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Mahmoud Fatouh[(1)] and Simone Giansante[(2)]

Abstract

We model the evolution of stylised bank loan portfolios to assess the impact of IFRS 9 and US GAAP expected loss model (ECL) on the cyclicality of loan write-off losses, loan loss provisions (LLPs) and capital ratios of banks, relative to the incurred loss model of IAS 39. We focus on the interaction between the changes in LLPs' charges (the flow channel) and stocks (the stock channel) under ECL. Our results show that, when GDP growth does not demonstrate high volatility, ECL model smooths the impact of credit losses on profits and capital resources, reducing the procyclicality of capital and leverage ratios, especially under US GAAP. However, when GDP growth is highly volatile, the large differences in lifetime probabilities of defaults (PDs) between booms and busts cause sharp increases in LLPs in deep downturns, as seen for US banks during the Covid-19 crisis. Volatile GDP growth makes capital and leverage ratios more procyclical, with sharper falls in both ratios in deep downturns under US GAAP, compared to IAS 39. IFRS 9 ECL demonstrates less sensitivity to lifetime PDs fluctuations due to the existence of loan stages, and hence can reduce the procyclicality of capital and leverage ratios, even when GDP is highly volatile.

Key words: IFRS 9, IAS 39, US GAAP, expected credit loss model, loan loss provisions, cyclicality of bank profits, leverage ratio, risk-weighted assets.

JEL classification: D92, G21, G28, G31, L51.

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(1) Bank of England and Department of Economics, University of Essex.
Email: Mahmoud.Fatouh@bankofengland.co.uk

(2) University of Palermo. Email: Simone.Giansante@unipa.it

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Bank of England, Threadneedle Street, London, EC2R 8AH
Email: enquiries@bankofengland.co.uk

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1. Introduction

The newly adopted IFRS 9[1] and US GAAP[2] implement the *expected credit loss* (ECL) approach to calculate loan loss provisions (LLPs) for banks, aiming to address the delayed identification of potential credit losses caused by the *incurred loss* model of IAS 39[3] and FAS 5[4]. The incurred loss model allows banks to create LLPs only when there is 'objective evidence' of impairment. As a result, LLPs tend to be relatively low in good economic conditions and inflate significantly in downturns. In addition to limiting resources available to cover higher losses in downturns (Linsmeier (2011) and Acharya & Ryan (2016)), the increase in LLPs would put additional strain on already reducing capital resources and ratios during such periods. Some have argued that these impacts under the backward-looking, incurred loss framework have the potential to reinforce pro-cyclicality effects of capital regulations on bank lending (e.g., Joint FSF-BCBS Working Group on Bank Capital Issues (2009) Novotny-Farkas (2016)). Others claim that a more forward-looking provisioning approach, such as that of IFRS 9 or US GAAP CECL, could reduce fluctuations in the financial system (e.g., Borio et al (2001), Bouvatier & Lepetit (2008), Agénor & Zilberman (2015), and Agénor & da Silva (2017)) and improve transparency of banks' asset quality (e.g., Bushman & William (2012), Bushman (2014), and Ryan (2017)).

Relative to the incurred loss model, the ECL model is more forward-looking (Fatouh et al. (2022)). It reflects changes in credit quality of financial assets in a more timely way. This is anticipated to reduce the counter-cyclicality of LLPs relative to the incurred loss model, and hence the pro-cyclicality of profits. Both IFRS 9 and US GAAP use ECL model, but differ slightly in terms of its implementation. Unlike IFRS 9, loans under US GAAP aren't categorised depending on credit quality, and attract LLPs equal to their lifetime expected credit losses. IFRS 9's ECL model is more sensitive to credit quality, as it classifies assets into three buckets (stages). As long as the credit quality of a loan hasn't deteriorated significantly (relative to origination), the loan is considered Stage 1, and its ECL is equal to the 12-

[1] International Financial Reporting Standard 9 *Financial Instruments*. See International Accounting Standards Board (2013).

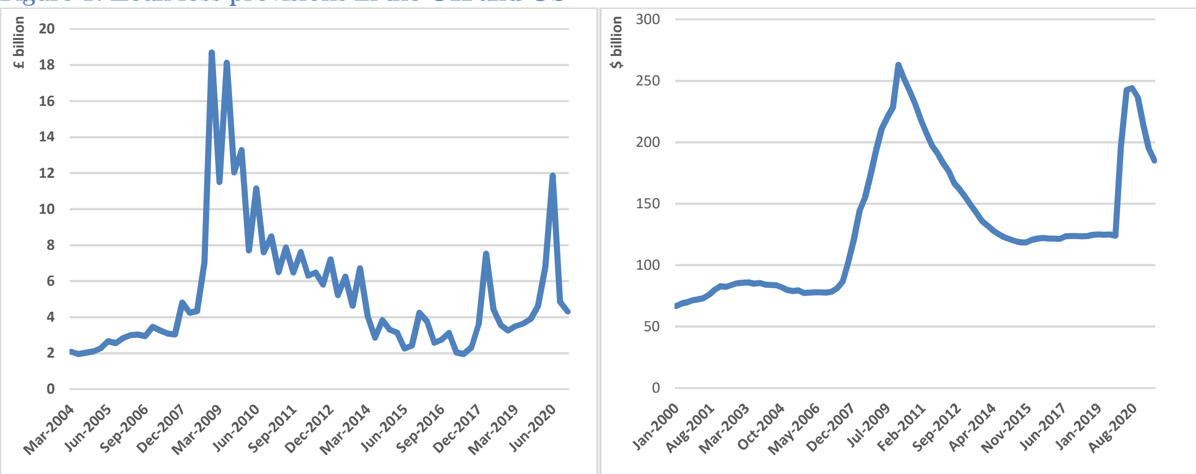
[2] Current Expected Credit Losses (CECL) standards under US Generally Accepted Accounting Principles (US GAAP – Accounting Standards Code Topic 326). See Financial Accounting Standards Board (2016).

[3] International Accounting Standard 39 *Financial Instruments: Recognition and Measurement*.

[4] Financial Accounting Standard No 5: Accounting for Contingencies (ASC 450-20) and related standards under US GAAP, codified by the FASB

month expected loss. Once credit quality deteriorates significantly, the loan becomes Stage 2 and its ECL will be equal to lifetime expected loss. The same applies when the loan becomes a Stage 3 (non-performing) loan. The more timely recognition of potential credit losses makes ECL LLPs more responsive to changes in economic conditions. This could mean large surges and reductions in LLPs when the economy is hit by significant shocks, such as that experienced in several major economies during the Covid-19 pandemic. As Figure 1 demonstrates, LLPs increased significantly during the Covid-19 stress in 2020 H1, but then fell back afterwards. The increase in LLPs is clearer for US banks than UK banks, as LLPs almost reached the levels they witnessed during the Great Financial Crisis (2007-2008). We argue that this is resulting from the differences between the two ECL models mentioned above, in particular the use of life-time expected credit losses for all loans under US GAAP.

Figure 1: Loan loss provisions in the UK and US



Source: [1] Bank of England. Quarterly total of Monetary financial institutions sterling and all foreign currency provisions residents and non-residents (in sterling millions) not seasonally adjusted, available at: https://www.bankofengland.co.uk/boeapps/database/fromshowcolumns.asp?Travel=NIxAZxSUx&FromSeries=1&ToSeries=50&DAT=RNG&FD=1&FM=Jan&FY=1963&TD=31&TM=Dec&TY=2025&FNY=Y&CSVF=TT&html.x=66&html.y=26&SeriesCodes=GFQB6SS&UsingCodes=Y&Filter=N&title=GFQB6SS&VPD=Y.

[2] Federal Reserve Bank of St. Louis. Balance Sheet: Total Assets: Reserve for Losses, available at: https://fred.stlouisfed.org/series/QBPBSTASTLNLESSRES

This paper assesses the impact of the two variants of the ECL approach on the cyclical behaviour of loan write-off losses (write-off losses[5]), LLPs and (risk-based) capital ratios and leverage ratios of banks, and compares these impacts to those under the incurred loss model. It is worth noting that, throughout the paper, we measure cyclicality by the correlation with GDP growth. That is, variables

[5] Write-off losses are equal to gross carrying amount of a defaulted loan minus LLPs for that loan.

that are positively (negatively) correlated with GDP growth are pro-cyclical (counter-cyclical). For our comparisons, we focus only on the impacts under the incurred loss model as set out under IAS 39, which we also consider to be suitable proxy for the incurred loss model under US accounting standards FAS 5 and FAS 114[6]. We are interested in the behavioural aspects or how the ECL accounting standards are implemented rather than the mechanical differences between incurred loss and ECL standards.

Based on stylised data-driven loan portfolios, we simulate the evolution of LLPs, write-off losses and capital and leverage ratios of 405 banks, calibrated to the UK banking sector, under ECL and incurred loss models. Banks in our model vary in size and riskiness of their loans, as well as ECL implementation approaches. They all use 3-scenario method (baseline-up-down), but can have 5 different strategies to determine the expected future path of the economy (the baseline scenario). Additionally, when assigning probabilities to the scenarios, banks can be neutral, optimistic, or pessimistic. These variations in the baseline scenario setup and the level of optimism translate into 15 unique (scenario-expectation) implementation approaches (or types) banks can adopt. Bank implementation approaches are also affected by economic conditions. We assume they tend to be longer-term and more optimistic in booms and shorter-term and less optimistic in busts. Hence, the approaches become closer to the through-the-cycle (TTC) estimation, as explained by ESRB (2017), in upturns, and closer to a point-in-time (PIT) in downturns. The swings between over-optimism and over-pessimism have been mentioned by several authors as a key driver of cyclicality of economic activity and asset markets (for example, De Grauwe (2012), Williams (2013), and Adam et al. (2017)). To the best of our knowledge, we are the first to use a simulation setup that accounts for changes in banks' forecasting approaches at different stages of the credit cycle.

LLPs appear as expenses[7] (in the profit and loss account) and reserves to recognise potential losses (on the balance sheet). Our model focuses on two channels through which ECL can affect bank profits and equity capital resources: (i) the **LLPs flow channel** (the flow channel) and (ii) the **LLPs stock channel** (the stock channel). In line with literature (for example, Kruger et al. (2018)), we show that

[6] Financial Accounting Standards Board's standard number 5 and standard number 114.

