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Same same but different: credit risk provisioning under IFRS 9

Abstract

We analyse the impact of the adoption of expected credit loss accounting (IFRS 9) on the timeliness and potential procyclicality of banks' loan loss provisioning. We use granular loan-level data from the euro area's credit register and investigate both firm-level credit events and macroeconomic shocks (2020 COVID-19 pandemic, 2022 energy price shock). We find that provisions under the new standard are higher before default and more responsive to shocks. However, the majority of provisioning still occurs at the time of default and the dynamics around default events are similar to pre-existing national standards. Additionally, banks with a larger capital headroom provision significantly more, particularly for loans using IFRS 9. This suggests a higher risk of underprovisioning for less capitalized banks.

Keywords: bank regulation, financial stability, loan loss accounting, credit risk
JEL classification: G21, G28, G32

Non Technical Summary

In this paper, we examine how the adoption of expected credit loss accounting (IFRS 9) and bank conditions have affected euro area banks' provisioning behaviour around individual credit events, over the course of the COVID-19 pandemic, and after the outbreak of war in Ukraine. Using 30 million quarterly loan observations from the European credit register (AnaCredit), our study compares provisioning dynamics for IFRS 9 loans to those using national Generally Accepted Accounting Principles (nGAAP). The comparison aims to assess whether post-crisis reforms have fundamentally altered provisioning patterns. The study also examines whether well- and less-capitalized banks exhibit divergent provisioning dynamics under IFRS 9 and nGAAP, to gain insights on the role of discretion under different accounting approaches.

The paper finds that some features of IFRS 9 seem to work as intended, with ex ante provisioning generally higher than with nGAAP and provisions increasing in the run-up to a default. However, the pre-default increase is small, and the bulk of provisioning under IFRS 9 still occurs at the time of or shortly after a default. This results in provisioning dynamics around credit risk shocks being similar between loans using IFRS 9 and those using nGAAP. One reason for this is that banks appear to have problems with identifying significant increases in credit risk (that trigger a move to "stage 2" and thus higher provisioning under IFRS 9) at a sufficiently early stage, so that a large share of IFRS 9 loans continues to be classified as fully performing ("stage 1") shortly ahead of a default. Moreover, even loans in stage 2 exhibit sizable jumps in provisioning at default, although smaller ones than stage 1 loans.

We also find evidence that IFRS 9 has amplified the impact of banks' capital position on their provisioning practices. Specifically, we find that banks with less capital headroom over their capital requirements provision less than other banks, even for similar loans to the same borrower in the same period. This is consistent with capital management motives and a strategy of "provisioning as much as you can afford", indicating that discretion seems to play a role under both accounting approaches. However, when looking at provisioning dynamics around credit risk shocks, we find that banks with more capital headroom increase provisions ahead of default more than other banks for loans using IFRS 9 but not for loans using nGAAP. One interpretation for this is that IFRS 9 affords banks with greater flexibility to avoid substantial increases in provisions in cases where capital is scarce. Consistent with this interpretation, we also find that

less capitalised banks are less likely to move exposures to the higher credit risk stage 2 under IFRS 9 and, if they do, to increase their provisions less after this move, so that they appear to be using all levers available to them to reduce provisions. Thus, the new approach may have fostered stronger divergence in accounting practices across banks, where less capitalised banks in particular may be tempted to exploit available discretion for capital management purposes.

We then also analyse provisioning dynamics around two macroeconomic shocks (the COVID-19 pandemic and the energy price shock in early 2022), which are particularly relevant from a financial stability perspective. The findings show that provisioning for IFRS 9 loans and the share of stage 2 loans increased over the course of the pandemic, even without a significant increase in default rates. However, the implications for banks' capital ratios are modest, and even a doubling or tripling of the observed effects should have been manageable without procyclical adjustment actions on the side of banks. Capital headroom had a strong impact on provisioning behavior both during the pandemic and after the energy price shock, indicating capital management motives also around systemic events. Finally, provisions for IFRS 9 loans are increased more risk-sensitively (i.e., more strongly for firms more exposed to the energy price shock), in line with the new framework's intended functioning.

Our findings have several important policy implications. First, the dynamics around default events and the overall muted reaction by banks after two macroeconomic shocks suggest that discussions on possible procyclicality of IFRS 9 may have been exaggerated, since the overall patterns are not much different from those of previously existing nGAAP standards. Specifically, our results suggest that IFRS 9 offers enough flexibility to spread provisioning increases around macroeconomic shocks over several quarters, reducing the risk of sharp increases in provisioning. Consistent with such flexibility, we also document a strong impact of capital headroom on provisioning practices. While this requires close supervisory scrutiny, the overall implications in terms financial stability are *a priori* ambiguous. On a positive side, flexibility can smooth the potential procyclical impact of ECL accounting when the economy weakens: as mentioned above, poorly capitalised banks can avoid a jump in provisions that would dent their capital and force them to procyclically reduce lending. However, this reduces transparency and may imply an underestimation of credit risk, potentially leading to stronger negative repercussions when risks materialise eventually. Moreover, less capitalised banks may be at greater risk of being underprovisioned, with potentially negative implications in terms of bank stability.

1 Introduction

The adequate and timely provisioning of credit risk is key for banks. It ensures that they can withstand the materialisation of such risk without endangering their own solvency and the stability of the financial system. It also makes the underlying risks transparent for investors and supervisors, thus improving market discipline and facilitating supervision. Additionally, proper provisioning creates incentives for banks to avoid engaging in overly risky behavior such as zombie lending or evergreening of loans, which can destabilise the financial system over the medium term. Given the implications for bank solvency and financial stability, determinants of bank provisioning have long been studied by academics and policymakers alike, and provisioning frameworks have substantially evolved in recent years to address identified shortcomings.

Following the crisis of 2007-09, existing provisioning methods were accused of inducing banks to provision "too little, too late." These methods mostly relied on backward-looking Incurred Loss (IL) approaches, requiring the booking of provisions only after the occurrence of specific credit events that made repayment unlikely.[1] Consequently, aggregate provisioning ratios increased substantially over the course of the crisis, quadrupling relative to previously observed levels (see Figure 1). This sharp increase in provisioning triggered concerns about procyclicality and a lack of transparency with further hidden risks in banks' balance sheets. The Financial Stability Forum (2009), predecessor of today's Financial Stability Board, called on accounting standard setters to reconsider the IL model and aim for more forward-looking approaches instead. This resulted in the development and eventual adoption of Expected Credit Loss (ECL) approaches such as the International Financial Reporting Standard 9 (IFRS 9). These approaches aim to anticipate loss recognition by requiring provisions to be based on estimated future credit losses, usually obtained from dedicated provisioning models operated by banks themselves. Using these models, loan exposures are classified as performing ("stage 1"), underperforming ("stage 2"), or non-performing ("stage 3"), with substantially higher provisioning expected already for loans that saw a significant increase in credit risk and are thus placed in stage 2.

While ECL approaches were supposed to enhance transparency by inducing speedier and more accurate loss recognition, their implementation soon triggered discussions on possible malfunctioning and side effects (see Basel Committee on Banking Supervision 2021 for a review

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[1] The prime example for an IL accounting approach is the International Accounting Standard 39 (IAS 39).

of the literature). First, there were concerns that a sudden and significant deterioration in economic conditions could trigger significant loss provisioning in the early stages after a shock, which might itself induce procyclical effects, only front-loading them when compared with the IL approach (see, e.g., the simulation study by Abad and Suarez 2018). Specifically, increased provisioning reduces bank capital, potentially leading banks to reduce credit supply in order to protect their capital ratios and avoid breaching capital requirements. This can deprive firms and households of necessary financing soon after a shock, which may in turn exacerbate the crisis.[2] Second, there were doubts that a move to an ECL approach alone would be sufficient to change the incentives for banks to delay loss recognition (e.g., Bischof et al. 2021), given an inherent reluctance to impair assets and recognise losses (e.g., Laux and Leuz 2009, 2010, Huizinga and Laeven 2012). There were even concerns that the reliance on internal models and the discretion afforded to banks in estimating expected losses could facilitate such delays and induce more dispersion in provisioning practices, potentially conflicting with the objective of enhanced transparency (e.g., European Systemic Risk Board 2017).[3] The temptation to underestimate expected losses and thus reduce provisioning needs could be particularly strong for less capitalised banks that are pressured to preserve capital.

In this paper, we pick up on these points and investigate how accounting rules and bank conditions have affected euro area banks' provisioning behaviour, around individual credit events and over the course of the COVID-19 pandemic and after the outbreak of war in Ukraine. Using a sample of around 30 million quarterly loan observations from the European credit register ('AnaCredit'), we compare provisioning dynamics for IFRS 9 loans to those of loans using national Generally Accepted Accounting Principles (nGAAP). The latter contain forward-looking elements in some cases but are mostly of an IL nature (see Section 2). More importantly, they have existed since long ago, so that the comparison with IFRS 9 allows to assess whether post-crisis reforms have fundamentally altered provisioning patterns.[4] Moreover, we examine

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[2]See Berrospide et al. (2021) and Couaillier et al. (2022a) for recent evidence of such protective behaviour by banks during the COVID-19 pandemic. Importantly, this procyclicality concern is similar to previous concerns under the IL approach, where the main difference is in the timing of losses that may trigger procyclical adjustments. Under the IL approach, the booking of provisions would induce sizable losses rather late in the crisis, potentially triggering procyclical adjustments at that stage (or somewhat earlier if banks anticipate future losses), while the concern under IFRS 9 is that substantial provisioning and losses may be observed soon after a shock.

[3]For the case of capital regulation, such side effects of relying on banks' internal models for regulatory purposes are well-documented (e.g., Begley et al. 2017, Colliard 2019, Plosser and Santos 2018, Behn et al. 2022).

[4]In the EU, application of IFRS 9 is mandatory for consolidated financial statements of public companies listed in any Member State. In several member states, other companies (e.g., unconsolidated or non-listed entities) have to or may choose to resort to nGAAP. For this reason, AnaCredit contains both IFRS 9 and nGAAP loans,

whether well- and less-capitalised banks exhibit divergent provisioning dynamics under IFRS 9 and nGAAP, respectively, to derive insights on the role of discretion under the different accounting approaches. Thanks to the granularity of our data set, we can compare provisioning levels and dynamics for loans to the same borrower in the same period but issued by banks using different accounting standards or differently capitalised banks. Thus, our identification strategy systematically controls for the borrower's credit quality and other borrower-specific factors that may affect provisioning behaviour, akin to the the seminal paper by Khwaja and Mian (2008). Moreover, the inclusion of loan-specific control variables ensures that we are comparing provisioning for similar types of exposures.

