THE EXPECTED CREDIT LOSS MODEL'S IMPACT ON THE CYCLICALITY OF CREDIT SUPPLY

A STUDY OF THE IMPLEMENTATION OF IFRS 9

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Abstract:

The accounting standard for recognizing loan loss provisions changed in 2018 from IAS 39 to IFRS 9. IFRS 9 introduced the expected credit loss model (ECL), intended to be an improved alternative to its predecessor, the incurred credit loss model (ICL), which was criticized for the "too little, too late" provisioning during the 2008 financial crisis. The ECL model was expected to mitigate procyclicality through a timelier recognition of loan losses. However, concerns have been raised that the ECL model will have the opposite effect. Therefore, this paper aims to provide empirical evidence on the implications of the ECL model on credit supply procyclicality by researching the question: Does the switch to the ECL model affect banks' lending sensitivity to changes in regulatory capital ratios when credit risk is high? Using a sample of listed banks in the EEA, we conduct regression analysis and find that when credit risk is high, the lending sensitivity to changes in capital ratios is lower for banks with assets greater than EUR 1,000 million after the implementation of IFRS 9. However, for banks with total assets between EUR 300 million and 1,000 million, we see an increased lending sensitivity to changes in capital ratios when credit conditions deteriorate. Several explanations are proposed, among which the greater resources available to larger banks for an accurate implementation of the ECL model, the higher regulatory and market scrutiny that these banks receive, as well as their superior risk-taking discipline. Our study contributes to the discussion regarding potential negative effects of the ECL model, which is of particular importance in the current conditions of economic uncertainty.

Keywords:

IFRS 9, Expected credit loss, Incurred credit loss, Procyclicality, Capital Requirements, Capital crunch

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1. Introduction

The 2008 crisis shed light on many issues in the financial system, one of which was the accounting for loan losses. In line with the financial reporting standards in force at the time, banks calculated their loan loss provisions using the incurred credit loss (ICL) model. The ICL model relied on the assumption that all loans will be repaid unless existing evidence points to the contrary. A loan could be written down only if such evidence was identified – a loss or trigger event. This raised two important concerns regarding the ICL model. First, loan loss provisioning had to be delayed until evidence that a loss is highly probable became available. Second, only past and current data could be used to estimate loan loss provisions. This resulted in provisioning that turned out to be insufficient and ill-timed during the 2008 financial crisis, earning the incurred loss approach the "too little, too late" criticism (Riksbanken, 2018).

In response to the criticism received by the ICL model, the International Accounting Standards Board (IASB) proposed a new impairment model for loan losses as part of a new set of reporting standards, IFRS 9. The new model, known as the expected credit loss (ECL) model, came into effect on January 1, 2018, marking the start of a more forward-looking approach to estimating loan loss provisions (IASB, 2014). The adoption of the ECL model introduced the following fundamental changes. First, it eliminated the requirement of a trigger event in order to impair a loan. Second, it required that all reasonable and supportable forward-looking information be used to estimate loan loss provisions (IASB, 2014). Consequently, the ECL model was expected to result in adequate and less volatile loan loss provisions that are recognized on a timelier basis and provide higher-quality information, as well as mitigate the procyclical effects of the previous impairment loss model.

Procyclicality refers to the negative feedback effects between the financial system and the real economy that amplify the swings in the business cycle. At the core of this phenomenon in the banking system is the capital crunch effect, which asserts that decreases in the regulatory capital of banks will lead to decreases in lending (Beatty & Liao, 2011). This association is due to the fact that banks tend to cut back on loan issuance if they are at risk of falling below the required capital ratio, which is more likely to happen during economic downturns (Bernanke & Lown, 1991; Van den Heuvel, 2006; Wheeler, 2019). This creates cyclical moves in lending volume that we refer to as credit supply procyclicality. Procyclicality in the credit supply is troublesome, because it leads to a shortage of liquidity during periods of financial stress, just when businesses are in dire need of cash in order to continue their operations.

The benefit of earlier recognition of credit losses for remedying procyclicality has been researched extensively in several studies. Laeven and Majnoni (2003) provide evidence that delays of credit loss provisions are common among banks and lead to a more severe impact of economic downturns on the banks' profit and loss account and capital. Beatty and Liao (2011) find that banks with greater delays in loan loss recognition are more dependent on the level of their regulatory capital ratio and are more likely to reduce lending during the contractionary phase of the economic cycle, which consequently increases lending procyclicality. Bushman and Williams (2012) show that banks that create forward-looking provisions with the intention to provide prompt information about future losses tend to have enhanced discipline. Bushman and Williams (2015) conclude that delayed recognition of non-performing loans is associated with greater bank vulnerability.

However, some researchers have brought up concerns that the expected credit loss model introduced by IFRS 9 might not be as effective at counteracting procyclicality as previously thought. Several simulation studies that examined the behaviour of the ECL model in hypothetical scenarios show that early loss recognition significantly deteriorates the banks' income and capital levels, indicating that IFRS 9 could have cyclical effects (Abad & Suarez, 2018; Barclays, 2017; Krüger et al., 2018; Plata et al., 2017). López-Espinosa et al. (2021) point out that higher provisioning could have a negative impact on lending during downturns through lower capital, which would exacerbate procyclicality.

In light of this debate, we aim to explore the following question: Does the switch to the ECL model affect banks' lending sensitivity to changes in regulatory capital ratios when credit risk is high? Overall, it appears that academics, regulators, and practitioners agree that loan loss recognition timeliness has important economic consequences for procyclical bank lending, and the amount of contradicting evidence explains, in our view, why further research is warranted. Additionally, previous research has mainly looked at cross-sectional differences of the ICL model or used simulations to assess the implications of the ECL model. Little empirical evidence of the effects of IFRS 9 on procyclicality is available after the standard was implemented in 2018. Finally, one main reason for the implementation of the new standard was to reduce the procyclical effects that loan loss accounting can have on the real economy. However, consensus does not exist that IFRS 9 would reduce procyclicality in lending. Hence, it is of interest to examine if the ECL model is associated with procyclical lending by trying to assess data after IFRS 9 was implemented in January 2018.

1.2. Summary of findings and contributions

To answer our research question, we have formulated two hypotheses. First, we test how vulnerable loan growth is to changes in capital requirements ratios in periods of high credit risk. Second, we test how the switch from an ICL to an ECL model in 2018 impacts the relationship between loan growth and changes in regulatory capital ratios in a high credit risk environment. These hypotheses are tested in further detail for different bank sizes.

Our analysis is conducted on a sample of listed banks in European Economic Area, which are required to apply IFRS. For the first hypothesis, we find that loan growth is positively correlated to changes in the Tier 1 capital ratio, indicating that lower capitalization contributes to reductions in lending. However, the lending-capital ratio sensitivity is not significantly different for periods when credit risk is high relative to periods of low credit risk. Thus, we do not observe a capital crunch effect in our sample. For the second hypothesis, we find that large banks, with total assets greater than EUR 1,000 million, are less sensitive to changes in capital ratios in times of high financial stress after the implementation of IFRS 9 in 2018. This would indicate that, as far as large financial institutions are concerned, the International Accounting Standards Board has succeeded in its mission to reduce procyclicality. However, the switch to the ECL model has had the opposite effect in the case of mid-sized banks, for which we see a higher loan growth to changes in capital ratios sensitivity when credit risk is high after the implementation of IFRS 9. Similarly, the loan growth of small banks has become more strongly associated with capital growth in the post-IFRS 9 period, independent from credit risk conditions. This indicates that the new accounting standard has not had the intended effect for both small and mid-sized banks.

Our findings contribute to the literature regarding accounting methods for loan loss recognition by providing empirical evidence on the consequences of the shift to a more forward-looking approach. Namely, we show that instead of having a homogeneous impact on the banking system, this shift has affected banks of different sizes in opposite ways, with large banks benefitting from this change and becoming more resilient in the face of economic downturns, while smaller banks ended up more exposed to procyclicality. This research should be of interest for both financial institutions, whose ability to continue to provide liquidity through downswings is vital for the well-being of the real economy, and regulators, whose supervisory intervention is critical for the effective implementation of the new standard. Furthermore, as previous recessionary episodes have shown, credit loss provisions play a central role in maintaining the financial stability. Finally, understanding the nature of the ECL model is a subject of particular importance in current times, as the economy appears to be heading towards another contractionary period on the back of the geopolitical tensions in Europe and declining growth. Having enough provisions will prove key in ensuring that the banking system is able to face these headwinds.

1.2. Disposition

We have structured the thesis in the following way. Section 2 describes the reason for implementing IFRS 9, technical specifications of the new standard, arguments for and against the new accounting standard, and the concept of procyclicality and capital crunches. Section 3 develops our hypothesis and argues for how our research contributes to the existing literature. Section 4 explains our methodology and the regression models we use to test our hypotheses. In section 5, we display the result of our regressions and analyse the data in relation to previous literature. Finally, in section 6 we present our conclusions, discuss limitations of this study and present suggestions for future research.

2. Literature review

The literature review section starts by describing the reason for implementing IFRS 9 and the method for recognizing loan loss provisions it introduced. Thereafter it puts forward arguments against the new accounting standard and describes the concept of capital crunches and procyclicality. Previous research that advocates an accounting standard that is forward-looking when recognizing loan loss provisions is then described. Finally, the literature review ends with a short summary of the arguments for and against the implementation of IFRS 9.

2.1. The implementation of IFRS 9

IFRS 9 was issued by the IASB in July 2014, following a mandate received from the G20, which were concerned about the relationship between accounting rules and procyclicality after the performance of the previous reporting standard during the 2008 financial crisis (ESRB, 2017). At the time, the prevailing standard was IAS 39, according to which provisions for loan losses had to be recognized using an incurred credit loss model. Under IAS 39, loan loss provisions were recognized only when there was objective evidence of impairment (IASB, 2014). When credit losses were measured, banks only had to consider past events and current conditions. Even if banks expected losses on financial instruments in the future, these were not disclosed in the financial statements. As a result, the provisions turned out to be “too little, too late” during the global financial crisis.

Critics of the ICL model argue that the “too little, too late” provisioning exacerbated procyclicality (ESRB, 2017). Specifically, they explain that at the onset of the crisis, banks had set aside insufficient reserves to cover potential losses that could arise during a downturn. When the crisis ensued, additional provisions needed to be created and recognized as expenses in the profit and loss statement. This constituted a further hit for the banks’ bottom line, which was already weakened due to the loss of interest income from non-performing loans. The reduction in income led to a reduction in regulatory capital that banks must adhere to and many institutions found themselves facing considerable funding and capital pressure. These were forced to decrease the amount of risk-weighted assets (RWAs) on their balance sheet in an attempt to deleverage. A common way of achieving lower levels of RWA is to cut down lending (Lown & Bernanke, 1991), which reinforces procyclicality by reducing the availability of credit at a time when it is most needed.