[7] Throughout the paper, LLPs refer to LLPs expenses. We refer to the reserves on the balance sheet as LLPs stock.

during periods with no major crises, the stock channel dominates the flow channel under ECL, smoothing the impact of credit losses on profits and capital resources, and reducing the pro-cyclicality of capital ratios and leverage ratios, especially under US GAAP. This result suggests that ECL can improve the stability of individual institutions and the banking system as a whole. However, when GDP is highly volatile (e.g. during crisis periods), the flow channel dominates, under US GAAP. This is due to the large differences in lifetime probabilities of default (PDs) between boom and bust, which cause LLPs to shoot up sharply during deep downturns. We show that this can explain the spike in LLPs for US banks during the Covid-19 stress. LLP patterns reflect on bank capital resources, making capital and leverage ratios more pro-cyclical, and causing sharp falls in the two ratios in deep downturns. The existence of stages reduces ECL sensitivity to fluctuations in lifetime PDs under IFRS 9, reducing pro-cyclicality of the two ratios, even when GDP is volatile (see Section 5.3 for a critical discussion on the implications of PDs sensitivity to GDP on the impact of both IFRS 9 and US GAAP on the cyclicality of the variables we simulate). The reminder of the paper proceeds as follows. Section 2 reviews the related literature. Section 3 presents the data used to calibrate the model. Section 4 outlines our model. Section 5 presents the analysis, and Section 6 concludes.

2. Related Literature

The provisioning of loans with higher credit quality means the stock of LLPs would be higher under ECL model than under the incurred loss model. Several studies confirm this using surveys and simulation techniques[8]. For instance, based on surveys of banks, Kengla et al. (2018) and EBA (2018) show that the move from IAS 39 to IFRS 9 would on average increase LLPs by 5-10% and 9%, respectively. Using European banks' data between 2005 and 2014 to simulate LLPs, Seitz et al. (2018) conclude that LLPs under IFRS 9 are no less than those under IAS 39. ECL effects are likely to vary across the cycle, affecting the cyclicality of LLPs, write-off losses, and capital ratios of banks. As pointed out by many studies (e.g., Borio et al. (2001), Pool et al. (2015) Novotny-Farkas (2015), and Kund & Rugilo (2018)), by creating LLPs for higher quality loans during economic upturns, ECL reduces the so-

[8] See also Novotny-Farkas (2015) and Deloitte (2016).

called “cliff effect” in downturns when impairment charges under incurred loss accounting increase significantly, making LLPs less counter-cyclical. This impact is especially true for the US GAAP, and less so for IFRS 9. IFRS 9 involves a cliff effect, when loans move from Stage 1 to Stage 2, which likely overlaps with periods of economic contraction. Using Irish mortgage data, Gaffney & McCann (2019) point out that the share of Stage 2 loans rises from 5% to 50% in such periods. In terms of the impact on the volatility of profits, Laeven & Majnoni (2003), Balla & McKenna (2009), and Buesa et al. (2020) suggest that ECL should smooth profits across the cycle reducing their pro-cyclicality. Others (e.g. Hashim et al. (2016) and EBA (2017)) argue that the spikes caused by the IFRS 9 cliff effect can increase the pro-cyclicality of profits. ESRB (2019) suggests that a 5% increase in Stage 2 loans can increase impairment charges for the median bank by 56.55%. Abad & Suarez (2017) state that spikes in LLPs under IFRS 9 tend to concentrate at the beginning of downturns, when credit losses start to pile up. The increase in the pro-cyclicality of profits further increases the pro-cyclical behaviour of bank capital, as indicated by Krüger et al. (2018). Barclays (2017) estimates that, in a typical downturn, Common Equity Tier 1 (CET1) resources could decline by 300 bps under IFRS 9, compared to 100 bps under IAS 39. We argue that the two contradicting views above can be reconciled by taking ECL implementation approaches into consideration. If banks created more LLPs in good conditions, considering the potential cliff effect in downturns, then ECL would reduce the pro-cyclicality of bank profits, and vice versa. Our model not only allows banks to have different implementation approaches, but also incorporates an endogenous switching approach at different stages of the cycle. This is in line with the literature, which argues that banks’ ability and incentives to incorporate adequate forward-looking information in ECL calculation and to set appropriate criteria for loan classification can have considerable implications for the cyclical effects of ECL. Chae et al. (2018) argue that in order to deliver desired impact of ECL in reducing pro-cyclicality, banks have to be able to fairly accurately predict future economic downturn. Gaffney and McCann (2018) confirm this and indicate that high accuracy in predictions is unlikely for most banks in practice. ESRB (2017) concludes that the use of (less accurate) point-in-time (PIT) rather than through-the-cycle (TTC) estimates can generate lower LLPs in booms and higher LLPs in busts, causing higher cyclicality.

3. The data

Our model follows the data-driven forecasting approach proposed by Markose (2013), in the sense that the initial values and the evolution of some variables are calibrated to the actual values or distributions extracted from the data. We use data on UK GDP growth, interest rates, bank leverage exposures and ratios from multiple sources including confidential regulatory data and publically available data from the Bank of England (BOE) and Office for National Statistics (ONS).

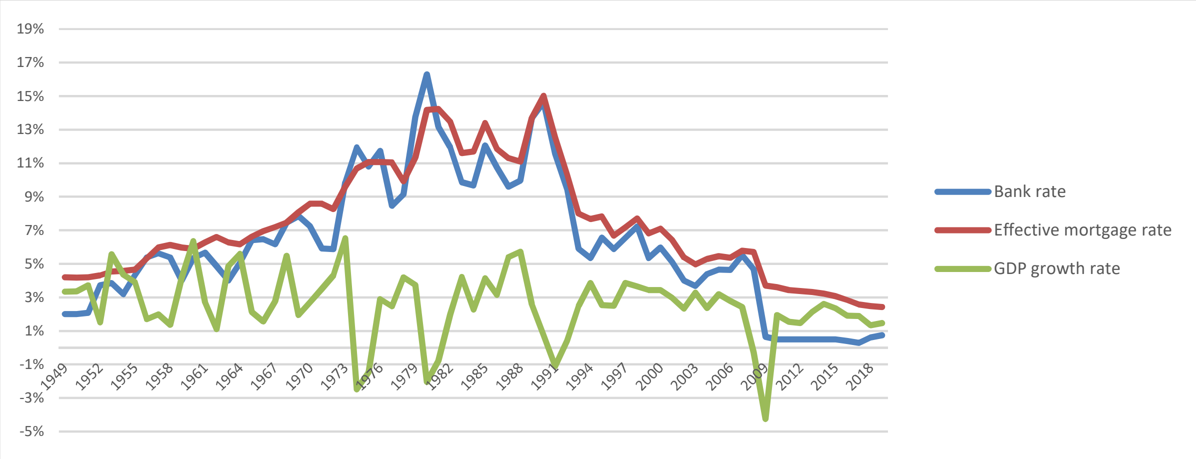
We calculate annual GDP growth based on ONS GDP data between 1948 and 2019. We use the GDP growth series as a basis to set up ECL scenarios and determine the evolution of the transition matrix over time. We collect interest rate data from BOE's public database. We use BOE Bank rate data as a discount rate to calculate LLPs, and average interest rates on mortgages to calculate interest income. Figure 2 presents information on the GDP growth and interest rates time series.

We use confidential regulatory data on leverage exposure, Core Equity Tier 1 (CET1) capital ratios and leverage ratios[9] of 405 banks supervised by BOE, as of end 2017 (just before IFRS 9 was introduced). This dataset allows us to initialise size and capital levels of banks. As

Figure 3 and Table 1 show, our sample includes many small banks and a few large banks, making the distribution of size log-normal. We use this distribution to determine the number of loans assigned to each bank. Based on the number of loans and the balance of each loan, we determine the leverage exposure of the bank. We use the leverage exposure with a random leverage ratio from the distribution shown in Figure 4 to create equity capital resources for each bank at the start of the simulation. Credit ratings of loans in our model range between AAA and D. Ratings of individual loans evolve over time based on a transition matrix, which shows the probabilities a loan with a given credit rating will have a certain rating in the next year. We use a time-varying transition matrix in the sense that probabilities change over time depending on the status of the economy. The starting structure of this matrix is based on the long-term transition matrix from JP Morgan (1998) shown in Table 2. The last column of the transition matrix includes PDs.

[9] Leverage ratio here is the regulatory leverage ratio, which is caluclaed by divding capital resources on the leverage ratio exposure measure. This exposure measure considers not only on-balance sheet assets, but also off-balance sheet exposures such as gurantees, unused credit facilities, and derivatives. See the Basel Consolidated Framework on the Bank for International Settlements' website (https://www.bis.org/basel_framework/index.htm?m=3_14_697) for more details.

Figure 2: UK GDP growth, Bank of England rates and effective mortgage rates (1949-2019)

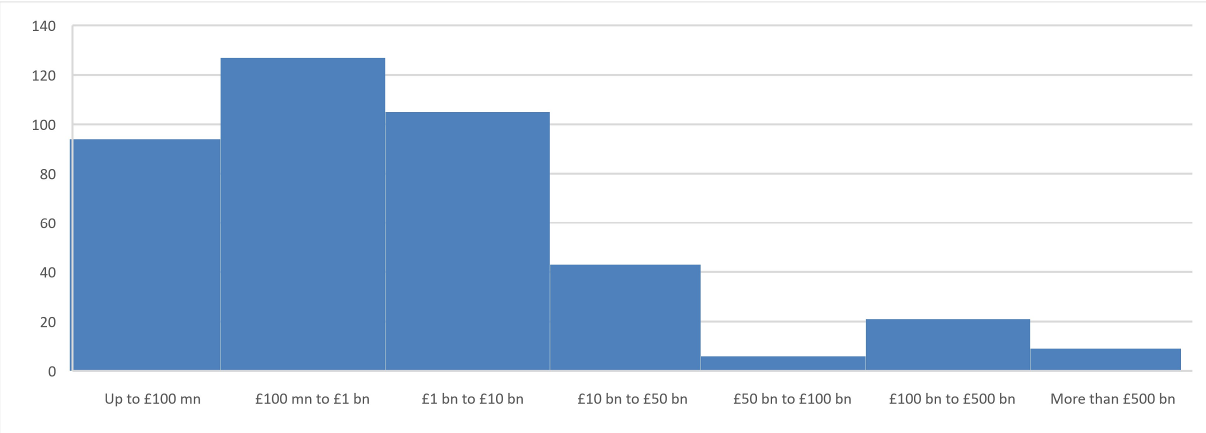


	Mean	Median	St. deviation	Min	Max
GDP Growth	2.56%	2.58%	1.98%	-4.25%	6.52%
Bank rate	6.19%	5.62%	3.97%	0.29%	16.30%
Effective mortgage rate	7.38%	6.63%	3.34%	2.43%	15.02%

Source: [1] GDP data from ONS data series (Gross Domestic Product: chained volume measures: Seasonally adjusted; available at: https://www.ons.gov.uk/economy/grossdomesticproductgdp/timeseries/abmi/pn2.