Our findings indicate that some features of IFRS 9 seem to be working as intended: ex ante provisioning is generally higher than with nGAAP and provisions increase in the run-up to a default. However, this pre-default increase is rather small, and the bulk of provisioning under IFRS 9 continues to occur at the time of or shortly after a default. As a result, provisioning dynamics around credit risk shocks are rather similar between loans using IFRS 9 and those using nGAAP. One reason for this is that banks appear to have problems with identifying significant increases in credit risk (that trigger a move to "stage 2" and thus higher provisioning under IFRS 9) at a sufficiently early stage, so that a large share of IFRS 9 loans continues to be classified as fully performing ("stage 1") shortly ahead of a default. Moreover, even loans in stage 2 exhibit sizable jumps in provisioning at default, although smaller ones than stage 1 loans. Somewhat in contrast with expectations, this suggests that the new approach has not fundamentally altered provisioning patterns. Importantly, the results hold in a number of robustness checks that control for support measures implemented during the pandemic and differences between IFRS 9 and nGAAP banks and loans that could influence the regressions.

We also find evidence that IFRS 9 has amplified the impact of banks' capital position on their provisioning practices. Specifically, we find that banks with less capital headroom over their capital requirements provision less than other banks, even for similar loans to the same borrower in the same period. This is consistent with capital management motives and a strategy

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where the accounting standard used for the reporting may vary also for loans from the same parent institution. Of the 1,721 banks in our sample, 1,318 (including 47 Significant Institutions supervised by the ECB) report under nGAAP for at least some of their loans. Such nGAAP exposures are particularly prevalent in Austria and Germany but also observed in other countries. Banks mostly using IFRS 9 differ from banks mostly using nGAAP on several dimensions, which we account for via econometric techniques such as propensity score matching (see Appendix A), or by restricting the sample to loans from banks that rely on both types of approaches.

of "provisioning as much as you can afford", indicating that discretion seems to play a role under both accounting approaches. However, when looking at provisioning dynamics around credit risk shocks, we find that banks with more capital headroom increase provisions ahead of default more than other banks for loans using IFRS 9 but not for loans using nGAAP. One interpretation for this is that IFRS 9 affords banks with greater flexibility to avoid substantial increases in provisions in cases where capital is scarce. Consistent with this interpretation, we also find that less capitalised banks are less likely to move exposures to the higher credit risk stage 2 under IFRS 9 and, if they do, to increase their provisions less after this move, so that they appear to be using all levers available to them to reduce provisions. Thus, the new approach may have fostered stronger divergence in accounting practices across banks, where less capitalised banks in particular may be tempted to exploit available discretion for capital management purposes.

Finally, we analyse provisioning dynamics around the macroeconomic shocks induced by the COVID-19 pandemic and the energy price shock in early 2022. Doing so is particularly relevant from a financial stability perspective, given the potential systemic repercussions that can occur around correlated credit risk events, if many banks suffer losses and adjust their behaviour simultaneously. Our findings show that provisioning for IFRS 9 loans and the share of stage 2 loans increased around these shocks, even in the absence of a material increase in default rates. However, implications for banks' capital ratios have been very modest, and back-of-the-envelope calculations suggest that even a doubling or tripling of the observed effects should have been manageable for banks without triggering procyclical adjustments. This confirms the rather muted relevance of stage 2 transitions for overall provisioning patterns. Moreover, in line with the previous findings, capital headroom had a strong impact on provisioning behaviour around these shocks, consistent with a strong impact of capital management motives also around systemic events. Finally, we also find that provisions for IFRS 9 loans are increased in a more risk sensitive manner (i.e., more strongly for firms that are more exposed to the energy price shock), in line with the intended functioning of the new framework.

Our findings have several important policy implications. First, the dynamics around default events and the overall muted reaction by banks after two macroeconomic shocks (that did not trigger waves of default) suggest that discussions on possible procyclicality of IFRS 9 may have been exaggerated, since the overall patterns are not much different from those of previously existing nGAAP standards. While provisioning increases during the pandemic could have been

more forceful in the absence of support measures, our results suggest that IFRS 9 offers enough flexibility to spread these increases over several quarters, reducing the risk of sharp increases in provisioning. Consistent with such flexibility, we also document a strong impact of capital headroom on provisioning practices. While this requires close supervisory scrutiny, the overall implications in terms financial stability are *a priori* ambiguous. On a positive side, flexibility can smooth the potential procyclical impact of ECL accounting when the economy weakens: as mentioned above, poorly capitalised banks can avoid a jump in provisions that would dent their capital and force them to procyclically reduce lending. However, this reduces transparency and may imply an underestimation of credit risk, potentially leading to stronger negative repercussions when risks materialise eventually. Moreover, less capitalised banks may be at greater risk of being underprovisioned, with potentially negative implications in terms of bank stability.

Our paper contributes to a growing literature on the role of discretion and risk modelling in banking and financial regulation. In a context of bank capital regulation, several papers point out incentive problems and undesired effects that may be associated with the use of banks' internal risk models for regulatory purposes (e.g., Mariathasan and Merrouche 2014, Begley et al. 2017, Behn et al. 2016, 2022, or Plosser and Santos 2018). Similarly, evidence on the impact of discretion in insurance regulation is provided by Koijen and Yogo (2015, 2016). But modelling choices and discretion affect the behaviour and performance of financial institutions also beyond the regulatory perimeter. For example, Rajan et al. (2015) demonstrate that failure to account for changes in economic agents' behaviour due to an increased level of securitisation led to a failure of banks' statistical default models, while Huizinga and Laeven (2012) and Bischof et al. (2021) show that accounting discretion on the side of banks contributed to delayed loss recognition during the global financial crisis.[5] We add to this literature by examining the performance of accounting risk models and the impact of banks' capital on their provisioning practices. To the best of our knowledge, our paper is the first to empirically assess whether the recent shift to ECL accounting has altered the role of discretion in banks' loss recognition.

We also add to literature that examines the interaction between accounting standards, bank regulation, and financial stability. A focal point of this literature has been on the impact of provisioning practices on bank lending and real economic outcomes, often in a context of discussions on potential procyclicality of certain accounting features (e.g., Jiménez et al. 2017,

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[5] On the role of accounting discretion during the global financial crisis, see also Balasubramanyan et al. (2017).

Huizinga and Laeven 2019, Blattner et al. 2020).[6] Following the shift to expected loss accounting after the global financial crisis, several studies examined how the new approach would impact banks' lending behaviour, for example by making use of simulation methods or theoretical models (Abad and Suarez 2018, Buesa et al. 2019, Mahieux et al. 2022, Kund and Rugilo 2023), by analysing the effects of forward-looking elements of the previous incurred loss approach (Beatty and Liao 2011, Bushman and Williams 2012), or by analysing earlier accounting reforms at the national level (Morais et al. 2022). We expand on this literature by examining how expected loss accounting performed and compared with incurred loss accounting during the period of the pandemic and after the energy price shock in 2022. That is, we analyse the functioning of the new approach under real life stressed economic conditions, which is highly relevant from a financial stability perspective and provides important insights for academics and policymakers.

The remainder of this paper is organised as follows: In Section 2, we briefly describe institutional arrangements and discussions surrounding the introduction of ECL accounting in recent years. We introduce our data set in Section 3 and describe the empirical strategy in Section 4. Section 5 presents our estimation results and Section 6 concludes.

2 Institutional background

2.1 Introduction of IFRS 9 in Europe

Expected credit loss (ECL) accounting was introduced after the global financial crisis of 2007-09, as the previously prevalent incurred loss (IL) approach was widely criticised for delaying the recognition of loan losses and inducing banks to provision "too little, too late." Delayed loss recognition under the "backward-looking" IL approach complicated the identification of weaker institutions and may have amplified financial system procyclicality when losses eventually materialised and banks constrained credit supply (e.g., Financial Stability Forum 2009). The more "forward-looking" ECL approach is supposed to enhance transparency and promote speedier and more accurate recognition of losses by considering not only realised but also expected credit risk losses (e.g., International Accounting Standards Board 2013, Cohen and Edwards 2017).

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[6]The role of fair value accounting has also been examined in this context (e.g., Laux and Leuz 2010, Xie 2016). Moreover, there is a rich empirical literature studying potential procyclical implications of certain features in bank capital regulation (see, e.g., Behn et al. 2016, Gropp et al. 2019, or Fraisse et al. 2020, among many others).

Provisions under ECL accounting reflect predicted credit risk losses from the time of loan origination onward, making use of dedicated provisioning models and the available set of information at each point in time. The move towards ECL accounting eventually resulted in the adoption of the International Financial Reporting Standard 9 (IFRS 9) at a global level, which is in the focus of our paper, and the similar U.S. Current Expected Credit Losses (CECL) standards.

The final version of IFRS 9 was published in July 2014 and replaced the previously applicable International Accounting Standard 39 (IAS 39) in January 2018. Since the move to ECL accounting was expected to lead to an initial increase in provisions, European legislators made use of transitional arrangements that mitigated the initial impact on regulatory capital ratios.[7] Application of IFRS 9 is mandatory for consolidated financial statements of public companies that are listed in any member state of the European Union. Other companies (e.g., unconsolidated or non-listed entities) have to report under national Generally Accepted Accounting Principles (nGAAP), although they have the option to voluntarily apply IFRS 9 in some but not all member states.[8] For this reason, our sample contains both IFRS 9 and nGAAP loans. While national accounting standards contain forward-looking or discretionary elements in some cases (see detailed discussion by Domikowsky et al. 2015, 2017), they are generally of an incurred loss nature and expected to be *less* forward-looking than IFRS 9. Most importantly, they have existed since long ago, so that the comparison with IFRS 9 allows to assess whether post-crisis reforms have fundamentally altered provisioning patterns relative to pre-existing national regimes.