In 2009, the G20 called upon standard setters to “reconsider the incurred loss model by analysing alternative approaches for recognising and measuring loan losses that incorporate a broader range of available credit information” (FSB, 2009). This request was based on previous research showing that more timely recognition of loan losses could mitigate procyclicality. The new standard came into force in January 2018 and the most important change it introduced was the shift to an expected credit loss approach (ESRB, 2017), forcing banks to start recognizing provisions before a loss event has actually occurred (IASB, 2014). It was no longer possible to solely rely on past information to assess credit risk. Instead, banks need to use reasonable and supportable forward-looking information.

Because banks are required to update the amount of expected credit losses at each reporting date to reflect changes in credit risk since initial recognition, the ECL model provides timelier information compared to the ICL model (IASB, 2020), which leads to several advantages. First, a forward-looking approach to recognizing credit losses can mitigate concerns relating to capital inadequacy during economic recessions because it leads to lower build-ups of loss overhangs and does not allow the overstatement of regulatory capital during the expansionary episodes of the cycle. Second, it can result in better risk-management decisions, since overstated profits are used to create earlier and larger loan loss provisions instead of being distributed as dividends and bonuses. Furthermore, more timely recognition of loan losses informs market participants about changes in credit risk earlier, which can lower financing frictions during periods of deteriorating credit conditions and enhance market discipline. Due to these improvements, the ECL model is expected to mitigate the procyclical effects of its predecessor and increase financial stability (Novotny-Farkas, 2015).

2.1.1. Accounting for loan losses under the ECL model

To compute the loan loss provisions under IFRS 9, the probability of default (PD), exposure at default (EAD) and loss given default (LGD) need to be taken into account. The equation is displayed below, where PD is the likelihood that the loan will not be repaid, EAD amounts to the remaining value of the loan, and LGD is the portion of the remaining value of the loan that might default. For example, if the loan has collateral, the LGD would be lower.

$$Loan\ loss\ provision = PD \times EAD \times LGD$$

The expected credit loss model is built on a three-stage model. Loans are placed in either stage 1 (performing), stage 2 (under-performing), or stage 3 (impaired) (Riksbanken, 2018). In stage

1 of the impairment model, banks must immediately recognize provisions for a loan that has been originated or purchased (IASB, 2014). The stage 1 provision covers a 12-month expected credit loss. For the stage 1 provision, the probability of default in the upcoming 12 months is multiplied by the bank's exposure at default and loss given default. If the credit risk of the loans has not increased significantly on the next reporting day, banks continue to report the 12-month expected credit loss. However, if a significant increase in credit risk has occurred on the next reporting day compared to when the loan was originated or purchased, the loan moves from stage 1 to stage 2 (IASB, 2014).

In stage 2, banks need to recognize the lifetime expected credit loss of the loan. This is calculated by multiplying the probability that the loan will default during its lifetime by the exposure at default and loss given default. However, the opposite can also occur. In cases where banks deem that the risk has no longer increased since initial recognition, the loan moves from stage 2 to stage 1, and only the 12-month expected credit loss is recognized. The previous loan allowance that was related to the life-time expected credit loss is reversed. Finally, if the credit risk of a financial asset reaches a point where it is considered credit-impaired, it moves into stage 3 (IASB, 2014). Stage 3 loans have a 100% probability of default.

Estimating credit losses using the expected model requires extensive data sourcing and management. In order to correctly allocate a loan to one of the three stages, banks must engage in timely collection of data on their borrowers that could be used to identify significant increases in credit risk (Deloitte, 2021). Furthermore, in order to react to changes in the credit risk environment appropriately, they need to make estimations for the 12-month and lifetime probability of default in various macroeconomic scenarios (López-Espinosa et al., 2021). Such meticulous data analysis demands a substantial amount of investment, which is why large banks are expected to have a more accurate implementation of the ECL model, since it is likely that they are already equipped with the infrastructure needed in order to efficiently process high volumes of data and use it to evaluate the borrowers' credit risk (Deloitte, 2021).

2.2. Potential drawbacks of the ECL model

A number of academics and regulatory organisations call into question whether the expected credit loss approach would be able to achieve its goals and contribute to financial stability. When analysing the systemic implications of adopting IFRS 9, the European Systemic Risk Board (ESRB) takes into consideration the possibility that the ECL model could, in contrast to its intended goal, exacerbate procyclicality. Specifically, ESRB (2017) points out that due to how unpredictable business cycle fluctuations can be and how unexpectedly the economy can veer from an expansionary to a contractionary period, there is a significant risk that receiving information that suggests deteriorating economic conditions could lead to a simultaneous increase in expected losses for a large number of banks. This would have a negative impact on the banks' profit and capital because the provisions needed to cover expected losses need to be expensed. Consequently, banks may resort to reducing assets and new lending in an effort to maintain their capital levels. ESRB (2019) restate the conclusions drawn in the previous report and underline that the implications of the ECL model in IFRS 9 on procyclicality and the behaviour of banks remain uncertain, declaring that further analysis is necessary.

López-Espinosa et al. (2021), who provide early evidence on the information content of the ECL model, find that the ECL model leads to increased provisions during economic downturns and conclude that this could have a negative effect on lending through lower capital. Specifically, the authors regress the change in loan loss allowances on the change in the spread of the five-year sovereign credit default swap for individual countries. Their results indicate that the association between changes in loan loss allowances and credit spreads is stronger after IFRS 9 was implemented. A one standard deviation change in the credit default swap spread is associated with a 3.6% difference in loan loss allowances before and after IFRS 9 was implemented. However, a limitation of the paper is that the data available at the time covers only one year from the time that IFRS 9 was implemented.

Among the other papers that have assessed the possible cyclical behaviour of the ECL model, a considerable share of them relied on simulated hypothetical scenarios due to the lack of historical data. These look at how the ECL model would impact the regulatory capital ratios that banks must adhere to. Abad and Suarez (2018) use a simulation to assess the procyclical effects of the ECL model. They find that compared to the incurred credit loss model, the expected credit loss model leads to a steeper increase in loan loss provisions when the economy switches from expansion to contraction. This means that the common equity tier 1 level (CET1) of banks would decline at the beginning of a contraction. A large impact on the CET1 level is especially likely if banks fail to anticipate a turning point in the economy. Related to the difficulties of predicting a turning point in the economy is the work done by Borio and Restoy (2020), who argue that introducing a more forward-looking method for estimating loan loss provisions would mitigate excessive procyclicality but not prevent it entirely because the standard's "excessive point-in-time nature" is inherently procyclical. Furthermore, they highlight that since the new standard is focused on *expected* losses and creating provisions ahead of defaults, it amplifies procyclicality when it comes to *unexpected* shocks to the economy, such as the Covid-19 pandemic. To adjust to the sudden worsening CET1 levels, banks might need to reduce their risk-weighted assets by cutting down on new loans or selling assets (Abad & Suarez, 2018). Banks' behaviour to improve CET1 levels at the beginning of a contraction could therefore impact procyclicality.

Plata et al. (2017) conduct several stress tests to estimate the impact of IFRS 9 on the fourteen largest Spanish banking groups. Their results indicate that the changeover to IFRS 9 leads to an increase in provisions and erodes the CET1 capital levels. This effect is more severe when the stress tests simulate a downturn. Thus, the authors state that the benefits of the expected loss approach could be limited due to its cyclical effects. Barclays (2017) examine the disclosures of 28 large European banks and estimate that the increase in provisions due to the adoption of IFRS 9 is equivalent to a reduction in the CET1 ratio of about 50bp. When EBA (2018) examined the actual day one impact on CET1 after the implementation of IFRS 9, the simple average for the 38 studied banks corresponded to a 47bp decrease in CET1, while the weighted average equaled 27bp. However, under a "typical downturn" scenario, the CET1 ratio could decline by as much as 300 bp, which would likely result in a reduction in lending (Barclays, 2017). Krüger et al. (2018) point out that IFRS 9 increases procyclicality and would have caused an additional deduction in CET1 of 145bp and 221bp respectively during past recessions and the global financial crisis. The impact becomes more or less prominent depending on the asset quality and reinvestment strategy of the banks. How banks choose to define a significant increase in credit risk also has an impact on the CET1 level.

2.3. Procyclicality and the capital crunch

From the point of view of the real economy, procyclicality is the feedback mechanism that happens between the real and financial sectors of the economy (FSB, 2009). When these two sectors interact with each other, business cycle fluctuations tend to magnify, which harms financial stability. As financial institutions make losses because of defaulting clients, it becomes harder to raise new capital. Instead, they need to improve stability by cutting down on credit extension and selling of assets. During the 2008 financial crisis, lending to large US corporations fell by 47% in the fourth quarter of 2008 compared to the third quarter. Compared to the second quarter of 2007, the level of lending in the fourth quarter of 2008 was 79% lower

(Ivashina & Scharfstein, 2010). This behaviour further weakens the real economy, which in turn affects the financial institutions negatively.

The general definition of procyclicality can be connected to the capital crunch theory, which states that banks are more sensitive to regulatory capital requirements in economic downturns (Beatty & Liao, 2011). As banks need to improve their minimum capital ratio, external financing is also less available. Banks that have unrecognised provisions at the start of an economic downturn are therefore particularly sensitive to procyclicality. If banks have capital ratios close to the regulatory minimum and struggle to raise outside capital, they need to reduce lending or sell risky assets to satisfy regulatory requirements and cover the negative impact on the profit and loss from loss overhangs (Wheeler, 2019). Van den Heuvel (2006) shows through his model that to avoid the costs of raising new equity, banks facing capital inadequacy will resort to reducing lending. In fact, this remains true even if capital requirements are not binding because banks that are not at the capital constraint could still cut lending fearing future capital inadequacy. Bernanke and Lown (1991) conduct an empirical study using both a state-level analysis and a bank-level analysis for New Jersey from the early 1990s recession and find strong support for a positive association between the beginning-of-the-period capital to assets ratio and loan growth, concluding that capital shortage contributes to slowdowns in lending.

The capital crunch effect, therefore, is one of the factors that create the procyclical effect that was previously described. One solution to mitigate the effect of procyclicality is Basel's counter cyclical capital buffer, which became fully effective in 2019 (Financial Stability Institute, 2019). The counter cyclical capital buffer aims to protect banks from periods of excess credit growth, which can create system-wide risk. When credit supply is increasing, banks need to build up a buffer of CET1 capital that can be used to absorb losses in economic downturns. When an economic downturn hits, banks should still be able to supply credit to the economy. Because of the countercyclical nature of the requirement, the buffer varies between 0 and 2.5%.