[2] Bank rate and effective mortgage rate data till 2016 from the spreadsheet "a-millennium-of-macroeconomic-data-for-the-uk" available at: https://www.bankofengland.co.uk/statistics/research-datasets, from the worksheet "A31. Interest rates & asset ps" (Bank Rate in column B and Effective Mortgage Rate in column L). The reminder is sourced from the Bank of England's databases.

Figure 3: Distribution of banks by size



Source: Bank of England regulatory returns

Table 1: Descriptive statistics of leverage exposures and leverage ratios of UK banks

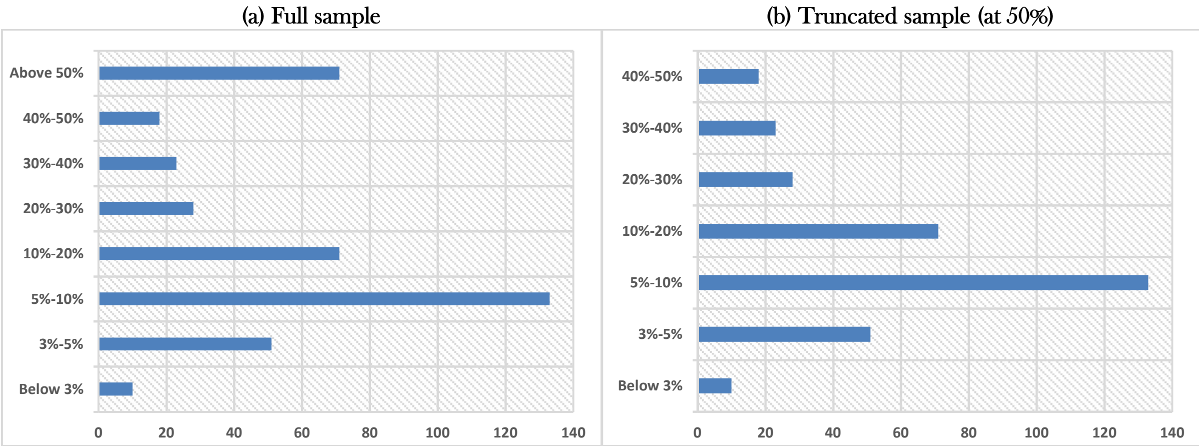
Category	No. banks	Leverage exposure (£ million)		Leverage ratio			
				full sample		truncated at 50%	
		Average	Std. deviation	Average	Std. deviation	Average	Std. deviation
Less than £100 mn	94 (45)*	27.3	26.6	63.81%	58.77%	28.73%	12.28%
£100 mn to £1 bn	127 (108)	397.6	248.3	23.10%	21.87%	15.46%	11.56%
£1 bn to £10 bn	105 (102)	3,761.2	2,694.3	12.05%	14.90%	9.86%	7.60%
£10 bn to £50 bn	43	25,416.3	12,344.2	7.08%	3.64%	7.08%	3.64%
£50 bn to £100 bn	6	69,691.8	22,985.6	3.88%	1.51%	3.88%	1.51%
£100 bn to £500 bn	21	299,612.8	93,024.3	5.09%	2.43%	5.09%	2.43%
More than £500 bn	9	864,087.7	437,917.1	4.96%	0.76%	4.96%	0.76%
All banks	405 (334)	39,574.6	155,127.5	5.37%**	3.30%**	5.29%**	2.31%**

Notes: **Source:** Bank of England regulatory returns

* Numbers in brackets are bank counts in the truncated sample (banks with leverage ratios exceeding 50% dropped)

** The weighted means and standard deviations of leverage ratios, using leverage exposures as weights

Figure 4: Distribution of leverage ratios



Source: Bank of England regulatory returns

Table 2: Smoothed historical average transition matrix

	Initial rating	End-of-year credit rating							
		AAA	AA	A	BBB	BB	B	CCC	D
Smoothed historical average transition matrix	AAA	91.13%	8.00%	0.70%	0.10%	0.05%	0.01%	0.01%	0.01%
	AA	0.70%	91.03%	7.47%	0.60%	0.10%	0.07%	0.02%	0.01%
	A	0.10%	2.34%	91.54%	5.08%	0.61%	0.26%	0.01%	0.05%
	BBB	0.02%	0.30%	5.65%	87.98%	4.75%	1.05%	0.10%	0.15%
	BB	0.01%	0.11%	0.55%	7.77%	81.77%	7.95%	0.85%	1.00%
	B	0.00%	0.05%	0.25%	0.45%	7.00%	83.50%	3.75%	5.00%
	CCC	0.00%	0.01%	0.10%	0.30%	2.59%	12.00%	65.00%	20.00%

Source: JP Morgan's CreditMetrics® Monitor Third Quarter 1998

4. The methodology

Using a data-driven forecasting approach, we model stylised loan portfolios[10] of 405 banks, replicating the banking system in the UK, over a period of 60 years. We aim to assess the impact of the two variants of the ECL model on the cyclicality and volatility of write-off losses, LLPs and leverage and capital ratios of banks, relative to the incurred loss model. We measure cyclicality and volatility by the correlation with GDP growth[11] and the mean standard error (MSE) relative to trend, respectively. Our model and simulations are data-driven in that initial conditions and simulation events are extracted based on actual data. However, as with any model, we use some simplifying assumptions. Table 3 includes a list of the distributional facts and simplifying assumptions we use.

[10] BOE holds loan-level data, but it does not include all the details needed to calculate LLPs under IFRS 9, US GAAP and IAS 39 (especially life time/12-months PDs and PDs at origination of the loans). Hence, to have a meaningful comparison between the three standards, we need to make sure the underlying loan books are the same, and having hypothetical loan portfolios allows us to do so. Yet, despite being hypothetical, loan portfolios have been generated based on actual data.

[11] It is important to note that there are multiple alternative ways to define cyclicality or pro-cyclicality. For instance, ESRB (2019) defines it as "the mutually reinforcing ('positive feedback') mechanisms through which the financial system can amplify business fluctuations and possibly cause or exacerbate financial instability". We used correlation with GDP as it is simpler to implement in our simulation, and hence our results are based on this definition.

Table 3: List of assumptions used in the forecasting approach

Assumption	Explanation	Implications/mitigation
Number of years	Our simulation runs over 120 years. The first 50 years are used to initiate the model and the next 60 years are used to extract the results.	We tried longer simulation periods, such as 180 years and 360 years. The results don't change. We chose 120 years to save processing time
GDP growth	Follows actual GDP growth between 1949 and 2019 for the high volatility experiment; excluding highly volatile years for the low volatility experiment. This happens in a circular pattern within our simulation. I.e., once the model used 2019 GDP growth, it starts using GDP growth from 1949 onwards again	This is a simplifying assumption. Generally, history repeats itself in terms of patterns but not necessarily with exact values or the way we set it up (2020 is significantly different from 1949). A potential extension is to use a guided random generation of GDP growth that relies on the patterns seen in the sample period. This is out of our analysis scope, as we don't aim to create a comprehensive way to predict GDP growth
Interest/discount rates	Follow data on the rates from the Bank of England between 1949 and 2019 for the high volatility experiment; excluding highly volatile years for the low volatility experiment. This happens in a circular pattern within our simulation as for GDP	This is a simplifying assumption. A potential extension is to use a guided random generation of rates that relies on the patterns seen in the sample period. This is out of the scope of the paper
ECL scenarios	The model is based on a 3 scenario setup to calculated LLPs	Most banks use such setup. Yet, some banks use different setups (e.g. 5 scenarios). Increasing the number of scenarios wouldn't necessarily lead to better predictions. The impact of implementation approaches would be valid even with a different number of scenarios
Optimism levels	Banks can be optimistic, neutral or pessimistic when predicting future. They also change their sentiment depending on the current economic conditions (more pessimistic when GDP growth is below trend and more optimistic when it is above trend)	The distribution of optimism levels is likely continuous rather than discrete, but likely changes with economic conditions. Yet, we think the three-type setup we use is a good characterisation of reality
Expectation types	Banks can use naïve, short-term, medium-term, long-term, or cycle-based approaches to predict future GDP growth (for the baseline scenario of ECL). They also change approaches depending on the current economic conditions	In reality, banks might use many other approaches. Yet, we think the 5 approaches we use provide a good approximation of reality
Bank types	There are 15 types (3 x 5) bank types, or implementation approaches	Banks may have many more types in reality
Changes in bank types	The composition of bank in terms of types changes depending on the current economic condition, as shown in Table 4.	The numbers are averages of 50 random numbers generated based on our assumptions about how optimism levels and expectation types change with the economic condition. For example, when GDP growth is 2 percentage points or less below trend 80% of banks are neutral, 5% optimistic, and 15% are pessimistic. Meanwhile, 60%, 25%, 10%, 3% and 2% of banks use naïve, short-term, medium-term, long-term, or cycle-based approaches, respectively.
Loan portfolios	Loan portfolios are hypothetical, and include fixed number of loans that reflects a bank's size	Hypothetical loan portfolios allow for more meaningful comparison between the three standards, as the underlying loan books are the same. Despite being hypothetical, loan portfolios have been generated based on the actual data
Loan IFRS 9 stages	Loans with ratings AAA to A, BBB to B and C are Stage 1, Stage 2 and Stage 3 loans respectively	Stage 2 loans are those with significant credit risk increase, compared to origination. Our definition of Stage 2 may seem inconsistent with that definition. Yet, since all loans in our model have good creditworthiness at origination (ratings AAA to BBB), loans with current ratings of BBB to B would likely have had a deterioration in their credit quality. The only exception would be loans with a credit rating of BBB at origination and a current rating of BBB, which is very rare across all our simulations.
ECL PDs	For each 1% deviation in a bank's expected GDP growth from trend PDs used in LLPs calculation change by 1/100 x 1%	The relationship between economic conditions and PDs is likely not random. When GDP is well away from trend, PDs would likely be more sensitive. The magnitude of this relationship can change over time. A potential extension would be to estimate the elasticities of PDs to GDP growth in different economic conditions and use that to determine changes in PDs.

