisis, and the bank capital would have been more procyclical. Under the assumption that the bank can anticipate the turn in the business cycle, Cohen and Edwards (2017) and Chae et al. (2019) show that the EL approach achieves better smoothing of provisions compared to the IL approach. Abad and Suarez (2018) quantify the procyclical effect of the EL approach on bank capital in a dynamic model of a bank with exogenous lending and heterogeneous loans. In our paper, we evaluate the effect of the EL approach on loan supply and bank stability under the bank's optimal behavior, as our settings allow for endogenous lending, financing, and default. Thus, our analysis is less prone to the Lucas critique, since we allow the bank to optimally respond to the adoption of the EL approach.

Finally, our paper broadly relates to the growing literature on the interaction between accounting practice, on the one hand, and financial stability and prudential regulation, on the other (see Goldstein and Sapra 2014 and Acharya and Ryan 2016 for a survey). Laux and Leuz (2010) provide critical analysis of the role of fair-value accounting in the recent financial crisis. Mahieux, Sapra, and Zhang (2023) examine the effect of mandatory earlier loss recognition on bank risk-taking. We contribute to this literature by pointing out

that provisioning rules and capital regulation are two sides of the same coin and, thus, should not be designed independently.

The rest of the paper proceeds as follows. Section 2 provides institutional details on provisioning, the expected loss models of IFRS 9, and the new U.S. GAAP. Section 3 introduces a simple three-date model of a bank to highlight the economic mechanism through which the EL approach affects bank lending and stability. Section 4 presents a quantitative dynamic model of a bank, while the calibration of the model is found in Section 5. Section 6 contains the quantitative analysis and results of the long-term effect of adopting provisioning requirements based on the EL approach. Finally, Section 7 concludes.

2. Institutional Details

A loan loss provision is a non-cash expense set aside as an allowance for impaired loans. It is an accounting entry that increases loan loss reserves (a contra asset account on the balance sheet) and reduces net income. Empirically, such provisions constitute a large fraction of bank expenses (Huizinga and Laeven 2018). As a result, they substantially reduce a bank's profit in financial statements, thereby affecting regulatory capital. In the future, when the losses realize, they are charged off against the loss reserves. The rules for loan loss provisioning for internationally active banks and U.S.-based banks are formulated by the International Accounting Standards Board (IASB) and the U.S. Financial Accounting Standards Board (FASB), respectively.

The International Accounting Standards (IAS) 39, which was effective until the end of 2017, employed the so-called incurred loss model (ILM) for loan loss recognition. The ILM did not allow banks to recognize credit losses based on the events expected to happen in the future. Under the ILM, it was assumed that all loans would be repaid until the evidence to the contrary is established. Only at that point, the impaired loan (or portfolio of loans) could be written down to a lower value. Therefore, only those losses that were factually documented could be recognized.

In the aftermath of the financial crisis of 2007–08, IAS 39 was criticized for potentially contributing to the credit crunch, as it

did not allow for timely loss recognition (Financial Stability Forum 2009). The policy response was to adopt a more “forward-looking” provisioning approach based on *expected* rather than incurred credit losses. To reduce the procyclical effect of provisioning and improve transparency, the IASB and the FASB created new accounting standards. Each of these standards introduces its own version of the expected loss model (ELM). IFRS 9 replaced IAS 39 in January 2018, while the implementation of the new U.S. GAAP was planned for the end of 2020 but has been delayed due to the COVID-19 pandemic.⁷

Under the ELM, banks’ provisions must constitute *unbiased* estimates of future losses over a specified horizon. The defining feature of the ELM is that it employs the so-called point-in-time (PiT) loan default probabilities when estimating expected credit losses. That is, expected losses are estimated not just based on historical data but also with the incorporation of all presently available relevant information.⁸ Thus, under the ELM, banks must employ statistical inference to provide an unbiased estimate of expected loan losses taking into account all currently available information.

The model of IFRS 9 adopts a mixed-horizon approach: either one-year or lifetime discounted expected losses are recognized depending on the risk category of loans. The bank must recognize one-year discounted expected losses on stage 1 (good-quality) loans and lifetime discounted expected losses on stage 2 (sub-quality) loans.⁹ The current expected credit loss (CECL) model of the new U.S. GAAP adopts a lifetime horizon for the entire portfolio of loans irrespective of their credit risk. Moreover, whereas under IFRS 9 expected losses are discounted at the loan’s contractual interest

⁷The adoption of IFRS 9 is still in the transitional period especially due to the COVID-19 pandemic (see Borio and Restoy 2020 for details).

⁸For example, according to the IFRS 9, “an entity shall adjust historical data, such as credit loss experience, on the basis of current observable data to reflect the effects of the current conditions and its forecasts of future conditions that did not affect the period on which the historical data is based and to remove the effects of the conditions in the historical period that are not relevant to the future contractual cash flows” (paragraph B 5.5.52 in IASB 2014).

⁹IFRS 9 also specifies stage 3 loans, which are non-performing loans (NPLs). The accounting treatment of such loans under IFRS 9 is similar to that of incurred losses under IAS 39.

rate, banks can use their own discount rates under the new U.S. GAAP.

3. A Simple Model

3.1 Setup

There are three dates labeled as $t = 0, 1, 2$. At $t = 0$, the bank starts with an initial equity endowment of $E_0 > 0$. At $t = \{0, 1\}$ the bank's risk-neutral manager maximizes the present value of expected future dividends by investing in a risky portfolio of loans L_t , which matures over one period at $t + 1$. The loan portfolio L_t has a stochastic net repayment rate $r_{t+1}^L \sim \mathcal{N}(\mu_t, \sigma_t)$. The loan portfolio is funded with the bank's equity capital E_t and one-period deposits B_t . Deposits are assumed to be fully insured, with the deposit insurance priced at a flat rate normalized to zero.¹⁰ To keep the model simple, both the deposit repayment rate and the discount rate are set to zero.

The bank operates in a regulatory environment characterized by the capital regulation and provisioning requirement for expected future loan losses. In the model, the minimum capital requirement serves to minimize the probability of bank failure, thus minimizing the implicit cost of the deposit insurance. When investing in loan portfolio at t , at least a fraction of $\kappa_t \in [0, 1]$ of the portfolio must be financed with equity—that is, the minimum capital requirement takes the standard form of

$$E_t \geq \kappa_t L_t. \quad (1)$$

The provisioning requirement for future loan losses is specified in terms of a requirement on loan loss reserves. Specifically, the provisioning requirement stipulates that when the bank originates new loans, L_t , the expected losses on the entire portfolio must be recognized. Let the expected losses on portfolio L_t be $\theta_t L_t$, where

¹⁰When the bank fails, it defaults on deposits and their interest. In that case, the deposit insurance agency fully repays the depositors the principal and the interest. Therefore, although from the point of view of the insurance agency deposits are risky, from the point of view of depositors these are risk-free claims.

$0 \leq \theta_t < 1$ is the expected loss rate; then the bank's loss reserves R_t are given by¹¹

$$R_t = \theta_t L_t. \quad (2)$$

Consequently, once the investment and provisioning have been made, the bank's balance sheet identity is given by

$$L_t - R_t = B_t + E_t. \quad (3)$$

The bank's profits are subject to corporate taxes. To account for loss limitations, the bank's profits are taxed at the marginal tax rate $\tau > 0$ when the profits are positive, while the tax rate is zero when the profits are negative.¹² Therefore, the corporate tax rate is a function of the bank's profits π_t is given by

$$\tau(\pi_t) = \tau \mathbb{I}_{\pi_t > 0}, \quad (4)$$

where $\mathbb{I}_{\pi_t > 0}$ denotes an indicator functions which is equal to one when $\pi_t > 0$ and zero otherwise.

Raising equity externally is assumed to be prohibitively expensive. Thus, the bank can increase its equity capital only internally—via profit retention. The bank is subject to limited liability constraint—if the value of its equity drops below zero, the bank optimally defaults generating a zero payoff to the shareholders.

Finally, we introduce the last two ingredients into our model, which are important for the analysis of the expected provisioning requirement. First, we assume that at $t = 2$ the economy is characterized by the aggregate state s_2 , which is either good, $s_2 = g$, or bad, $s_2 = b$. The aggregate state affects the expected loan repayment rates at $t = 2$: under the good aggregate state the expected

¹¹It is important to stress that in our model the loan loss reserves R_t are composed of only provisions for expected credit losses and not of realized ones. In practice, banks also keep loan loss reserves against realized losses. However, since our analysis is on the requirement for recognition of expected loss, we assume that the bank does not hold reserves against realized losses—that is, the realized losses are written off immediately as they are realized without being accumulated in the form of non-performing loans.

¹²We follow Hennessy and Whited (2007), who adopt this parsimonious approach to model a corporate tax schedule that accounts for loss limitations. Loss limitations are introduced as a kink in the tax schedule producing convexity.

loan repayment is higher than under the bad one. Furthermore, we assume that at $t = 1$ the bank receives a signal z_1 over the aggregate state at $t = 2$, which is either good, g , or bad, b . The signal is informative in that $P(s_2 = a|z_1 = a) > P(s_2 = a)$ for $a \in \{g, b\}$. As discussed in the previous section, under the expected provisioning requirement the bank incorporates all presently available information to estimate and recognize expected losses. Thus, the expected provisioning rate at $t = 1$ depends on the signal and, thus, is denoted as $\theta_{1|z}$. Since the expected provisioning rate effectively corresponds to an expected loss rate, it follows that $\theta_{1|g} < \theta_{1|b}$.

3.2 Solution

The model is solved backwards starting at $t = 2$. The $t = 2$ profits are given by

$$\pi_2 = (1 - \tau(\pi_2)) \left[r_{2|s}^L L_{1|z} + R_1 \right], \quad (5)$$

where the first term is the net repayment on loan portfolio, $L_{1|z}$, and the second term captures the fraction of losses on the portfolio that has already been recognized via provisioning at $t = 1$. Since the world ends at $t = 2$, the manager uses all available funds to pay out the dividend. Thus, the $t = 2$ dividend $X_2 = \pi_2 + E_1$. If $X_2 < 0$, which happens under a relatively low realization of $r_{2|s}^L$, then the bank fails at $t = 2$, in which case the value of the bank is zero due to the limited liability constraint.

At $t = 1$, the bank's manager maximizes the sum of the $t = 1$ dividend and the next period dividend, provided the bank does not fail $t = 1$, which happens under a low realization of r_1^L .¹³ That is, the problem is given by

$$V_1 = \max_{\{L_1\}} \left\{ X_1 + \mathbb{E}[X_2|z_1, X_2 > 0] \right\}, \quad (6)$$

subject to $X_1 \geq 0$,

¹³The bank fails at $t = 1$ if $X_1 < 0$, even if the bank does not lend—that is, $L_{1|z} = 0$.

where, from a basic accounting identity, the $t = 1$ dividend is given by

$$X_1 = E_0 + \pi_1 - E_1, \quad (7)$$

and the $t = 1$ after-tax profits are given by

$$\pi_1 = (1 - \tau(\pi_1)) [r_1^L L_0 + R_0 - R_1], \quad (8)$$

where the first term inside the square bracket is the net repayment on the initial loan portfolio L_0 , and the last two terms capture provisioning for expected losses.

If the bank does not fail at $t = 1$ —that is, if the realization of r_1^L is sufficiently high—then conditional on the realization of the signal z_1 the bank chooses its optimal loan portfolio $L_{1|z}$. Since the bank is protected by the limited liability constraint, the expected $t = 2$ dividend is always positive, $\mathbb{E}[\max\{0, X_2\}] > 0$, and increasing in $L_{1|z}$. Therefore, it is straightforward to show that the manager invests as much as possible in $L_{1|z}$ until $X_1 \geq 0$ is binding. For the same reason, the minimum capital constraint is also binding at $t = 0, 1$. The optimal $L_{1|z}$ is then derived by setting $X_1 = 0$, in which case one obtains

$$L_{1|z} = \frac{\kappa_0 + (1 - \tau(\pi_1))(\theta_0 + r_1^L)}{\kappa_1 + \theta_{1|z}(1 - \tau(\pi_1))} L_0. \quad (9)$$

Similarly, one derives the optimal initial portfolio L_0 . Since the minimum capital constraint is binding and since recognizing expected losses at $t = 0$, $\theta_0 L_0$ brings the available equity down to $E_0 - \theta_0 L_0$, the optimal L_0 is given by

$$L_0 = \frac{E_0}{\theta_0 + \kappa_0}. \quad (10)$$

3.3 Analysis and Discussion

3.3.1 Provisioning Requirement vs. Capital Requirement

Despite its simplicity, our stylized model can be used to understand the implications of adopting expected provisioning requirement for future losses on bank lending and stability. To provide better intuition for the effect of the EL approach on bank lending and stability,

it is instructive to decompose the effect of the provisioning requirement for future losses into two channels: the capital requirement channel and the tax channel, which is accomplished in a proposition below.

PROPOSITION 1. *Let $(L_0^e, L_{1|z}^e)$ and P_t denote the optimal lending schedule and bank default probability at $t = 1, 2$, respectively, of a bank that is subject to the minimum capital requirement $E_t \geq \kappa_t L_t$ and the provisioning requirement $R_t = \theta_t L_t$. Then $(L_0^e, L_{1|z}^e)$ and P_t are also the optimal lending schedule and bank default probability at $t = 1, 2$, respectively, of a bank that is subject to the minimum capital requirement $E_t \geq (\kappa_t + \theta_t)L_t$ and the provisioning requirement $R_t = 0$, and receives a tax subsidy $\tau(\pi_t)(\theta_t L_t - \theta_{t-1} L_{t-1})$ at t .*

Proof. The proof is straightforward. By solving for $(L_0^e, L_{1|z}^e)$ when the bank is subject to the minimum capital requirement $E_t \geq (\kappa_t + \theta_t)L_t$ and the provisioning requirement $R_t = 0$, and receives a tax subsidy $\tau(\pi_t)(\theta_t L_t - \theta_{t-1} L_{t-1})$ at t , it is straightforward to show that $(L_0^e, L_{1|z}^e)$ are given by Equations (9) and (10). $\square$

It follows from Proposition 1 that when the future loan losses are not tax deductible, then the provisioning rate θ_t has the exact same effect on bank lending as does the required minimum equity rate κ_t . This is intuitive since accounting-wise the net income before provisions is the source for both equity capital (through retention) and loan loss reserves (LLRs) (through provisioning). Having to recognize future losses limits the bank's ability to increase equity through retention and vice versa. Therefore, the cost of provisioning is the same as those of increasing equity capital. At the same time, both LLRs and equity capital serve as a buffer to absorb the loan losses once they are realized. Our model, therefore, highlights that the minimum capital requirement and the provisioning requirement for future losses are in effect substitutes. This insight informs the policy debate around macro- and micro-prudential regulation that capital requirements (set by bank regulators) and accounting standards on provisioning (set by market regulators) cannot be isolated from each other. Moreover, the tax treatment of provisions will also influence the optimal lending policies. This has important policy implications, especially given that both the accounting standards

for loan loss recognition and the capital regulation under Basel III are undergoing drastic modifications.