Jiménez et al. (2017) find support for the effectiveness of Basel’s countercyclical buffer. They show that the dynamic provisioning model that was introduced in the Spanish banking system in 2000 has a smoothing effect on credit supply cycles. In good times a buffer is built up from retained profits. This buffer can then be used to cover recognized credit losses on loans in bad times. By taking on more dynamic provisions during booms, banks are equipped with higher capital buffers going into economic downturns. When the economy switches from good to bad, the retained profits can be used to cover realised losses. The authors find that firms that deal with banks holding one percentage point more in capital buffers compared to other banks, receive 9 percentage points more in committed credit in economically bad times.

2.4. Benefits of earlier loan loss recognition

By looking at the effect of delaying provisions on credit supply, we build on a large stream of academic research that studies the relation between loan loss provisioning and cyclicality. Laeven and Majnoni (2003) provide empirical evidence that banks tend to delay provisioning for bad loans and are unprepared to cover the losses incurred during recessions, which worsens the impact of economic downturns on banks' earnings and capital.

Related to this is the work done by Beatty and Liao (2011). The authors investigate whether the degree of delaying loan loss provisions affects banks' willingness to lend during recessionary periods, and, hence, whether the amount of recognized provisions has a procyclical effect. By looking at 1,370 publicly traded banks between 1993 and 2009, they find that banks that delay loan loss provisions less do not have to reduce lending during recessionary periods as much as banks that have greater delays in provisioning. More specifically, banks that have delays greater than the median in the sample cut lending by 2.1% in a recession, while banks that have delays lower than the median cut lending by 0.5%. Additionally, the authors find that banks with greater delays in provisions are more sensitive to regulatory capital ratios in recessions and therefore more exposed to credit crunches. Banks that delay more will have a greater unrecognised overhang loss going into a recession and therefore experience a greater impact on the profit and loss statement and regulatory capital ratios in the crisis. Consistent with the capital crunch theory, these banks will struggle to raise new capital and must instead reduce lending to improve their capital ratios (Beatty & Liao, 2011; Wheeler, 2019). By dividing the sample into different sizes with cut-off points at $300 million, $500 million, and $1,000 million, Beatty and Liao (2011) find that banks with assets greater than $500 million are more exposed to capital crunches.

Bushman and Williams (2012, 2015) also look at the impact of delaying loan loss provisions. They show that banks with a timelier recognition of loan loss provisions have better risk management, which mitigates procyclicality. By looking at banks across 27 countries in the period between 1995 and 2006, Bushman and Williams (2012) examine how discretion in forward-looking provisioning is associated with the discipline of bank risk-taking. Because all banks in the sample used the incurred loss model for loan loss provisions, the authors looked at cross country variation in allowable discretion for different banks. Their findings suggest that while forward-looking provisions intended for earnings smoothing reduce disciplinary pressure on banks' risk-taking, forward-looking provisions that try to predict changes in non-performing loans are associated with better bank risk-taking. Bushman and Williams (2015) conclude that banks that delay expected loan losses are more vulnerable to future capital inadequacy.

Wheeler (2019) investigates the link between regulatory actions, loan loss accounting and pro-cyclical lending by looking at a sample of private and public banks in the period 1990 to 2014. The author finds that regulatory pressure is negatively associated with loan growth. Firstly, banks with more inadequate allowances in economic downturns will be impacted by regulatory actions to improve their solvency to a greater extent compared with banks that have less inadequate allowances. Banks with inadequate allowances, therefore, lend less during economic downturns. Secondly, Wheeler (2019) finds that higher timeliness and transparency of loan loss provisions are not associated with higher loan growth for banks with lower regulatory ratings. Instead, banks that have lower regulatory ratings are under greater regulatory pressure and see a reduction in loan growth when timeliness increases.

2.5. Summary of literature review

The implementation of IFRS 9 is meant to result in loan loss provisions that are recognized in a timelier fashion. By making banks recognize provisions in a timelier fashion, the standard setters hope that banks will be able to provide higher-quality information and reduce procyclicality. Banks that operated under the incurred credit loss model and delayed provisions less compared to other banks have not been forced to reduce lending as much in economic downturns and are not as exposed to capital crunches. When credit risk increased, these banks had a lower loss overhang. Therefore, their capital ratios did not take the same hit as banks that entered the high credit risk period with inadequate loan loss provisions. Additionally, a more forward-looking loan loss provision approach has been proven to be associated with better risk-taking for some banks. The ability to predict future losses has allowed these banks to better mitigate the risk of deteriorating capital ratios. All in all, banks that delay provisions less and enter downturns with a lower loss overhang, have not been exposed to capital crunches to the same degree.

At the same time, the implementation of IFRS 9 has raised questions regarding the expected credit loss model's efficiency in reducing procyclicality in the economy. Concerns have been expressed by practitioners and academics that the new accounting standard will harm regulatory capital ratios at the start of an economic downturn, which in turn would induce procyclicality. Economic shocks are inherently difficult to predict, and the new accounting standard can therefore not reach its goal of creating a smoothing effect on the financial statements when it comes to unexpected increases in credit risk. It is possible that the switch from a low to a high credit risk environment will lead to a large increase in loan loss provisions, which will harm banks' capital ratios. Instead of reducing procyclical lending, the new accounting standard might further expose banks to capital crunches with the need to sell risky assets or reduce lending to meet regulatory capital requirements. Due to the lack of consensus, the implications of the switch to an expected model of recognizing credit losses warrants further research.

3. Hypothesis development and contribution

Based on the capital crunch theory, which states that banks will respond to concerns regarding future capital constraints by cutting back loan origination due to market imperfections that make raising new equity costly, we hypothesise that:

H1a: The sensitivity of loan growth to changes in regulatory capital ratios is greater when credit risk is high.

Previous articles studying the capital crunch tested this relationship for banks of different sizes. Thus, Beatty and Liao (2011) find that large banks are more vulnerable to capital crunches during recessions than small banks. Specifically, their results show that the capital crunch only occurs for banks with total assets of $500 million and above (Beatty & Liao, 2011). One potential explanation provided by the authors is that the more stringent capital regulations in the post-Basel period increased the concern of large banks regarding falling short of the required capital minimums and, therefore, increased the likeliness that they would be subjected to a capital crunch during recessions. Therefore, we test the same hypothesis for banks of different sizes:

H1b: The sensitivity of loan growth to changes in regulatory capital ratios is greater for large banks compared to small banks when credit risk is high.

As discussed previously, the accounting method for expected loss recognition is an important factor that influences the interaction between capital and lending. On the one hand, early recognition of credit losses should smooth out the impact of loan loss provisions on capital over the business cycle and have no significant influence on the lending capacity of banks. On the other hand, more recent studies highlight the risk that the adoption of IFRS 9 would lead to more precipitous drops in regulatory capital when the cyclical position of the economy switches from expansion to contraction, in response to which the banks would reduce the origination of new loans. Therefore, we aim to investigate whether the implementation of an impairment model that forces banks to create more provisions during boom times has had any effect on bank lending. Given the lack of consensus regarding the effect of IFRS 9, we refrain from predicting whether banks with earlier recognition of forthcoming losses, i.e. banks that estimate loan loss provisions using the expected loss approach, are more or less likely to issue fewer loans in times of financial stress.

H2a: The sensitivity of loan growth to changes in regulatory capital ratios differs in the period after the implementation of IFRS 9 relative to the period before the implementation of IFRS 9 when credit risk is high.

Large banks are expected to have a more accurate application of accounting standards and to be better at making predictions with regard to loan loss provisions (Marton & Runesson, 2017). This could be due to higher political costs if they report questionable financial statements. Moreover, they are subject to more intense regulatory supervision, which prompts them to have more rigorous processes for identifying stressed financial assets. One such example is the Asset Quality Review (AQR), a prudential review process whose purpose is to stress test the resilience of banks' balance sheet that systemically important banks in the euro area are subject to (López-Espinosa et al., 2021). Finally, the data analysis systems used to estimate loan loss provisions are expected to be more advanced for large banks. The ability of European banks to predict loan loss provisions accurately under IFRS 9 could therefore depend on bank size. Because it is still unclear how IFRS 9 and different levels of provisioning impacts lending, we formulate our sub hypothesis as follows:

H2b: The sensitivity of loan growth to changes in regulatory capital ratios differs for large banks compared to small banks in the period after the implementation of IFRS 9 when credit risk is high.

Although little empirical evidence of the effects of IFRS 9 on procyclicality is available at this point, the findings of existing papers present contradicting views on the subject. Our study sheds light on the current debate regarding the potential cyclical effects of the expected loss approach to provisions introduced by IFRS 9. Even though previous papers have looked at the relationship between capital ratios, timelier loan loss provisions and volume of credit, to our best knowledge no other paper has examined this relationship in the context of the switch from the incurred credit loss model to the expected credit loss model. Conducting this research after the implementation of the new standard enables us to provide empirical evidence by analysing actual data instead of relying on simulation models. Furthermore, our data covers at least one year since the beginning of the Covid-19 pandemic, allowing us to observe the behaviour of IFRS 9 during a downturn. Additionally, we contribute to the accounting literature by looking at how financial reporting quality affects the interaction between regulatory capital and the supply of credit and whether that effect varies for different levels of credit risk.

4. Methodology

The methodology section starts by describing the sample selection process for choosing and retrieving data relevant to the study. Then the lending model we use to test our hypotheses is explained. Finally, descriptive statistics are displayed.

4.1. Sample selection

To study the effect of IFRS 9 on lending capacity, we focus on publicly traded banks in the European Economic Area (EEA). All listed banks in the EU have been required to apply IFRS since 2005. Bank-related data is collected from the Thomson Reuters Eikon database. We impose that the banks included in our sample have non-missing data for at least two years after the implementation of IFRS 9, which occurred in 2018. Furthermore, we remove observations with a total asset value below EUR 100 million, both because we expect the quality of reporting to be lower for these firms and because they are less likely to have lending operations.

As a proxy for credit risk, we use the iTraxx Europe CDS crossover index. The iTraxx is a family of indices that tracks the performance of tradable credit default swaps contracts in specific geographies or segments of the bond market. The iTraxx Europe CDS crossover index consists of the 75 most liquid European names that are rated sub-investment grade, which are equally-weighted and updated every 6 months, on the basis of liquidity. While previous research has used sovereign credit default swaps as an indicator of credit risk, we choose the iTraxx index because its focus on the high-yield segment of the market makes it more sensitive to deteriorating credit conditions. Data regarding the iTraxx Europe CDS crossover index level is collected from Capital IQ. The country-specific GDP-growth is obtained from the World Bank.