4.1. Stock channel vs. flow channel

ECL changes the amount of LLPs charges expensed in the profit and loss (P&L) account (the row highlighted in grey in Figure 5), reflecting on profits and equity capital. We call this **LLPs flow channel** (flow channel). Meanwhile, the ECL approach changes the stock of LLPs and hence the amount available to cover eventual defaults on the balance sheet. This reduces write-off losses (losses on defaulted loans – LLPs for these loans), which end up in P&L account (the row highlighted in blue in Figure 5). We call this **LLPs stock channel** (stock channel). The interaction between these two channels determines the impact of ECL on profits, capital resources and capital ratios of banks. In a given year, profits would be higher under ECL if the higher LLPs stock reduces write-off losses by more than the increase in LLPs charges ECL model leads to, and vice versa. For example, if ECL reduced write-off losses in a given year by £50mn (because more LLPs have been created earlier), and increased LLPs charges by £30mn, the pre-tax profits for that year would be £20mn higher than they would otherwise be under IL. Contrarily, if LLPs charges rose by £60mn, the pre-tax profit would be £10mn lower (relative to the IL model). Changes in LLPs and write-off losses affect both the numerator and denominator of the leverage and capital ratios. The impact on profits reflects on retained earnings, which represent the main source of equity capital. Likewise, the increase in LLPs stock also reflects on the denominators of the two ratios, total leverage exposure (LE) and risk-weighted assets (RWAs). Our analysis focuses on the impact of ECL versus incurred loss accounting on capital resources and ratios from a regulatory perspective. Regulatory capital and exposures are generally based on the accounting treatment, but deviate from that treatment in some aspects. First, regulatory (common equity) capital is referred to as Common Equity Tier 1 (CET1) capital, which is equal to the accounting capital after some regulatory adjustments (deductions). The impact of ECL accounting on CET1 capital is also affected by the presence of the regulatory expected loss adjustment (regulatory expected loss – LLPs) term for banks that follow the internal-rating based (IRB) approach[12]. While LE is always calculated after deducting LLPs, RWAs calculation depends on whether the bank uses the standardised (SA) approach or IRB approach. SA banks can deduct LLPs from exposures at default (EADs) that are multiplied by the relevant risk weights to calculate RWAs, whereas IRB banks have to use gross EADs (LLPs are not deducted). For simplicity, we abstract from these differences and rely on the accounting

[12] If this term is large enough, then increases in LLPs would increase CET1 resources rather than decreasing them.

treatment, which means our results may not fully reflect ECL interactions with capital regulation, and the extent to which exposures are modelled under the SA or IRB approaches.

Figure 5: Channels of ECL impact

Profit and Loss Account	IAS 39	IFRS 9
Interest income	£10,000	£10,000
Interest expenses	-£5,000	-£5,000
Net interest income	£5,000	£5,000
Non-interest income	£2,500	£2,500
Gross operating income	£7,500	£7,500
Operating expenses	-£3,500	-£3,500
Net operating income	£4,000	£4,000
Loan loss provisions	-£500	-£1,100
Credit losses	-£1,000	-£500
Net income before tax	£2,500	£2,400
Tax (20%)	-£500	-£480
Net income after tax	£2,000	£1,920
Ordinary dividends	-£500	-£500
Retained income	£1,500	£1,420

Balance Sheet	IAS 39	IFRS 9
Assets		
Loans	£700,000	£699,900
Trading assets	£200,000	£200,000
other assets	£100,000	£100,020
Total assets	£1,000,000	£999,920
Liabilities		
Deposits	£650,000	£650,000
Trading Liabilities	£190,000	£190,000
Debt	£110,000	£110,000
Common equity	£50,000	£49,920
Paid-in capital	£10,000	£10,000
Retained earnings	£40,000	£39,920
Total liabilities and equity	£1,000,000	£999,920
Leverage ratio	5.00%	4.99%

Notes: Loans on the balance sheet are net loans (gross loans – LLPs);
Credit losses = write-off losses

4.2. ECL implementation approaches

Banks in our setup vary in size and riskiness of their lending books, as well as ECL implementation approaches. Although all banks use a three-scenario method to calculate ECL, each creates the baseline scenario based on its expectation of the future path of the economy, then constructs the other two scenarios (up and down) relative to the baseline scenario. Also, each bank determines the probabilities assigned to the scenarios based on its level of optimism. In terms of baseline scenario setup, banks in our model can follow 5 approaches: naïve setup (expected GDP growth is equal to the GDP growth anticipated for the same year, $E[\Delta GDP_{t+1}] = E[\Delta GDP_t]$), short-term setup (using GDP growth in the preceding year, $E[\Delta GDP_{t+1}] = \Delta GDP_{t-1}$), medium-term setup (using the average GDP growth in the preceding five years, $E[\Delta GDP_{t+1}] = \frac{1}{5}\sum_{i=1}^{5}\Delta GDP_{t-i}$), long-term setup (using the average GDP growth in the preceding ten years, $E[\Delta GDP_{t+1}] = \frac{1}{10}\sum_{i=1}^{10}\Delta GDP_{t-i}$), and cycle-based setup (using the historical GDP growth for the same stage of the business cycle[13]).

In terms of expectations, banks can be neutral (up and down scenarios have the same probability), optimistic (assign a higher probability for the up scenario) or pessimistic (assign a higher probability

[13] In our setup, GDP growth follows the exact same patterns every 50 years (when GDP volatility is low) or every 71 years (when GDP volatility is high). Banks incorporate these patterns when they use the cycle-based setup. For example, if GDP is not volatile, the GDP growth a bank following the cycle-based setup uses to create the baseline scenario would be the average of GDP growth of years -49, -48 and -47. Mathematically, $E[\Delta GDP_{t+1}] = \frac{1}{3}\sum_{i=1}^{3}\Delta GDP_{t-CY+i}$, where CY is cycle length.

for the down scenario). For simplicity, we assume that neutral banks assign the baseline scenario a probability of 90%, compared to 5% for each of the up and down scenarios. While optimistic banks assign 70%, 25% and 5% to the baseline, up and down scenarios, pessimistic banks assign 70%, 5% and 25% for the to the three scenarios respectively[14]. The variations in the baseline scenario setup approach and level of optimism translate into 15 unique (scenario-expectation) implementation approaches (or types) banks can adopt. We assume that bank types change with economic conditions. In poorer economic conditions, the levels of pessimism and uncertainty increase, making estimates of the future more conservative and highly linked to the most recent conditions. Meanwhile, when conditions are good, estimates would be less reliant on recent conditions and more linked to the longer-term path of the economy. In our context, this means banks tend to follow shorter-term and less optimistic approaches in downturns and longer-term and more optimistic approaches in upturns. We achieve this by changing the composition of the population of bank types depending on GDP growth. For instance, if GDP growth is more than 2 percentage points below its trend, the proportion of the naïve-pessimistic bank type becomes at its highest value, whereas the proportion of the cycle-optimistic type is at its lowest. Table 4 shows the proportions we use at different levels of GDP growth. Based on simulation results, we assess the impact of ECL on the pro-cyclicality and the volatility of each variable. It is important to note here that variations in implementation approaches do not refer to whether ECL (especially under IFRS 9) is applied “correctly” or not. It rather refers to the behavioural aspects that affect the way banks predict future, which can change depending on economics conditions. Hence, our suggestion (later in the paper) of regulatory guidance to prevent over-optimism in booms and over-pessimism in busts aims to address these aspects, rather than ensuring correct application of accounting standards.

Table 4: Proportions of bank types in different economic conditions

GDP growth	> 2 pps below trend			=< 2 pps below trend			=<2 pps above trend			> 2 pps above trend		
Bank types	Pe	Ne	Op	Pe	Ne	Op	Pe	Ne	Op	Pe	Ne	Op
Naïve	64.80%	2.70%	22.50%	45.00%	4.20%	10.80%	30.00%	4.00%	6.00%	21.60%	4.50%	3.90%
Short-term	5.76%	0.24%	2.00%	18.75%	1.75%	4.50%	15.00%	2.00%	3.00%	12.60%	2.63%	2.28%
Medium-term	0.72%	0.03%	0.25%	7.50%	0.70%	1.80%	15.00%	2.00%	3.00%	16.20%	3.38%	2.93%
Long-term	0.50%	0.02%	0.18%	2.25%	0.21%	0.54%	9.38%	1.25%	1.88%	14.40%	3.00%	2.60%
Cycle	0.22%	0.01%	0.08%	1.50%	0.14%	0.36%	5.63%	0.75%	1.13%	7.20%	1.50%	1.30%

Notes: Pe: pessimistic, Ne: neutral and Op: optimistic

[14] It is worth noting that changing composition of banks’ population makes our results less sensitive to the scenario probabilities used. We tried other assumptions about scenarios probabilities under different expectation strategies, and results are robust. Tables are omitted for conciseness, and are available from the authors upon request.

4.3. Simulation events

Each bank is initialised with a random number of loans drawn from a log-normal distribution, to reflect the fact that there are few big banks and many small banks in the banking system (Figure 3). Each loan is allocated a random balance between £10,000 and £300,000 and a credit rating. Credit ratings range from AAA (1; high quality) to D (8; in-default), and are used to calculate LLPs. For IFRS 9 purposes, loans with ratings 1-3 are Stage 1 loans, loans with ratings 4-6 are Stage 2 loans, and loans with credit rating 7 are Stage 3. For IAS 39 purposes, loans with ratings 6-7 are considered impaired, and hence attract LLPs. The credit rating of a loan evolves based on a time-varying transition matrix, as long as the loan is not defaulted or paid-off. The time-varying transition matrix is initiated with the transition probabilities in the long term matrix shown in Table 2. It is then updated every year depending on the changes in PDs (the last column of the matrix), which we link to GDP growth. More specifically, PDs decrease when GDP growth is above trend, and increase when it is below trend. To ensure the sum of probabilities in each row of the matrix is equal to 1, the probabilities in each row are normalised by the 1-norm. Once a loan is in default, it is written off, and its net balance (the difference between the loan remaining balance and the stock of LLPs created for it) becomes a write-off loss. Paid-off and defaulted loans are replaced immediately with new loans. The new loans have a fixed principal at origination (£300,000) and credit ratings ranging between 1 and 4 assigned to them randomly. Table 5 includes details on variables initiation. LLPs are calculated (at loan level) as the weighted average of expected losses under each of the three scenarios (i.e., baseline, up, and down). Expected losses are the product of PD and loss given default (LGD), which we assume is equal to the loan balance. Loan-level LLPs are aggregated to get the bank-level LLP_t at time *t*.