Therefore when future losses are not tax deductible, we can understand the effect of θ_t on lending through κ_t . In particular, increasing θ_t will lower lending, since it forces the bank to rely more on equity financing, which raises the cost of capital. Moreover, imposing a countercyclical (procyclical) provisioning requirement—that is, $\theta_{1|g} < \theta_{1|b}$, ($\theta_{1|g} > \theta_{1|b}$)—will aggravate (mitigate) lending procyclicality. This follows immediately from a well-established result in the literature: imposing a more countercyclical (procyclical) capital requirement results in a more (less) procyclical lending (Kashyap and Stein 2004; Repullo, Saurina, and Trucharte 2010).

The second channel of the effects of provisioning requirement for future losses is due to the tax deductibility of these provisions. Note that this channel is present even if the bank is not subject to the minimum capital requirement and cannot be directly offset by adjusting the minimum capital requirement.¹⁴ According to Proposition 1, when provisions are tax deductible they generate the tax subsidy. Due to the convexity of the tax schedule $\tau(\pi_t)$, the tax subsidy has a higher value in good times, when the profits tend to be higher. Therefore, this subsidy allows the bank to lend more aggressively when times are good vis-à-vis when times are bad, thereby amplifying lending procyclicality.¹⁵

3.3.2 *Incurred Loss Approach vs. Expected Loss Approach*

Recall that under the IL approach, banks are not allowed to recognize losses that are based on events expected to happen in the future. Therefore, we accommodate the IL approach in our model by setting $\theta_t = 0$.¹⁶ In contrast, under the EL approach the banks must

¹⁴The capital regulation under Basel III is conditional on banks' portfolio risk and cannot be conditioned directly on banks' profits.

¹⁵Naturally, reducing the convexity of the tax schedule—that is, improving the banks' ability to shift losses intertemporally—could reduce the procyclical effect of tax deductibility.

¹⁶We assume incurred losses are provisioned for and charged off as soon as they are incurred.

recognize expected losses on loans already at their inception. Importantly, expected losses must be estimated using all presently available information—that is, conditional on the current state. Without going too much into details on how exactly θ_t is set under the EL approach at this moment, we set $\theta_{1|a} = \theta_0 > 0$ and $\theta_{1|b} = \theta_0 + \epsilon$, where $\epsilon > 0$, so that $\theta_{1|a} < \theta_{1|b}$, which reflects the fact that expected losses are higher conditional on the bad signal about the aggregate state.

Mathematically, replacing the IL with EL approach is equivalent to simultaneously raising θ_0 and ϵ . Proposition 1 then helps us understand the implications of replacing the IL approach with the EL approach on bank lending and stability. In line with Proposition 1, adopting the EL approach is equivalent to tightening the capital requirement (increasing θ_0) and making it more countercyclical (increasing ϵ). Thus, even absent the tax deductibility of expected provisions, adopting the EL approach will depress lending, worsen lending procyclicality, and improve stability.

The following proposition formalizes our results with regard to the implications of adopting the EL approach for loan loss recognition on bank lending and stability:

PROPOSITION 2. *Let $(L_0^i, L_{1|z}^i)$ and $(L_0^e, L_{1|z}^e)$ denote optimal lending under the IL and EL approaches, respectively. Let P_t denote the probability of bank failure at $t = 1, 2$. Finally, define provisioning rates for expected losses as $\theta_{1|g} := \theta_0 > 0$ and $\theta_{1|b} := \theta_0 + \epsilon$, where $\epsilon > 0$. Then replacing the IL approach with the EL approach*

- *lowers lending, $dL_0^e/d\theta_0 < 0$ and $dL_{1|z}^e/d\theta_0 < 0$,*
- *amplifies lending procyclicality, $d(L_{1|g}^e - L_{1|b}^e)/d\epsilon > 0$,*
- *improves stability, $dP_1/d\theta_0 < 0$ and $dP_2/d\theta_{1|z} < 0$.*

Proof. See proof in Appendix A. □

That the model predicts a more procyclical lending under the EL approach is problematic. One of the two objectives of adopting the more forward-looking EL approach is to reduce lending

procyclicality.¹⁷ Intuitively, this cannot be achieved under the EL approach for as long as the expected credit losses are computed based on the point-in-time (PiT) default probabilities. By construction the PiT probabilities are countercyclical—defaults are relatively more common in a recession—and thus, so are the expected credit losses.¹⁸ While some of the countercyclicality of the EL approach can be undone via adjustments to the capital requirements, it cannot be fully eliminated due to the tax-deductibility channel discussed above. Moreover, such adjustments would make bank regulatory policy dependent on accounting rules, thus further raising its complexity.

In the next section, we extend our simple model to *quantitatively* evaluate the effect of replacing the IL approach with EL one. With a richer dynamic model, we can calibrate the model's parameters using their observed counterparts in real-world data and generate simulations to quantitatively compare the two provisioning approaches.

4. Quantitative Dynamic Model

The is a partial equilibrium model and the bank takes all prices as given. Time is discrete and the horizon is infinite. The timing notation in the model is such that the predetermined (i.e., state) variables at time t have subscript $t - 1$, while exogenous shocks realized at t as well as the choice variables at time t are all indexed by t .

The bank's risk-neutral manager, acting on the behalf of shareholders, invests in a risky and illiquid portfolio of long-term loans L_t funding this investment with one-period deposits B_t and equity E_t .

¹⁷The second objective is to improve transparency via more timely loan loss recognition. In our analysis, we do not analyze the effects of potential changes in transparency. While this is an extremely interesting question, our dynamic model cannot accommodate such complexity. Thus, our focus is solely on the interaction of regulatory requirements—in the form of capital constraint—and accounting standards—in the form of provisioning requirements.

¹⁸Incidentally, the procyclical effect of PiT default probabilities was appreciated when the internal ratings-based framework was introduced in Basel II, which makes use of the so-called through-the-cycle (TTC) default probabilities that reflect expected default rates under normal business conditions.

Deposits are assumed to be fully insured with the deposit insurance priced at a flat rate normalized to zero.¹⁹ The bank provisions for loan losses and, thus, holds LLRs R_t . The following balance sheet identity holds:

$$L_t - R_t = B_t + E_t. \quad (11)$$

4.1 Aggregate State

The economic environment characterized by the aggregate state s_t . The aggregate state follows a discrete-time Markov chain. The state space of s_t consists of two values g and b corresponding to expansionary and contractionary aggregate state, respectively. The transition probability from state s_t to s_{t+1} is denoted by $q_{s_t, s_{t+1}}$.

4.2 Loan Portfolio

The bank's loan portfolio consists of two types (categories) of loans: stage 1 (good credit quality) and stage 2 (impaired credit quality) loans.²⁰ Let $\xi_t^i \sim F(\xi_t^i; s_t)$ denote a random fraction of stage i loans that defaults at the beginning of period t . Conditional on aggregate state, default rate ξ_t^i is iid. The cumulative distribution function (CDF) is ranked in terms of first-order stochastic dominance with respect to aggregate so that $F(\xi_t^i; s_t = g) \leq F(\xi_t^i; s_t = b)$ holds.²¹

All non-defaulted loans repay the same interest $r_{s_{t-1}}^L$ at time t and a fraction $\delta \in (0, 1)$ of them matures, repaying the principal.²² Defaulted loans are resolved and written off in the same period they

¹⁹When the bank fails, it defaults on deposits and their interest. In that case, the deposit insurance agency fully repays the depositors the principal and interest. Therefore, although from the point of view of the insurance agency deposits are risky, from the point of view of depositors these are risk-free claims.

²⁰Heterogeneity of loans based on quality is crucial for capturing regulatory aspects of different versions of the EL approach.

²¹In the calibration section, we show that under assumption that individual loans are exposed to a single common factor, and thus have imperfectly correlated defaults, $F(\xi_t^i; s_t)$ takes the form of the Vasicek distribution (Vasicek 2002).

²²Every period, a loan matures with probability δ . Therefore, the average maturity of the loan portfolio is then given by $1/\delta > 1$. Thus, the bank is engaged in maturity transformation.

default.²³ Defaulted loans yield a recovery rate of $1 - \lambda_{s_t}^i \in [0, 1]$. Thus, $\lambda_{s_t}^i$ is a loss given default rate.

The fraction of type 1 loans is given exogenously and is denoted by ω_{s_t} . Therefore, the default rate for the portfolio of all loans is given by $\xi_t = \omega_{s_t} \xi_t^1 + (1 - \omega_{s_t}) \xi_t^2$.

Every period the bank originates new loans, $N_t \geq 0$, thus, the total portfolio of loans evolves according to the following law of motion

$$L_t = (1 - \xi_t)(1 - \delta)L_{t-1} + N_t. \quad (12)$$

Loan origination is a costly process.²⁴ Following De Nicolò, Gamba, and Lucchetta (2014) and Mankart, Michaelides, and Pagratis (2020), we assume a quadratic lending cost function

$$C(N_t) = \frac{\phi}{2} N_t^2, \quad (13)$$

where $\phi > 0$. We restrict N_t to non-negative values—that is, the bank is not allowed to sell its loans.

4.3 Provisioning Requirement for Future Losses

As in the simple stylized model, the provisioning requirement for future loan losses is specified in terms of a requirement on LLRs. The provisioning rate $\theta_{s_t} \in [0, 1]$ depends now on the aggregate state. Under the assumption that the bank does not accumulate defaulted loans in the form of NPLs and writes the losses off in the same period they materialize, its loan loss reserves are given by

$$R_t = \theta_{s_t} L_t. \quad (14)$$

²³ Assuming that a loan that defaulted during period t is resolved and is written off during the same period t is a simplifying assumption, as it greatly reduces the state space of the model. The consequence of this assumption is that the bank does not accumulate NPLs—all defaulted loans are resolved and written down immediately. For our purposes, this assumption is not restrictive because, as we discuss it in the later section, the incurred and expected loss approaches treat NPLs in the same way.

²⁴ For example, the screening cost of processing new loan applications.

The law of motion of the bank's loan loss reserves can then be written as

$$R_t = R_{t-1} - \xi_t \lambda_{s_t} L_{t-1} + LLP_t, \quad (15)$$

where LLP_t denotes the bank's *total* loan loss provision: provisions for incurred losses, $\xi_t \lambda_{s_t} L_{t-1}$, and expected losses, $R_t - R_{t-1}$.

4.4 Profits

The bank's profits are given by loan repayments less interest expense, operating expense, loan losses, and provisioning—that is,

$$\pi_t := r_{s_{t-1}}^L (1 - \xi_t) L_{t-1} - r_{t-1} B_{t-1} - C(N_t) - LLP_t - \iota. \quad (16)$$

The first term above is the repayment on non-defaulted loans; the second term is the interest expense on deposits, which repay risk-free rate r_t ; the third term is the loan adjustment costs associated with new loans; the fourth term is the total loan loss provisions; the last term, a constant ι , is the fixed cost of running the bank.

As in the simple stylized model, the bank's profits are subject to a convex corporate tax schedule

$$\tau(\pi_t) = \tau \mathbb{I}_{\pi_t > 0}, \quad (17)$$

where $\mathbb{I}_{\pi_t > 0}$ denotes an indicator function which is equal to one when $\pi_t > 0$ and zero otherwise. The bank's net income—that is, the after-tax profits—is given by $(1 - \tau(\pi_t)) \pi_t$.²⁵

4.5 Equity

The bank's after-tax profits are either paid out as dividends or retained to increase the stock of equity. Let X_t be a dividend pay-out at time t ; then the bank's book equity evolves according to the following accounting identity:

$$E_t = E_{t-1} - X_t + (1 - \tau(\pi_t)) \pi_t. \quad (18)$$

²⁵If, however, provisions for future losses are not tax deductible, then the net income is given by $(1 - \tau(\pi_t + (R_{t+1} - R_t))) (\pi_t + (R_{t+1} - R_t)) - (R_{t+1} - R_t)$. We proceed under the assumption that the provisions are tax deductible and state it explicitly when it is not the case.

Negative values of X_t mean that the bank is raising external equity. We assume that raising external equity is costly. This cost reflects the direct transactional costs (e.g., underwriter fees (Altinkılıç and Hansen 2000)) and indirect costs of raising external equity (i.e., debt overhang (Myers 1977 and Admati et al. 2018) or signaling issues (Myers and Majluf 1984)). These costs do not apply if banks retain earnings (in line with pecking-order theories).

Following Hennessy and Whited (2007), the cost of raising external equity is modeled in a reduced form. In particular, for every dollar raised in terms of equity, the bank will have to pay $1 + \eta_{s_t}$, where $\eta_{s_t} > 0$ is a flotation cost for equity. Therefore, the cost of external equity is given by

$$\eta(X_t) := \eta_{s_t} X_t \mathbb{I}_{X_t < 0}, \quad (19)$$

where indicator function $\mathbb{I}_{X_t < 0}$ is equal to 1 when $X_t < 0$, and 0 otherwise. Thus, $\eta(X_t)$ is strictly negative when the bank raises equity and zero otherwise.

4.6 Capital Requirement

As in the simple stylized model, the bank is subject to the minimum capital requirement. Every period t , the bank's choice over the portfolio of loans and equity must satisfy the following minimum capital constraint

$$E_t \geq \kappa_{s_t} L_t, \quad (20)$$

where $\kappa_{s_t} \in [0, 1]$.²⁶

4.7 Optimization Problem

The bank's manager maximizes the present value of all future dividends.²⁷ The effective control variables are the next-period stock of

²⁶The current regulatory regime (i.e., Basel III) is the one with risk-based capital requirements. Therefore, κ_{s_t} is an increasing function of loan default probability. We present the formula for κ_{s_t} in the calibration section. When constraint (20) is not binding, we say that the bank holds a voluntary capital buffer.

²⁷It is straightforward to show that in our model maximizing the present value of future dividends is equivalent to maximizing the present value of the future free cash flows to equity.

equity, E_t , and loans, L_t . The choice over these controls, in turn, determines the bank’s dividend payout, X_t , and lending, N_t .

Formally, given the current state of the bank, $\Xi_t = [E_{t-1}, L_{t-1}, \xi_t, s_t, s_{t-1}]$, the bank’s manager maximizes the present value of all future dividends net the cost of recapitalization subject to a set of the constraints—that is, it solves

$$\begin{aligned}
 V(\Xi_t) = & \max_{\{E_t, L_t\}} \left\{ 0, X_t + \eta(X_t) + \beta_t \mathbb{E}[V(\Xi_{t+1}) | s_t] \right\}, \\
 \text{subject to } & \begin{aligned}
 & a) \quad E_t \geq \kappa_{s_t} L_t, \\
 & b) \quad L_t - R_t = B_t + E_t \\
 & c) \quad E_t = E_{t-1} - X_t + (1 - \tau(\pi_t)) \pi_t, \\
 & d) \quad L_t = (1 - \xi_t)(1 - \delta) L_{t-1} + N_t, \\
 & e) \quad \pi_t = r_{s_{t-1}}^L (1 - \xi_t) L_{t-1} - r_{t-1} B_{t-1} - C(N_t) \\
 & \quad \quad - LLP_t - \iota, \\
 & f) \quad R_t = (R_{t-1} - \xi_t \lambda_{s_t} L_{t-1}) + LLP_t, \\
 & g) \quad N_t \geq 0.
 \end{aligned}
 \end{aligned} \tag{21}$$

The solution to the above problem is the policy functions $E_t^* : \Xi_t \rightarrow \mathcal{R}_+$ and $L_t^* : \Xi_t \rightarrow \mathcal{R}_+$, which satisfy the above system. Default takes place at time t when the bank finds itself insolvent. This happens when the sum of the bank’s current cash flows, $X_t + \eta(X_t)$, and continuation value, $\beta \mathbb{E}[V(\Xi_{t+1}) | s_t]$, is negative—that is, when the limited liability constraint is binding.