Our resulting sample consists of 18,141 firm-quarter observations from 2006 Q2 to 2021 Q4, representing 373 banks from 15 countries. This choice of sample period allows us to have periods of low and high credit risk, both before and after the implementation of IFRS 9. To reduce the impact of extreme observations on our results, we winsorize all continuous variables at the 1st and 99th percentiles. Table 1 displays descriptive statistics for all continuous variables for the period between 2006 and 2021. Statistics are shown both for the entire dataset and for the subgroups of different bank sizes.

Table 1. Descriptive statistics.

	Sample European Banks											
Variables	Pooled			Large			Mid			Small		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
$\Delta Lending$	0.007	0.000	0.063	0.009	0.000	0.068	0.004	0.000	0.056	0.007	0.000	0.063
$\Delta Tier\ 1\ Ratio$	0.013	0.000	0.059	0.013	0.000	0.054	0.012	0.000	0.056	0.013	0.000	0.068
$Deposits$	0.831	0.818	0.278	1.017	0.999	0.266	0.764	0.768	0.224	0.687	0.671	0.224
$GDP\ rate$	0.242	0.396	1.601	0.209	0.417	1.483	0.228	0.400	1.669	0.297	0.362	1.653
$Size$	20.204	20.269	0.883	21.149	21.149	0.231	20.202	20.231	0.334	19.077	19.142	0.332
σ_{ret}	0.015	0.014	0.017	0.015	0.014	0.016	0.015	0.014	0.015	0.016	0.013	0.020

Note: This table presents descriptive statistics of the sample including a panel of 18,141 firm-quarter observations from 2006 to 2021. See Appendix A for variable definitions. All variables are winsorized at the 1st and 99th percentiles.

In line with previous research, which has shown that the capital crunch does not affect banks of different sizes to the same extent, we split the sample into three subsamples based on the size of the banks' total assets, choosing EUR 1,000 million and EUR 300 million as cut-off points (Beatty & Liao, 2011). The resulting large, mid, and small subsamples contain 6,389, 6,404, and 5,348 firm-quarter observations, respectively. Since larger banks have higher quality reporting standards, represent a larger share of the banking system, and are better monitored by regulators, we expect the data in the large subsample to be less noisy, and thus the results to be more accurate than the ones based on the other two subsamples.

4.2. Lending model

4.2.1. Hypothesis 1

To test if the capital crunch theory holds and thereby if the lending volume of banks is more sensitive to changes in regulatory capital ratios when credit conditions deteriorate, we examine the association of the change in total loans with changes in Tier 1 ratio and the level of credit risk as suggested by the iTraxx Europe CDS crossover index. We estimate the following equation to test the first hypothesis:

$$\begin{aligned}\Delta Lending_t = \alpha &+ \beta_1 \Delta Tier\ 1\ Ratio_{t-1} + \beta_2 \Delta Tier\ 1\ Ratio_{t-1} * High\ risk_{t-1} \\ &+ \beta_3 Deposits_{t-1} + \beta_4 GDP\ rate_{t-1} + \beta_5 Size_{t-1} + \beta_6 \sigma_{ret_{t-1}} \\ &+ Fixed\ effects + \varepsilon_t \end{aligned} \tag{1}$$

where

$\Delta Lending_t$	The percent change in total loans of the current quarter
$\Delta Tier\ 1\ Ratio_{t-1}$	The percent change in the Tier 1 capital ratio of the previous quarter
$High\ risk_{t-1}$	An indicator variable that takes a value of 1 when the quarterly value of the iTraxx Europe CDS crossover index is above the median and 0 otherwise
$Deposits_{t-1}$	Total deposits divided by total loans of the previous quarter
$GDP\ rate_{t-1}$	The growth rate of the GDP in the previous quarter
$Size_{t-1}$	The natural log of total assets of the previous quarter
$\sigma_{ret_{t-1}}$	The standard deviation of daily stock returns of the previous quarter

The variables of interest in equation (1) are $\Delta Tier\ 1\ Ratio_{t-1}$, which is the change in the ratio of Tier 1 capital to total risk-weighted assets, and $High\ risk_{t-1}$, which is based on the iTraxx Europe CDS crossover index and is used as a proxy for deteriorating credit conditions. $\Delta Tier\ 1\ Ratio_{t-1} * High\ risk_{t-1}$ is included in the equation to capture the interaction between different credit risk levels and Tier 1 ratio. In this case, we want to see how much a change in the Tier 1 ratio impacts lending given the risk level in the iTraxx credit default swap index. This interaction is meant to capture a possible capital crunch effect. A positive coefficient on the interaction would indicate that the impact of a change in the regulatory capital ratio on lending is even higher when credit risk is high, i.e. the lending-capital ratio sensitivity would be higher. A negative coefficient would instead indicate that changes in the regulatory capital ratio don't affect lending as much when credit risk is high, i.e. the lending-capital ratio sensitivity would be lower.

We expand the model by adding the following control variables. First, we include $Deposits_{t-1}$, which reflects the value of deposits on a bank's balance sheet, scaled by total loans. According to Ivashina and Sharfstein (2010), banks with better access to deposit financing cut lending less during the financial crisis, specifically in the August to December 2008 period. Second, the $GDP\ rate_{t-1}$ of each country in the sample is added in order to control for the effect of macroeconomic trends in the overall economy on loan demand (Wheeler, 2019). Third, to control for potential size effects between different banks, $Size_{t-1}$ is included. Finally, following the work of Beatty and Liao (2011), $\sigma_{ret_{t-1}}$ is used as a control variable to capture differences in asset risk across banks.

To avoid bias generated by omitted variables in our model, we take the first difference of all variables of interest. While first differencing solves the issue of unobserved time-invariant effects, it does not address unobserved effects that vary through time but are constant in the cross section, which is why we include time fixed effects in the model. Due to the use of time fixed effects, the model does not include cross-sectionally invariant variables unless they are included in an interaction term. Additionally, because the level of lending is more correlated with values from the previous quarter, all dependent variables are lagged by one period. Finally, to ensure that our coefficients are unbiased under heteroskedasticity, we estimate heteroskedasticity-consistent ("robust") standard errors.

In accordance with previous literature, which states that better capitalized banks will lend more as they are less concerned about falling below the regulatory capital requirements, we predict a positive coefficient on $\Delta Tier\ 1\ Ratio_{t-1}$, implying that an increase in the regulatory capital held by the bank will lead to an increase in the level of lending. Furthermore, during periods of adverse credit conditions banks face higher monitoring from regulatory institutions, it becomes more costly to raise outside equity, and profitability declines, all of which increase the importance of the regulatory capital held by the bank. Therefore, we expect changes in capitalization to be more strongly associated with changes in lending during times of financial stress, which corresponds to a positive coefficient on the interaction between $\Delta Tier\ 1\ Ratio_{t-1}$ and $High\ risk_{t-1}$. In regard to $Deposits_{t-1}$ we predict a positive coefficient, which would reflect that banks with better liquidity have a more robust lending capacity. Finally, we expect a positive coefficient on $GDP\ rate_{t-1}$, because declining macroeconomic trends correspond to lower loan demand, and make no predictions for the sign of the coefficients on $Size_{t-1}$ and $\sigma_{ret_{t-1}}$.

4.2.2. Hypothesis 2

To estimate whether IFRS 9 has had an impact on the sensitivity of bank lending to changes in regulatory capital ratios, we augment our initial model by adding an indicator variable, $IFRS\ 9_i$, that is equal to one for periods after the implementation of IFRS 9 in 2018, and zero otherwise. Our aim is to test whether the coefficient on $\Delta Tier\ 1\ Ratio_{t-1} * High\ risk_{t-1}$ will differ for periods after the implementation of IFRS 9 relative to the periods before the new standard came into force, which would indicate the impact of the new standard on the capital crunch effect, and thus, whether it has been effective in alleviating procyclicality. Therefore, we interact $\Delta Tier\ 1\ Ratio_{t-1} * High\ risk_{t-1}$ with the indicator variable $IFRS\ 9_i$, creating a three-way interaction. Additionally, we add all combinations of two-way interactions between the variables of interest, thus obtaining the following equation (2):

$$\begin{aligned}\Delta Lending_t = \alpha &+ \beta_1 \Delta Tier\ 1\ Ratio_{t-1} + \beta_2 \Delta Tier\ 1\ Ratio_{t-1} * High\ risk_{t-1} \\ &+ \beta_3 \Delta Tier\ 1\ Ratio_{t-1} * IFRS\ 9_i + \beta_4 \Delta Tier\ 1\ Ratio_{t-1} * High\ risk_{t-1} \\ &* IFRS\ 9_i + \beta_5 Deposits_{t-1} + \beta_6 GDP\ rate_{t-1} + \beta_7 Size_{t-1} + \beta_8 \sigma_{ret_{t-1}} \\ &+ Fixed\ effects + \varepsilon_t \qquad (2)\end{aligned}$$

Because of the contradicting evidence regarding the effect of IFRS 9 on lending presented in the previous section, we make no prediction for the direction of the effect of $IFRS\ 9_i$ on the lending-capital ratio sensitivity.

In addition to the main tests, we run equation (1) and (2) under a slight modification in order to check the robustness of the results. Specifically, we conduct the tests on a subsample that excludes year 2018, which was the first year of the new standard's implementation, to avoid a potential "day-one impact" that could result from differences in how loan loss provisions are calculated under IFRS 9 compared to IAS 39.

5. Results and discussion

The following section describes the results from our regressions and analyses them in relation to previous research.

5.1. The capital crunch effect

The findings of the test of our first hypothesis, which surmises that lending is negatively impacted by a capital crunch when credit risk is high, are presented in Table 2. The results for the overall sample, which includes the entire period between Q2 2006 and Q4 2021, are shown in Panel A, while the results in Panel B are based on a subsample that excludes year 2018. For each panel, column (1) displays the results for the pooled sample and columns (2), (3), and (4) correspond to subsamples defined by total asset size.

Table 2. Analysis of the effects of capital ratio and credit risk on change in loans for banks of different sizes.