$$LLP_t = \sum z_{i,j,t} PD_{i,j,m,t} B_{n,t} \tag{1}$$

where $z_{i,j,t}$: weight of scenario *i* assigned by a bank of type *j* at year *t*; $PD_{i,j,m,t}$: probability of default of a loan with credit rating *m* assigned by bank type *j* for scenario *i* at year *t*; $B_{n,t}$: balance of loan *n* at year *t*. PDs for the baseline scenario are extracted from the last column of the time-varying transition matrix, for each credit rating. PDs for the up and down scenarios are determined by subtracting (up scenario) or adding (down scenario) an amount that depends on the expected GDP growth by the bank (the baseline scenario setup approach). Banks' profits for each period (π_t) are the difference between interest income and the sum of the change in LLPs, write-off losses and funding costs:

$$\pi_t = \sum r_t B_{n,t} - R_t \left(\sum B_{n,t} - E_t \right) - \Delta LLP_t - \sum \left(\overline{B_{n,t}} - \overline{LLP_{n,t}} \right) \quad (2)$$

where r_t: interest rate on loans; R_t: interest rate paid on debt funding; E_t: equity capital; $\overline{B_{n,t}}$: balance of defaulted loan *n*; $\overline{LLP_{n,t}}$: LLPs stock for defaulted loan *n*. A bank decides the portion retained of profits depending on its projected end-of-year leverage ratio[15]. Specifically, we assume that if the expected leverage ratio is above 6.5%, the bank distributes all profits. If it is below 6.5%, we assume the bank retains a portion of profits sufficient to make up the shortfall. Lower projected leverage ratios mean higher portions retained, up to 100% when the ratios are equal to (or below) the average leverage ratio requirements of banks subject to the UK leverage ratio (currently 3.7%)[16]:

$$\left\{ \begin{array}{ll} RE_t = \pi_t & if\ \pi_t < 0 \\ RE_t = \pi_t & if\ \frac{E_t}{LE_t} = \frac{E_{t-1} + E_t}{LE_t} < 3.7\% \\ RE_t = 0.9 \times \pi_t & if\ 3.7\% < \frac{E_t}{LE_t} < 4.0\% \\ RE_t = 0.8 \times \pi_t & if\ 4.5\% < \frac{E_t}{LE_t} < 4.5\% \\ RE_t = 0.7 \times \pi_t & if\ 4.5\% < \frac{E_t}{LE_t} < 5.0\% \\ RE_t = 0.3 \times \pi_t & if\ 5.0\% < \frac{E_t}{LE_t} < 5.5\% \\ RE_t = 0.1 \times \pi_t & if\ 5.5\% < \frac{E_t}{LE_t} < 6.5\% \\ RE_t = 0.0 \times \pi_t & if\ 6.5\% < \frac{E_t}{LE_t} \end{array} \right\} \quad (3)$$

Retained profits add to the bank equity resources. A bank's end-of-year capital and leverage ratios (CR and LR) are calculated by dividing the end-of-year equity (E) by RWAs and LE respectively:

$$CR_t = \frac{E_t}{RWAs_t} \quad (4)$$

$$LR_t = \frac{E_t}{LE_t} \quad (5)$$

As discussed earlier, ECL can affect capital and leverage ratios through two channels. It increases the stock of LLPs, providing more provisions to cover credit losses (stock channel), but also change LLPs

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[15] We assume no banks do not fail. We also assume banks maintain ratios only by adjusting capital, and do not ration lending.

[16] This is a simplification of reality, as banks would try to maintain healthy capital ratios, to avoid regulatory (distribution restrictions) or market reactions. The Basel III Accords introduced a 3% minimum Tier 1 leverage ratio, and supplement it with a buffer for globally systematically important banks (GSIB), set to 50% of the equivalent buffer in the risk-based framework. The UK leverage ratio sets the minimum leverage ratio at 3.25%, but exempt central bank reserves from the calculation. It also sets the GSIB leverage ratio buffer at 35% of the risk-based buffer, and introduces a counter-cyclical leverage ratio buffer set at 35% of the counter-cyclical buffer (CCyB). The ratio sets capital quality restriction, under which 75% of minimum and 100% of buffer requirements have to be met in CET1 capital. At the time, the average UK leverage requirements was 3.69%. Additionally, banks tend to hold some "voluntary" buffers, for a number of reasons (e.g. to avoid potential breach of requirements, or to avoid failing stress tests). We think this provides enough support for our assumption for a conservative capital management, and is in line with leverage ratios data reported in Table 1.

charges (flow channel). Hence, the impact on the two ratios relies mainly on the interaction between the two channels, which in turn depends on the level of economic fluctuations. As shown later, when the economic fluctuations are high, banks tend to create relatively less LLPs in good times and significantly more LLPs in bad conditions, amplifying pressures on capital resources in such conditions. These pressures are likely stronger under US GAAP than IFRS 9.

4.4. Initial values

The calibration of variables is summarised in **Table 5**. Our model replicates the paths of write-off losses, LLPs, capital ratios and leverage ratios of individual banks and the whole banking system[17] over a period of 60 years, under IFRS 9 and US GAAP, and compares them to those resulting under the incurred loss model of IAS 39. Our model forecasts suggest that under IAS 39, LLPs and write-off losses are counter-cyclical, whereas capital ratios and leverage ratios are pro-cyclical.

Table 5: The Initial Values/Distributions of the Model's Variables

Panel (a): Initial values

Variable	Value/Distribution	Assumptions/Empirical facts
Number of banks	405	405 banks with data on capital & leverage ratios
Bank size	Number of loans determined using an exponential distribution with an avg. of 50+50 (floor of loans per bank)	221 banks (54.6%) with leverage exposure LE<£1bn, 105 banks (25.9%) with LE between £1-10bn, 43 banks (10.6%) with LE between £10-50bn, 27 banks (6.7%) with LE between £50-500bn, and 9 banks (2.2%) with LE>£500bn
Loan balances	Random between £10,000 and £300,000, in £10,000 increments	Principal payment of £10,000 a year over 30 years.
Leverage ratios	Randomly selected within each bucket	E.g. avg. leverage ratio for banks with LE<£1bn is 19.4% (st. dev. 13.2%). For banks with LE>£500bn the average is 5% (st. dev. 0.8%).
Equity capital	Initial leverage ratio × total balance of the loans	
Initial transition matrix	Long-term transition matrix from JPMorgan (1998)	
Loan credit rating at origination	1 to 4	All loans have good credit quality (BBB or higher) at origination. The credit rating at origination is randomly selected between 1 (AAA) and 4 (BBB)
Loan credit rating at the start of simulation	1 to 7	Credit rating of loans evolves from credit rating at origination based on the transition matrix in Table 2. It ranges between 1 and 7 (C). Credit rating 8 is for defaulted loans, which are assumed to be dealt with before the start of the simulation (period -1)
Risk weights	10%, 20%, 35%, 50%, 80%, 100%, and 150%, for credit ratings 1 o 7	Weights are based on author judgment
Capital ratio	Initial equity divided by risk-weighted assets (sum of loan balances × risk weights)	
Bank types	Randomly selected from the 15 types	
Scenario weights (up-baseline-down)	Neutral (5%-90%-5%); Optimistic (25%-70%-5%); Pessimistic (5%-70%-25%)	
Initial LLPs (depending on the regime)	PDs from the transition matrix × loan balance for IAS39, Eq.((**2**) for IFRS9 and US-GAAP	

[17] System-wide LLPs and net credit losses are the sum across banks, whereas system-wide capital and leverage ratios are the weighted averages of individual bank ratios (using RWAs and LEs as weights, respectively).

Panel (B) within simulation

Variable	Value/Distribution	Assumptions/Empirical facts
GDP growth	Actual GDP growth between 1949 and 2019 for the high volatility scenario; excluding highly volatile years for the low volatility scenario	Periods with GDP growth greater than 3.75% and below -2% are considered highly volatile.
Interest rate on loans	Effective mortgage rate from BOE	
Interest rate on bank debt	BOE policy-rate	
New loans creation	Only when a loan matures or is defaulted	Banks keep the number of loans fixed over time. A further extension could be adding a demand for loans
New loans balance	£300,000	All loans have the same face value at origination
New loans maturity	30 year	All loans have the same maturity at origination
New loans credit rating	1 to 4	All loans have good credit quality (BBB or higher) at origination. The credit rating at origination is randomly selected between 1 (AAA) and 4 (BBB)
Actual PDs	For each 1% deviation in actual GDP growth from the trend PDs change by 1/100 x 1%	PDs increase when GDP growth is below trend and decrease if above trend. Transition matrix is updated accordingly
Transition matrix	For each 1% deviation in a bank's expected GDP growth from the trend PDs change by 1/100 x 1%	PDs increase when GDP growth is below trend and decrease if above trend. Transition matrix is updated accordingly
Bank type distribution	Depends on GDP growth as shown in Table 4	Banks become more conservative if GDP growth was below trend and less conservative if it was above trend
ECL PDs	For each 1% deviation in a bank's expected GDP growth from the trend PDs used in LLPs calculation change by 1/100 x 1%	Banks increase PDs in ECL if expected GDP growth is below trend and decrease them if above trend
LLPs	Depend on the loan credit rating, bank type, remaining maturity, and discount rate	Under ECL, LLPs are the sum of expected future losses discounted to the present
LGD	The remaining balance of the loan in the previous period	LGD is 100%, to simplify simulation. A further extension is by integrating house prices into the model to allow for LGD estimation
Write-off losses	Remaining gross carrying amount for the loan – LLPs stock for that loan	Default corresponds with a full write-off of the net balance of a defaulted loan. In practice, when a default happens, a bank does no write-off the loan immediately. Hence, there is a time lag between default and the write-off of a loan.
Risk weights (for loans with ratings from 1 to 7)	• 7.5%, 13%, 20%, 35%, 60%, 80%, and 120%, if GDP growth is >1% above trend • 10%, 20%, 35%, 50%, 80%, 100%, and 150%, if GDP growth is [-1%,1%] around the trend • 15%, 25%, 35%, 55%, 80%, 100%, and 160%, if GDP growth is more than 1% below trend • 20%, 33%, 45%, 70%, 100%, 125%, and 190%, if GDP growth is more than 2.5% below trend	RWs decrease if GDP growth was more than 1 percentage point above trend and increase if it was more than 1 percentage point below trend
Interest income	Interest rate x balance of the loan	
Interest expenses	Total assets (sum of loans – LLPs) – equity capital at the end of last year x interest rate on borrowing	
Non-interest expenses	Write-off losses + change in LLPs for all loans	
Profit	Interest income – interest and non-interest expenses	
Retained earnings	0% to 100% of profit depending on the distance between projected end-year leverage ratios and the required level	Banks with lower projected leverage ratios retain larger portions of their profit to maintain these ratios
Year-end capital	Capital at the start of the year + retain earnings	
Risk-weighted assets	Sum of loans x risk weights	
Capital ratio	Capital/risk-weighted assets	
Leverage ratio	Capital/total assets	