5. Calibration

5.1 Loan Default Rate Distribution

Following Martinez-Miera and Repullo (2010), we assume that the probability distribution of the aggregate default rate ξ_t^i is implied by the single common risk factor model of Vasicek (2002). This specification allows for imperfectly correlated individual loan defaults: the performance of an individual bank loan depends on the common and idiosyncratic factors, while the aggregate default rate ξ_t^i

depends only on the common factor. Moreover, this specification is adopted by the Basel Accords to provide a value-at-risk foundation to the minimum capital requirements. Appendix B provides more detailed information on this specification.

The CDF of ξ_t^i conditional on aggregate state is then given by

$$F(\xi_t^i; s_t) = \Phi \left(\frac{\sqrt{1 - \rho_{s_t}^i} \Phi^{-1}(\xi_t^i) - \Phi^{-1}(p_{s_t}^i)}{\sqrt{\rho_{s_t}^i}} \right), \quad (22)$$

where $\Phi(\cdot)$ is the standard normal CDF. We derive the distribution of ξ_t^i in Appendix B. Note, $F(\xi_t^i; s_t)$ has two parameters: $p_{s_t}^i$ and $\rho_{s_t}^i \in (0, 1)$. The stage i loan default probability $p_{s_t}^i$ is identical across all loans and is equal to the mean of ξ_t^i —that is, to $\mathbb{E}[\xi_{t+1}^i | s_t]$. The loan default correlation $\rho_{s_t}^i \in (0, 1)$ captures the dependence of individual loan on the common risk factor and, thus, determines the degree of correlation between individual loan defaults. To calibrate the correlation coefficient $\rho_{s_t}^i$, we use the formula adopted by the Basel framework (see Equation (B.5) in Appendix B).

5.2 Capital Requirement

The empirical counterpart of capital in our model is Tier 1 capital, which primarily consists of common equity. Under the risk-based approach of Basel capital regulation, κ_{s_t} is an increasing function of loan default probability. We calibrate the capital requirement for a bank that follows the internal ratings-based (IRB) approach. Most of the largest banks adopt the IRB approach. Moreover, Basel Accords specify an explicit formula for the capital requirement under the IRB approach, which is a function of loan characteristics such as default probability, maturity, and loan loss default rate. This allows us to calibrate the minimum capital requirement so that it is consistent with the characteristics of the bank's loan portfolio. Under the IRB approach, the capital requirement for corporate and bank exposures is meant to ensure sufficient capital to cover loan losses with a confidence level of 99.9 percent. The exact formula for $\kappa_{s_t}^i$ is reported in Equation (B.6) in Appendix B.

One of the defining elements of Basel III is the countercyclical capital buffer (CCyB). The CCyB is a regulatory instrument designed to smooth lending procyclicality, which requires banks to

build up an extra capital buffer during good times to increase their loss-absorption capacity for bad times. Specifically, under the CCyB a bank is required to hold the extra 2.5 percent of its risk-weighted assets (RWA) in equity during an expansion. Practically, the release and the accumulation of the CCyB should normally be implemented stage-wise over some period of time. However, to keep our model tractable, we assume that the CCyB is fully released once the aggregate state deteriorates and it must be fully accumulated right upon the improvement of the aggregate state. As such, for the calibration purposes, we assume a smaller size of the CCyB, namely 1.5 percent of its RWA. Thus, in our model, the CCyB is implemented by raising the minimum capital requirement in expansion from κ_g to $1.188\kappa_g$.²⁸ We further provide robustness results when the required CCyB is at 2.5 percent of RWA.

5.3 Provisioning Requirement

As discussed in Section 2, the IL approach does not allow recognition of losses that are expected to happen in the future. However, aside from accounting provisions, banks that follow the IRB approach must recognize one-year prudential expected losses on the entire portfolio of loans. These prudential expected losses, however, are computed in a different way than those under the EL approach. In particular, the prudential expected losses are computed using the so-called through-the-cycle (TTC) default probabilities and a conservative (downturn) estimate of loss given default. In our model, the TTC default probabilities correspond to the *unconditional* on the aggregate state default probabilities, $\bar{p}^i$, and the downturn estimate of loss given default is given by λ_b^i . Thus, under the ILM the bank recognizes a loss $\theta^{IRB,i}$ on a marginal loan i , where

$$\theta^{IRB,i} = \mathbb{E}[\lambda_b^i \xi_{t+1}] = \lambda_b^i \bar{p}^i. \quad (23)$$

²⁸As per the Basel III's formula for RWA, in our model these are given by $RWA_t = \kappa_{s_{t-1}} 12.5 L_t$ at time t (see paragraph (53) of the section Internal Ratings-Based Approach for Credit Risk in Basel Committee on Banking Supervision 2017). Therefore, the capital requirement conditional on an expansion increases from κ_g to $\kappa_g + 0.015 \times 12.5 \kappa_g = 1.188\kappa_g$ due to the CCyB.

Thus, the provisioning rate for the entire portfolio of loans is given by

$$\theta_{s_t}^{IRB} = \omega_{s_t} \theta^{IRB,1} + (1 - \omega_{s_t}) \theta^{IRB,2}. \quad (24)$$

Note, however, that the prudential provisions are not accounting losses and, thus, are not tax deductible.²⁹

The discounted expected losses under the EL approach instead employ the point-in-time (PiT) default probabilities—that is, the expected losses are conditional on the current aggregate state. The one-year discounted expected loss rate under the EL approach is given by

$$\theta_{s_t}^{1Y,i} = \frac{1}{1 + d_{s_t}} \mathbb{E}[\lambda_{s_{t+1}}^i \xi_{t+1} | s_t] = \frac{1}{1 + d_{s_t}} p_{s_t} \mathbb{E}[\lambda_{s_{t+1}}^i | s_t], \quad (25)$$

while the lifetime discounted expected loss rate is given by

$$\theta_{s_t}^{LT,i} = \frac{1}{1 + d_{s_t}} \mathbb{E}[\lambda_{s_{t+1}}^i \xi_{t+1} + (1 - \xi_{t+1})(1 - \delta) \theta_{s_{t+1}}^{LT,i} | s_t]. \quad (26)$$

The discount rate d_{s_t} is equal to the contractual interest rate $r_{s_t}^L$ under IFRS 9, while under the U.S. GAAP it is implied by the bank's discount factor β_t . Note that in Equations (25) and (26), the expectations are conditional on the aggregate state, which reflects the PiT estimation of the EL approach. The closed-form solution to Equation (26) is provided in Appendix B.

Since under IFRS 9 the bank recognizes one-year and lifetime expected losses on stage 1 and stage 2 loans, respectively, the provisioning rate for the entire portfolio of loans is given by

$$\theta_{s_t}^{IFRS9} = \omega_{s_t} \theta_{s_t}^{1Y,1} + (1 - \omega_{s_t}) \theta_{s_t}^{LT,2}. \quad (27)$$

The provisioning rate for the entire portfolio of loans under the U.S. GAAP is given by

$$\theta_{s_t}^{GAAP} = \omega_{s_t} \theta_{s_t}^{LT,1} + (1 - \omega_{s_t}) \theta_{s_t}^{LT,2}, \quad (28)$$

²⁹See Abad and Suarez (2018) for an in-depth discussion on prudential provisions.

since in this case the lifetime expected losses are recognized on all types of loans.

It is important to note that when we compare the IL and EL approaches, we include the IRB provisions in both scenarios. That is, regardless of the accounting approach the bank must still meet the IRB requirement. We do, however, assume that if accounting provisions for future loan losses are in excess of the prudential provisioning (under IRB), then the regulator does not object to count the accounting provisions for regulatory requirement of prudential provisions.³⁰

5.4 Parameter Values

The parameters of the model are listed in Table 1, along with their values and sources of calibration. Below, we present a detailed summary of how we calibrate the model.

The model features aggregate and idiosyncratic uncertainty. We set the transition probabilities for the aggregate state, $q_{s_t, s_{t+1}}$, to obtain contractions that last for 2 years, on average, and expansions that last for 6.8 years, on average, which is consistent with the National Bureau of Economic Research’s dating of business cycle.³¹ To that end, we set $q_{g,g} = 0.852$ and $q_{b,b} = 0.5$.³²

Idiosyncratic uncertainty depends upon the aggregate state and is captured by the loan default process. The absence of detailed micro-level data on banks’ loan portfolios creates a problem for calibrating the bank loan default process. To circumvent this problem, we follow the approach in Abad and Suarez (2018) and use the Global Corporate Default reports produced by Standard & Poor’s (S&P) over the period 1981–2015 to calibrate the bank loan default process. To that end, we set the default probability of stage 1 (2) loans to 0.54 percent (6.05 percent) and 1.9 percent (11.5 percent) in expansion and contraction, respectively. These probabilities

³⁰This assumption ensures there is no double provisioning problem. For example, the total provision rate under IFRS 9 is given by $\max\{\theta_{s_t}^{IFRS9}, \theta_{s_t}^{IRB}\}$, which may also require some adjustments to after tax profits since, unlike the EL provisions, the IRB provisions are not tax deductible.

³¹<http://www.nber.org/cycles.html>.

³²The unconditional probability of good and bad aggregate state are given by $q_g = (1 - q_{b,b}) / (2 - q_{g,g} - q_{b,b}) = 0.77$ and $q_b = 1 - q_g = 0.23$, respectively.

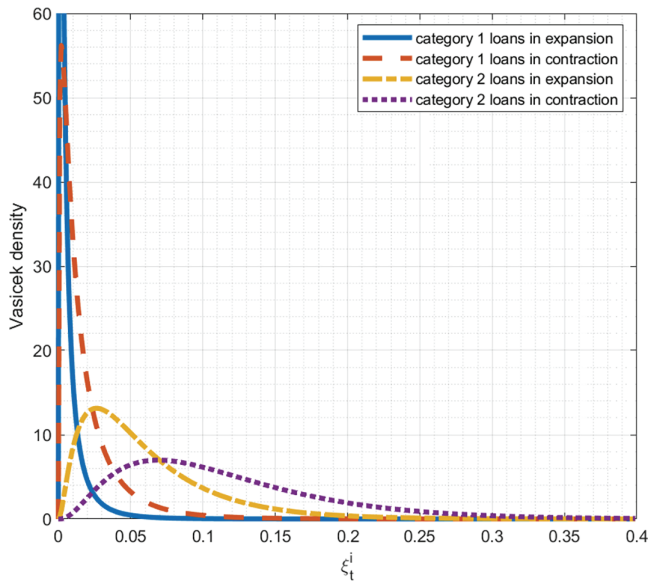
Table 1. Model Parameters

Parameter	Description	Contraction	Expansion	Source
A. Parameters Set Outside the Model				
Loan Default Process				
$\lambda^1_{s_t}$	Loss Given Default Rate Stage 1 Loans	40%	30%	Standard & Poor's Abad and Suarez (2018)
$\lambda^2_{s_t}$	Loss Given Default Rate Stage 2 Loans	40%	30%	
$p^1_{s_t}$	Default Probability of Stage 1 Loans	1.90%	0.54%	
$p^2_{s_t}$	Default Probability of Stage 2 Loans	11.50%	6.05%	
$\rho^1_{s_t}$	Loan Default Correlation Stage 1 Loans	0.166	0.212	
$\rho^2_{s_t}$	Loan Default Correlation Stage 2 Loans	0.120	0.126	Equation (B.5)
Loan Portfolio and Repayment				
$1/\delta$	Average Maturity of Loans (in Years)	5	5	Call Reports Abad and Suarez (2018) FRED: U.S. Net Interest Margins
$\omega^L_{s_t}$	Fraction of Stage 1 Loans	0.81	0.85	
$r^L_{s_t}$	Loan Repayment Rate	5.00%	4.29%	
Other Parameters				
β	Bank Discount Factor	0.95	0.95	De Nicolò, Gamba, and Lucchetta (2014)
τ	Corporate Tax Rate	0.20	0.20	De Nicolò, Gamba, and Lucchetta (2014), Dinger and Vallascas (2016)
η_{s_t}	Flotation Cost of Equity	∞	0.06	
r	Cost of Debt (Risk-Free Rate)	1.00%	1.00%	NBER Business Cycle Dating
$q_{s_t, s_{t+1}}$	Transition Probability of the Aggregate State	0.5	0.852	
B. Parameters Calibrated Inside the Model				
ι	Fixed Cost of Running the Bank	0.0045	0.0045	Calibrated to match the annual bank failure rate
ϕ	Loan Adjustment Cost Parameter	0.60	0.60	Calibrated to match the loan growth rate volatility

(continued)

Table 1. (Continued)

Parameter	Description	Contraction	Expansion	Source
<i>C. Residual Parameters</i>				
Capital Requirement				
κ_{st}^1	Minimum Capital Requirement for Stage 1 Loans	8.50%	8.50%	IRB approach; see Equation (B.6)
κ_{st}^2	Minimum Capital Requirement for Stage 2 Loans	14.4%	14.4%	
κ_{st}	Total Minimum Capital Requirement	9.70%	9.40%	Equation (B.7)
Provisioning Rates				
$\theta_{st}^{1,ILM}$	Stage 1 Loan Provisioning Rate under ILM (IRB)	0.34%	0.34%	Equation (23)
$\theta_{st}^{2,ILM}$	Stage 2 Loan Provisioning Rate under ILM (IRB)	2.92%	2.92%	Equation (24)
θ_{st}^{LLM}	Average (Portfolio) Loan Provisioning Rate under ILM (IRB)	0.84%	0.73%	
$\theta_{st}^{1,IFRS9}$	Stage 1 Loan Provisioning Rate under IFRS 9	0.44%	0.24%	Equation (25)
$\theta_{st}^{2,IFRS9}$	Stage 2 Loan Provisioning Rate under IFRS 9	8.84%	7.83%	Equation (26)
θ_{st}^{IFRS9}	Average (Portfolio) Loan Provisioning Rate under IFRS 9	2.06%	1.38%	Equation (27)
$\theta_{st}^{1,GAAP}$	Stage 1 Loan Provisioning Rate under U.S. GAAP	1.35%	1.09%	Equation (26)
$\theta_{st}^{2,GAAP}$	Stage 2 Loan Provisioning Rate under U.S. GAAP	8.68%	7.61%	Equation (28)
θ_{st}^{GAAP}	Average (Portfolio) Loan Provisioning Rate under IFRS 9	2.77%	2.07%	
Note: This table summarizes the parameters of the model, their values, and the sources of their calibration. The values of some parameters vary with the aggregate state. Parameters listed in panel A have been calibrated outside the model due to the observability of their data counterparts. Panel B lists the parameters which were calibrated inside the model to match the moments in the real data; the data counterparts of these parameters are directly observable. Finally, panel C presents the residual parameters; the values of these parameters are determined by the value of the parameters set outside the model.				