Under IL accounting, provisions are generally established only following a credit event, resulting in low impairment ratios before a default and large increases at the time of default. In contrast, under IFRS 9, loans are sorted into three distinct buckets – referred to as 'stages' – which determine the amount of provisions that a bank needs to set aside for the respective exposures (see Figure 2 for an overview). Performing loans are sorted into stage 1 from the time at which they are originated or purchased. Provisions for stage 1 loans need to reflect the

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[7]Specifically, over the transition period from 2018 to 2022, the Capital Requirements Regulation (CRR) allowed banks to add back to their Common Equity Tier 1 (CET1) capital a declining share of the higher provisions arising from the application of IFRS 9. That is, the provisions themselves were not altered and in line with IFRS 9 as of 2018, but their impact on regulatory capital ratios was partially neutralised via a prudential filter.

[8]More specifically, individual Member States have an option to require or permit IFRS 9 as adopted by the EU (Member State Option) for the individual financial statements of listed companies, and the consolidated or individual financial statements of non-listed companies (for further details, see the IFRS Jurisdictional Profile for the European Union, published online under https://www.ifrs.org/content/dam/ifrs/publications/jurisdictions/pdf-profiles/european-union-ifrs-profile.pdf). Our empirical analysis accounts for structural differences between institutions using IFRS 9 and those using nGAAP, as explained in Section 4.

12-month expected credit risk loss, defined as the product of the one-year ahead probability of default and the expected lifetime loss given default. A loan is moved to stage 2 if it experiences a significant increase in credit risk according to the bank's criteria, and it is moved to stage 3 if in addition there are objective indications of credit impairment.[9] In both cases, banks need to provision an amount corresponding to the full lifetime expected credit risk loss, defined as the product of the expected lifetime loss given default and the probability that the borrower defaults at any point during the life of the loan. The switch in the provisioning horizon from 12 months under stage 1 to the loan's full lifetime under stages 2 and 3 is supposed to account for the deterioration in credit quality and the resulting higher likelihood of loss materialisation.[10]

Overall, IFRS 9 introduces three key modifications: (i) it induces higher ex ante provisioning by resorting to expected credit losses; (ii) it makes provisioning more responsive to changes in credit risk; and (iii) it enhances the role of internal models in estimating credit risk losses.

2.2 Discussions on possible procyclicality of IFRS 9

A first objective of our paper is to assess whether IFRS 9 has fundamentally altered provisioning patterns around credit risk shock, which could have implications in terms of financial system procyclicality. A certain degree of cyclicality is inherent in banking activity, inter alia because the occurrence of losses usually depends on economic conditions and may induce banks to shrink their balance sheets by putting pressure on bank capital (e.g., Bernanke and Lown 1991 and many papers that followed). However, in recent years there has been a fierce debate on whether specific elements of the accounting framework may act procyclically (for a comprehensive discussion, see Basel Committee on Banking Supervision 2021). In fact, the introduction of ECL accounting was supposed to address certain procyclical features of the IL approach, since it was widely believed that earlier recognition of credit risk losses would have reduced uncertainty and dampened cyclical fluctuations in the global financial crisis (e.g., Financial Stability Forum 2009). However,

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[9]The precise sorting of loans into stages depends on the bank's accounting practices. IFRS 9 requires that a loan is sorted into stage 2 if the borrower is 30 days past due on payment obligations. Significant increases in the estimated probability of default (PD), crossing of a specific PD threshold, or other credit events could also indicate a significant increase in credit risk that would require a sorting into stage 2. A sorting into stage 3 is required if credit losses are incurred, so that stage 3 provisions are often portrayed as being similar to provisions under the IL approach. Stage 3 exposures usually correspond to defaulted exposures, since there is a strong overlap between the prudential definition of default and the accounting definition of credit-impaired.

[10]The shorter provisioning horizon for stage 1 loans distinguishes IFRS 9 from CECL in the U.S., since the latter requires banks to provision for expected lifetime credit risk losses from loan origination onward.

concerns that certain features of IFRS 9 might themselves be procyclical arose even before the new standard was implemented. Specifically, some commentators feared that a sudden and significant deterioration in economic conditions could trigger significant loss provisioning in the early stages after a shock and before the defaults actually occur, which in turn could exacerbate the downturn if banks constrained credit supply in reaction to the initial losses (see, e.g., European Systemic Risk Board 2017, Abad and Suarez 2018), potentially amplifying the coming wave of defaults. These concerns were aggravated by the possibility of so called "cliff effects" that could occur if a large number of exposures are suddenly moved to stage 2 or stage 3 and subjected to full lifetime provisioning (recall Figure 2), resulting in a sudden increase in overall provisioning. To be clear, the mechanism behind these concerns is similar to the one that motivated the initial adoption of IFRS 9. The main difference is in the timing: under IL approaches, concerns related to sizable provisions and losses trigger procyclical adjustments late in a crisis, whereas under IFRS 9 such effects may occur soon after a shock.

The shock of the pandemic in early 2020 occurred while banks were still transitioning to IFRS 9 and concerns about possible the procyclicality of the new approach were floating around the regulatory and supervisory community. As a result, authorities around the globe adopted several ad hoc support measures that aimed to prevent excessive procyclicality and facilitate banks' ability to support the economy throughout the economic downturn that followed the initial pandemic shock. With respect to provisioning, support measures can be broadly grouped into two categories (see Figure 3 for a brief chronology of the events): first, authorities encouraged banks to make use of the flexibility embedded in IFRS 9 and provided guidance to banks on how to avoid excessive procyclicality in their provisioning models, e.g., in relation to the use of forecasts or the role of public support measures. Second, authorities encouraged the use of IFRS 9 transitional arrangements and later expanded the set of provisions that could be added back to CET1 capital, to mitigate the impact of higher provisions on regulatory capital ratios. Conceptually, the impact of these support measures on observed provisions may have gone in different directions and is likely to have varied across measures, across banks, and over time.[11]

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[11] Guidance on avoiding excessive procyclicality is not a support measure per se, since it mainly points to existing flexibility within IFRS 9. Nevertheless, such guidance may have reduced provisioning, depending on how it was interpreted by individual banks. Importantly, the tone of the guidance started to change towards the end of 2020, as ECB Banking Supervision put increasingly more emphasis on sound credit risk management and ensuring that loan exposures are allocated into the appropriate IFRS 9 stages (see Figure 3). Hence, it is likely that any impact of the guidance on banks' provisioning behaviour was strongest in 2020. In contrast, the possibility to add back provisions to CET1 may have had a more neutral effect or may even have encouraged IFRS 9 banks to provision more, since the impact of higher provisions on regulatory capital was neutralised.

Moreover, provisioning may have been affected also by other public support measures such as loan moratoria or state guarantees, since the former may have reduced the need to classify loans as under- or non-performing, whereas the latter reduced the amount of expected losses in the case of a loan default. As we will explain in Section 4, our empirical analyses account for the impact of public support measures and guidance during the pandemic in several ways.

2.3 Role of discretion in banks' accounting practices

A second objective of our paper is to assess whether IFRS 9 has altered the role of discretion in accounting standards. As pointed out in the literature reviews by Beatty and Liao (2014) and the Basel Committee on Banking Supervision (2021), discretionary elements had a strong influence on banks' accounting practices even under the IL approach, where possible motives for discretionary adjustments in provisions relate to earnings smoothing and capital management (see, e.g., Laeven and Majnoni 2003, Bushman and Williams 2012, Bischof et al. 2021). Put simply, accounting discretion could induce banks to provision "as much as they can afford" given current headroom on top of capital requirements. While the use of discretion in this manner could potentially help to mitigate procyclical effects during economic downturns (when earnings are typically lower and capital headroom is tighter), it also undermines transparency and may reduce trust in the accuracy of banks' balance sheets.

IFRS 9 arguably affords banks with more discretion than IL accounting, since the calculation of expected losses entails substantial judgment almost by definition. While the new approach established broad operational principles, ultimate provisioning needs heavily depend on banks' interpretation of the standards, their modelling approaches and the assumptions taken (European Systemic Risk Board 2017). Thus, given an inherent reluctance to impair assets and recognise losses (Laux and Leuz 2009, 2010, Huizinga and Laeven 2012), discretion offered by the reliance on internal risk models may have tempted some banks to make modelling or data choices that minimise provisioning needs or attenuate their responsiveness to macroeconomic variables, where the latter was partly encouraged by authorities during the period of the pandemic (see previous subsection). Such behaviour would be similar to what has been documented for bank capital regulation, where banks exploited discretion offered by the internal ratings-based approach to reduce regulatory capital requirements (see, e.g., Begley et al. 2017, Plosser and

Santos 2018, Behn et al. 2022). While we are not aiming for an ultimate judgment on the desirability of accounting discretion from a financial stability perspective, our empirical setup allows exploring the role of capital management motives and comparing the relevance of discretionary factors under IFRS 9 and IL approaches.

3   Data

3.1   Corporate loan data

We combine three different data sets to examine the evolution of euro area banks' provisioning practices in the period from 2018-Q3 to 2022-Q4. Our primary source of information is the Eurosystem's "Analytical Credit Database" (short "AnaCredit"), i.e., the euro area's corporate credit register. The data set includes granular information on euro area banks' corporate loan exposures, with data collection harmonised across the 20 member states. Specifically, banks have to report all loans to euro area or non-euro area corporate borrowers for which their aggregate exposure to the respective borrower is above EUR 25,000.[12] Overall, AnaCredit covers more than 30 million loans per quarter. We focus on loans to the non-financial private sector and collect quarterly information on the following loan characteristics: the carrying amount, the provisioning ratio, the maturity, the protection ratio (covering collateral and guarantees) and whether the loan benefits from a COVID-related public credit guarantee and/or moratorium and whether the accounting framework is IFRS 9 or nGAAP.[13] We aggregate this information at the bank-firm level, so that the unit of observation in our main data set is at the bank × firm × quarter level. Specifically, we sum up loan-level volume variables and compute weighted averages for the maturity (using the loan-level sum of carrying amount and provisions as a weight). In this aggregation, we consolidate banks at the level of the lender's ultimate parent in the euro area (making use of the ECB's RIAD data set), which is necessary since a banking group can separate its different credit relations with a single borrower across different subsidiaries. For

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[12] For additional documentation on AnaCredit, see https://www.ecb.europa.eu/stats/money_credit_banking/anacredit/html/index.en.html as well as the descriptive paper by Israel et al. (2017).