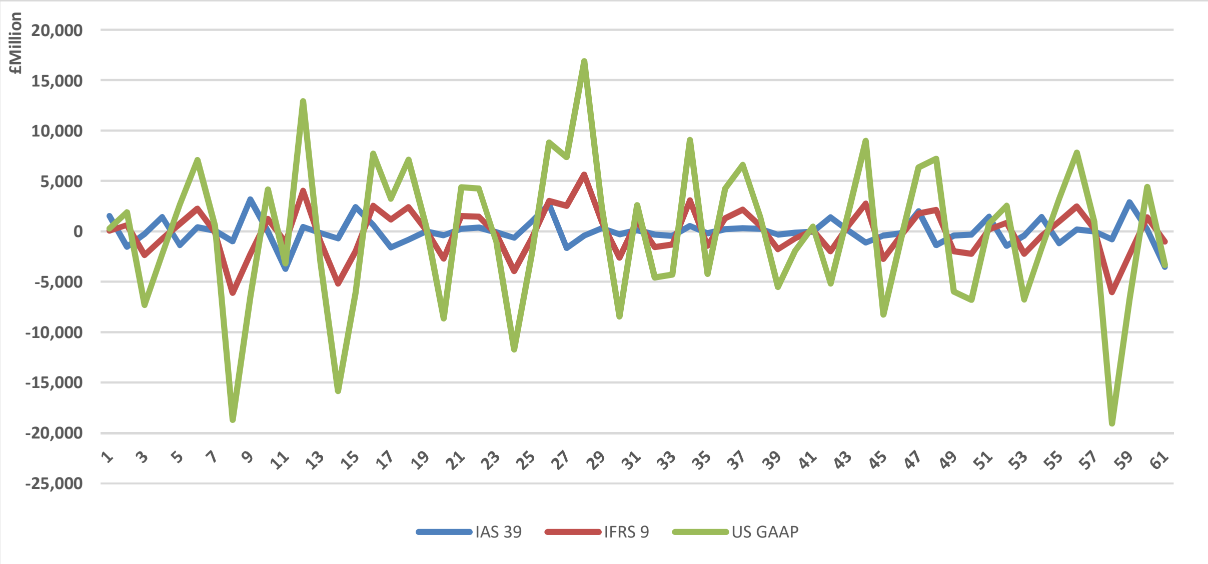
5. Analysis and Results

As mentioned above, we allow the composition of bank population (in terms of implementation approaches) to vary over time with GDP growth in the ECL simulations. To assess the impact of GDP volatility, we setup our simulation period in two ways, by excluding and including GDP growths for high volatility years.

5.1. Periods with low GDP volatility

Our results show that when GDP volatility is relatively low, the two ECL approaches increase the volatility of LLPs, but reduce their counter-cyclical behaviour, relative IAS 39 (Figure 6[18]). The increase in volatility is larger under US GAAP, as PDs used to calculate LLPs are more sensitive to economic fluctuations. The effects on the counter-cyclicality of LLPs are marginally stronger for IFRS 9, under which the correlation coefficient between LLPs and GDP growth decreases from -51.2% to -24.5% (-25.1% for US GAAP). Meanwhile, the two ECL approaches increase the counter-cyclicality of write-off losses; the correlation coefficient with GDP growth increases from -14% under IAS 39 to -19.6% and -26.9% under US GAAP and IFRS 9, respectively.

Figure 6: System-wide LLPs under IAS 39, IFRS 9 and US GAAP – low GDP volatility

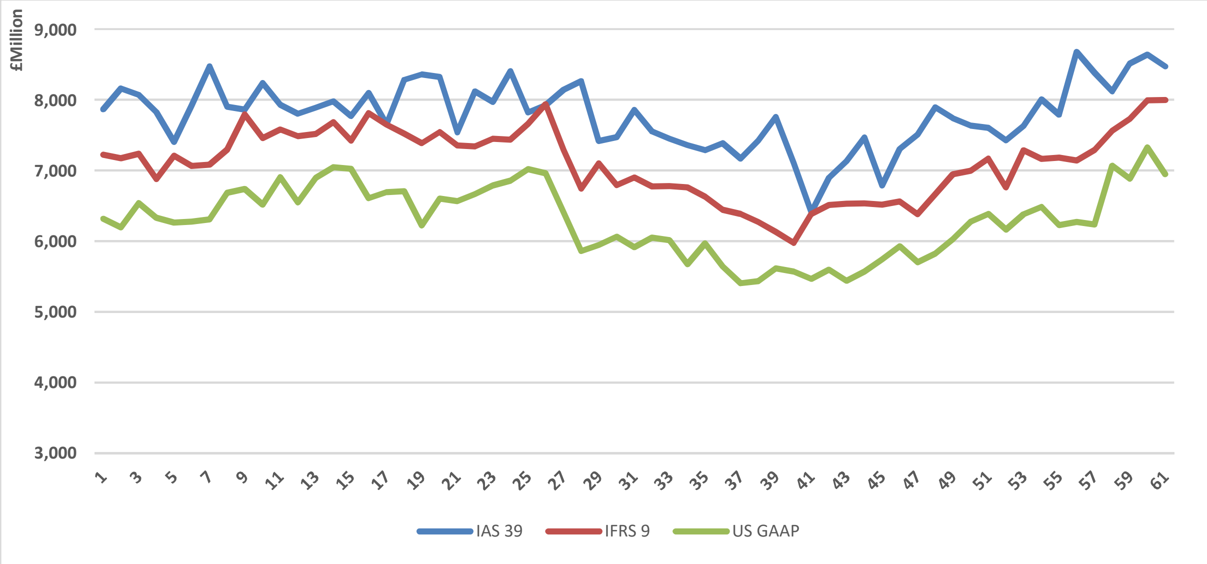


However, the level of write-off losses is considerably lower under the two ECL approaches. The earlier build-up of LLPs stock during the cycle means more provisions have been made earlier to cover

[18] Negative values in LLPs charts indicate reductions in LLPs stock, as the preceding year's stock exceed LLPs needed this year.

increasing credit losses in downturns. As **Error! Not a valid bookmark self-reference.** shows, write-off losses are on average 20% and 10% lower under US GAAP and IFRS 9, compared to IAS 39.

Figure 7: System-wide write-off losses under IAS 39, IFRS 9 and US GAAP – low GDP volatility



The changes in the cyclical patterns of LLPs and write-off losses reflect on equity capital as well as LE and RWAs, reducing the pro-cyclicality of both capital ratio (Figure 8) and leverage ratio (Figure 9). Specifically, the correlation coefficient between the leverage ratio and GDP growth decreases from 40.9% under IAS 39 to 19.2% under US GAAP and 28.1% under IFRS 9. Moreover, while IFRS 9 reduces the pro-cyclicality of capital ratio (correlation coefficient with GDP growth falls from 42% under IAS 39 to 20.6% under IFRS 9), this ratio becomes slightly counter-cyclical under US GAAP.

Figure 8: System-wide capital ratio under IAS 39, IFRS 9 and US GAAP – low GDP volatility

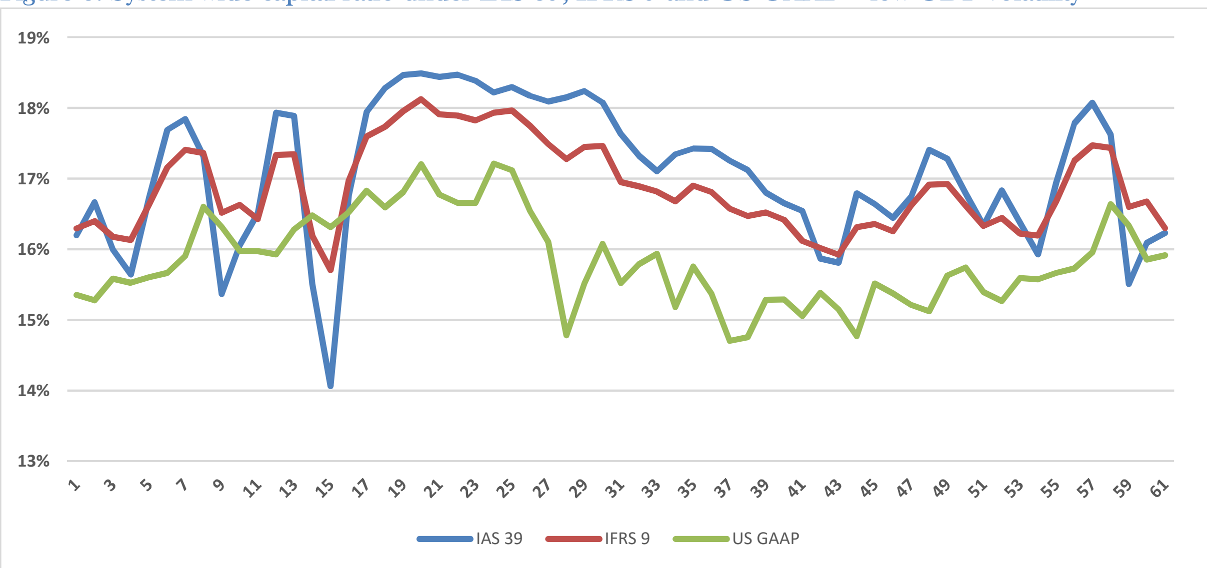
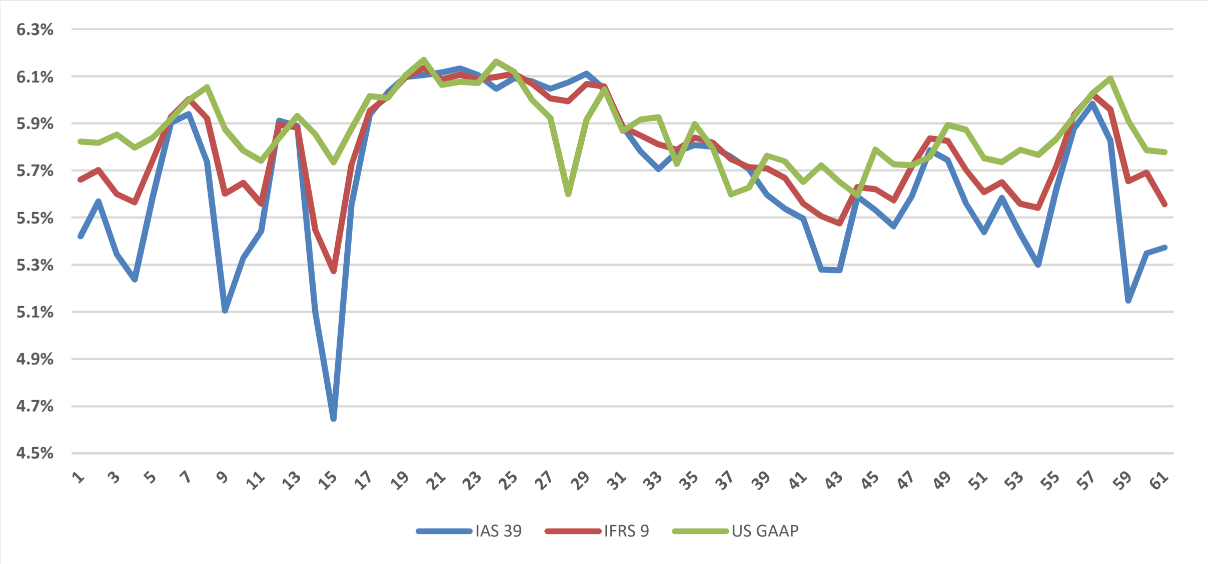


Figure 9: System-wide leverage ratio under IAS 39, IFRS 9 and US GAAP – low GDP volatility



In summary, ECL modelling, especially under US GAAP approach, should enhance the stability of individual institutions and the banking system as a whole, during periods with no severe crises. LLPs accumulate in good conditions and don't shoot up sharply in slumps. This means more provisions to cover increasing eventual defaults and relatively mild increases in LLPs charges in downturns (i.e. the stock channel dominates the flow channel), reducing pressures on profits and capital resources in such periods, and making capital and leverage ratios less pro-cyclical.