Figure 1. Loan Default Rate Density

Note: This figure plots the calibrated Vasicek density function for the aggregate loan default rate ξ_t^i .

are consistent with the alignment of stage 1 loans with corporate bonds with ratings AAA to BB in the S&P classification and stage 2 loans with ratings B to C. Furthermore, in line with Abad and Suarez (2018), we set the fraction of stage 1 loans, ω_{s_t} , to 0.85 and 0.81 in expansion and contraction, respectively. Finally, the loss given default rates $\lambda_{s_t}^i$ for both types of loans are set to 0.4 and 0.3 in contraction and expansion, respectively. Figure 1 depicts the calibrated Vasicek density function of the aggregate default rate ξ_t^i .

Given the parameterization of the loan default process, we can compute the implied values for the residual parameters: $(\rho_{s_t}^1, \rho_{s_t}^2, \kappa_{s_t}^1, \kappa_{s_t}^2, \theta_{s_t}^1, \theta_{s_t}^2)$. Equation (B.5) from Appendix B implies the value of the loan default correlation coefficient for stage 1 (2) loans, $\rho_{s_t}^1$ ($\rho_{s_t}^2$), is 0.166 (0.12) in contractions and 0.212 (0.126) in expansions. Similarly, Equation (B.6) from Appendix B implies the minimum capital requirement for stage 1 and 2 loans, $\kappa_{s_t}^1$ and $\kappa_{s_t}^2$, is 8.5 percent and 14.4 percent, respectively. The overall capital requirement, κ_{s_t} , is then 9.4 percent in expansion and 9.7 percent

in contraction. Finally, the values of the provisioning rates, θ_{s_t} , are assigned according to Equations (23)–(26).³³

We set the interest rate on debt, r , to 1.0 percent. To calibrate the interest on the loan portfolio, $r_{s_t}^L$, we match the first and second moments of the interest margins, $r_{s_t}^L - r_{t-1}$, to their data counterparts. For the U.S. banks, the mean and the standard deviation of the bank interest margins are 3.45 percent and 0.29 percent, respectively.³⁴ Imposing a restriction that $r_g < r_b$, which reflects the pricing of risk, we thus set $r_{s_t}^L$ to 4.29 percent and 5.00 percent in expansion and contraction, respectively. Finally, consistent with the U.S. banks’ Reports of Condition and Income (Call Reports), we set the average loan maturity to five years, which implies $\delta = 0.20$. The corporate tax rate, τ , is 0.20.³⁵

Following De Nicolò, Gamba, and Lucchetta (2014), we set the flotation cost of equity conditional on expansion, η_g , to 0.06 and the banker’s discount factor, β_t , to 0.95. Empirical evidence suggests that banks seldom issue new equity during a downturn (Dinger and Vallascas 2016). To accommodate this stylized fact, we make issuing equity in a bad aggregate state prohibitively expensive setting η_b to infinity—that is, we effectively impose a non-negativity constraint on X_t when the aggregate state is bad.

The remaining two parameters, namely ϕ and ι , are calibrated inside the model to match the relevant data moments. The parameter ϕ , which is from the loan lending cost function, directly relates to the volatility of bank loans. The higher ϕ is, the costlier it is to increase the stock of loans through new lending. This in turn lowers the volatility of loan growth. This parameter is thus calibrated to match the volatility of the annual loan growth rate, which

³³Note that since provisioning rates under the EL approaches exceed those under the IRB approach, we assume that the regulator accepts accounting-expected provisions under the EL approach as prudential provisions of the IRB approach—that is, under the EL approach the bank no longer has to recognize the prudential losses since those are already covered by the accounting provisions.

³⁴Data source: Federal Reserve Economic Database (FRED) time series on U.S. banks’ net interest margins “USNIM.”

³⁵It is important to note that since this is a partial equilibrium model, where the bank takes prices as given, we cannot comment on how provisioning requirements may affect loan demand, and therefore the indirect effect coming from loan prices that are general equilibrium outcomes.

**Table 2. Data and Model Moments
under Benchmark Calibration**

Moments	Model	Data	Source
<i>Matched Moments</i>			
Mean Interest Margins	3.45%	3.45%	FRED (Time Series: “USNIM”)
St. D. Interest Margins	0.29%	0.29%	FRED (Time Series: “USNIM”)
Bank Failure Rate	0.39%	0.37%	Mankart, Michaelides, and Pagratis (2020)
St. D. of Loan Growth Rate	3.90%	3.70%	FRED (Time Series: “TOTLL”)
<i>Not Matched Moments</i>			
Mean Charge-Off Rate	0.66%	0.86%	FDIC: Charge-Off and Delinquency Rates
St. D. Charge-Off Rate	0.49%	0.60%	On Loans and Leases at Commercial Banks
Mean ROE	10.2%	11.2%	FRED (Time Series: “USROE”)
Mean ROA	0.95%	0.99%	FRED (Time Series: “USROA”)
Note: This table presents the matched and not matched moments implied by the model and real data. The moments implied by the model are computed under the benchmark—that is, the ILM case. The model moments are computed based on the data from simulating the model for 80,000 periods and excluding the first 200 observations. The sources for the real data moments are representative of U.S. banks.			

is about 3.8 percent in the data.³⁶ To that end, we set $\phi = 0.6$. Finally, the fixed cost of running the bank, ι , needs to be set sufficiently high to ensure that the bank’s profits are not too large and, thus, the bank occasionally fails. We set ι to 0.0045 to match the bank (annual) failure rate of 0.37 percent (Mankart, Michaelides, and Pagratis 2020).

To assess the results of our calibration, we report some relevant moments implied by our model under the benchmark case of the ILM and the corresponding real data moments in Table 2. Despite its parsimonious structure, the model matches the data moments reasonably well.

³⁶Data source: FRED, Federal Reserve Bank of St. Louis, time series “TOTLL”—Loans and Leases in Bank Credit, All Commercial 1975–2019.

Note that under the calibrated parameter values, our model predicts that the minimum capital requirement is binding all the time.³⁷ We verify this numerically using the simulated data from the model when the bank’s choice consists of both E_t and L_t . Therefore, to increase the precision of the numerical solution of our model, we solve the model by imposing that the capital constraint is binding. See Appendix C for more details on this matter.

6. Quantitative Results

6.1 Cyclical Effect of the EL Approach

First, we examine the effect of the EL approach on the cyclicity of the key endogenous variables of the model, such as loan loss provisions (LLPs), profits, lending, and bank failure rate. Table 3 reports the moments of the endogenous variables, conditional on the aggregate state. These are obtained by simulating the model for 80,000 periods under the three scenarios: the ILM (benchmark) and two variations of the ELM, namely, IFRS 9 and U.S. GAAP.

The last two columns of Table 3, which provide a relative comparison between ILM and ELM, suggest a profoundly large procyclical effect of the EL approach on bank lending in our model. For example, while, on average, the bank lending is about 3.6 percent (2.7 percent) lower under IFRS 9 (U.S. GAAP) than ILM, conditional on a contraction the bank originates, on average, as much as 7.1 percent (5.9 percent) fewer new loans under IFRS 9 (U.S. GAAP). The procyclicality of the EL approach can also be assessed by examining the ratio of new loans to outstanding loans or loan growth rate.

³⁷The bank’s shareholders are relatively impatient (low β) and deposits are cheap (due to mispriced deposit insurance and the tax deductibility of the interest expense on deposits). Thus, holding an equity buffer is costly. That is why in our calibration the bank does not optimally hold buffer. The benefit of holding the buffer comes from the insurance it provides against having to increase equity following a large loss. Thus, when equity is costly to issue, and when the probability of facing a high loss is sufficiently high, then the bank might find it optimal to hold equity buffer. If we increase the likelihood of large losses and make the cost of issuing equity prohibitively expensive even in good times ($s_t = g$), then we could generate some capital buffers. However, the limited liability constraint makes it much harder to obtain a voluntary capital buffer in the model—the ability to walk away from the bank with insufficient capital reduces the incentives of the bankers to hold the buffer.

Both of these measures also indicate increased procyclicality under the EL approach.

Table 3 also helps to understand the mechanics behind the procyclicality of the EL approach. As we discussed earlier, the PiT default probabilities of the EL approach amplify the cyclical movement of the total LLPs. This, in turn, raises the volatility of the bank's profits over the cycle, which can be seen in Table 3. With the combination of the minimum capital requirement and costly external equity issuance, increased profit volatility translates into more severe lending procyclicality.

Our model further predicts that IFRS 9 is slightly more procyclical than U.S. GAAP. While the volatility of the provisioning rate, θ_{st} , under both variants of the EL approach is roughly the same, which is about 0.29 percent, because of its mixed-horizon approach, IFRS 9 produces smaller loan loss reserves (LLRs), thus providing a weaker loss-absorption capacity than U.S. GAAP. As a result, the bank lends more procyclically under IFRS 9. Relatedly, our model also predicts that U.S. GAAP does a better job in terms of improving bank stability than IFRS 9. In fact, we find that with the adoption of IFRS 9, the bank failure rate may even increase. Again, this has to do with IFRS 9 being characterized by both larger procyclicality and lower loss-absorption capacity relative to U.S. GAAP. Recall that, on the one hand, since the bank holds larger LLRs under the EL approach, it should lower the bank failure rate. On the other hand, the procyclicality of the EL approach effectively increases the volatility of banks' profits, which increases bank failure rate.

Next, we examine the cyclical implication of the EL approach when the bank is subject to the CCyB. The CCyB is one of the most prominent features of Basel III that has been introduced to combat lending procyclicality by requiring the banks to hold extra capital during good times to support their lending activities upon the arrival of a contraction. Thus, it is particularly important to assess the joint cyclical effect of the EL approach and the CCyB. To do so, we report in Table 4 the moments of various endogenous variables under the ILM (benchmark), IFRS 9, and U.S. GAAP scenarios (conditional on the aggregate state), when the bank is subject to the CCyB.

First, Table 4 predicts a sizable effect of the CCyB on bank lending. By comparing the first (“ILM”) and second (“ILM+CCyB”)

columns in the table, we can see that while unconditional on the aggregate state, the bank originates about 2 percent fewer loans, it is able to increase its lending in a contraction by about 2.6 percent, on average. Thus, the model suggests that the countercyclical capital buffer quantitatively smooths aggregate loan dynamics and it also attenuates bank failures in the contractionary aggregate state. Second, the last two columns in Table 4 suggest that the CCyB is indeed able to considerably dampen the procyclical effect of the EL approach on bank lending. In particular, when the bank is subject to both IFRS 9 (U.S. GAAP) and the CCyB, it originates, on average, about 3.5 percent (3.3 percent) fewer new loans in a contraction compared to that under the ILM without the CCyB. Nevertheless, our model does suggest that the introduction of the EL approach considerably reduces the efficacy of the CCyB to smooth lending dynamics over the cycle.

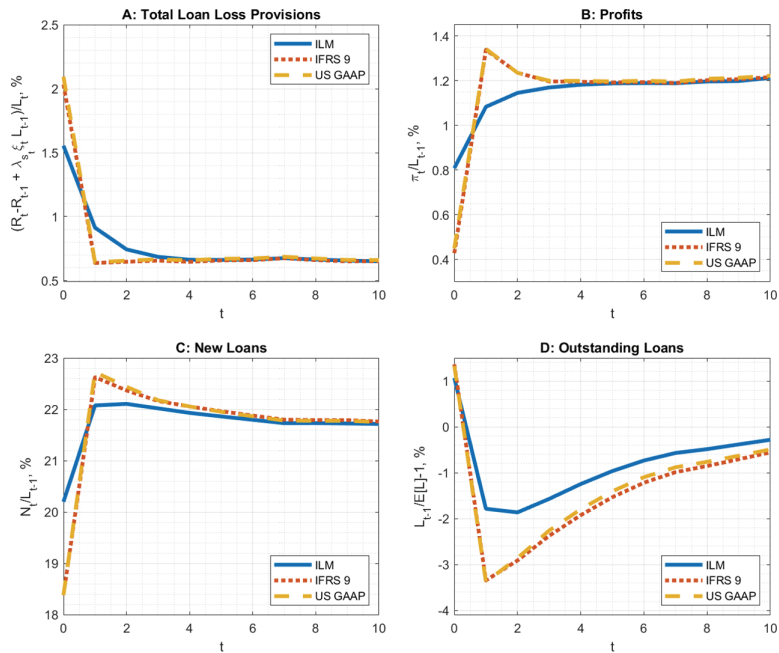
6.2 *Effect of the Arrival of a Contraction*

Next, we examine a dynamic (i.e., multi-period) response of the key endogenous variables of our model to the arrival of a contraction. Since our model is solved fully non-linearly, we analyze the dynamic response to the arrival of a contraction using the generalized impulse response analysis (Koop, Pesaran, and Potter 1996).

A generalized impulse response of the variable Y_t to a contractionary aggregate shock at time $t = 0$ constitutes a sequence of conditional expectations of the form $\mathcal{Y}_i = \mathbb{E}[Y_i | L_{-1}, s_{-1} = g, s_0 = b]$ for $i = 0, 1, 2, \dots$. The bank's endogenous initial state is set to the average values in an expansion—that is, $L_{-1} = \mathbb{E}[L_t | s_t = g]$. The condition $s_{-1} = g$ implies that prior to the arrival of a contraction the bank is in expansionary aggregate state. Appendix C provides more details on the numerical procedure to evaluate $\{\mathcal{Y}_i\}_0^T$.