[13] Specifically, our data set includes loans and revolving credit other than overdrafts, convenience credit, extended credit, credit card credit, reverse repurchase agreements, and trade receivables and financial leases. COVID-guaranteed loans have been identified by using registry information (e.g., LEI and RIAD codes) of the promotional lenders charged with this task in each country since March 2020 (for example, ICO in Spain, KfW in Germany, BPI in France, or SACE/Fondo di Garanzia in Italy).

simplicity, we refer to a bank-firm observation as a "loan" hereafter, although in practice each bank-firm observation may comprise several individual loans, as just explained. Following the supervisory definition, the provisioning ratio (or impairment ratio, as the terms "provision" and "impairment" are used interchangeably throughout the paper) is defined as the ratio of provisions over the sum of provisions and the carrying amount. From AnaCredit we also extract information on borrowers' economic sector. The latter is defined with the NACE (Nomenclature of Economic Activities), the European statistical classification of economic activities. We use the second level of granularity in NACE (hereafter NACE-2 level), which defines 86 sectors.

Panel A of Table 1 shows summary statistics for the 30,166,459 loans in our data set, while Panel B shows the correlation matrix for the loan-level variables. All explanatory variables are winsorised at the 1% and 99%.[14] As expected, given the holistic nature of AnaCredit, the loans differ massively in size and maturity. About 14 percent of them benefited from public credit guarantees schemes and 2 percent from moratoria put in place during the COVID-19 pandemic. Moreover, about 6 percent of the loans are in default, while the provisioning ratio stands at 4.3 percent on average but exhibits large heterogeneity (standard deviation of 15 percentage points). Panel C of Table 1 reports how our sample loans are split across accounting classifications. Although our sample includes more banks using nGAAP (see Appendix A), almost 85 percent of the loan observations are under IFRS 9, since larger banks that originate the bulk of corporate loans in the euro area are primarily using the latter approach.[15] Not surprisingly, the bulk of observations is in the performing loan classes, i.e., stage 1 for IFRS 9 and the general allowance category under nGAAP (which corresponds to performing nGAAP loans), which account for 79 percent and 87 percent of IFRS 9 and nGAAP loans, respectively.

3.2 Bank balance sheet and income statement information

We match the loan data with bank-level information from supervisory statistics (COREP/FIN-REP reporting templates). The quarterly reporting covers accounting and prudential data, providing us with information on banks' balance sheets and income statements. Descriptive statistics at the quarterly level for the 1,721 distinct banks in our sample are provided in Panel A

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[14]The protection ratios are capped at 200% to avoid distorting the regressions with very high values, as many loans have protection ratios well above 1000%.

[15]In very few cases (less than 1 percent of the data), a bank has both IFRS 9 and nGAAP loans with the same firm in the same quarter. For these, aggregation is performed at the bank × firm × quarter × framework level.

of Table 2, while Panel B shows the correlation matrix. The table shows that banks typically have capital headroom (CAP HEAD) on top of regulatory requirements, although there is substantial heterogeneity (standard deviation of around 6 pp). While correlation coefficients are not excessively high, banks with more capital headroom tend to have lower risk weights and fund themselves with fewer deposits. As we explain in Section 4, a potential identification issue for our empirical analysis is that banks using IFRS 9 could be systematically different from those using nGAAP.[16] For this reason, we perform in a robustness exercise a Propensity Score Matching (PSM) to arrive at a reduced sample of banks with comparable characteristics for banks using the two approaches. As described in Appendix A, IFRS 9 banks are indeed different from nGAAP banks in the full sample, while the PSM successfully mitigates significant differences.

3.3 Exposure to energy price shocks at the industry level

To explore the impact of the energy price shock in 2022 on banks' provisioning behaviour, we match the loan data with an energy intensity measure constructed by the European Central Bank. The measure is defined at the economic sector (NACE-2 × country) level and computed as the sum of (direct and indirect) inputs from the electricity, gas, steam and air conditioning industries, expressed as a share of sectoral output. We exclude the energy production sectors, as they are highly exposed to energy but benefit from higher energy prices. Data on industry input and output are taken from the Trade in Value Added (TiVA) statistics of the Organisation for Economic Cooperation and Development (OECD), using the OECD's conversion table to match TiVa and NACE-2 economic sectors.[17] A higher value of the measure implies that energy plays a larger role in the respective sector's inputs, hence a stronger exposure of the sector to an energy supply shock (see Gunnella et al. 2022 for further details). Descriptive statistics for the measure are provided in Table 3, which shows that industrial and construction sectors are particularly dependent on energy inputs. Importantly, there is ample intra-group heterogeneity within the three sectoral categories displayed in Table 3, providing us with sufficient variation that allows to identify the impact of the energy shock on provisions.

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[16]We classify banks according to the most frequent accounting framework in their corporate credit portfolio.

[17]See https://www.oecd.org/industry/ind/TiVA-2021-industries.pdf.

4 Estimation strategy

We perform three types of tests to assess how accounting standards and bank characteristics have affected provisioning behaviour during our sample period. First, we analyse determinants of provisioning ratios in the entire sample of quarterly loan observations to obtain insights on general drivers of provisioning behaviour. Second, we study provisioning dynamics around idiosyncratic credit events, to assess potential cyclical implications of accounting patterns. Third, we look at provisioning dynamics around macroeconomic shocks, to analyse cyclical patterns around correlated credit events that are particularly relevant from a financial stability perspective.

In a first step, we use the entire quarterly loan data and investigate general determinants of provisioning behaviour by estimating the following equation:

$$Prov_{b,f,t} = \alpha_{f,t} + \beta X_{b,f,t-1} + \gamma Z_{b,t-1} + \epsilon_{b,f,t}, \tag{1}$$

where b denotes the bank, f the firm, and t the quarter. The dependent variable is the loan-level provisioning ratio in a given quarter. Explanatory variables include a set of loan-level variables, $X_{b,f,t-1}$, comprising a dummy variable indicating the accounting standard (IFRS 9 vs. nGAAP), the loan volume (in log), the residual maturity, the protection ratio, and variables indicating whether the loan benefits from a public credit guarantee scheme or a credit moratorium established during the COVID-19 pandemic; and a set of bank-level variables, $Z_{b,t-1}$, capturing the bank's capitalisation (capital headroom), size (logarithm of total assets), profitability (return on assets), asset risk (risk weight density), liability structure (deposit over total assets), liquidity (cash over total assets), business model (total credit over total assets), and reliance on central bank funding (central bank liquidity over total assets). The regression includes firm $\times$ quarter interactions, $\alpha_{f,t}$, which control for any observed and unobserved heterogeneity across firm-quarters and ensure that the regression coefficients are identified from variation in provisioning by different banks for loans to the same firm in the same period (see Khwaja and Mian 2008). Thus, our regressions control systematically for any differences in borrower risk that may affect provisioning ratios. Finally, to account for potential correlation, standard errors in all our regressions are double clustered at the firm $\times$ quarter and bank level, unless indicated otherwise.

As discussed in Sections 2 and 3, structural differences between banks using IFRS 9 and

those under national approaches as well as support measures implemented during the pandemic complicate econometric identification of the effects we are interested in. We address these issues in several ways. First, we use Propensity Score Matching (PSM) to construct a sample of IFRS 9 and nGAAP banks with comparable characteristics and repeat our regressions on this reduced sample, thus controlling for bank heterogeneity and improving identification (see Appendix A for details on the PSM). Alternatively, we restrict the sample to banks using both types of approaches for at least 20 percent of their loan exposures and re-estimate our main regressions on this subsample, thus ensuring that we are looking at similar types of banks. Second, we exclude the imminent period of the pandemic in 2020, where the impact of supervisory guidance on provisioning practices was strongest, and check whether our observed patterns persist also outside this period. Moreover, we also analyse dynamics around the energy price shock induced by the outbreak of war in Ukraine, which occurred at a time when the pandemic support measures had already been phased out (see below). Third, we directly control for the impact of COVID-related guarantees and moratoria by including corresponding control variables (see above). Fourth, also the inclusion of firm × quarter interactions helps to control for additional direct or indirect support measures that were implemented at the country- or firm-level. Finally, while some of the support measures may have affected observed differences between IFRS 9 and nGAAP loans (with potential biases going in different directions; see footnote 11), we note that the differentiation between well- and less capitalised banks should be unaffected, since both types of banks benefitted from the support measures in an equal manner.[18]

By estimating Equation 1, we can obtain important insights on how certain variables of interest, such as the applicable accounting standard or the bank's capitalisation, affect provisioning behaviour during our sample period. However, as we want to derive insights on the cyclicality of provisioning patterns under different standards or by different types of banks, we also need to look at provisioning dynamics. Hence, in a second step, we restrict the sample to firms that defaulted during our sample period, and estimate equations of the following type:[19]

$$Prov_{b,f,t} = \alpha_{f,t} + \sum_{h=-3}^{2} \delta_h I_h W_{b,f} + \zeta W_{b,f} + \beta X_{b,f,t-1} + \gamma Z_{b,t-1} + \epsilon_{b,f,t} \tag{2}$$

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[18]We also conduct sample splits and differentiate between well- and less-capitalised banks among IFRS 9 or nGAAP loans only, to exclude that correlation between the accounting and capital variables is driving our results.

[19]More specifically, the estimation sample for this test comprises all loan-quarter observations of firms that default at least once with at least one bank, provided the firm has both IFRS 9 and nGAAP loans in the quarter.

Most of the variables in this equation are defined as above. Additionally, $h \in [-3, 2]$ is an index variable that aligns observations around the default event of the respective loan. Thus, the variables I_h are a set of dummies that take the value one if the respective default occurred h quarters ago and zero otherwise.[20] Depending on the specification, $W_{b,f}$ is a dummy variable that indicates the accounting framework (IFRS 9 vs. nGAAP), or the bank's capital headroom. Thus, by estimating Equation 2, we can assess whether provisioning dynamics around default events differ between banks using IFRS 9 and those using nGAAP, or between well- and less-capitalised banks. In an alternative specification, we align observations around the date where an IFRS 9 loan is moved to stage 2 (rather than the default date), and re-estimate Equation 2 for this different type of credit event. In addition, we also examine the drivers of banks' decisions to place a loan in stage 2 in the run-up to default by estimating the following equation:

$$D(Loan\ in\ S2)_{b,f,t} = \alpha_{f,t} + \sum_{h=-3}^{-1} \delta_h I_h W_{b,f} + \zeta W_{b,f} + \beta X_{b,f,t-1} + \gamma Z_{b,t-1} + \epsilon_{b,f,t} \qquad (3)$$

The left-hand-side variable in this equation is a dummy taking the value one if the loan is in stage 2 in quarter t and zero otherwise. The right-hand-side is the same as above, except for the event window that ends in the quarter before default (since defaulting loans move to stage 3).