Panel A: Overall sample				
	Dependent variable:			
	$\Delta Lending$			
	Pooled	Large	Mid	Small
	(1)	(2)	(3)	(4)
$\Delta Tier\ 1\ Ratio$	0.0113^{***}	0.0289^{***}	0.0136^{**}	0.0195^{***}
	(0.0032)	(0.0089)	(0.0054)	(0.0060)
$\Delta Tier\ 1\ Ratio * High\ risk$	0.0035	-0.0117	-0.0102	0.0009
	(0.0064)	(0.0142)	(0.0088)	(0.0082)
$Deposits$	0.0187^{***}	0.0297^{***}	0.0029	0.0126^{***}
	(0.0019)	(0.0028)	(0.0036)	(0.0034)
GDP	0.0013^{***}	0.0036^{***}	-0.0042^{***}	0.0020^{**}
	(0.0005)	(0.0010)	(0.0007)	(0.0009)
$Size$	-0.0051^{***}	-0.0415^{***}	-0.0365^{***}	-0.0179^{***}
	(0.0008)	(0.0054)	(0.0034)	(0.0039)
σ_{ret}	-0.0823^{**}	-0.1462^{**}	0.0280	-0.1370^{**}
	(0.0324)	(0.0611)	(0.0438)	(0.0591)
Time FE	Yes	Yes	Yes	Yes
Observations	18,141	6,389	6,404	5,348
R^2	0.0089	0.0319	0.0560	0.0184

Panel B: Subsample that excludes year 2018

	Dependent variable:			
	$\Delta Lending$			
	Pooled	Large	Mid	Small
	(1)	(2)	(3)	(4)
$\Delta Tier\ 1\ Ratio$	0.0053*	0.0253***	0.0009	0.0161**
	(0.0032)	(0.0090)	(0.0063)	(0.0064)
$\Delta Tier\ 1\ Ratio * High\ risk$	0.0097	-0.0079	0.0033	0.0050
	(0.0064)	(0.0140)	(0.0098)	(0.0084)
$Deposits$	0.0180***	0.0293***	-0.0016	0.0157***
	(0.0022)	(0.0030)	(0.0040)	(0.0041)
GDP	0.0013***	0.0028***	-0.0044***	0.0021**
	(0.0005)	(0.0010)	(0.0007)	(0.0009)
$Size$	-0.0051***	-0.0445***	-0.0398***	-0.0186***
	(0.0008)	(0.0056)	(0.0035)	(0.0041)
σ_{ret}	-0.0832**	-0.1484**	0.0255	-0.1366**
	(0.0330)	(0.0621)	(0.0449)	(0.0601)
Time FE	Yes	Yes	Yes	Yes
Observations	16,779	5,957	5,876	4,946
R^2	0.0083	0.0332	0.0653	0.0199

Note: This table presents an analysis of the effects of capital ratio and credit risk on change in lending for banks of different sizes using the following model:

$$\Delta Lending_t = \alpha + \beta_1 \Delta Tier\ 1\ Ratio_{t-1} + \beta_2 \Delta Tier\ 1\ Ratio_{t-1} * High\ risk_{t-1} + \beta_3 Deposits_{t-1} + \beta_4 GDP\ rate_{t-1} + \beta_5 Size_{t-1} + \beta_6 \sigma_{ret_{t-1}} + Fixed\ effects + \varepsilon_t$$

The dependent variable is $\Delta Lending$. $\Delta Tier\ 1\ Ratio$ is the percent change in the Tier 1 capital ratio at the beginning of the quarter. $High\ risk$ equals 1 for periods when the quarterly iTraxx index level is above the median, and 0 otherwise. See Appendix A for detailed other variable definitions. Regression (1) uses the pooled sample. Regressions (2), (3), and (4) partition the sample based on the size of total assets. The sample includes a panel of firm-quarter observations from 2006 to 2021, corresponding to our sample of European banks. Panel A uses the entire sample, while Panel B excludes year 2018. All regressions have heteroskedasticity-consistent standard errors and include time fixed effects. Due to the use of time fixed effects, cross-sectionally invariant variables are excluded. Standard errors are presented in parentheses.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Consistent with prior studies (Bernanke & Lown, 1991; Beatty & Liao, 2011), we find a positive association between changes in the Tier 1 capital and changes in the lending level, as indicated by the coefficient on $\Delta Tier\ 1\ Ratio$, which is significant for the pooled sample, as well as across all size subsamples. This coefficient measures the effect of capital on lending during periods of low credit risk, i.e. when the indicator variable $High\ risk$ takes a value of zero. Thus, for the pooled sample, a 1% decrease in capital growth would lead to a 0.011% decrease in loan growth when credit risk is low. For large banks, this relationship is stronger, with a 1% decrease in capital growth corresponding to a 0.029% decrease in loan growth in a low-risk environment. For mid-sized and small banks, the coefficient corresponds to 0.014% and 0.020%, respectively (Table 2, Panel A). Thus, our findings lend support to previous research on the relationship between capital and lending, which has pointed out that capital shortage is one of the main factors that negatively impact lending activity in a bank, since reducing loan issuance is a common tactic among financial institutions that face the risk of capital inadequacy (Van den Heuvel, 2006; Wheeler, 2019).

To assess the association between capital and lending for periods of adverse credit conditions, we look at the coefficient on the $\Delta Tier\ 1\ Ratio * High\ risk$ variable. Earlier studies have concluded that in a high credit risk environment, the role played by capital adequacy in determining lending capacity becomes even more important (Beatty & Liao, 2011; Van den Heuvel, 2006; Wheeler, 2019). This is due to the fact that the banks' profit tends to be lower during economic crises, which leads to a higher risk of capital inadequacy. At the same time, the costs of raising outside capital go up, forcing banks to limit the supply of credit in order to avoid falling below minimum capital requirements. Consequently, we would expect the association between capital and lending to be stronger for periods of high credit risk, which would correspond to a positive coefficient on the interaction term. However, we do not observe a capital crunch effect when conducting our test, either for the pooled sample or for the size subsamples, as the coefficient on the interaction term is statistically insignificant. While these findings could indicate that the sensitivity of banks to regulatory capital requirements does not increase significantly in times of financial stress, they could also be a result of the model's specifications or the limitations of this study, which are described in detail in a later section. Therefore, even though we do not find support for our first set of hypotheses, which stated that bank lending becomes more sensitive to changes in the Tier 1 capital ratio during periods of high risk and that this effect is more noticeable for large banks, we refrain from drawing definitive conclusions regarding the prevalence of the capital crunch effect.

For the control variables, we find a positive correlation between deposits and changes in lending, which remains significant for both the large and small subsamples. This suggest that liquidity issues constrain loan growth across different bank sizes. Furthermore, banks with a higher value of total assets tend to have a lower loan growth. Finally, for most of the banks in the sample, loan growth is negatively impacted by a lower GDP growth rate, as well as by a higher standard deviation of returns.

5.2. IFRS 9 and procyclicality

IFRS 9 was the regulators' response to concerns regarding the connection between the timing of credit loss recognition and cyclical moves in credit supply, which were heightened in the aftermath of the 2008 financial crisis, when the ineffectiveness of recognizing losses on a financial asset after they have already been incurred was highlighted. The aim of the new standard was to reduce procyclicality by introducing a more forward-looking expected loss method, which relies on a larger volume of available credit information to estimate probable future losses. The consequences of the switch to an expected approach to recognizing loan losses are expected to be especially noticeable, if not exclusively present, in large financial institutions, which are often the target of financial regulation and receive more scrutiny from supervisory bodies due to their considerably greater importance for financial stability (López-Espinosa et al., 2021).

The concept of procyclicality is highly intertwined with the capital crunch theory, which states that banks will resort to reducing lending during economic downturns in order to maintain their capital level above regulatory requirements. Thus, in our second hypothesis, we examine whether the recently introduced ECL model has achieved its goal of alleviating procyclicality by estimating the impact of the adoption of IFRS 9 on the lending-capital ratio sensitivity, with the results being displayed in Table 3. For this set of tests, we look at the coefficient on the interaction term $\Delta Tier\ 1\ Ratio_{t-1} * High\ risk_{t-1} * IFRS\ 9_i$, which is our coefficient of interest.

While the result for the pooled sample does not show statistical significance, we find a strong significant difference for the large banks (Table 3, Panel A). Specifically, the coefficient of interest is negative for these banks, which implies that after the implementation of IFRS 9, their lending became less correlated with changes in capitalization when credit risk is high. Thus, the switch to the ECL model reduced the sensitivity of lending growth to changes in the regulatory capital ratio for large banks by 0.171 in periods of high credit risk relative to periods of low credit risk. We continue to see a significant negative coefficient of 0.103 for large banks when excluding year 2018 from the sample, which suggests that this effect is robust to sample specifications (Table 3, Panel B). Moreover, this additional test reveals that the new standard could potentially influence the importance of capital adequacy for loan issuance even in times of low credit risk, as we observe that the lending-capital ratio sensitivity is lower by 0.045 in the post-IFRS period when the $High\ risk$ variable is zero (Table 3, Panel B).

Table 3. Analysis of the effects of IFRS 9 on the relationship between capital ratio, credit risk, and change in loans for banks of different sizes.

Panel A: Overall sample

	Dependent variable:			
	$\Delta Lending$			
	Pooled	Large	Mid	Small
	(1)	(2)	(3)	(4)
$\Delta Tier\ 1\ Ratio$	0.0104***	0.0271***	0.0104**	0.0142**
	(0.0031)	(0.0086)	(0.0050)	(0.0066)
$\Delta Tier\ 1\ Ratio * High\ risk$	0.0042	-0.0061	-0.0074	0.0014
	(0.0065)	(0.0140)	(0.0097)	(0.0091)
$\Delta Tier\ 1\ Ratio * IFRS\ 9$	0.0069	0.0267	0.0204	0.0412**
	(0.0180)	(0.0257)	(0.0200)	(0.0169)
$\Delta Tier\ 1\ Ratio * High\ risk * IFRS\ 9$	-0.0041	-0.1708***	-0.0178	0.0227
	(0.0278)	(0.0499)	(0.0379)	(0.0321)
$Deposits$	0.0187***	0.0297***	0.0028	0.0124***
	(0.0019)	(0.0028)	(0.0036)	(0.0035)
GDP	0.0013***	0.0037***	-0.0042***	0.0019**
	(0.0005)	(0.0010)	(0.0007)	(0.0009)
$Size$	-0.0051***	-0.0417***	-0.0365***	-0.0180***
	(0.0008)	(0.0054)	(0.0034)	(0.0040)
σ_{ret}	-0.0822**	-0.1459**	0.0283	-0.1373**
	(0.0324)	(0.0612)	(0.0439)	(0.0590)
Time FE	Yes	Yes	Yes	Yes
Observations	18,141	6,389	6,404	5,348
R^2	0.0089	0.0321	0.0560	0.0187