5.2. Periods with high GDP volatility

As in the previous section, IFRS 9 and US GAAP increase volatility of LLPs (flows). However, this volatility rises significantly under US GAAP, when GDP volatility is high, as differences in lifetime PDs between booms and busts become large (Figure 10). Also, while the two ECL approaches would still reduce counter-cyclicality of LLPs relative to IAS 39, their effects are considerably weaker when GDP is more volatile. The correlation coefficient between LLPs and GDP growth decreases from -51.7% under IAS 39 to -36.1% and -35.6% under US GAAP and IFRS 9, respectively. Similar to the previous section, write-off losses are noticeably lower under ECL, as Figure 11 demonstrates. On average, these losses are about 15% and 6% lower under US GAAP and IFRS 9 than under IAS 39. The counter-cyclicality of write-off losses reduces under US GAAP (-5.5%) and IFRS 9 (-2.5%), compared to IAS 39 (-10.6%).

Figure 10: System-wide LLPs under IAS 39, IFRS 9 and US GAAP – high GDP volatility

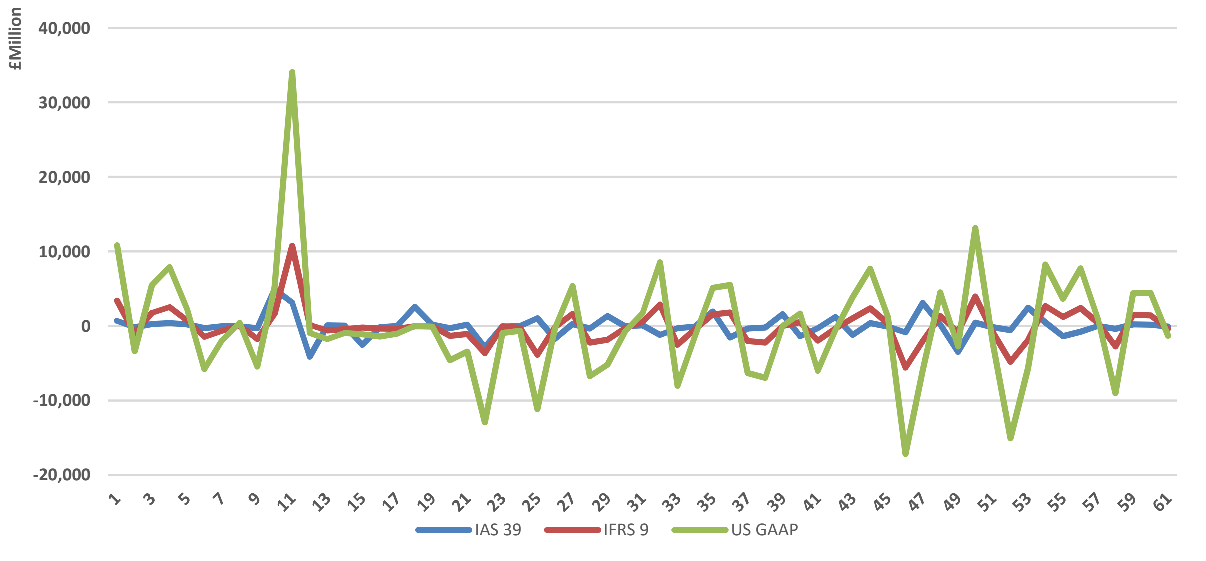
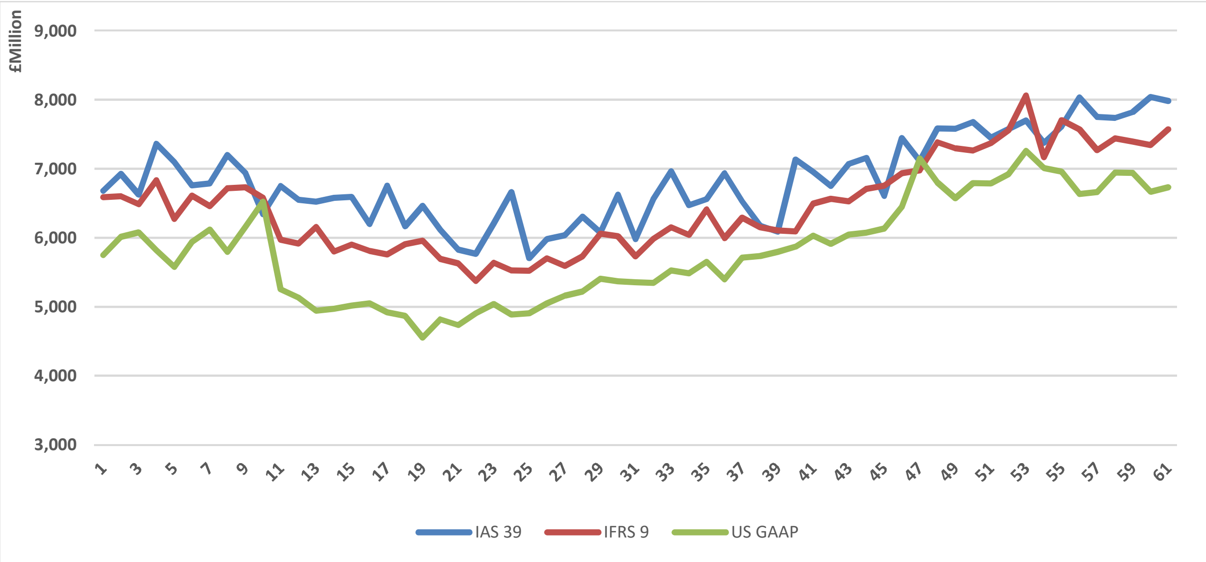


Figure 11: System-wide write-off losses under IAS 39, IFRS 9 and US GAAP – high GDP volatility



The significant increase in LLPs volatility means the flow channel would dominate the stock channel, increasing the pro-cyclicality of profits and hence capital ratios (Figure 12) and (especially) leverage ratios (Figure 13). The correlation coefficients between GDP growth and capital and leverage ratios increase from 44.8% and 42% under IAS 39 to 45.9% and 50.1% under US GAAP. Yet, the stock channel would dominate under IFRS 9 when GDP volatility is high, reducing the pro-cyclicality of the two ratios, with the correlation coefficients with GDP falling to 44.5% (capital ratio) and 40.3% (leverage ratio).

To sum up, when GDP growth is highly volatile, LLPs accumulation in good times would enhance the banks' ability to cover increasing credit losses during downturns, under both ECL approaches, especially US GAAP. However, higher GDP volatility increases differentials in lifetime PDs between booms and bust, causing LLPs to shoot up sharply during deep downturns under US GAAP (Figure 10), as seen for US banks during the COVID-19 stress (Figure 1). This increases pressures on bank capital resources, not only making capital and leverage ratios more pro-cyclical than under IAS 39, but also causing sharp falls in the two ratios in deep downturns. IFRS 9 ECL would still reduce the pro-cyclicality of capital and leverage ratios, even when GDP is highly volatile. The existence of loan stages means LLPs would not increase as significantly under IFRS 9 as under US GAAP.

Figure 12: System-wide capital ratio under IAS 39, IFRS 9 and US GAAP – high GDP volatility

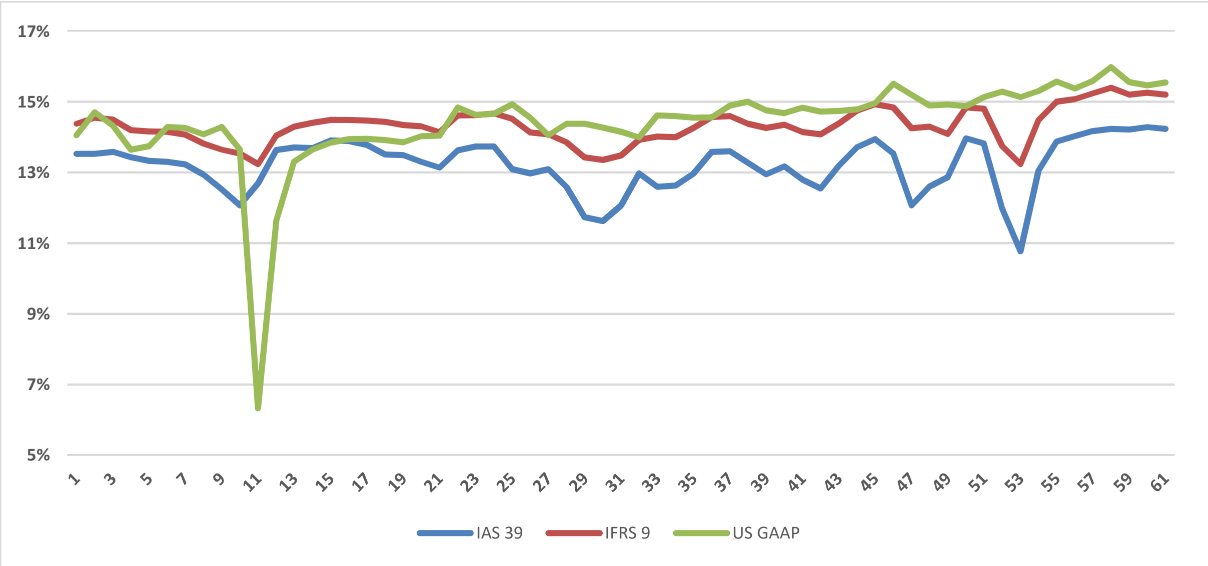
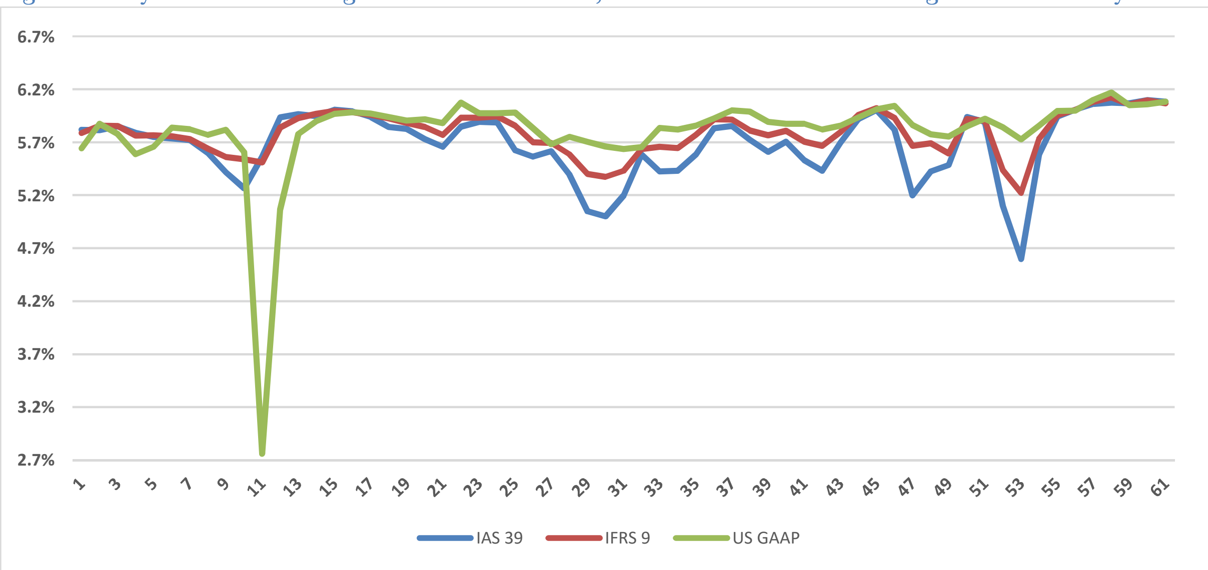