Figure 2 depicts the impulse response functions of the total LLPs, profits, and new and outstanding loans to the arrival of a contraction at $t = 0$. The impulse response functions are evaluated under the following three scenarios: ILM (benchmark), IFRS 9, and U.S. GAAP. Panel A shows that the total LLPs react much stronger to the arrival of a contraction under the EL approach. When learning about the deterioration of the aggregate state, the bank revises its point-in-time estimates of default probabilities upward and has

Figure 2. Effect of the Arrival of a Contraction



Note: This figure depicts the (generalized) impulse response functions of total loan loss provisions, profits, and new and outstanding loans to the arrival of a contraction at date $t = 0$. The impulse response functions are presented for three scenarios: incurred loss model (ILM) and two variants of the EL approach, namely, IFRS 9 and U.S. GAAP. The impulse response of outstanding loans is in terms of relative changes to the (unconditional) mean $\mathbb{E}[L]$. The impulse responses are evaluated by taking the average across 30,000 simulated paths of the variables of interest, with each path having the length of 11 periods and the identical initial condition (L_{-1}, s_{-1}) . The initial condition is such that prior to $t = 0$ the bank is in an expansionary aggregate state, $s_{-1} = g$, and its endogenous state is given by the conditional on an expansionary aggregate state mean value—that is, $L_{-1} = \mathbb{E}[L_t | s_t = g]$.

to abruptly front-load the increased expected losses. As a result, the bank’s profits drop sharper under the EL approaches upon the arrival of a contraction, as can be seen in panel B. Since the bank is subject to the minimum capital requirement and issuing external equity is too costly, we see in panel C that the bank cuts on new loans more aggressively under the EL approaches. As a result, the

bank’s outstanding loans plunge deeper under the EL approaches relative to their unconditional mean, as can be seen in panel D. We show that these results are qualitatively robust to setting the cost of external equity issuances to zero (Figure A.2), reducing an average duration of a contraction (Figure A.3), and imposing symmetric transition probabilities of the aggregate state (Figures A.4).

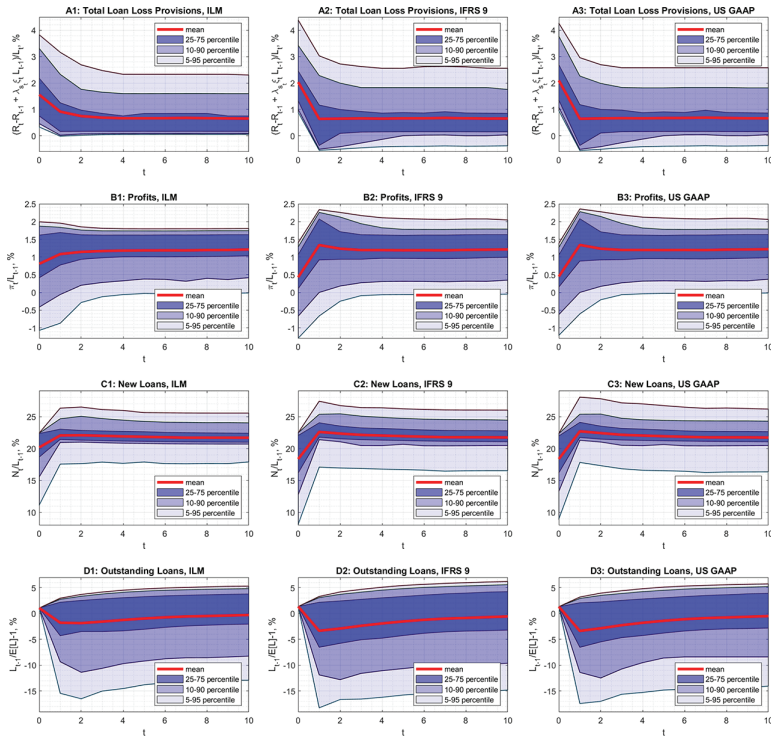
To gain better understanding of the dynamics, Figure 3 depicts the (generalized) impulse response functions (in red) and their confidence bounds (in the shades of blue) of total LLPs, profits, and new and outstanding loans to the arrival of a contraction at date $t = 0$. The confidence bounds of the impulse responses are computed as 25–75, 10–90, and 5–95 percentiles of the response to the arrival of a contraction. This figure allows us to see that not only do the EL approaches worsen the procyclicality of bank lending, but they also increase the volatility of the responses, which can be seen from the widened bounds.

To follow up on our earlier discussion about the two channels of the provisioning requirement for future losses, we try to disentangle the procyclical effects of the EL approaches that are due to the tax deductibility and the minimum capital regulation. Figure 4 plots the impulse response functions of the new and outstanding loans under the two EL approaches when the expected provisions are tax deductible and when they are not. As seen from the figure, lending procyclicality is only modestly increased when the tax deductibility of the expected provisions is assumed. Thus, we conclude that the procyclicality of an EL approach comes primarily from the capital regulation channel rather than the tax channel.

Lastly, we examine the impulse responses to the arrival of a contraction when the bank is subject to the CCyB. Figure 5 depicts the impulse response functions of profits, and new and outstanding loans to the arrival of a contraction at $t = 0$ when the bank must hold the CCyB of 1.5 percent.³⁸ First, by comparing the impulse responses of the new and outstanding loans under the ILM with and without the CCyB, we note a quantitatively strong countercyclical effect of the CCyB on bank lending. For example, the on-impact effect of the contraction on the ratio of new to total loans improves from

³⁸Note, we do not plot the impulse response of the LLPs since their response is not directly affected by the CCyB.

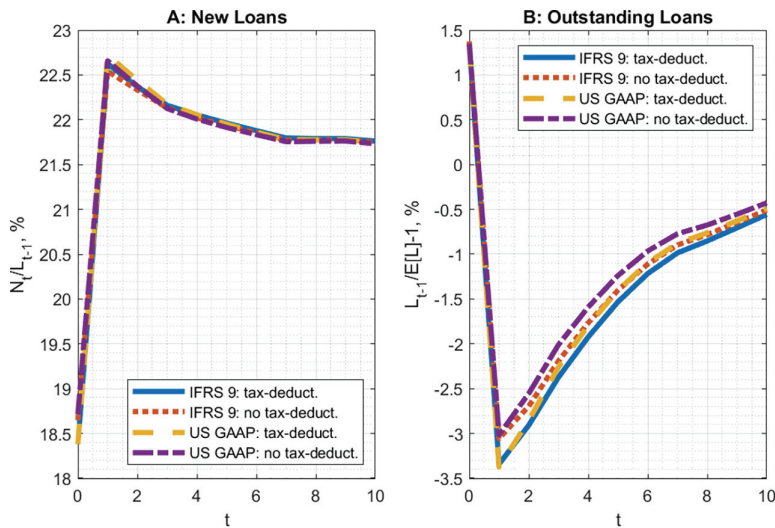
Figure 3. Effect of the Arrival of a Contraction: Confidence Bounds



Note: This figure depicts the (generalized) impulse response functions (in red) and their confidence bounds (in shades of blue) of total loan loss provisions, profits, and new and outstanding loans to the arrival of a contraction at date $t = 0$. The impulse response functions are presented for three scenarios: incurred loss model (ILM) and two variants of the EL approach, namely, IFRS 9 and U.S. GAAP. The impulse response of outstanding loans is in terms of relative changes to the (unconditional) mean $\mathbb{E}[L]$. The impulse responses are evaluated by taking the average across 30,000 simulated paths of the variables of interest, with each path having the length of 11 periods and the identical initial condition (L_{-1}, s_{-1}) . The initial condition is such that prior to $t = 0$ the bank is in an expansionary aggregate state, $s_{-1} = g$, and its endogenous state is given by the conditional on an expansionary aggregate state mean values—that is, $L_{-1} = \mathbb{E}[L_t | s_t = g]$.

20.25 percent to 21.2 percent. At the same time, panel A shows that even when the introduction of an EL approach is accompanied by the simultaneous adoption of the CCyB, new lending falls sharper

Figure 4. Effect of the Arrival of a Contraction: Tax vs. Capital Regulation Channel

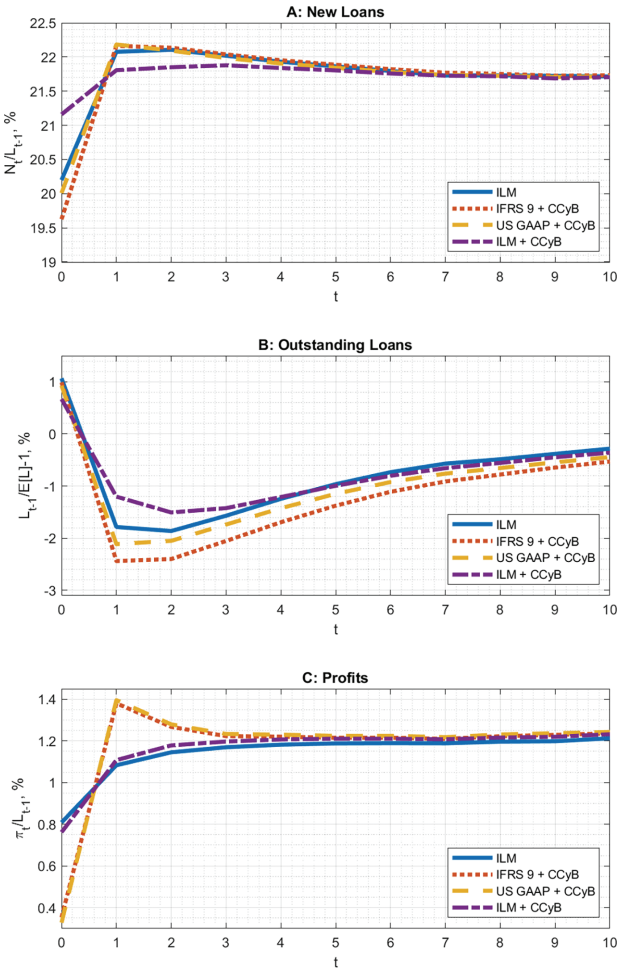


Note: This figure depicts the (generalized) impulse response functions of new and outstanding loans to the arrival of a contraction at date $t = 0$ when the expected provisions are tax deductible (blue and yellow plots) and when they are not (red and purple plots). The impulse response functions are presented for two variants of the EL approach: IFRS 9 and U.S. GAAP. The impulse response of outstanding loans is in terms of relative changes to the (unconditional) mean $\mathbb{E}[L]$. The impulse responses are evaluated by taking the average across 30,000 simulated paths of the variables of interest, with each path having the length of 11 periods and the identical initial condition (L_{-1}, s_{-1}) . The initial condition is such that prior to $t = 0$ the bank is in an expansionary aggregate state, $s_{-1} = g$, and its endogenous state is given by the conditional on an expansionary aggregate state mean values—that is, $L_{-1} = \mathbb{E}[L_t | s_t = g]$.

on impact. Figure 6 depicts the same impulse response when the CCyB is set at a higher level of 2.5 percent of RWA.³⁹ In this case, while the procyclical effect of the EL approach is largely mitigated

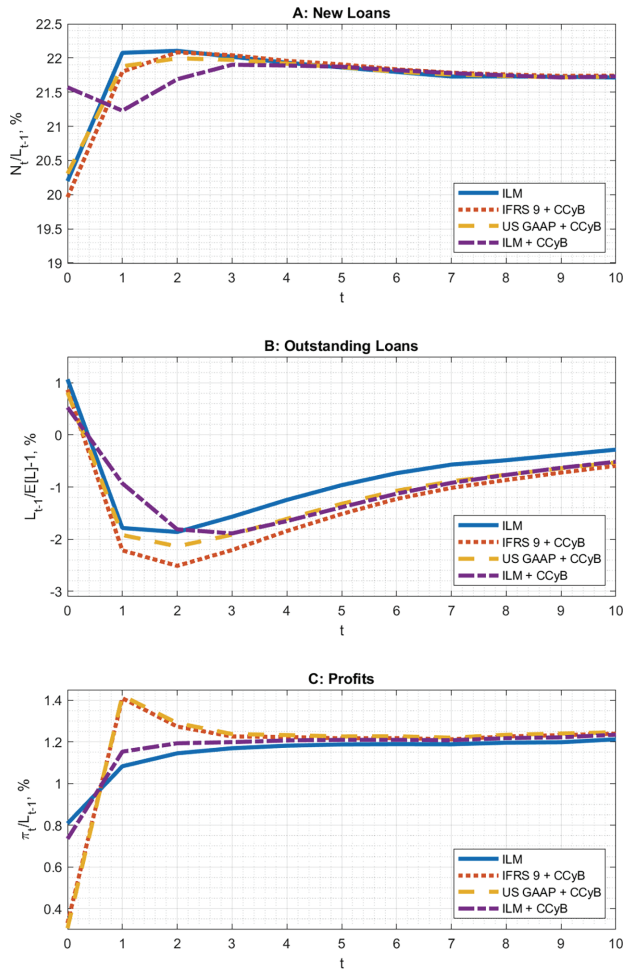
³⁹Since in our model the CCyB is fully released once the aggregate state deteriorates and must be fully accumulated right upon the improvement of the aggregate state, a higher level of the CCyB suppresses lending activity following the net period after the shock.

Figure 5. Effect of the Arrival of a Contraction under the 1.5 Percent CCyB



Note: This figure depicts the (generalized) impulse response functions of new and outstanding loans, and profits to the arrival of a contraction at date $t = 0$. The impulse response functions are presented for four scenarios: incurred loss model (ILM) with and without the 1.5 percent CCyB, and two variants of the EL approach, namely, IFRS 9 and U.S. GAAP with the CCyB. The impulse response of outstanding loans is in terms of a relative changes to the (unconditional) mean $E[L]$. The CCyB is characterized by an increase in the minimum capital requirement conditional on the aggregate state being good. The impulse responses are evaluated by taking the average across 30,000 simulated paths of the variables of interest, with each path having the length of 11 periods and the identical initial condition (L_{-1}, s_{-1}) . The initial condition is such that prior to $t = 0$ the bank is in an expansionary aggregate state, $s_{-1} = g$, and its endogenous state is given by the conditional on an expansionary aggregate state mean values—that is, $L_{-1} = E[L_t | s_t = g]$.

Figure 6. Effect of the Arrival of a Contraction under the 2.5 Percent CCyB



Note: This figure depicts the (generalized) impulse response functions of new and outstanding loans, and profits to the arrival of a contraction at date $t = 0$. The impulse response functions are presented for four scenarios: incurred loss model (ILM) with and without the 2.5 percent CCyB, and two variants of the EL approach, namely, IFRS 9 and U.S. GAAP with the CCyB. The impulse response of outstanding loans is in terms of a relative changes to the (unconditional) mean $\mathbb{E}[L]$. The CCyB is characterized by an increase in the minimum capital requirement conditional on the aggregate state being good. The impulse responses are evaluated by taking the average across 30,000 simulated paths of the variables of interest, with each path having the length of 11 periods and the identical initial condition (L_{-1}, s_{-1}) . The initial condition is such that prior to $t = 0$ the bank is in an expansionary aggregate state, $s_{-1} = g$, and its endogenous state is given by the conditional on an expansionary aggregate state mean values—that is, $L_{-1} = \mathbb{E}[L_t | s_t = g]$.

(at least in the case of U.S. GAAP), this comes at a large contraction in the average level of outstanding loans of 3–4 percent, which we do not report in the paper.

6.3 Effect of the Arrival of a Prolonged Contraction

We have so far shown that having to recognize the bulk of expected losses at the start of a contraction can impede the bank's lending. It does, however, improve the bank's loss-absorption capacity in the following periods, thus allowing the bank to lend more later on. It is natural then to examine the bank's lending activities when a contraction persists for a longer period. Thus, we proceed to examine the lending response to a prolonged contraction that lasts for at least two periods—that is, a contraction that arrives at $t = 0$ and persists at least until $t = 1$.