Panel B: Subsample that excludes year 2018

	Dependent variable:			
	$\Delta Lending$			
	Pooled	Large	Mid	Small
	(1)	(2)	(3)	(4)
$\Delta Tier\ 1\ Ratio$	0.0103***	0.0280***	0.0093*	0.0138**
	(0.0031)	(0.0086)	(0.0052)	(0.0066)
$\Delta Tier\ 1\ Ratio * High\ risk$	0.0045	-0.0068	-0.0066	0.0026
	(0.0065)	(0.0138)	(0.0098)	(0.0092)
$\Delta Tier\ 1\ Ratio * IFRS\ 9$	-0.0744**	-0.0452**	-0.1137***	0.0447**
	(0.0326)	(0.0197)	(0.0261)	(0.0201)
$\Delta Tier\ 1\ Ratio * High\ risk * IFRS\ 9$	0.0778**	-0.1026**	0.1243***	0.0186
	(0.0385)	(0.0439)	(0.0399)	(0.0361)
$Deposits$	0.0180***	0.0293***	-0.0016	0.0157***
	(0.0021)	(0.0030)	(0.0040)	(0.0041)
GDP	0.0013***	0.0029***	-0.0044***	0.0021**
	(0.0005)	(0.0010)	(0.0007)	(0.0009)
$Size$	-0.0052***	-0.0447***	-0.0400***	-0.0187***
	(0.0008)	(0.0056)	(0.0035)	(0.0041)
σ_{ret}	-0.0838**	-0.1482**	0.0240	-0.1368**
	(0.0330)	(0.0621)	(0.0449)	(0.0600)
Time FE	Yes	Yes	Yes	Yes
Observations	16,779	5,957	5,876	4,946
R^2	0.0084	0.0334	0.0657	0.0202

Note: This table presents an analysis of the effect of IFRS 9 on the relationship between capital ratio, credit risk, and change in lending for banks of different sizes using the following model:

$$\begin{aligned}\Delta Lending_t = \alpha &+ \beta_1 \Delta Tier\ 1\ Ratio_{t-1} + \beta_2 \Delta Tier\ 1\ Ratio_{t-1} * High\ risk_{t-1} + \beta_3 \Delta Tier\ 1\ Ratio_{t-1} * IFRS\ 9_i \\ &+ \beta_4 \Delta Tier\ 1\ Ratio_{t-1} * High\ risk_{t-1} * IFRS\ 9_i + \beta_5 Deposits_{t-1} + \beta_6 GDP\ rate_{t-1} \\ &+ \beta_7 Size_{t-1} + \beta_8 \sigma_{ret_{t-1}} + Fixed\ effects + \varepsilon_t\end{aligned}$$

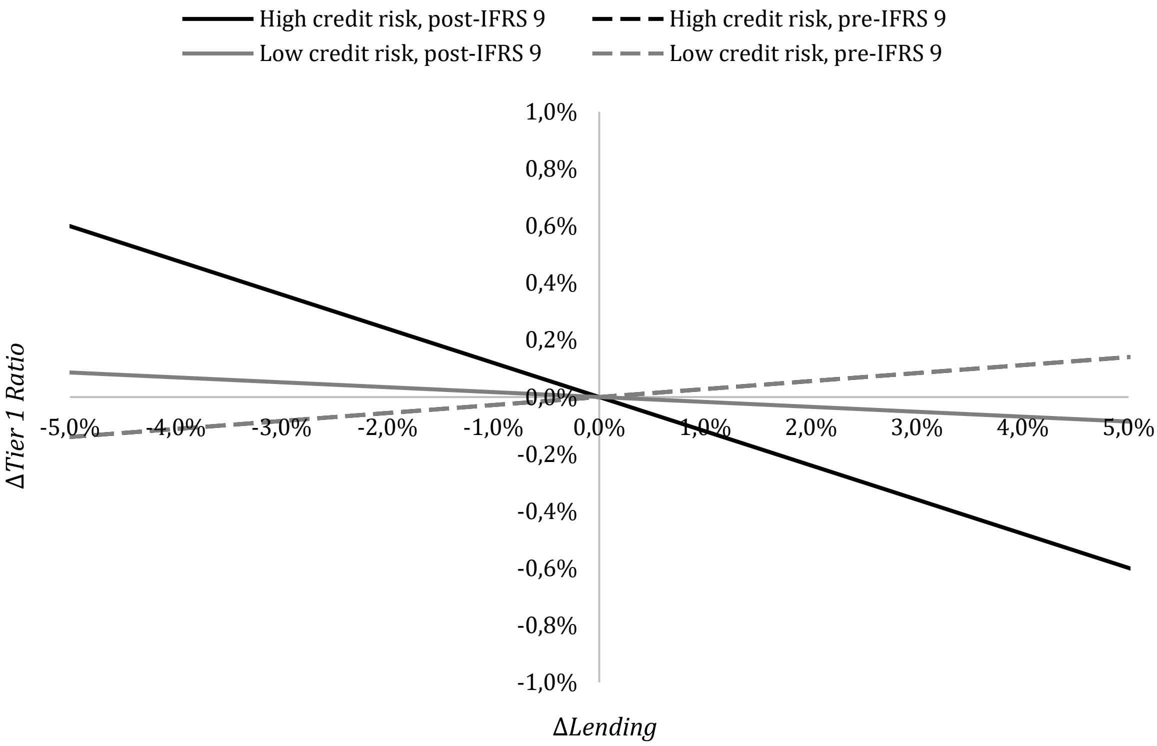
The dependent variable is $\Delta Lending$. $\Delta Tier\ 1\ Ratio$ is the percent change in the Tier 1 capital ratio at the beginning of the quarter. $High\ risk$ equals 1 for periods when the quarterly iTraxx index level is above the median, and 0 otherwise. $IFRS\ 9$ equals 1 for all quarters after January 1, 2018, and 0 otherwise. See Appendix A for detailed other variable definitions. Regression (1) uses the pooled sample. Regressions (2), (3), and (4) partition the sample based on the size of total assets. The sample includes a panel of firm-quarter observations from 2006 to 2021, corresponding to our sample of European banks. Panel A uses the entire sample, while Panel B excludes year 2018. All regressions have heteroskedasticity-consistent standard errors and include time fixed effects. Due to the use of time fixed effects, cross-sectionally invariant variables are excluded. Standard errors are presented in parentheses.

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

For a better understanding of how the relationship between loan growth and changes in regulatory capital differs in the post-IFRS 9 period compared to the pre-IFRS 9 one in low and high credit risk environments, we plot the slope of the partial derivative with respect to $\Delta Tier\ 1\ Ratio$ for the large banks, focusing on the subsample that excludes year 2018 since the overall effect of the switch to the ECL model appears to be more evident in this set of tests (Table 3, Panel B). Appendix B demonstrates in detail how the equations for each plot line were derived from the initial model.

Figure 1 presents the resulting plot, which illustrates the differences in the lending-capital ratio sensitivity between the two accounting regimes. Whereas we continue to observe that in the pre-IFRS 9 period the lending-capital ratio sensitivity does not differ for periods of high and low credit risk, the introduction of the new standard has significantly changed this relationship. Specifically, we observe a lower sensitivity of loan growth to changes in the Tier 1 capital ratio in both low and high credit risk environments after the implementation of the new accounting standard. Thus, before IFRS 9 came into force, a 1% decrease in capital growth was associated with a 0.028% decline in loan growth regardless of credit risk conditions. However, after the new standard came into force, a 1% decrease in capital growth led to a loan growth increase of 0.017% in a low credit risk environment. This difference becomes more pronounced when credit conditions are deteriorating, with a 1% fall in capital growth corresponding to a 0.120% increase during the post-IFRS 9 period in the case of high credit risk.

The decrease in the sensitivity of loan growth to changes in the Tier 1 capital ratio after the adoption of IFRS 9 suggests that, when it comes to large banks, the switch to a forward-looking approach to estimating loan losses has contributed to mitigating the capital adequacy concerns, particularly during contractionary phases of the business cycle. The result is aligned with the initial aim of the new accounting standard, which was to temper cyclical moves in lending volume by imposing an earlier recognition of credit losses. Namely, banks are now required to recognize provisions before the occurrence of a loss event by using all available forward-looking information (IASB, 2014). Smoothing impairments over the business cycle was expected to diminish capital concerns during economic downturns because it results in lower build-ups of loss overhangs, better risk-management, and more transparency towards market participants (Novotny-Farkas, 2015). Combined, these factors make banks more resilient to swings in the business cycle, which is the effect that we observe for the large banks in our sample.

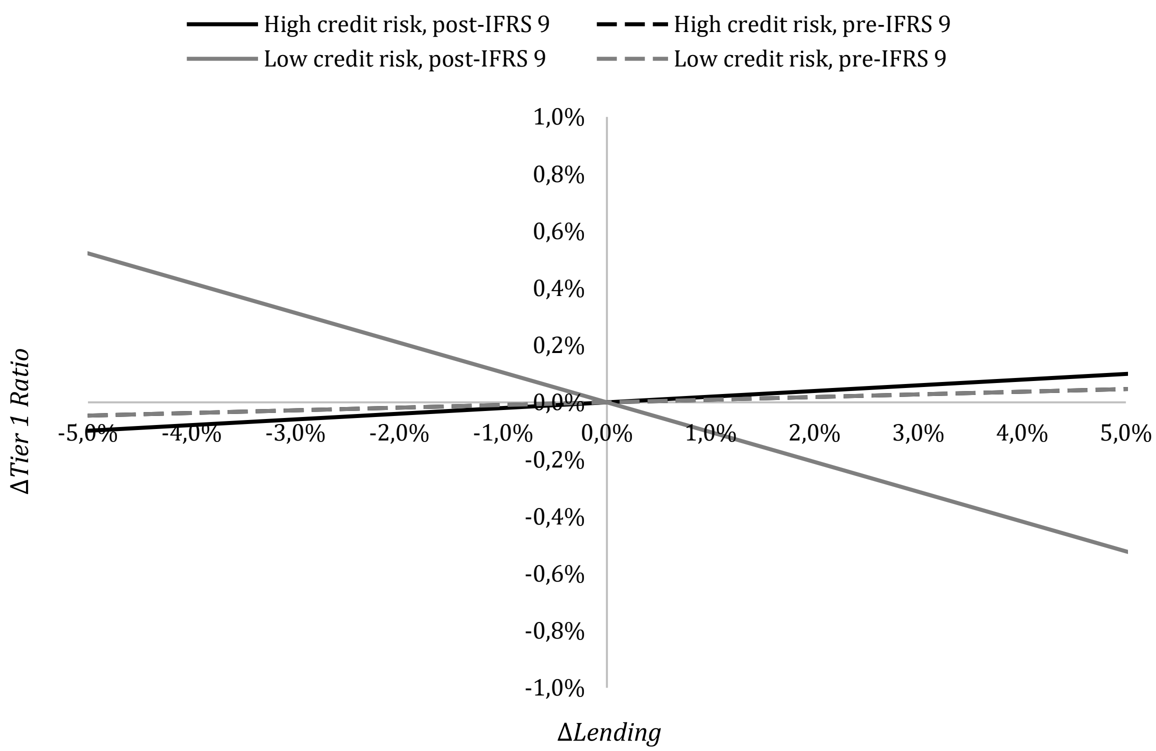


Note: *Change in lending is displayed on the y-axis and change in the Tier 1 ratio is displayed on the x-axis.*

Figure 1. The relationship between changes in capital ratio and changes in lending for large banks in different credit risk environments before and after the implementation of IFRS 9, excluding 2018.