Figure 13: System-wide leverage ratio under IAS 39, IFRS 9 and US GAAP – high GDP volatility



5.3. The role of ECL implementation approaches

As mentioned earlier, we assume that the composition of the bank population in terms of implementation approaches changes over time with economic fluctuations (Table 4). Our results in the sections above hold even using proportions that differ sizably from those shown in Table 4. This may indicate that implementation approaches don't play a role in determining the impact of ECL. However, our analysis assumes that the sensitivity of PDs to economic fluctuations is fixed over time. Allowing PDs to have different levels of sensitivity to economic fluctuations at different stages of the cycle could have strong implications for the impact of ECL and the role of implementation approaches. With sufficiently large differences in PDs sensitivity between booms and busts, the impact of ECL would rely on the composition of banks' population. For instance, increasing the proportion of shorter-term pessimistic approaches during busts would make capital and leverage ratios more pro-cyclical under both ECL approaches.

5.4. The role of bank business models

Banks in our model have a specialised business model, which involves granting mortgage-like loans funded by a stable source of funding (like deposits). However, in reality banks have generally less specialised business models, and when they have specialised models, they can differ in terms of the assets they focus on (e.g. holding securities, intermediating in repo market, etc.). While our model does not cover variations in business models, it can provide insights about the impact of ECL on banks specialising in activities other than lending, as well as less specialised more universal banks. Our results show that ECL may increase the pro-cyclicality of banks' profits and capital ratios, when GDP growth is volatile, as the higher volatility of LLPs charges dominates the smoothing effect of the higher LLPs stock. Expected losses on loans are likely to be strongly linked to the economic conditions, as the last has implications for the creditworthiness of clients, such as households and businesses. Incomes of such clients take hit during downturn affecting their (actual or perceived) ability to repay their loans. That is, LLPs on loans increase during busts as creditworthiness deteriorates. As such, bank specialising in retail lending (as in our model) can be expected to be more affected when the volatility driving changes in PDs originates in the real economy (e.g. Covid-19). Banks specialising in other exposures (e.g. sovereign exposures) would likely be less affected, as their assets less sensitive to real economy changes. Nevertheless, such banks would be more affected by volatility arising from sovereign debt crises than retail banks. In other words, the impact of ECL for specialised banks rely mainly on whether shocks they face have implications for exposures they specialise in. Accordingly, ECL can be expected to have weaker impact on more universal banks than what our model anticipates, as their diversified portfolios make them less sensitive to idiosyncratic shocks than specialised banks.

5.5. Policy implications

The previous sections have shown that variations in the level of optimism embedded within banks' ECL models between boom and bust can potentially lead to significant falls in capital positions and ratios of banks, when the economy is hit by a large negative shock, such as the Covid-19 stress. While this is more likely under US GAAP, it can also happen under IFRS 9, if prior to the shock banks were strongly over-optimistic in their expectations about the future path of the economy. As such, it is helpful for regulators to monitor ECL implementation over time and provide guidance when needed, to limit unjustifiable levels of over and under optimism. Particularly, regulators should observe the sensitivity of PDs to economic fluctuations, especially in deep downturns. Indeed, regulatory authorities did intervene during the Covid-19 stress. The interventions included providing guidance on ECL implementation. For example, the Bank of England[19] and the European Central Bank (ECB)[20] issued a guidance encouraging banks to consider the range of significant government support and loan holiday schemes, and to make use of the extended transitional arrangements designed to phase-in the capital impact of IFRS 9. The Federal Reserve Board, alongside other US supervisory agencies,

[19] On 26 March 2020, BOE provided guidance on IFRS 9 implementation in a letter to the CEOs of UK banks (https://www.bankofengland.co.uk/prudential-regulation/letter/2020/covid-19-ifrs-9-capital-requirements-and-loan-covenants). A further guidance to banks was provided in another letter sent to bank CEOs on 4 June 2020 (https://www.bankofengland.co.uk/-/media/boe/files/prudential-regulation/letter/2020/covid-19-ifrs-9-capital-requirements-further-guidance.pdf).

[20] On 1 April 2020, the ECB sent a letter to banks under its supervision on IFRS 9 implementation during COVID-19 pandemic: (https://www.bankingsupervision.europa.eu/press/letterstobanks/shared/pdf/2020/ssm.2020_letter_IFRS_9_in_the_context_of_the_coronavirus_COVID-19_pandemic.en.pdf).

issued a revised version of the transitional arrangements aiming to delay the anticipated capital impact of US GAAP[21]. The Basel Committee on Bank Supervision[22] and the International Accounting Standards Board[23] also issued guidance on the application of ECL in the context of the Covid-19 pandemic. We argue that monitoring and guidance should be the main tools, as they can reduce the cyclical effects of ECL implementation on capital positions. Other tools, including potentially capital measures, might be used as a complement, if required.

5.6. Further research

As Table 3 demonstrates, our model uses a number of assumptions to make simulations efficient and manageable, and allows us to focus on the main implications of ECL implementation on capital positions of banks. Our model can be enriched by introducing more sophisticated methods to estimate/simulate different variables, such as GDP growth, interest rates and PDs. Nevertheless, our modelling technique focuses mainly on ECL implementation approaches (or bank types), and how they change with economic fluctuations. We setup implementation approaches based on assumptions on the level of optimism and the way the future path of the economy is estimated. Over time, ECL models would be more established, leading to more data on ECL impacts at different stages of the cycle. This would allow the analytical insights on the effects of ECL approaches, including ours, to be tested empirically. Additionally, more information about how banks implement ECL will become available, allowing for more realistic models to be built.

6. Conclusion

Using stylised data-driven loan portfolios, we model the evolution of LLPs, write-off losses and capital and leverage ratios of 405 UK banks. We assess the impact of ECL models of IFRS 9 and US GAAP on the cyclical behaviour of the four variables, relative to the incurred loss model of IAS 39. ECL models

[21] Regulatory Capital Rule: Revised Transition of the Current Expected Credit Losses Methodology for Allowances (on 31 March 2020): (https://www.federalregister.gov/documents/2020/03/31/2020-06770/regulatory-capital-rule-revised-transition-of-the-current-expected-credit-losses-methodology-for).

[22] Measures to reflect the impact of Covid-19 (on 03 April 2020): (https://www.bis.org/bcbs/publ/d498.htm)

[23] Application of IFRS 9 in the light of the coronavirus uncertainty (on 27 March 2020): (https://www.ifrs.org/news-and-events/news/2020/03/application-of-ifrs-9-in-the-light-of-the-coronavirus-uncertainty/)

can affect bank profits and equity capital resources by changing the size of LLPs charges expensed in P&L account (the flow channel), as well as write-off credit losses by increasing LLPs stock available to meet these losses (the stock channel). The interaction between these two channels determines the impact of ECL on profits, and capital resources and ratios of banks. In a given year, profits would be higher under ECL if the higher LLPs stock reduces write-off losses by more than the increase in LLPs charges ECL results in, and vice versa. These effects differ across the cycle affecting the cyclicality of profits, equity capital and capital and leverage ratios.

All banks in our setup use a three-scenario method to calculate LLPs (baseline, up and down), but can follow 15 approaches to setup ECL scenarios and probabilities (5 scenario setup and 3 expectation approaches). In our model banks change their implementation approaches over the cycle, where they tend to use longer-term and more optimistic approaches in booms, and shorter-term and less optimistic approaches in busts. We inspect the role of the level of economic volatility by including and excluding high volatility periods in our simulations.

Our model results show that during periods with no major crises, the stock channel dominates the flow channel under ECL, smoothing the impact of credit losses on profits and capital resources, and reducing the pro-cyclicality of capital and leverage ratios, especially under US GAAP. However, when GDP is highly volatile, the flow channel dominates under US GAAP, due to large differences in lifetime PDs between booms and bust. LLPs shoot up sharply during deep downturns, as seen for US banks during the COVID-19 stress. This increases pressures on bank capital resources, making capital and leverage ratios more pro-cyclical, and causing sharp falls in the two ratios in deep downturns. The existence of loan stages reduces ECL sensitivity to fluctuations in lifetime PDs under IFRS 9, under which the pro-cyclicality of capital and leverage ratios still falls, even when GDP is highly volatile.

Our analysis assumes that PDs sensitivity to economic fluctuations is constant at different stages of the cycle. Relaxing this assumption can make the role played by implementation approaches in determining ECL impact more apparent. In such case, increasing the proportions of shorter-term pessimistic approaches during busts can make capital and leverage ratios more pro-cyclical under both ECL approaches.

Our results have notable policy implications. It is important that regulators monitor ECL implementation, especially the sensitivity of PDs to economic fluctuations. They can also provide guidance in such times to prevent considerable unjustifiable drops in capital and leverage ratios, as what major regulators did during the Covid-19 stress. We argue that monitoring and guidance should be the main tools, as they can reduce the cyclical effects of ECL implementation on capital position. Other measures, including potential capital buffer release, might be used as a complement, if required.

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