By looking at idiosyncratic credit events we can analyse whether provisioning dynamics are generally different between loans using different accounting standards or loans issued by different types of banks, which allows to derive insights on cyclical implications. However, from a financial stability perspective it is particularly relevant to look at correlated credit events as they are often induced by macroeconomic shocks, since such events can have broader systemic implications if many banks simultaneously adjust their behaviour and constrain credit supply. Therefore, in a third step, we look at provisioning dynamics around the macroeconomic shocks induced by the COVID-19 pandemic and the outbreak of war in Ukraine.

The COVID-19 pandemic triggered a massive negative economic shock, due to heightened uncertainty, health concerns and the economic disruptions due to the containment measures adopted to tackle the pandemic. Many firms were forced to close altogether or to work under strict conditions, massively reducing their income while they still had to pay their employees. To examine how the resulting increase in corporate credit risk affected provisioning dynamics

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[20]More specifically, a negative (positive) h indicates that the default is in the past (future).

during the pandemic, we estimate the following two local projections equations:

$$\Delta Prov_{b,f,h} = \alpha_{f,h} + \zeta_h W_{b,f} + \beta_h X_{b,f} + \gamma_h Z_b + \epsilon_{b,f,h}, \tag{4}$$

$$D(Move\,S2)_{b,f,h} = \alpha_{f,h} + \zeta_h W_{b,f} + \beta_h X_{b,f} + \gamma_h Z_b + \epsilon_{b,f,h}, \tag{5}$$

with h the number of quarters since 2019-Q4. The first equation measures the change in the provisioning ratio at the bank $\times$ firm level, while the second is a logit model with the dependent variable taking the value one if the loan was placed in stage 2 in the respective quarter and zero otherwise (this regression only includes loans that were in stage 1 in 2019-Q4).

As explained above, we already control for the support measures implemented during the pandemic in several ways. However, to address remaining concerns about their possible impact, we analyse provisioning dynamics around a second macroeconomic shock that occurred during our sample period, namely the energy price shock induced by the outbreak of war in Ukraine. While there was a clear upward trend in energy prices already in the second half of 2021, prices spiked up in the first and second quarter of 2022, particularly after the start of the war. The strong increase in gas and energy prices had a particularly pronounced effect on the European economy, given its strong import dependence.[21] Assuming that firms that are more reliant on input from energy sectors were hit harder by the shock, we estimate the following equation to assess the timeliness and risk sensitivity of the resulting provisioning adjustments:

$$\Delta Prov_{b,f} = \alpha_f + \theta W_{b,f} \times E_f + \zeta W_{b,f} + \beta X_{b,f} + \gamma Z_b + \epsilon_{b,f}, \tag{6}$$

with $\Delta Prov_{b,f}$ the change in provisioning ratio at bank $\times$ firm level between 2022-Q1 and 2022-Q2 (or, alternatively, Q3 or Q4), E_f the sectoral energy dependence measure described in Section 3.3, and all other variables defined as above. As before, $W_{b,f}$ is a dummy that either indicates the accounting framework or the magnitude of the bank's capital headroom. Hence, the regression allows assessing whether different types of banks adjusted provisions in response to the energy shock in a generally stronger (coefficient ζ) and/or in a a more risk-sensitive (coefficient θ) manner. Importantly, this test is unaffected by support measures adopted during the pandemic, since the latter had already been phased out at the time when the shock occurred.

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[21]For further discussion, see chapter 2.3 of the ECB's Financial Stability Review (November 2022): https://www.ecb.europa.eu/pub/financial-stability/fsr/html/ecb.fsr202211~6383d08c21.en.html#toc13.

5 Empirical results

5.1 General determinants of provisioning ratios

We start the analysis by looking at general provisioning patterns during our sample period. Figure 4 plots the evolution of aggregate provisioning ratios since 2018-Q3. In the upper panel, we distinguish between loans under IFRS 9 and those using national accounting approaches. Not surprisingly, and in line with the reform's objectives, provisioning under IFRS 9 is generally higher than under nGAAP. Specifically, towards the end of our sample period in 2022, aggregate provisioning stood at around 2.0 percent for loans under IFRS 9, compared with around 1.5 percent for loans under nGAAP. The striking decline in provisioning ratios at the beginning of our sample period reflects continuous improvement in euro area banks' asset quality in the years leading up to the pandemic, driven by a reduction in non-performing loans (NPL) in particular.[22] NPL ratios continued to improve throughout the pandemic, but at the same time banks saw an increase in stage 2 provisions (see Figure 5), so that aggregate provisioning ratios stabilised around the levels mentioned above.[23] In the lower panel of Figure 4, we distinguish between banks with below and above median capital headroom (i.e., distance between capital ratio and overall capital requirement). Less capitalised banks started off with higher provisioning ratios because they were, on average, more affected by legacy issues relating to high NPL ratios after the Great Financial Crisis and the European sovereign debt crisis.[24] Strikingly, less capitalised banks exhibit continuously declining provisioning ratios until 2020 and relatively stable ratios thereafter, whereas better capitalised banks markedly increased aggregate provisions at the onset of the pandemic in early 2020. Albeit only illustrative, these patterns are overall consistent with capital management motives by which banks that can afford it increase provisions in a timely manner following a shock, whereas more capital constrained banks may prefer to delay loss recognition in order to avoid getting too close to the regulatory capital requirement.

To control for bank, firm and loan characteristics that may exert an impact on observed

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[22]For further details, see chapter 3.1 of the ECB's Financial Stability Review (November 2019): https://www.ecb.europa.eu/pub/financial-stability/fsr/html/ecb.fsr201911~facad0251f.en.html#toc20.

[23]The offsetting effect between higher stage 2 and lower (non-performing) stage 3 loans applies to loans under IFRS 9, since stage 2 provisioning exists only under this approach. As visible in Figure 5, aggregate provisioning ratios remained relatively stable also under the (incurred loss) nGAAP approaches, since a sizable increase in default rates was not observed during the pandemic.

[24]In 2018-Q3, banks with below median capital headroom had an average NPL ratio of 5.2 percent, compared with 3.0 percent for banks with above median capital headroom.

provisioning patterns, we complement the charts on aggregate developments with a regression analysis. Specifically, we study the determinants of provisioning ratios during our sample period by estimating Equation 1 and present the results in Table 4. In line with aggregate patterns, IFRS 9 loans generally exhibit higher provisioning ratios than loans subject to national accounting standards, also when controlling for a vast range of bank and loan characteristics as well as borrower heterogeneity via the inclusion of firm × quarter fixed effects. The estimates in column 1 indicate that provisioning ratios for IFRS 9 loans are, on average, about 0.50 percentage points (pp) higher than provisioning ratios for nGAAP loans to the same firm in the same quarter. This is in the same ballpark as the magnitudes observed in Figure 4 (upper panel), indicating that differences in provisioning practices (rather than differences in borrower composition) are a strong driver of the observed provisioning gap between IFRS 9 and nGAAP loans at the aggregate level. Moreover, the effect is economically meaningful, considering the average provisioning ratio of 4.31 percent during our sample period. We also find that the coefficient estimate for the bank's capital headroom is positive and highly statistically significant, meaning that banks with more headroom generally provision more, consistent with capital management motives. Again, the effect is economically meaningful: an increase of one standard deviation in capital headroom (5.76 pp) implies a corresponding increase in provisioning ratios of around 0.48 pp. Other bank characteristics have a relatively muted impact on provisioning ratios, whereas loan control variables affect ratios in the expected manner.

In columns 2 and 3 of Table 4, we replicate regressions on the subsamples of IFRS 9 and nGAAP loans, respectively, with broadly similar results. Specifically, coefficients for capital headroom are statistically significant and of similar magnitude in both subsamples, indicating that general capital management motives may be prevalent under both accounting approaches. Moreover, results persist in a number of robustness checks, housed in Table 5. First, we use a Propensity Score Matching to build comparable samples of banks using IFRS 9 and nGAAP. Specifically, we first classify banks as "IFRS 9" or "nGAAP" according to their dominant accounting framework. The matching procedure then uses the "nearest neighbor" approach, a caliper of 0.2, and matching on the bank-level explanatory variables of Equation 1 (see Appendix A for details). Results are reported in columns 1 to 3. Alternatively, to ensure that we are looking at comparable banks, we restrict the sample to banks using both IFRS 9 and nGAAP for at least 20% of their loans each, and re-estimate the regressions on this subsample

of banks (see columns 4 to 6 for the results). As a third alternative, in column 7, we saturate the specification by including bank × quarter fixed effects. In this way, we control systematically for any observed and unobserved time-varying bank heterogeneity that may affect provisioning, but are no longer able to identify the impact of bank-level variables such as capital headroom (since the same bank can have both IFRS 9 and nGAAP loans, we can still identify the coefficient on the dummy indicating the loan's accounting framework). Finally, we use an alternative data set aggregating loans at the more granular bank-firm-quarter-*type of loan* level, to control for the possibility that a firm contracts different types of loans from different banks, which could in turn drive differences in provisioning.[25] Results are reported in columns 8 to 10. As shown in Table 5, our results persist in all these robustness checks.

For IFRS 9, we can further split the sample into loans in different stages. This additional sample split is reported in Table 6 and reveals that differences in provisioning for banks with different levels of capital headroom are particularly pronounced for under- and non-performing loans in stages 2 and 3, as the coefficient estimate on capital headroom increases in magnitude and statistical significance as the loan quality deteriorates. One explanation for this could be that provisioning ratios are generally higher in the upper stages, so that there may also be room for larger adjustments in both directions. In line with this argument, also the mitigating effect of COVID-19 related guarantees is particularly pronounced in stage 3. Interestingly, some bank characteristics have a differential impact on provisioning ratios in different stages: for example, larger banks tend to provision less in stage 1 but more in stage 3. This illustrates that IFRS 9 affords banks with a lot of discretion, so that different types of banks may adopt different accounting strategies, according to their respective preferences. That is, some banks (in this case, smaller banks) may prefer to provision in a rather pre-cautious manner at an early stage, resulting in higher stage 1 provision for the whole stock of loans, while other banks (in this case, larger banks) may prefer to provision in a more targeted manner on loans identified as credit impaired, possibly in line with higher market scrutiny on larger banks for such types of exposures. Overall, the results indicate that accounting strategies differ with respect to the timing and the magnitude of provisioning, leading to vast heterogeneity in accounting practices. In the next sections, we examine what this implies in terms of provisioning dynamics.