Interestingly, we note the same effect cannot be observed for other size groups in this study. In the case of mid-sized banks, we do not see any significant impact on lending growth due to the introduction of IFRS 9 after conducting the main test. When the first year of the new standard's implementation is removed from the sample, we find that lending is more robust to changes in capital when credit risk is low, with the lending-capital ratio sensitivity decreasing by 0.114 in the post-IFRS 9 period. However, in contrast to their larger peers, mid-sized banks appear to become more sensitive to changes in capital ratios in times of financial stress after the implementation of IFRS 9, as suggested by the positive coefficient on $\Delta Tier\ 1\ Ratio_{t-1} * High\ risk_{t-1} * IFRS\ 9_i$ (Table 3, Panel B). For this group, the lending-capital ratio sensitivity increases by an additional 0.124 in the post-IFRS 9 period when credit risk is high. This result reflects fears expressed by critics of the new standard (Abad & Suárez, 2018; Barclays, 2017), who employed simulation models to show that the expected loss approach can have a greater negative impact on P&L and capital level than the incurred loss approach when there is an unexpected increase in risk and will result in a concentration of future losses at the very start of a recessionary episode. Consequently, banks will reduce lending to avoid falling below capital requirements, shrinking credit supply at a time when liquidity is most needed and creating a negative feedback loop.

To illustrate the relationship between lending and capital for mid-sized banks in relation to the credit risk environment, we plot this relationship before and after the implementation of IFRS 9, using the coefficients from Table 3, Panel B. The corresponding plot is presented in Figure 2. As shown, when credit risk is low, there is a weaker association between loan growth and changes in regulatory capital in the post-IFRS 9 period compared to pre-IFRS 9 one. While before the new standard came into force, a 1% decrease in capital growth led to a corresponding drop in loan growth of 0.009%, after the accounting standards for loan losses were changed, a similar decrease in capital growth was associated with an increase in loan growth of 0.104%.



Note: *Change in lending is displayed on the y-axis and change in the Tier 1 ratio is displayed on the x-axis.*

Figure 2. The relationship between changes in capital ratio and changes in lending for mid-sized banks in different credit risk environments before and after the implementation of IFRS 9, excluding 2018.

However, when credit risk is high, the relationship between capital and lending has a slightly steeper slope in the post-IFRS 9 period compared to the pre-IFRS 9 one. This indicates that the sensitivity of loan growth to changes in capital ratio increases after the implementation of the new standard in a high credit risk environment, as a 1% decline in capital growth in this case is associated with a 0.020% decrease in loan growth. Although the effect is only significant when the year 2018 is excluded from the subsample, we conclude that in the case of mid-sized banks, the switch to the ECL model has not been as beneficial as for large banks. Despite its effectiveness in reducing the reliance of loan issuance on capital constraints during good economic times, when the tide turns mid-sized banks could potentially become even more vulnerable to capital crunches under the new accounting regime. This echoes concerns raised by regulators, who highlighted the risk of relying on forward-looking information to estimate future losses in conditions of unpredictable business cycle fluctuations, suggesting that IFRS 9 could have a negative influence on the procyclicality of credit supply (ESRB, 2017; ESRB, 2019).

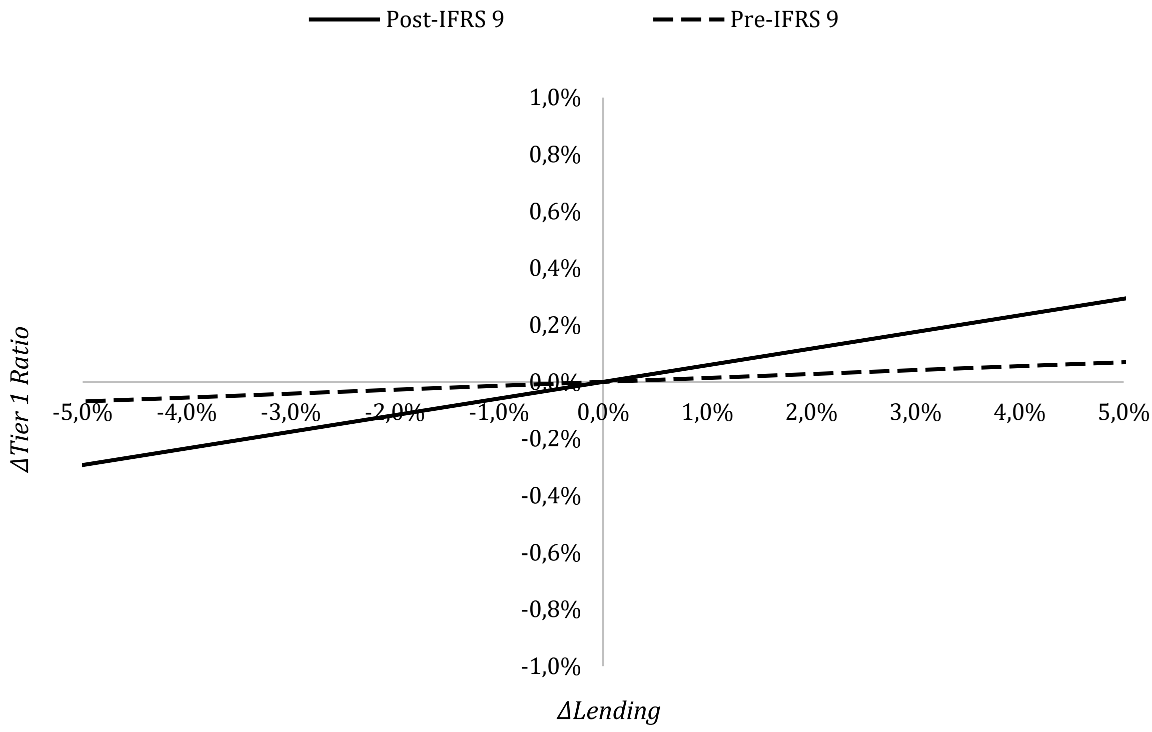
In other words, a forward-looking method for calculating loan losses is only effective for financial institutions that are capable of foreseeing a downturn ahead of time, which would allow them to record an increase in future losses during the expansionary phase of the economic cycle, when their P&L position is still strong and better able to absorb this outflow. This requires a significant amount of resources to be invested in making accurate estimations of a financial asset's probability of default under various macroeconomic scenarios, as well as the likeliness of each scenario to become true (López-Espinosa et al., 2021). In this respect, large banks, who have more access to the tools and talent necessary for such a high volume of data gathering and modelling, have an advantage over their mid-sized counterparts. Moreover, higher regulatory supervision and market scrutiny constitute additional incentives for large banks to ensure a diligent and precise application of the new standard (Marton & Runesson, 2017). Therefore, an explanation for the increased lending-capital ratio sensitivity in the post-IFRS 9 period that we observe for the subsample of mid-sized banks is that having less resources available to ensure an accurate implementation of the forward-looking approach, combined with less monitoring from financial regulators, makes them vulnerable to the "excessive point-in-time nature" of the ECL model, thereby amplifying procyclicality (Borio & Restoy, 2020).

Another possible explanation for the different outcomes between large and mid-sized banks is the underlying intention when recognizing loan loss provisions. Following the work of

Bushman and Williams (2012), we know that discretion in loan loss accounting can allow for better risk taking or earnings smoothing. It could be that large banks are trying to recognize provisions to predict future non-performing loans to a greater extent compared to mid-sized banks, and therefore have better risk-taking discipline. Mid-sized banks might instead to a greater extent engage in earnings smoothing instead of mitigating risk. We also know that banks that have a loss overhang and inadequate provisions in economic downturns are more likely to be impacted by regulatory actions to improve their solvency compared to banks that more adequate provisions recognized (Wheeler, 2019). Whereas the large banks in our sample might have entered the Covid-19 crisis with a lower loss overhang, mid-sized banks might have had more inadequate provisions and therefore greater pressure to improve their capital ratios to continue lending. Nonetheless, we take the results for the mid-sized subsample with a grain of salt, both because of the fact that the estimates are only significant when we run the tests on a subsample that excludes year 2018, and because the quality of the reported information is likely to be lower relative to the one in large banks.

Finally, we note that the introduction of IFRS 9 has also had an influence on the subsample of small banks. For this group, the sensitivity of loan growth to changes in regulatory capital increases by 0.041, suggesting that the risk of capital inadequacy has become an even greater concern for the smallest financial institutions in our sample since the switch to the ECL model (Table 3, Panel A). Furthermore, we find that this effect does not differ substantially for periods of high credit risk, as suggested by the statistically insignificant coefficient on $\Delta Tier\ 1\ Ratio_{t-1} * High\ risk_{t-1} * IFRS\ 9_i$. The findings remain consistent when we exclude the first year of the standard's implementation from the sample (Table 3, Panel B).

Figure 3 depicts the impact of the new accounting standard for loan losses on the relationship between lending and capital in small banks. As illustrated, the markedly steeper slope for the post-IFRS 9 period indicates that the association between loan growth and capital growth has become stronger under the new accounting rules, with a 1% decrease in capital growth leading to a 0.317% fall in loan growth. By contrast, a 1% decrease in capital growth was associated with a loan growth reduction of only 0.075% in the pre-IFRS 9 period. Unlike in the case of mid-sized banks, the negative effect for small banks is independent of credit risk conditions. Thus, while we cannot draw conclusions regarding whether the supply of credit from small banks has become more procyclical after the switch to the ECL model, we observe that it has become more dependent on the banks' capitalization, which could potentially leave them more exposed to capital crunches.



Note: *Change in lending is displayed on the y-axis and change in the Tier 1 ratio is displayed on the x-axis.*

Figure 3. The relationship between changes in capital ratio and changes in lending for small banks before and after the implementation of IFRS 9, excluding 2018.