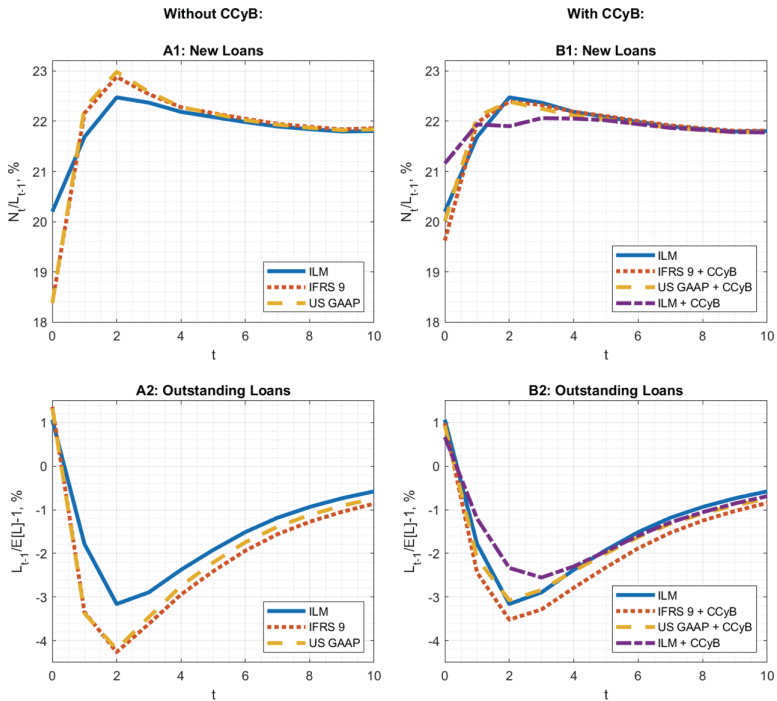
Figure 7 reports the impulse responses of the new and outstanding loans to the arrival of the prolonged contraction at $t = 0$ under the same three provisioning approaches, with and without the CCyB. The figure shows that the EL approach produces less procyclicality during the later stages of a contraction, which is consistent with our intuition outlined above.

6.4 Effect of the Arrival of a Contraction under a Delayed Response of Balance Sheet to Aggregate Shock

So far we have maintained an assumption that the arrival of a contraction has a contemporaneous effect on the distribution of the bank's losses. Under this assumption, the EL approach effectively implies a “double blow” to the bank's profitability, as both realized and expected losses increase simultaneously upon the deterioration of the aggregate state. This assumption can be questioned since empirical evidence suggests that banks often report positive profits at the start of a recession.⁴⁰ Likewise, there might be some time lag between the deterioration of the aggregate state and an increase in consumer and corporate defaults. To account for this, we modify the timing of our model so that the distribution of the bank's

⁴⁰For example, the return on average assets for U.S. banks was positive in 2007. Even Lehman Brothers reported a net income of a record \$4.2 billion in 2007.

Figure 7. Effect of the Arrival of a Prolonged Contraction with and without the CCyB



Note: This figure depicts the (generalized) impulse response functions of new and outstanding loans to the arrival of a contraction at date $t = 0$ that persists for at least two periods—that is, $s_0 = s_1 = b$. The impulse response functions are presented for six scenarios: incurred loss model (ILM) with and without the CCyB, and two variants of the EL approach, namely, IFRS 9 and U.S. GAAP with and without the CCyB. The impulse response of outstanding loans is in terms of a relative changes to the (unconditional) mean $E[L]$. The CCyB is characterized by an increase in the minimum capital requirement conditional on the aggregate state being good. The impulse responses are evaluated by taking the average across 30,000 simulated paths of the variables of interest, with each path having the length of 11 periods and the identical initial condition (L_{-1}, s_{-1}). The initial condition is such that prior to $t = 0$ the bank is in an expansionary aggregate state, $s_{-1} = g$, and its endogenous state is given by the conditional on an expansionary aggregate state mean values—that is, $L_{-1} = E[L_t | s_t = g]$.

losses responds with a one-period delay to the arrival of a contraction. While a one-year delay is admittedly an exaggeration, it should really be viewed as an upper bound for the length of such a delay.

Table 5. Provisioning Rates under Delayed Response of Profits

		ILM	IFRS 9	U.S. GAAP
Stage 1 in Expansion	θ_g^1	0.34%	0.16%	1.19%
Stage 1 in Contraction	θ_b^1	0.34%	0.72%	1.99%
Stage 2 in Expansion	θ_g^2	2.92%	7.37%	8.38%
Stage 2 in Contraction	θ_b^2	2.92%	10.36%	11.54%
Average (Portfolio) in Expansion	θ_g	0.73%	1.24%	2.27%
Average (Portfolio) in Contraction	θ_b	0.84%	2.59%	3.83%
Difference across Aggregate State	$\theta_b - \theta_g$	0.11%	1.35%	1.56%
Note: This table reports the calibrated values of the provisioning rates, θ_{st} (%), under various provisioning approaches when the bank's losses respond with a one-year delay to the change in the aggregate state.				

Formally, we denote the aggregate loan default rate at t by $\hat{\xi}_t$ and assume that its distribution is given by

$$\hat{\xi}_t \sim F(\hat{\xi}_t; s_{t-1})$$

(29)

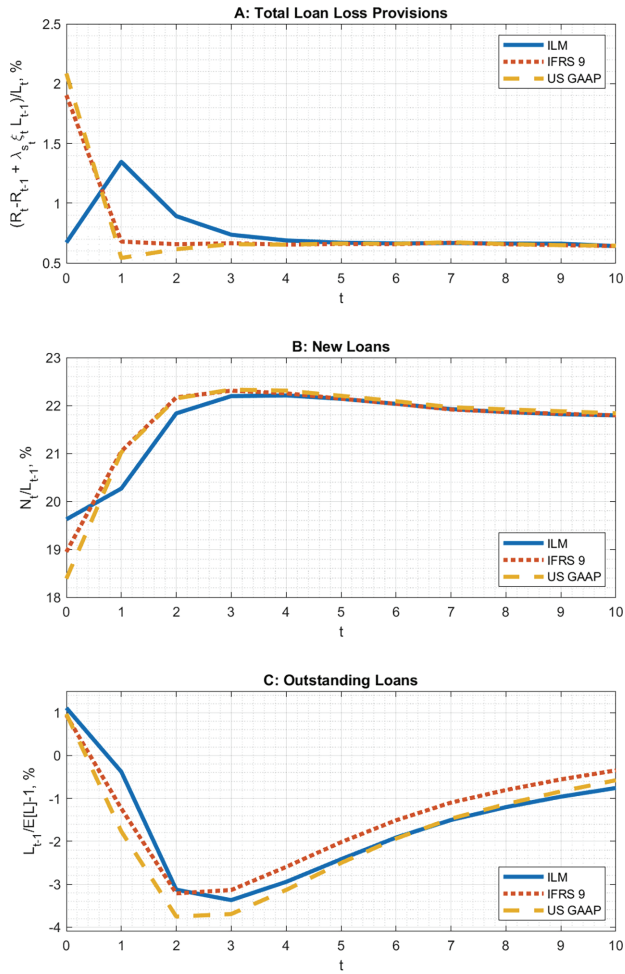
so that the distribution of the loss rate at time t now depends on the previous-period aggregate state. This effectively implies that from the point of view of the current period, the next-period losses are determined up to the aggregate state.

Since the delay in the response of loan loss distribution affects the conditional expected losses, we have to recompute provisioning rates under the EL approach. The one-year discounted expected loss for a loan stage i is now given by $\hat{\theta}_{s_t}^{1Y,i} = 1/(1 + d_{s_t})\lambda_{s_t}^i p_{s_t}^i$, whereas the lifetime discounted expected loss is given recursively by $\hat{\theta}_{s_t}^{LT,i} = 1/(1 + d_{s_t})(\lambda_{s_t}^i p_{s_t}^i + (1 - p_{s_t}^i)(1 - \delta)\mathbb{E}[\hat{\theta}_{s_{t+1}}^{LT,i} | s_t])$.

Table 5 presents the recalibrated provisioning rates under IFRS 9 and U.S. GAAP, which reflects the modified version of the loan loss distribution in Equation (29). As a result of this modification, the provisioning rates under IFRS 9 and GAAP become even more countercyclical than before. Intuitively, the delay in the response of loan losses implies that the bank anticipates the next-period losses better; therefore, it provisions for expected losses more when times are bad and less when they are good.

Figure 8 depicts the generalized impulse responses of the total LLPs, and new and outstanding loans key to the arrival of a

Figure 8. Effect of the Arrival of a Contraction under Delayed Losses



Note: This figure depicts the (generalized) impulse response functions of total loan loss provisions and new and outstanding loans to the arrival of a contraction at date $t = 0$ when the bank’s losses respond with a one-year delay to the change in the aggregate state. The impulse response functions are presented for three scenarios: incurred loss model (ILM) and two variants of the EL approach, namely, IFRS 9 and U.S. GAAP. The impulse response of outstanding loans is in terms of a relative changes to the (unconditional) mean $\mathbb{E}[L]$. The impulse responses are evaluated by taking the average across 30,000 simulated paths of the variables of interest, with each path having the length of 11 periods and the identical initial condition (L_{-1}, s_{-1}) . The initial condition is such that prior to $t = 0$ the bank is in an expansionary aggregate state, $s_{-1} = g$, and its endogenous state is given by the conditional on an expansionary aggregate state mean values—that is, $L_{-1} = \mathbb{E}[L_t | s_t = g]$.

contraction at $t = 0$ under the ILM, IFRS 9, and U.S. GAAP when the bank's losses respond with a one-year delay to the change in the aggregate state. Overall our results suggest that even when the arrival of a contraction erodes the bank's balance sheet with a one-year delay, which allows the bank to anticipate the upcoming losses, the ELM is still more procyclical than the ILM, at least, on impact. Intuitively, as the bank learns about the increase in its expected losses, it must recognize them. This erodes the bank's profits and forces it to cut new loans more than under the ILM. However, this time the effect is not as pronounced, because the current losses are smaller and, thus, they do not lower the current profits too much. Thus, the procyclicality of the ELM is now partially mitigated, as the bank recognizes the bulk of expected losses before these losses actually realize. This allows the bank to originate more new loans in the following periods after the arrival of a contraction.

Nevertheless, even with the delayed response of losses, the EL approach produces a stronger procyclical effect on lending upon the arrival of a contraction than the ILM. If we were to allow a delayed response over a number of years, which would be equivalent to assuming that the bank could anticipate or forecast the increase in expected losses well in advance, then in this case the EL would be able to smooth lending procyclicality. Intuitively, in this case, the EL approach would be very similar to the CCyB, as it would allow the bank to build up the reserves well in advance of the arrival of a contraction. However, neither theoretically nor empirically would it be possible to justify either such long delays in loss responses or such great ability of banks to foresee the future losses.

7. Conclusion

Our quantitative dynamic model of a bank predicts that under the expected provisioning approach of IFRS 9 and the new U.S. GAAP, banks lend substantially more procyclically than under the incurred loss approach. Moreover, the procyclicality of the EL approach can worsen the bank's stability despite providing an extra loss-absorption capacity. Naturally, the ultimate question is whether the ELM is better or worse than the ILM. Our partial equilibrium model cannot answer this question, as it does not allow for welfare analysis.

However, the literature on optimal capital regulation helps to shed some light on that issue.

It is rather well understood that the countercyclicality of capital requirements is likely to amplify the business cycle (Kashyap and Stein 2004; Repullo, Saurina, and Trucharte 2010). Moreover, most scholars advocate in favor of procyclical capital requirements—that is, to tighten the capital requirement during good times (Kashyap and Stein 2004, Dewatripont and Tirole 2012, Repullo 2013, Gersbach and Rochet 2017, and Malherbe 2020). In line with these studies, the increased procyclicality of bank lending under the ELM would lead to welfare losses.

The welfare analysis of expected provisioning is further complicated by one important aspect of the ELM that we do not consider in our analysis—that is, the information content of expected provisions. One of the potential benefits of the ELM as argued in Financial Stability Forum (2009) is that it “is consistent with financial statement users’ needs for transparency regarding changes in credit trends.” When there is asymmetric information such that the bank insiders know more about the state of the bank than other market participants, expected provisions, provided that they are properly estimated and truthfully disclosed, can be informative for the outsiders. Therefore, any potential cost of expected provisioning should be further compared to a potential benefit it may create by increasing the transparency about the credit risk of the bank. However, the mere fact that there will be more information disclosed under the ELM does not necessarily translate into welfare benefits either. There is theoretical literature suggesting that more transparency is not necessarily beneficial (Goldstein and Sapra 2014). Mahieux, Sapra, and Zhang (2023) show that expected provisioning may improve efficiency by allowing for timely regulatory intervention to curb inefficient ex post asset substitution. They also argue that banks, however, may respond to timely intervention by originating riskier loans so that timely intervention induces timelier risk-taking.