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[25]Specifically, for each bank-firm relationship, these tests additionally distinguish between overdrafts, credit card debt, revolving credit other than overdrafts and credit card debt, credit lines other than revolving credit, trade receivables, financial leases, and other loans, with the latter being by far the dominant category.

5.2 Provisioning dynamics around idiosyncratic credit risk shocks

5.2.1 IFRS 9 vs. nGAAP

To analyse the cyclical implications of accounting standards, it is particularly relevant to look at provisioning dynamics, since large adjustments in provisioning following adverse events may trigger the type of procyclical adjustment behaviour by banks that regulators and policy makers usually seek to avoid (see discussion in Section 2.2). Therefore, we proceed by analysing the evolution of provisioning ratios around credit events. Focusing on firms that defaulted during our sample period, the left panel of Figure 6 plots weighted average provisioning ratios around the respective default, separating loans according to their accounting approach. In line with expectations and consistent with previous results, IFRS 9 loans exhibit higher provisioning ratios ahead of default. However, provisioning dynamics are rather similar for IFRS 9 loans and those using nGAAP. Specifically, a significant jump in provisioning at the time of default occurs under both approaches, while increases in provisioning ahead of default are small and gradual. This is markedly different from the conceptual illustration for IFRS 9 loans that is shown in Figure 2, which exhibits substantial frontloading of provisions ahead of default.

To investigate the drivers of this striking difference between conceptual and observed patterns, Figure 7 plots the share of IFRS 9 loans in different stages before default. While there is a clear increase in the share of stage 2 loans in the run-up to a default, it is remarkable that around 50 percent of the loans are still in stage 1 two quarters ahead of the default, and around 35 percent of the loans are still in stage 1 one quarter ahead of the default. Thus, banks appear to be either unwilling or unable to identify significant increases in credit risk at a sufficiently early stage, so that many loans remain in stage 1 and continue to exhibit very low provisioning ratios shortly ahead of default. This is illustrated in the right panel of Figure 6, which continues to show aggregate provisioning dynamics around default but additionally separates IFRS 9 loans into those consistently in stage 1 in the four quarters before the default, those consistently in stage 2, and those that switched from stage 1 to stage 2 in one of the four quarters ahead of default. Indeed, provisioning ratios for stage 1 loans are markedly below those of stage 2 loans ahead of default. Switcher loans are somewhere in between the two groups and gradually catch up with the loans consistently in stage 2, with the most pronounced effect occurring only shortly before default, however. Overall, the patterns suggest that IFRS 9 induces early provisioning

as intended, but only for the roughly 50 percent of loans that are moved to stage 2 sufficiently early. Still, also these loans exhibit a sizable jump in provisioning at default, albeit a smaller one than the other loans.[26] This is mainly because the move to stage 2 induces a rather modest increase in provisioning. First, the average provisioning ratio for a loan increases from 1.0% in stage 1 to 3.8% in stage 2 in the quarter after the move, mitigating concerns about large "cliff effects" at the time of the transition. Second, the average provisioning ratio in stage 2 is only 4.4%, rising to 6.0% for loans that eventually default and 8.5% just before default. As such, this increase is far from enough to avoid a sizeable jump in provisions when the loan defaults, so that the cliff effect at the time of default persists even for loans in stage 2.

We further substantiate the descriptive analysis by estimating Equation 2, thereby assessing dynamics around default while controlling for bank, firm and loan heterogeneity. Regression coefficients are plotted in Figure 8 and yield similar patterns as the descriptive charts. Specifically, IFRS 9 loans exhibit significantly higher provisioning ratios than loans under national standards to the same firm in the same period ahead of a default event, but the jump at the time of default remains substantial under both approaches, suggesting that IFRS 9 has not fundamentally altered provisioning patterns. Differences between the two approaches become statistically insignificant at default and, somewhat surprisingly, even reverse sign after the default event. One possible explanation for the latter could be the support measures implemented during the pandemic: as explained in Section 2.2, some of these measures may indeed have induced IFRS 9 banks to avoid large increases in provisions, at least in the early stages of the pandemic. However, we find very similar results when re-estimating Equation 2 while excluding the imminent phase of the pandemic (2020-Q2 to 2020-Q4), suggesting that the supervisory guidance at that time is unlikely to be a main driver of the observed inversion (Figure 9). Instead, we think that the pattern is likely due to an inherent reluctance of banks to recognise losses, and greater flexibility to avoid such loss recognition for impaired assets under the IFRS 9 approach.[27] We further investigate the validity of this assertion in the next subsection.

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[26]In fact, the absolute magnitude of the jump in provisioning at default is not much different between loans in stage 1 and those stage 2, since the former continue to exhibit markedly lower provisioning ratios also after default. In the next subsection, we further examine the drivers of these patterns.

[27]Indeed, we find that the provisioning gap between IFRS 9 and nGAAP loans gradually closes when further extending the sample after the default event (see Figure 10).

5.2.2 Capital headroom

To gauge the impact of accounting flexibility, we examine whether provisioning patterns around default events depend on banks' capital headroom, since less capitalised banks may have higher incentives to reduce or delay provisions for impaired assets.[28] As explained in Section 2.1, IFRS 9 offers discretion on both the classification of loans into stages and on the level of provisioning for loans in a given stage. Therefore, in principle, less capitalised banks have two levers to limit provisioning increases around credit events under IFRS 9: (i) they can delay the time at which loans are moved to stage 2 and thus provisioned for their entire life rather than 12-months;[29] and (ii) they can limit or delay the increase in provisions for loans in a given stage (either stage 2 or stage 3). In this section, we examine the practical relevance of these two levers.

The left panel of Figure 11 plots weighted average provisioning ratios for IFRS 9 loans around default events, distinguishing between banks with above and below median capital headroom. The chart shows that banks with more capital headroom book higher provisions than less capitalised banks, particularly after the default event. This is in line with a "provision as much as you can afford" strategy and consistent with the findings in Section 5.1, which showed that differences in capital headroom explain divergences in provisioning particularly in the higher stages of IFRS 9. The right panel of Figure 11 continues to distinguish banks by capital headroom but additionally separates loans according to the stages in which they are placed ahead of default (similarly to the right panel of Figure 6). Several aspects are worth noting: first, provisioning ratios for loans from less capitalised banks are always below those of loans from better capitalised banks. Second, ahead of default, this difference is particularly pronounced for loans consistently in stage 2, highlighting the impact of discretion in provisioning once substantial credit risk is identified. What is more, we also find that better capitalised banks showcase a higher proportion of loans that are placed in stage 2 in the quarter ahead of default (65.2% versus 63.4% for less capitalised banks), indicating that banks are using both levers to reduce provisioning needs. Finally, after the default, the difference in provisioning ratios between well-

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[28]Of course, banks cannot permanently avoid loss recognition on impaired loans since the assets will eventually have to be written off. The timing of the write-off varies across loans and depends on loan-, borrower- and country-specific factors. Unfortunately, write-off dates and write-off rates are not consistently reported in the credit register, which prevents us from analysing this issue in a systematic manner.

[29]In principle, they can also delay the time at which a loan is placed in stage 3. However, as explained in Section 2.1, the criteria for placing a loan in stage 3 largely overlap with the criteria for default and are more objective then the criteria for moving a loan to stage 2, thus offering less room for discretionary adjustments.

and less-capitalised banks is particularly pronounced for loans that are consistently in stage 1 ahead of the default. The muted reaction of less capitalised banks for this set of loans also explains why their aggregate provisioning ratio does not catch up with that of stage 2 loans after the default (recall Figure 6, right panel). Overall, the patterns suggest that less capitalised banks reduce provisioning needs under IFRS 9 by (i) moving less loans to stage 2, and (ii) delaying the eventual recognition of losses by reducing provisioning ratios.

As in the previous subsection, we complement the descriptive statistics with a regression analysis that controls for bank, firm and loan heterogeneity. Figure 12 presents regression coefficients for a variant of Equation 2 in which the dummies capturing the distance to default are interacted with the capital headroom. Banks with more capital headroom provision significantly more than less capitalised banks, and this gap increases in the run-up to the default and even more after the default. This corroborates the "provision as much as you can afford" strategy and again suggests that less capitalised banks may under-provision to avoid further weakening of their capital position. To assess whether IFRS 9 has altered the role of discretion in accounting standards, we re-estimate Equation 2 while differentiating between IFRS 9 and nGAAP loans. Indeed, Figure 13 shows a strong impact of bank capitalisation on provisioning for IFRS 9 loans (left panel), for which an increase in the capital headroom by one standard deviation increases banks' provisioning ratios by about 2.8 pp in the quarter of default. In contrast, divergences are smaller and mostly statistically insignificant for loans under national standards ahead of default (right panel). Only post-default, more capitalised banks provision more, reflecting some discretion already existing in the nGAAP standards. Overall, the findings corroborate the assertion that discretionary factors relating to capital management motives affect provisioning behaviour. The stronger effects for IFRS 9 loans could be related to more discretion and heterogeneity in banks' modelling approaches under the new accounting framework.

Next, we analyse the increase in provisioning when moving a loan to stage 2, and also formally assess whether less capitalised banks move fewer loans to stage 2. First, we estimate a logit regression with a dummy indicating whether a specific loan exposure is moved to stage 2 on the left-hand side, and a number of bank and loan characteristics as explanatory variables.[30]

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[30]More specifically, for all firms for which at least one bank moves its respective loan to stage 2 in at least one quarter, we estimate the following equation:

$$Stage2_{b,f} = \alpha_f + \beta X_{b,f} + \gamma Z_b + \epsilon_{b,f},$$

with $Stage2_{b,f}$ taking the value 1 if bank b moves its loan to firm f to stage 2 at any point in time. The other

Results are presented in Table 7 and show that banks with less capital headroom are generally less inclined to move a specific loan to stage 2. Second, we estimate Equation 3 and thereby assess whether a loan is more likely to be placed in stage 2 ahead of a default if it is provided by a bank with more capital headroom. The results in Figure 14 confirm the descriptive statistics reported above: in line with a "provision as much as you can afford" strategy, more capital is associated with a higher probability of moving a loan to stage 2 ahead of default, where the magnitude of this effect increases as default approaches. Third, we look at provisioning dynamics around the time when a loan is moved to stage 2. Specifically, we re-estimate Equation 2, this time aligning loans around the move to stage 2 rather than the default event.[31] Figure 15 shows that provisioning ratios for loans from better capitalised banks increase more after a move to stage 2, compared with loans from less capitalised banks to the same firm in the same period. Again, the results also hold when excluding the pandemic period, making it unlikely that the findings are driven by supervisory guidance on provisioning at that time (Figure 16).