Following our previous reasoning, some possible explanations for this effect are that small banks are less likely to have the required resources and infrastructure to collect and analyse credit risk data, which consequently means that they are not as effective in responding promptly to changes in credit risk, both at an individual client level and at a macroeconomic level, as large banks (Deloitte, 2021). Furthermore, small banks receive less guidance regarding credit risk identification and measurement from regulators and less monitoring of risk management practices. In light of this, concerns regarding the proper application of the new method for estimating future loan losses remain valid in the case of small banks.

Overall, our results provide support in favour of the ECL model's mitigating impact on procyclicality, but this outcome appears to be limited to large financial institutions. For this group, we observe a lower association between loan growth and capital growth after the IFRS 9 implementation, particularly during periods of high credit risk, suggesting that lending has become less constrained by the banks' capitalization and therefore is likely to be more robust in the face of economic downturns. This indicates that a timelier recognition of future loan losses has been successful in reducing cyclicality in the supply of credit for large banks. For mid-sized banks however, the switch to a forward-looking approach to estimating credit losses has not had the desired result, since the lending-capital ratio sensitivity increases when credit risk is high, suggesting that the risk of future capital inadequacy has become a greater concern in the post-IFRS 9 period and could potentially lead to cuts in loan issuance in times of financial stress, which would amplify credit supply procyclicality. We find that the switch to the ECL model has also had a detrimental effect on the relationship between lending and capital in small banks, with loan growth becoming considerably more dependent on changes in the Tier 1 ratio. However, this effect does not vary for different credit risk environments. We attribute the findings for small and mid-sized banks to a less accurate implementation of the new model due to high informational requirements, less regulatory scrutiny, and lower risk-taking discipline among these financial institutions relative to larger banks.

6. Conclusion

The expected credit loss model was introduced in 2018, when the new accounting standard IFRS 9 was adopted. It was the response of financial regulators to concerns raised regarding its predecessor, the incurred credit loss model, which was heavily criticized following the 2008 financial crisis, due to the fact that it left banks with insufficient reserves in the face of mounting defaults, further harming their ability to provide liquidity and, thus, exacerbating procyclicality. By contrast, the ECL model, which instituted a forward-looking approach to estimated loan losses, was expected to make lending less procyclical.

Credit supply procyclicality is a well-known issue that jeopardizes financial stability. One explanation for these cyclical moves in lending volume is provided by the capital crunch theory, which states that during economic downturns banks become more concerned about the risk of future capital inadequacy and are more likely to cut down loan issuance to avoid falling below the regulatory capital requirements. Therefore, this paper studies whether the adoption of IFRS 9 has had an impact on the capital crunch effect, focusing specifically on the implications for banks of different sizes.

In contrast to previous research, we do not find a capital crunch effect in times of high credit risk. Instead, banks sensitivity of loan growth to changes in capital ratio appears to be equally high for periods of low and high credit risk. However, after the implementation of IFRS 9, we observe a change in lending-capital ratio sensitivity in times of financial stress. The impact of the IFRS 9 adoption on this relationship varies for each subsample. The new standard has managed to reach its goal of alleviating procyclicality for large banks, whose lending-capital ratio sensitivity is lower in the post-IFRS 9 period. Meanwhile, mid-sized banks display a higher sensitivity during periods of high credit risk, implying that they have become more vulnerable to procyclicality after the new standard came into force. Finally, the loan growth of small banks is more strongly associated with changes in capital ratios after the new accounting standard came into force. However, the lending-capital ratio sensitivity does not change significantly in periods of high credit risk.

We outline several potential explanations for the divergence between large banks and their smaller counterparts. First, large banks are more likely to have the resources necessary for the implementation of ECL model, which requires a considerable amount of data gathering and forecasting in order to make accurate estimations of future losses. Unless banks are able to predict increases in the probability of default in advance, an unexpected economic shock would lead to credit losses being concentrated at the beginning of a downturn, which would inhibit lending activity even more. Second, large banks receive more supervision from financial regulators, which leads not only to a higher quality of reported information, but also to a more meticulous implementation of accounting standards. Finally, large banks are more likely to have better risk-taking discipline and create sufficient provisions compared to less monitored banks who might use loan loss accounting as a tool to smooth earnings.

6.1 Limitations and further research

The findings presented in this paper are subject to potential limitations. First, due to the categorization available in the Thompson Reuters database, we are unable to differentiate between different types of banks, which means that our sample could include some banks whose primary function is not to issue loans. Second, while we use the actual Tier 1 ratio of each bank in the study, we don't have access to data regarding their minimum required capital ratio, which is individual for each financial institution, depending on its importance to financial stability. Therefore, further research could shed more light on how the capital in excess of the minimum required affects a bank's ability to lend in various credit conditions and whether IFRS 9 has brought any changes to that relationship. Similarly, another factor that could have an influence on willingness to lend that we cannot control for due to lack of data is Basel's countercyclical capital buffer requirement. Because the aim of the countercyclical buffer is to reduce procyclicality, it might also affect banks' behaviour when credit risk increases, and thus constitutes another opportunity for future research.

Lastly, given that IFRS 9 was implemented in 2018, it continues to be a relatively recent accounting standard. Since its implementation, the EEA area has seen one economic crisis, caused by measures intended to prevent the spread of the Covid-19 pandemic, to which advanced economies responded with an unprecedented amount of monetary and fiscal policies intended to stimulate demand. Because this study is particularly focused on the association between capital and lending during periods of high credit risk, our findings could be skewed by the actions taken by central banks to avoid a liquidity shortage during this crisis. Therefore, further research on the topic could take into account longer time periods that would cover several business cycle phases, which would provide additional insight into the consequences of a forward-looking approach to estimating loan losses in times of financial stress.

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Appendices

Appendix A

Table 4. Overview of variable definitions

Variable name	Definitions
$\Delta Lending$	The percent change in total loans
$\Delta Tier\ 1\ Ratio$	The percent change in the Tier 1 capital ratio
$High\ risk$	An indicator variable equal to one for periods when the percent change in the iTraxx Europe CDS crossover index is above the median and zero otherwise
$IFRS\ 9$	An indicator variable equal to one for periods after the implementation of IFRS 9 in 2018 and zero otherwise
$Deposits$	Total deposits divided by total loans
GDP	The GDP growth rate for each country
$Size$	The natural log of total assets
σ_{ret}	The standard deviation of daily stock returns

Appendix B

Appendix B presents the derivations used to plot the relationship between changes in capital ratio and changes in lending and calculate the effect for each size subsample in different credit risk environments before and after the implementation of IFRS 9.

The following model is used to the test the effect of IFRS 9 on the lending-capital ratio sensitivity:

$$\begin{aligned}\Delta Lending_t = {} & \alpha + \beta_1 \Delta Tier\ 1\ Ratio_{t-1} + \beta_2 \Delta Tier\ 1\ Ratio_{t-1} * High\ risk_{t-1} \\ & + \beta_3 \Delta Tier\ 1\ Ratio_{t-1} * IFRS\ 9_i + \beta_4 \Delta Tier\ 1\ Ratio_{t-1} * High\ risk_{t-1} \\ & * IFRS\ 9_i + \beta_5 Deposits_{t-1} + \beta_6 GDP\ rate_{t-1} + \beta_7 Size_{t-1} + \beta_8 \sigma_{ret_{t-1}} \\ & + Fixed\ effects + \varepsilon_t\end{aligned}$$

Grouping together all factors that contain the $\Delta Tier\ 1\ Ratio$ variable, we obtain the partial derivative with respect to changes in the Tier 1 capital ratio, which shows how the effect of $\Delta Tier\ 1\ Ratio$ on lending growth is linearly changing depending on the value of $High\ risk$ and $IFRS\ 9$:

$$\begin{aligned}\Delta Lending_t = {} & (\beta_1 + \beta_2 * High\ risk_{t-1} + \beta_3 * IFRS\ 9_i + \beta_4 * High\ risk_{t-1} \\ & * IFRS\ 9_i) * \Delta Tier\ 1\ Ratio_{t-1} + (\alpha + \beta_5 Deposits_{t-1} + \beta_6 GDP\ rate_{t-1} \\ & + \beta_7 Size_{t-1} + \beta_8 \sigma_{ret_{t-1}}) + Fixed\ effects + \varepsilon_t\end{aligned}$$

Thus, for a given level of $High\ risk$ and $IFRS\ 9$, the additional effect of a change in capital growth on lending growth is equal to:

$$(\beta_1 + \beta_2 * High\ risk_{t-1} + \beta_3 * IFRS\ 9_i + \beta_4 * High\ risk_{t-1} * IFRS\ 9_i) * \Delta Tier\ 1\ Ratio_{t-1}$$

In the post-IFRS 9 period ($IFRS\ 9 = 1$), this expression can be simplified to:

$$(\beta_1 + \beta_2 * High\ risk_{t-1} + \beta_3 + \beta_4 * High\ risk_{t-1}) * \Delta Tier\ 1\ Ratio_{t-1}$$

Subsequently, we differentiate between periods of high or low credit risk.

$High\ risk_{t-1} = 1$: $(\beta_1 + \beta_2 + \beta_3 + \beta_4) * \Delta Tier\ 1\ Ratio_{t-1}$

$High\ risk_{t-1} = 0$: $(\beta_1 + \beta_3) * \Delta Tier\ 1\ Ratio_{t-1}$

These equations are then used to plot the conditional effect that a 1% change in capital growth has on lending growth after the implementation of the new accounting standard. For calculations, we use the regression coefficients presented in Table 3, Panel B. Where the coefficients of interest are not statistically significant, we assume that they are equal to zero.

We follow the same reasoning to obtain the expression for the pre-IFRS 9 period ($IFRS\ 9 = 0$):

$(\beta_1 + \beta_2 * High\ risk_{t-1}) * \Delta Tier\ 1\ Ratio_{t-1}$

Finally, we differentiate between periods of high or low credit risk, using the resulting equations to calculate the effect that a 1% change in capital growth has on lending growth before the implementation of IFRS 9:

$High\ risk_{t-1} = 1$: $(\beta_1 + \beta_2) * \Delta Tier\ 1\ Ratio_{t-1}$

$High\ risk_{t-1} = 0$: $\beta_1 * \Delta Tier\ 1\ Ratio_{t-1}$

Table 5. Overview of the effect of a change in the Tier 1 ratio on loan growth before and after the implementation of IFRS 9 under different credit risk conditions

	Post-IFRS 9	Pre-IFRS 9
High risk	$\beta_1 + \beta_2 + \beta_3 + \beta_4$	$\beta_1 + \beta_2$
Low risk	$\beta_1 + \beta_3$	β_1