Appendix A. Proof of Proposition 2

The first statement of the proposition is proved by taking the derivatives of L_0 and $L_1|_z$ with respect to θ_0 . Recall that we let

$\theta_g := \theta_{1|g} = \theta_0 > 0$, while $\theta_b := \theta_{1|b} = \theta_0 + \epsilon$, where $\epsilon > 0$. Using Equations (9) and (10), it follows that

$$\frac{d}{d\theta_0} L_0^e = -\frac{L_0^e}{\theta_0 + \kappa_0} < 0, \quad (\text{A.1})$$

while

$$\begin{aligned} \frac{d}{d\theta_0} L_{1|z}^e &= \frac{L_{1|z}^e}{L_0^e} \frac{dL_0^e}{d\theta_0} + \frac{(1 - \tau(\pi_1))}{\kappa_1 + \theta_{1|z}(1 - \tau(\pi_1))} L_0^e \\ &\quad - \frac{(1 - \tau(\pi_1))}{\kappa_1 + \theta_{1|z}(1 - \tau(\pi_1))} L_{1|z}^e. \end{aligned} \quad (\text{A.2})$$

The last term in the above equation is positive, and it is only present when $z = b$. Thus, to prove that $\frac{d}{d\theta_0} L_{1|z}^e < 0$, it is sufficient to show that the sum of the first two terms in Equation (A.2) are negative, which is the case since

$$\begin{aligned} &\frac{L_{1|z}^e}{L_0^e} \frac{dL_0^e}{d\theta_0} + \frac{(1 - \tau(\pi_1))}{\kappa_1 + \theta_{1|z}(1 - \tau(\pi_1))} L_0^e = \\ &= -\frac{\kappa_0 + (1 - \tau(\pi_1))(\theta_0 + r_1^L)}{\kappa_1 + \theta_{1|z}(1 - \tau(\pi_1))} \frac{L_0^e}{\theta_0 + \kappa_0} + \frac{(1 - \tau(\pi_1))L_0^e}{\kappa_1 + \theta_{1|z}(1 - \tau(\pi_1))} \propto \\ &= (1 - \tau(\pi_1))(\theta_0 + \kappa_0) - \kappa_0 - (1 - \tau(\pi_1))(\theta_0 + r_1^L) = \\ &= -\tau(\pi_1)\kappa_0 - (1 - \tau(\pi_1))r_1^L < 0. \end{aligned}$$

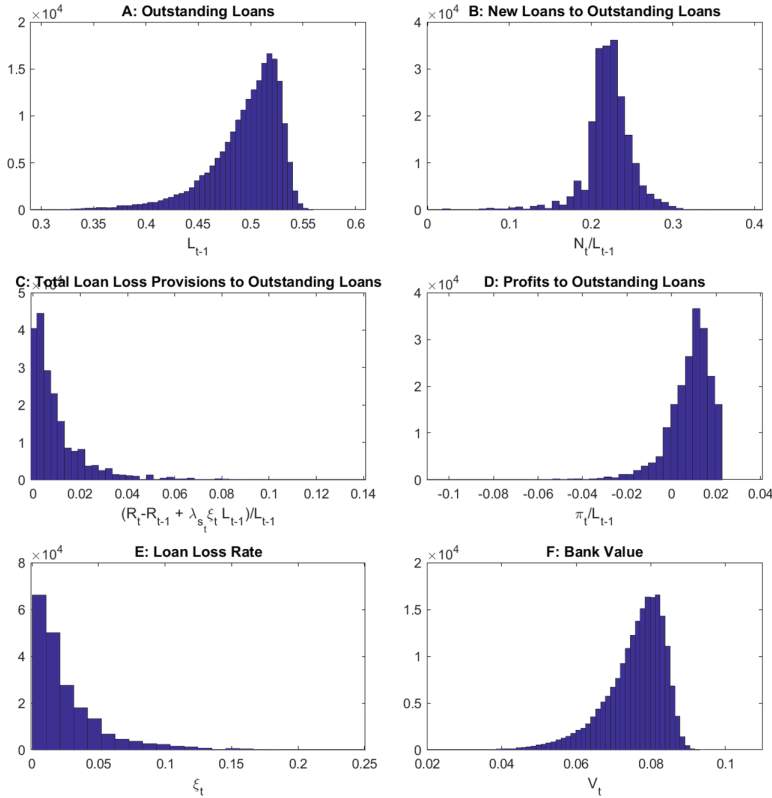
The second statement of the proposition is proved by taking the derivative of $L_{1|g} - L_{1|b}$ with respect to ϵ —that is,

$$\frac{d}{d\epsilon} (L_{1|g}^e - L_{1|b}^e) = -\frac{d}{d\epsilon} L_{1|b}^e = \frac{(1 - \tau(\pi_1))L_{1|b}^e}{\kappa_1 + \theta_b(1 - \tau(\pi_1))} > 0. \quad (\text{A.3})$$

To prove the last statement of the proposition, first, write the probability of bank failure at $t = 2$ as

$$\begin{aligned} P_2 &:= \mathbb{P}(X_2 < 0|z) \\ &= \mathbb{P}((1 - \tau(\pi_2))((r_2^L + \theta_{1|z}) + \kappa_1)) < 0|z) \\ &= \mathbb{P}\left(r_2^L < -\frac{\kappa_1}{1 - \tau(\pi_2)} - \theta_{1|z}|z\right) \end{aligned}$$

Figure A.1. Distributions of the Key Endogenous Variables



Note: This figure depicts distributions of the model’s key endogenous variables obtained from simulating the model under the incurred loss approach for 80,000 periods (with the first 200 observations excluded).

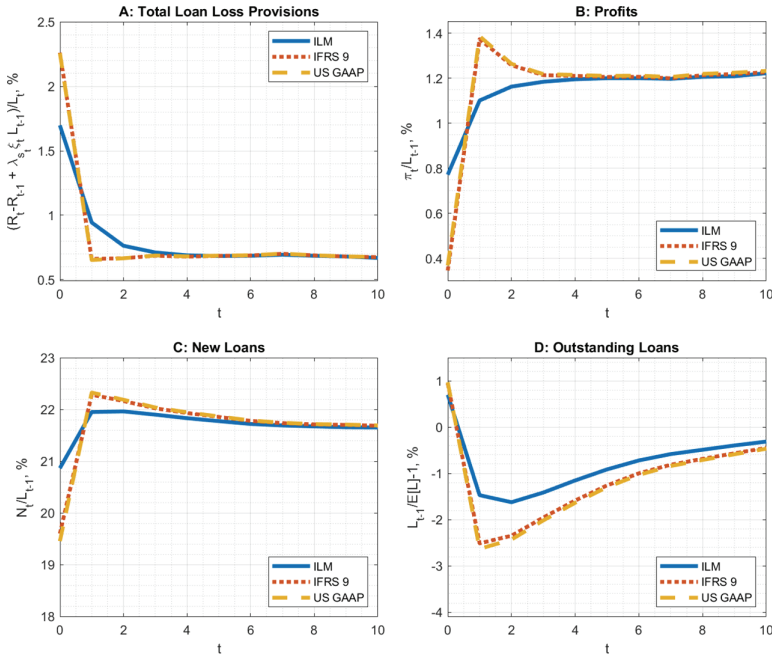
$$= \mathbb{P} \left(\frac{r_2^L - \mu_1}{\sigma_1} < -T_1 | z \right) = \Phi(-T_1) = 1 - \Phi(T_1),$$

where $T_1 = \frac{\kappa_1}{1-\tau(\pi_2)} + \theta_1 | z + \mu_1$ and $\Phi(\cdot)$ denotes the standard normal CDF. Then it follows that

$$\frac{d}{d\theta_1 | z} P_2 = -\frac{\phi(T_1)}{\sigma_1} < 0, \quad (\text{A.4})$$

where $\phi(\cdot)$ denotes the standard normal density function.

Figure A.2. Effect of the Arrival of a Contraction when Cost of External Equity Issuance Is Zero

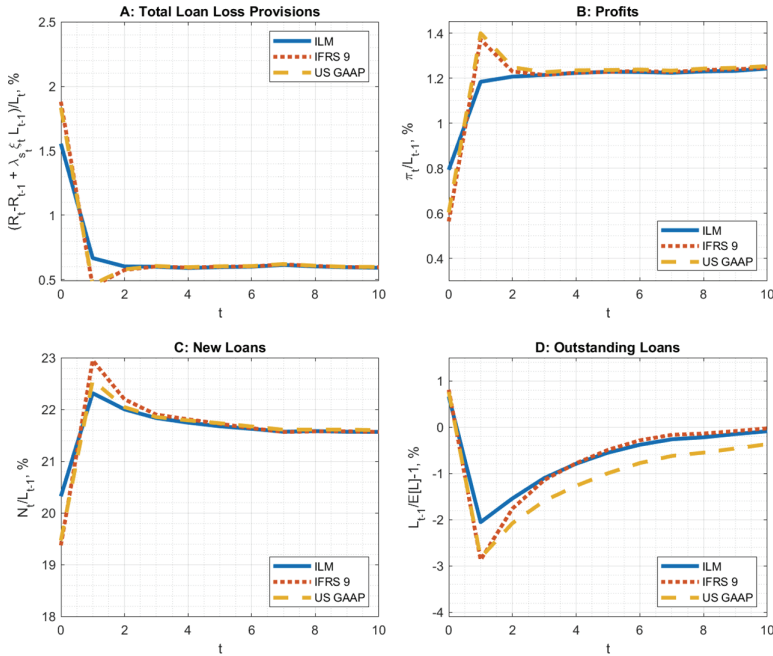


Note: This figure depicts the (generalized) impulse response functions of total loan loss provisions, profits, and new and outstanding loans to the arrival of a contraction at date $t = 0$ when the cost of external equity issuance are set to zero—that is, $\eta_{s_t} = 0$. The impulse response functions are presented for three scenarios: incurred loss model (ILM) and two variants of the EL approach, namely, IFRS 9 and U.S. GAAP. The impulse response of outstanding loans is in terms of relative changes to the (unconditional) mean $\mathbb{E}[L]$. The impulse responses are evaluated by taking the average across 30,000 simulated paths of the variables of interest, with each path having the length of 11 periods and the identical initial condition (L_{-1}, s_{-1}) . The initial condition is such that prior to $t = 0$ the bank is in an expansionary aggregate state, $s_{-1} = g$, and its endogenous state is given by the conditional on an expansionary aggregate state mean values—that is, $L_{-1} = \mathbb{E}[L_t | s_t = g]$.

Similarly, one proves $\frac{d}{d\theta_0} P_1 < 0$. First, write

$$\begin{aligned} P_1 &:= \mathbb{P}(X_1 < 0) \\ &= \mathbb{P}\left((1 - \tau(\pi_1)) \left((r_1^L + \theta_0) + \kappa_0\right) < 0\right) \end{aligned}$$

Figure A.3. Effect of the Arrival of a Lower Persistency Contraction

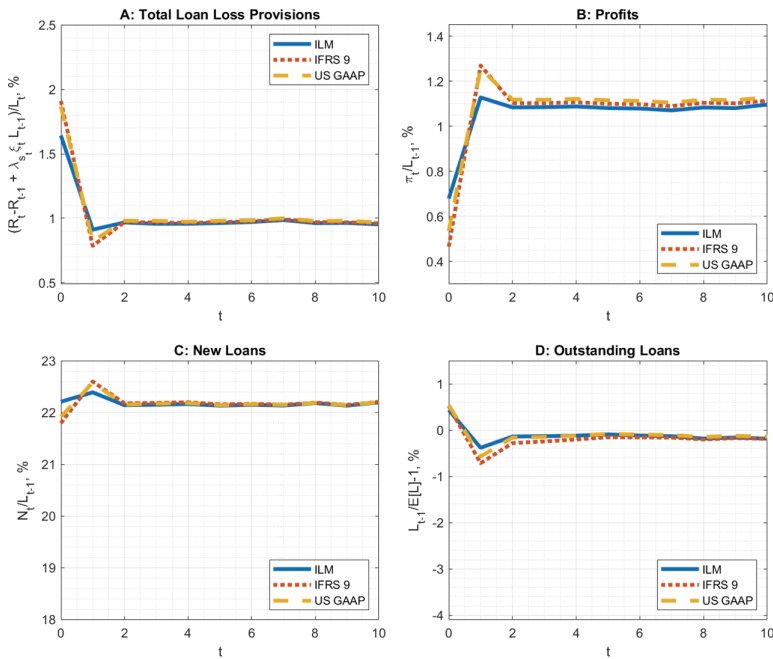


Note: This figure depicts the (generalized) impulse response functions of total loan loss provisions, profits, and new and outstanding loans to the arrival of a contraction at date $t = 0$ when the probability of remaining in a contraction is 0.2, implying that an average duration of a contraction is 1.25 year. The impulse response functions are presented for three scenarios: incurred loss model (ILM) and two variants of the EL approach, namely, IFRS 9 and U.S. GAAP. The impulse response of outstanding loans is in terms of relative changes to the (unconditional) mean $\mathbb{E}[L]$. The impulse responses are evaluated by taking the average across 30,000 simulated paths of the variables of interest, with each path having the length of 11 periods and the identical initial condition (L_{-1}, s_{-1}) . The initial condition is such that prior to $t = 0$ the bank is in an expansionary aggregate state, $s_{-1} = g$, and its endogenous state is given by the conditional on an expansionary aggregate state mean values—that is, $L_{-1} = \mathbb{E}[L_t | s_t = g]$.

$$\begin{aligned} &= \mathbb{P} \left(r_1^L < -\frac{\kappa_0}{1 - \tau(\pi_1)} - \theta_0 | z \right) \\ &= \mathbb{P} \left(\frac{r_1^L - \mu_0}{\sigma_0} < -T_0 \right) = \Phi(T_0) = 1 - \Phi(-T_0), \end{aligned}$$

where $T_0 = \frac{\frac{\kappa_0}{1 - \tau(\pi_1)} + \theta_0 + \mu_0}{\sigma_0}$.

Figure A.4. Effect of the Arrival of a Contraction under Symmetric Distribution of Aggregate States



Note: This figure depicts the (generalized) impulse response functions of total loan loss provisions, profits, and new and outstanding loans to the arrival of a contraction at date $t = 0$ when the probability of remaining in either a contraction or an expansion is 0.5. The impulse response functions are presented for three scenarios: incurred loss model (ILM) and two variants of the EL approach, namely, IFRS 9 and U.S. GAAP. The impulse response of outstanding loans is in terms of relative changes to the (unconditional) mean $\mathbb{E}[L]$. The impulse responses are evaluated by taking the average across 30,000 simulated paths of the variables of interest, with each path having the length of 11 periods and the identical initial condition (L_{-1}, s_{-1}) . The initial condition is such that prior to $t = 0$ the bank is in an expansionary aggregate state, $s_{-1} = g$, and its endogenous state is given by the conditional on an expansionary aggregate state mean values—that is, $L_{-1} = \mathbb{E}[L_t | s_t = g]$.

Then it follows immediately that

$$\frac{d}{d\theta_0} P_1 = -\frac{\phi(T_0)}{\sigma_0} < 0. \quad (\text{A.5})$$

Appendix B. Calibration Details

B.1 Vasicek Distribution

Following Vasicek (2002), we assume that the failure of an individual loan j at time t is driven by the realization of a latent random variable:

$$y_j = \Phi^{-1}(p_{s_t}) + \sqrt{\rho_{s_t}} z_t + \sqrt{1 - \rho_{s_t}} u_{j_t}, \quad (\text{B.1})$$

where $\Phi(\cdot)$ is the standard normal CDF, $z_t \sim \mathcal{N}(0, 1)$ is the common risk, $u_{j_t} \sim \mathcal{N}(0, 1)$ is idiosyncratic risk, and ρ_{s_t} is the correlation coefficient that determines a correlation between the performance of individual loans.

The loan defaults when $y_j < 0$, which happens with probability

$$\begin{aligned} \mathbb{P}(y_j < 0) &= \mathbb{P}\left(\sqrt{\rho_{s_t}} z_t + \sqrt{1 - \rho_{s_t}} u_{j_t} < -\Phi^{-1}(p_{s_t})\right) \\ &= \Phi\left(\Phi^{-1}(p_{s_t})\right) = p_{s_t}. \end{aligned} \quad (\text{B.2})$$

Since the probability of failure p_{s_t} is identical for all loans, by the law of large numbers, the failure rate ξ_t for a given realization of the systematic risk factor z_t equal to the probability of failure of a (representative) project j conditional on z_t . Thus,

$$\begin{aligned} \xi_t &= \xi_t(z_t, s_t) = \mathbb{P}\left(\sqrt{\rho_{s_t}} z_t + \sqrt{1 - \rho_{s_t}} u_{j_t} < -\Phi^{-1}(p_{s_t}) \mid z_t\right) \\ &= \Phi\left(\frac{\Phi^{-1}(p_{s_t}) - \sqrt{\rho_{s_t}} z_t}{\sqrt{1 - \rho_{s_t}}}\right). \end{aligned} \quad (\text{B.3})$$

We can now easily derive the distribution of $\xi_t(z_t, s_t)$, which is given by

$$F(\xi_t | s_t) = \mathbb{P}(\xi_t(z_t, s_t) \leq \xi_t) = \Phi\left(\frac{\sqrt{1 - \rho_{s_t}^i} \Phi^{-1}(\xi_t^i) - \Phi^{-1}(p_{s_t}^i)}{\sqrt{\rho_{s_t}^i}}\right), \quad (\text{B.4})$$

where the last equality comes from substituting Equation (B.3) for $\xi_t(z_t, s_t)$ above and rearranging terms.