In sum, the findings reported in this section indicate that there is considerable heterogeneity in accounting practices under IFRS 9, both with respect to the timing of transitioning across stages and with respect to the amount of provisions attached to loans in different stages. Banks with less capital headroom appear to be using two levers to manage aggregate provisioning levels, i.e., (i) they are less likely to move a loan to a higher stage, and (ii) conditional on the stage they attach lower provisions to a loan when compared with better capitalised banks.

5.3 Provisioning dynamics around macroeconomic shocks

5.3.1 The COVID-19 pandemic

Our analysis thus far has examined provisioning dynamics around credit risk shocks at the individual loan level. Although the analysis has provided several important insights, supervisors and policymakers are particularly interested in banks' reactions to correlated credit risk events (e.g., adverse economic shocks that weaken borrowers' repayment capacity across the board),

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variables are defined as above. We restrict the sample to loans from banks that were lending to firm f before (at least one quarter), at and after (at least one quarter) the time when the first bank moved its exposure to firm f to stage 2, to avoid including loans that terminated before or started after the period of high credit risk. The explanatory variables are fixed at their value at the time when this first move occurred. That is, there is no time dimension in this regression, which includes one observation for each bank $\times$ firm pair.

[31]Similarly to our approach for default events, we consider all firms whose loan is moved to stage 2 by at least one bank for at least one quarter.

given potential systemic repercussions that can occur if many banks suffer large losses and adjust their behaviour simultaneously. For this reason, we now examine provisioning dynamics in the aftermath of two recent macroeconomic shocks, starting with the COVID-19 pandemic.

The COVID-19 pandemic hit Europe in early 2020 and soon triggered discussions about possible procyclicality of provisioning under IFRS 9 (see Section 2.2). Results in the previous section have illustrated that provisioning dynamics for IFRS 9 loans are not much different from those of previously existing nGAAP loans. On the one hand, this suggests that concerns about possible procyclical effects late in a crisis (i.e., when a lot of loans default) have not been solved by the new approach, since the bulk of provisioning would occur at that time under both approaches. On the other hand, it suggests that concerns about procyclical effects of IFRS 9 early on in a crisis may have been exaggerated, since significant adjustments in provisioning ahead of default are not detectable. However, concerns could remain if a lot of loans are moved to stage 2 at an early stage of a crisis for precautionary reasons, without necessarily defaulting later on in the crisis. Indeed, while aggregate provisioning ratios for IFRS 9 loans remained rather stable throughout the pandemic (recall Figure 4), also due to a continuous decline in stage 3 loans, Figure 5 illustrates that the share of stage 2 loans increased from 9.2% in 2020-Q1 to 13.7% in 2021-Q2. Therefore, in this section, we study the evolution of provisioning during the pandemic in more detail, also aiming to quantify the magnitude of effects that could have occurred in the absence of confounding developments and support measures implemented.

For a start, we assess the implications of the 4.5 p.p. increase in the share of stage 2 loans for bank capital. The average provisioning ratio for a stage 1 loan in the quarter before it is moved to stage 2 is 1.0%, whereas the average ratio in the subsequent quarter is 3.8%. Thus, a move to stage 2 implies an immediate increase in provisioning of around 2.8%. Assuming that corporate loans account for 40% of a bank's total assets, moving 4.5% of its corporate loans to stage 2 implies a decrease of 0.05 p.p. in the equity over assets ratio, all other things equal. With an average risk weight density of 35%, this translates into a decline of the risk-weighted capital ratio by 0.14 p.p.[32] Thanks to the supervisory guidance during the pandemic, this increase was spread out over six quarters (and additionally muted by the confounding decline in stage 3 loans, as mentioned). However, while a decline of 0.14 p.p. is non-negligible, even an immediate

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[32]The decrease in the equity over assets ratio is calculated as $2.8 \times 0.045 \times 0.4 = 0.05$ p.p. This is then divided by 0.35 to translate it into the decline in risk-weighted capital ratios of 0.14 p.p.

decrease by such an amount should have been manageable for banks, not least because prudential authorities released capital requirements amounting to 0.7 p.p. [2.1 p.p. when including Pillar 2 Guidance] with immediate effect, thus easing pressure on capital ratios (see Couaillier et al. 2022b). One could still argue that the increase in stage 2 loans was smaller than it could have been, since the economy recovered quickly and the evolution of corporate credit risk was more favourable than initially expected. However, the conclusions are not altered much when considering a doubling [tripling] of the observed increase in the share of stage 2 loans, which would have implied declines of 0.28 p.p. [0.42 p.p.] in capital ratios, respectively.

As an alternative to looking at absolute effects, we can also analyse the relative evolution of provisioning ratios for IFRS 9 and nGAAP loans during the pandemic. Estimating the local projection model specified in Equation 4, Figure 17 shows the impact of the accounting approach on the change in provisioning since 2019-Q4. The impact was significantly positive since 2020-Q2, indicating that provisioning for similar types of loans to the same borrower increased relatively more for IFRS 9 exposures. The cumulative difference reached 0.4 p.p. in 2021-Q2, which compares with an average provisioning ratio of 4.3% in our sample. Applying a similar back-of-the-envelope calculation and using the same assumptions as above, a 0.4 p.p. increase in provisioning for the entire corporate loan portfolio translates into a decline of 0.46 p.p. in risk-weighted capital ratios, which again appears as non-negligible but manageable.

Finally, we also analyse the impact of capital headroom on provisioning during the pandemic. Figure 18 shows that higher capital headroom was associated with larger increases in provisions in all quarters but the first, where the cumulative impact increased over time. In economic terms, a one standard deviation (5.76 p.p.) increase in capital headroom resulted in an increase of 0.3 p.p. in provisions. Figure 19 provides similar estimates for IFRS 9 and nGAAP loans separately. As expected, given their large dominance, results for IFRS 9 are close to those for the whole sample. In contrast, the impact of capital headroom for nGAAP loans was less consistent and more muted, with a one standard deviation increase in capital headroom raising provisioning ratios by only 0.1 p.p. In a last step, Figure 20 focuses on IFRS 9 loans and shows the impact of capital headroom on banks' decision to move a loan to stage 2 during the pandemic (Equation 5). The impact was positive for the entire period and turned significant in 2020-Q4. In total, a one standard deviation increase in capital headroom increased the odds-

ratio of moving a loan to stage 2 between 2019-Q4 and 2021-Q2 by 27.5%[33]; this means that, for a loan with an initial 50% probability of being moved to stage 2, this probability increased to 56%. Overall, the results fully confirm those in the previous subsection, namely that (i) higher capital is associated with more provisioning, (ii) this effect is more pronounced for IFRS 9 loans, and (iii) better capitalised IFRS 9 banks are also more likely to move a loan to stage 2.

5.3.2 The energy price shock in 2022

In a last step, we focus on a second macroeconomic shock to further improve our identification and assess the robustness of our results. As explained in Section 4, the energy price shock in 2022 strongly affected the European economy largely dependent on imports for energy supply and represented a considerable increase in credit risk for energy intensive companies in particular. Moreover, when the shock occurred, the supervisory focus in the European Banking Union had already shifted towards ensuring appropriate credit risk management and staging of loans, so that provisioning patterns should be less affected by the supervisory guidance to avoid procyclical assumptions in provisioning models that was issued during the pandemic.[34] For these reasons, we consider this second macroeconomic shock in addition to the one induced by the pandemic.

Estimation results for Equation 6 are presented in Table 8. To test for divergences in the dynamics of provisioning after the outbreak of war in Ukraine, we regress the change in provisioning at the bank × firm level between 2022-Q1 and Q2 (columns 1 and 2), Q1 and Q3 (columns 3 and 4) and Q1 and Q4 (columns 5 and 6) on our usual variables of interest. Columns 1, 3 and 5 show that provisioning dynamics over the course of 2022 are similar for the average IFRS 9 and nGAAP loan, as the IFRS 9 dummy has no significant impact on the change in provisions. However, provisions for IFRS 9 loans are increased in a more risk sensitive manner after the credit risk shock, i.e., relatively more strongly for loans to firms in more energy intensive sectors. This is indicated by the positive and significant coefficients for the interaction terms between the IFRS 9 dummy and the energy dependence index described in Section 3.3 (see columns 2, 4 and 6). Thus, banks' IFRS 9 models seem to be capturing the heterogeneous

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[33]$exp(0.0422 \times 5.76) - 1$

[34]See the discussion in Section 2.2 and recent speeches by Andrea Enria, the Chair of the ECB's Supervisory Board, here: https://www.bankingsupervision.europa.eu/press/speeches/date/2021/html/ssm.sp210128~78f262dd04.en.html, and here: https://www.bankingsupervision.europa.eu/press/speeches/date/2022/html/ssm.sp221004~9c9e9504c2.en.html.

impact of the shock on European firms, in line with the intention to increase risk sensitivity. At the same time, all columns show that banks' with more capital headroom increase provisions more than other banks after the shock (positive coefficient on CAP HEAD). This effect seems to occur across the board, however, since the interaction term between capital headroom and energy dependence is statistically insignificant and close to zero. Overall, findings for the energy price shock in 2022 confirm that discretionary factors relating to capital management motives substantially affected provisioning behaviour in the most recent period.

6 Conclusion

In this paper, we examine how the implementation of IFRS 9 has affected the timeliness and risk sensitivity of banks' loan loss provisioning in the euro area. The introduction of IFRS 9 in the aftermath of the global financial crisis marked a major shift in policy making, aiming to reduce financial system procyclicality by addressing 'too little, too late' problems in provisioning. To the best of our knowledge, we are the first to analyse its functioning under real life economic stress with granular (loan-level) data and sophisticated econometric techniques. Specifically, we investigate the determinants of provisioning practices in general, around credit risk shocks at the individual loan level (default, move to stage 2 under IFRS 9), and around the macroeconomic shocks induced by the pandemic and the outbreak of war in Ukraine.