Note that the distribution function in Equation (B.4) has two parameters: $p_{s_t}^i$ and $\rho_{s_t}^i \in (0, 1)$. $p_{s_t}^i$ is the stage i loan default

probability. $\rho_{s_t}^i \in (0, 1)$ is the correlation parameter, which captures the dependence of individual loan on the common risk factor and, thus, determines the degree of correlation between individual loan defaults. While we calibrate $p_{s_t}^i$ from the data, the correlation coefficient is computed consistent with the Basel approach (paragraph (53) of the section Internal Ratings-Based Approach for Credit Risk in Basel Committee on Banking Supervision 2017) such that $\rho_{s_t}^i = \rho(p_{s_t}^i)$, where

$$\rho(p_{s_t}^i) = 0.12 \frac{1 - \exp^{-50p_{s_t}^i}}{1 - \exp^{-p_{s_t}^i}} + 0.24 \left(1 - \frac{1 - \exp^{-50p_{s_t}^i}}{1 - \exp^{-p_{s_t}^i}} \right). \quad (\text{B.5})$$

B.2 Capital Requirement

Under the internal ratings-based approach, the capital requirement for corporate and bank exposures is meant to ensure sufficient capital to cover loan losses with a confidence level of 99.9 percent. The formula for $\kappa_{s_t}^i$ is taken from paragraph (53) of Internal Ratings-Based Approach for Credit Risk in Basel Committee on Banking Supervision (2017) and is given by

$$\begin{aligned} \kappa_{s_t}^i = & \left[\lambda_b \Phi \left(\frac{\Phi^{-1}(\bar{p}_i)}{\sqrt{1 - \bar{\rho}_i}} + \sqrt{\frac{\bar{\rho}_i}{1 - \bar{\rho}_i}} \Phi^{-1}(0.999) \right) - \bar{p} \lambda_b \right] \\ & \times \frac{1 + (M - 2.5)b_i}{1 - 1.5b_i}, \end{aligned} \quad (\text{B.6})$$

where $\bar{p}_i := q_g p_g^i + q_b p_b^i$ is the through-the-cycle (i.e., unconditional on the aggregate state) default probability of stage i loans; $\bar{\rho}_i = \rho(\bar{p}_i)$ is the through-the-cycle loan default correlation coefficient of stage i loans; M is effective maturity in years, which in our model is given by $1/\delta$; $b_i = [0.11852 - 0.05478 \ln(\bar{p}_i)]$ is the maturity adjustment coefficient. Under the IRB approach, Basel III specifies the use of downturn loss given default in computing the capital requirement, which in our model corresponds to λ_b . The overall capital requirement is then given by

$$\kappa_{s_t} = \omega_{s_t} \kappa_{s_t}^1 + (1 - \omega_{s_t}) \kappa_{s_t}^2. \quad (\text{B.7})$$

B.3 Discounted Lifetime Losses

The discounted lifetime losses on a unit size stage i loan can be written recursively as

$$\theta_{s_t}^{LT} = \frac{1}{1 + d_{s_t}} \mathbb{E}[\lambda_{s_{t+1}} \xi_{t+1} + (1 - \xi_{t+1})(1 - \delta) \theta_{s_{t+1}}^{LT} | s_t]. \quad (\text{B.8})$$

The above equation can be written in matrix form as

$$\bar{\theta}^{LT} = A \bar{\theta}^{LT} + \mu, \quad (\text{B.9})$$

where

$$A = \frac{1 - \delta}{1 + d_{s_t}} Q \circ \begin{bmatrix} 1 - p_g & 1 - p_b \\ 1 - p_g & 1 - p_b \end{bmatrix}, \quad (\text{B.10})$$

and

$$\mu = \frac{1}{1 + d_{s_t}} Q \begin{bmatrix} \lambda_g p_g \\ \lambda_b p_b \end{bmatrix}, \quad (\text{B.11})$$

where Q is the 2×2 transition probability matrix and “ $\circ$ ” denotes the Hadamard (element-wise) product. Thus,

$$\bar{\theta}^{LT} = (I_{2 \times 2} - A)^{-1} \mu,$$

where $I_{2 \times 2}$ is a 2×2 identity matrix.

Appendix C. Numerical Solution Method

C.1 Model

We obtain a fully non-linear solution to the model numerically using the value function iteration method. In general, the model has two endogenous state variables, E_t and L_t . However, given the calibrated values of the parameters, we find that the minimum capital requirement $E_t \geq \kappa_{s_t} L_t$ is binding on the simulation path. Therefore, we solve our model under assumption that $E_t = \kappa_{s_t} L_t$. Thus, effectively,

the model has one endogenous state variable L_t . The grids for L_{t-1} consist of 120 points and include 119 equispaced points between 0.17 and 0.65, and 0. Furthermore, we use a linear interpolation method for the grid of choice variables L_t (implemented by applying the *interp1* MATLAB function to the original grids of L_{t-1} with the query point equal to 0.1). As a result of linear interpolation, the grids for L_t consist of 1,201 points. The high density of the grid for the choice variable is highly important to obtain a reliable approximation of the solution to our model. This is because the loss rate ξ_t and, thus, the provisioning rate θ_{s_t} have relatively small magnitudes. Therefore, to pick up any effect from a relatively small change in θ_{s_t} (say the difference between IFRS 9 and U.S. GAAP), it is crucial that the grid for L_t is sufficiently dense.

For the numerical representation of the exogenous state the random variable ξ_t is discretized. The grid of the ξ_t^i 's support consists of 41 points (in each aggregate state). As we show in Appendix B, the default rate ξ_t^i can be written as a function of the standard normal distribution:

$$\xi_t^i = g(u; s_t) = \Phi \left(\frac{\Phi^{-1}(p_{s_t}^i) - \sqrt{\rho_{s_t}^i} u}{\sqrt{1 - \rho_{s_t}^i}} \right),$$

where $\Phi(\cdot)$ is the standard normal $p_{s_t}^i$ and $\rho_{s_t}^i$ are defined in the text, and $u \sim \mathcal{N}(0, 1)$. Therefore the discrete approximation of ξ_t^i is obtained by discretizing u which is performed using the approach of Tauchen (1986) (we set the bounds of the support of u to $[-3.5; 3.5]$ allowing for extreme realizations of u). Because we have two possible realizations of aggregate states and also record the one-period history of the aggregate state (s_{t-1}), the space of exogenous state consists of $2 \times 2 \times 41 = 164$ points.

To compute the moments implied by the model, we simulate our model for 80,000 periods. The first 200 observations are dropped when computing the moments to avoid the initial value having any effect. When the bank defaults on the simulation path, it is replaced starting from the next period with a new bank with the average size (i.e., with L_t given by unconditional means). Given that default is a rare event, the replacement rule does not have any profound effect on the moments.

C.2 Generalized Impulse Response Functions

The generalized impulse response is approximated using a simulation method. That is, given the initial state variable, we perform $N = 30,000$ simulations of the model each with the length of $T = 20$ periods. Averaging the variable of interest across simulated paths for each period $t \in [0, T]$ then produces its generalized impulse response in that period. Taking p -th and $100-p$ -th percentile across the simulated paths produces the p percent confidence bounds. In our figures, we only plot the approximated responses for the first 11 periods.

References

- Abad, J., and J. Suarez. 2018. “The Procyclicality of Expected Credit Loss Provisions.” Working Paper.
- Acharya, V. V., and S. G. Ryan. 2016. “Banks’ Financial Reporting and Financial System Stability.” *Journal of Accounting Research* 54 (2): 277–340.
- Admati, A. R., P. M. DeMarzo, M. F. Hellwig, and P. Peiderer. 2018. “The Leverage Ratchet Effect.” *Journal of Finance* 73 (1): 145–98.
- Ahmed, A. S., C. Takeda, and S. Thomas. 1999. “Bank Loan Loss Provisions: A Reexamination of Capital Management, Earnings Management and Signaling Effects.” *Journal of Accounting and Economics* 28 (1): 1–25.
- Altınkılıç, O., and R. S. Hansen. 2000. “Are There Economies of Scale in Underwriting Fees? Evidence of Rising External Financing Costs.” *Review of Financial Studies* 13 (1): 191–218.
- Barclays. 2017. “European Banks: IFRS9 — Bigger than Basel IV.” Industry Update.
- Basel Committee on Banking Supervision. 2017. “Basel III: Finalising Post-Crisis Reforms.” Bank for International Settlements.
- Beatty, A., and S. Liao. 2011. “Do Delays in Expected Loss Recognition Affect Banks’ Willingness to Lend?” *Journal of Accounting and Economics* 52 (1): 1–20.
- Behn, M., R. Haselmann, and P. Wachtel. 2016. “Procyclical Capital Regulation and Lending.” *Journal of Finance* 71 (2): 919–56.

- Borio, C., and F. Restoy. 2020. "Reflections on Regulatory Responses to the COVID-19 Pandemic." FSI Briefs No. 1, Financial Stability Institute, Bank for International Settlements.
- Bushman, R. M., and C. D. Williams. 2015. "Delayed Expected Loss Recognition and the Risk Profile of Banks." *Journal of Accounting Research* 53 (3): 511–53.
- Chae, S., R. F. Sarama, C. M. Vojtech, and J. Wang. 2019. "The Impact of the Current Expected Credit Loss Standard (CECL) on the Timing and Comparability of Reserves." Finance and Economics Discussion Series No. 2018-020, Board of Governors of the Federal Reserve System.
- Cohen, B. H., and G. A. Edwards, Jr. 2017. "The New Era of Expected Credit Loss Provisioning." *BIS Quarterly Review* 1 (March): 39–56.
- De Nicolò, G., A. Gamba, and M. Lucchetta. 2014. "Microprudential Regulation in a Dynamic Model of Banking." *Review of Financial Studies* 27 (7): 2097–2138.
- Dewatripont, M., and J. Tirole. 2012. "Macroeconomic Shocks and Banking Regulation." *Journal of Money, Credit and Banking* 44 (s2): 237–54.
- Dinger, V., and F. Vallascas. 2016. "Do Banks Issue Equity When They Are Poorly Capitalized?" *Journal of Financial and Quantitative Analysis* 51 (5): 1575–1609.
- European Systemic Risk Board (ESRB). 2017. "Financial Stability Implications of IFRS 9."
- Financial Stability Forum. 2009. "Report of the Financial Stability Forum on Addressing Procyclicality in the Financial System."
- Gersbach, H., and J.-C. Rochet. 2017. "Capital Regulation and Credit Fluctuations." *Journal of Monetary Economics* 90 (October): 113–24.
- Goldstein, I., and H. Sapra. 2014. "Should Banks' Stress Test Results be Disclosed? An Analysis of the Costs and Benefits." *Foundations and Trends in Finance* 8 (1): 1–54.
- Hanson, S. G., A. K. Kashyap, and J. C. Stein. 2011. "A Macroprudential Approach to Financial Regulation." *Journal of Economic Perspectives* 25 (1): 3–28.
- Hennessy, C. A., and T. M. Whited. 2007. "How Costly Is External Financing? Evidence from a Structural Estimation." *Journal of Finance* 62 (4): 1705–45.

- Huizinga, H., and L. Laeven. 2018. “The Procyclicality of Banking: Evidence from the Euro Area.” Working Paper.
- International Accounting Standards Board (IASB). 2014. “International Financial Reporting Standard 9 Financial Instruments.”
- Jiménez, G., S. Ongena, J.-L. Peydró, and J. Saurina. 2017. “Macroprudential Policy, Countercyclical Bank Capital Buffers, and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments.” *Journal of Political Economy* 125 (6): 2126–77.
- Kashyap, A., and J. Stein. 2004. “Cyclical Implications of the Basel II Capital Standards.” *Economic Perspectives* (Federal Reserve Bank of Chicago) 28 (1): 18–31.
- Koop, G., M. H. Pesaran, and S. M. Potter. 1996. “Impulse Response Analysis in Nonlinear Multivariate Models.” *Journal of Econometrics* 74 (1): 119–47.
- Krüger, S., D. Rösch, and H. Scheule. 2018. “The Impact of Loan Loss Provisioning on Bank Capital Requirements.” *Journal of Financial Stability* 36 (June): 114–29.
- Laeven, L., and G. Majnoni. 2003. “Loan Loss Provisioning and Economic Slowdowns: Too Much, Too Late?” *Journal of Financial Intermediation* 12 (2): 178–97.
- Laux, C. 2012. “Financial Instruments, Financial Reporting, and Financial Stability.” *Accounting and Business Research* 42 (3): 239–60.
- Laux, C., and C. Leuz. 2010. “Did Fair-Value Accounting Contribute to the Financial Crisis?” *Journal of Economic Perspectives* 24 (1): 93–118.
- Mahieux, L., H. Sapra, and G. Zhang. 2023. “CECL: Timely Loan Loss Provisioning and Banking Regulation.” *Journal of Accounting Research* 61 (1): 3–46.
- Malherbe, F. 2020. “Optimal Capital Requirements over the Business and Financial Cycles.” *American Economic Journal: Macroeconomics* 12 (3): 139–74.
- Mankart, J., A. Michaelides, and S. Pagratis. 2020. “Bank Capital Buffers in a Dynamic Model.” *Financial Management* 49 (2): 473–502.
- Martinez-Miera, D., and R. Repullo. 2010. “Does Competition Reduce the Risk of Bank Failure?” *Review of Financial Studies* 23 (10): 3638–64.

- Myers, S. C. 1977. "Determinants of Corporate Borrowing." *Journal of Financial Economics* 5 (2): 147–75.
- Myers, S. C., and N. S. Majluf. 1984. "Corporate Financing and Investment Decisions when Firms Have Information that Investors Do Not Have." *Journal of Financial Economics* 13 (2): 187–221.
- Repullo, R. 2013. "Cyclical Adjustment of Capital Requirements: A Simple Framework." *Journal of Financial Intermediation* 22 (4): 608–26.
- Repullo, R., J. Saurina, and C. Trucharte. 2010. "Mitigating the Pro-cyclicality of Basel II." *Economic Policy* 25 (64): 659–702.
- Repullo, R., and J. Suarez. 2013. "The Procyclical Effects of Bank Capital Regulation." *Review of Financial Studies* 26 (2): 452–90.
- Tauchen, G. 1986. "Finite State Markov-Chain Approximations to Univariate and Vector Autoregressions." *Economics Letters* 20 (2): 177–81.
- Vasicek, O. 2002. "The Distribution of Loan Portfolio Value." *Risk* 15 (December): 160–62.