Our findings suggest that some aspects of IFRS 9 seem to be working as intended. The new standard generally induces higher ex ante (precautionary) provisioning, and provisions seem to react in a somewhat more timely and risk-sensitive manner to macroeconomic shocks. However, the forward-looking nature of IFRS 9 also appears to fail in some aspects. First, many loans are not moved to stage 2 ahead of default (or only shortly before default), as banks seem to be either unwilling or unable to identify significant increases in credit risk for these exposures at a sufficiently early stage. Second, provisioning appears particularly low for such exposures, indicating potential underprovisioning for seemingly safe IFRS 9 loans that the banks' provisioning models consider unlikely to default. Third, even loans that are moved to stage 2 experience only a modest (albeit statistically significant) increase in provisioning, so that the bulk of the adjustment under IFRS 9 occurs at the time of default as under national approaches.

Relating to these observations, our results do not suggest that the new approach had substan-

tial implications in terms of financial system procyclicality (neither negative nor positive ones), at least not during our sample period and when compared with national approaches. Specifically, provisioning dynamics around default events are rather similar between IFRS 9 loans and those using nGAAP, with significant cliff effects at the time of default occurring under both types of approaches. Moreover, the often cited cliff effect relating to the move of exposures to stage 2 under IFRS 9 is not detectable when looking at dynamics around default events (e.g., Figures 6 and 8) or the evolution of aggregate provisioning patterns during our sample period (Figures 4 and 5). Possible explanations for this are (i) substantial heterogeneity with respect to the timing of moving exposures to stage 2 (implying that only a small fraction of loans is moved in any given quarter; see Figure 7 for an illustration around default events), and (ii) the rather modest increase in provisioning ratios when a loan is moved to stage 2.

Provisioning levels appear to be affected by capital management motives ('provisioning as you can afford'), meaning that banks with less excess capital tend to provision less. IFRS 9 may have fostered this divergence in accounting strategies across banks, although discretionary elements are also present under national standards. Specifically, banks with more excess capital above requirements generally provision more than other banks, particularly for riskier exposures (i.e., those in stages 2 and 3 under IFRS 9). They also increase provisions more strongly around credit risk shocks at the individual loan level, particularly for loans using the IFRS 9 standard that affords banks with more discretion and allows for heterogeneity in banks' modelling approaches, and are more likely to move loans to stage 2. Finally, they react generally more strongly to the macroeconomic shocks induced by the pandemic and the war in Ukraine.

Importantly, it is difficult to say ex ante whether divergences in provisioning across banks are beneficial or harmful from a financial stability perspective. On the one hand, accounting flexibility may help to mitigate potential procyclical effects, as it can ease pressure on profits and capital ratios in the early stages after a shock. This, in turn, may make it easier for capital-constrained banks to maintain the supply of key financial services to the real economy. On the other hand, such behaviour reduces transparency and may imply underprovisioning by less capitalised banks ('too little'), possibly leading to broader systemic implications if and when (potentially larger) losses eventually materialise ('too late'). Thus, the ultimate outcome for the financial system and the broader economy is likely to depend on the specific nature of the shock (transitory vs. more persistent), including in particular the likelihood for and the

magnitude of potential further losses down the road. Assessing the net impact of all factors on financial stability and bank lending behaviour remains a key area for future research. In any case, our results suggest that banks with less capital headroom are at greater risk of being under-provisioned, possibly also due to the discretion offered by IFRS 9. This divergences point to a need to further assess the adequacy of current provisioning levels at the individual bank level, to address potential concerns in terms of credit risk management.

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Figures & Tables

**Figure 1:** Evolution of loan loss provisioning ratios during the global financial crisis
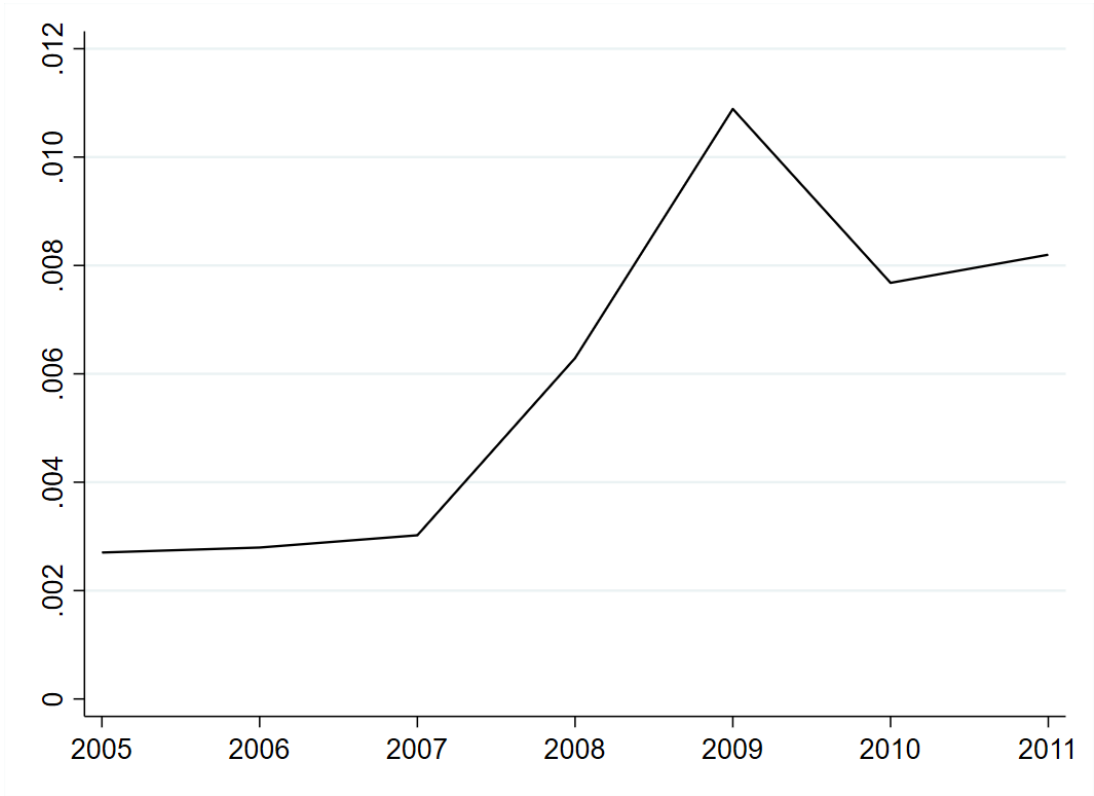
Note: This figure shows the evolution of weighted average provisioning ratios, defined as provisions for loan losses over total gross loans, for a sample 84 European banks that later came under direct supervision by the European Central Bank. The data is sourced from SNL Financial.

Figure 2: Overview of IFRS 9
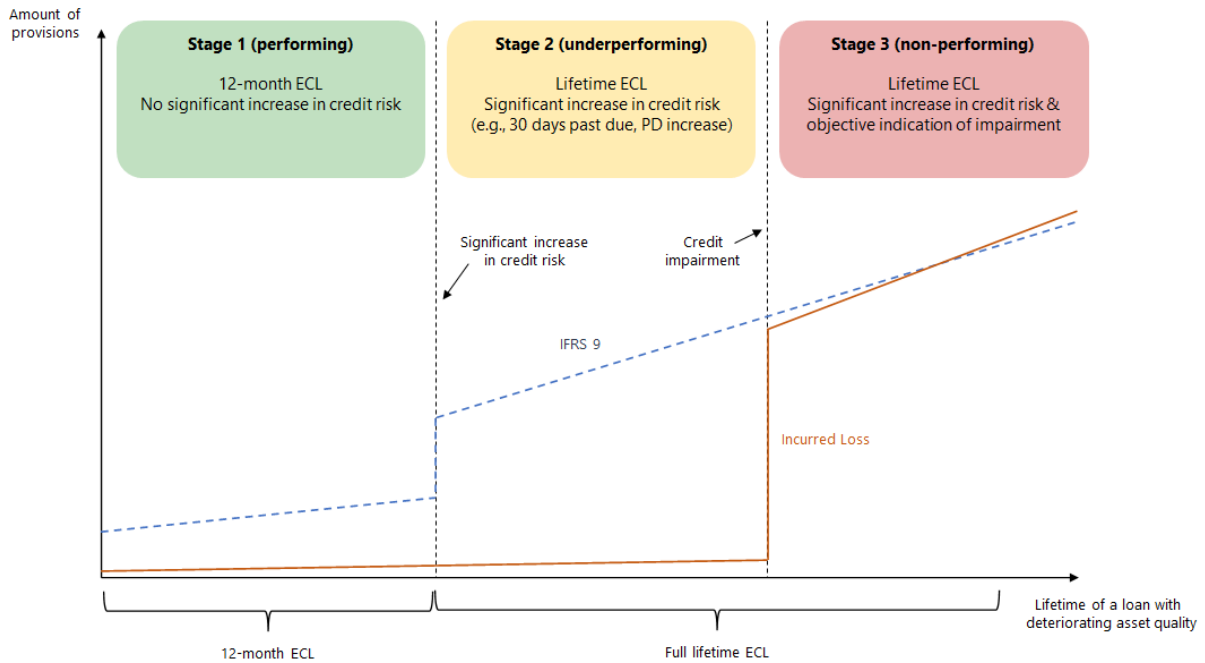
Note: This figure provides an overview of the main features of the IFRS 9 accounting standard and compares the evolution of provisions under IFRS 9 for a loan with deteriorating asset quality to the evolution of provisions for the same loan under an IL approach. Adapted from International Accounting Standards Board (2013).

**Figure 3:** Support measures during the pandemic
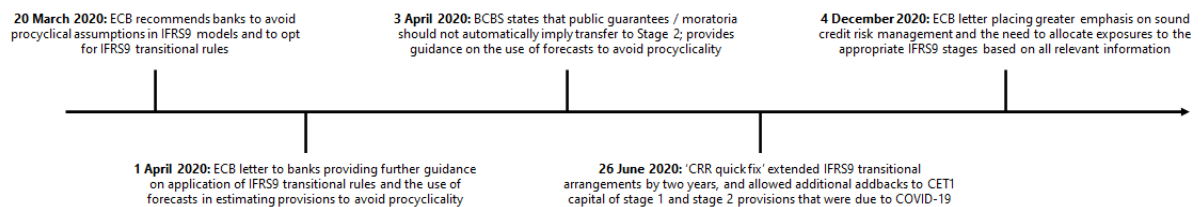
Note: This figure describes support measures and guidance in relation to provisioning that were adopted during the early stages of the pandemic in 2020.

**Figure 4:** Evolution of aggregate provisioning
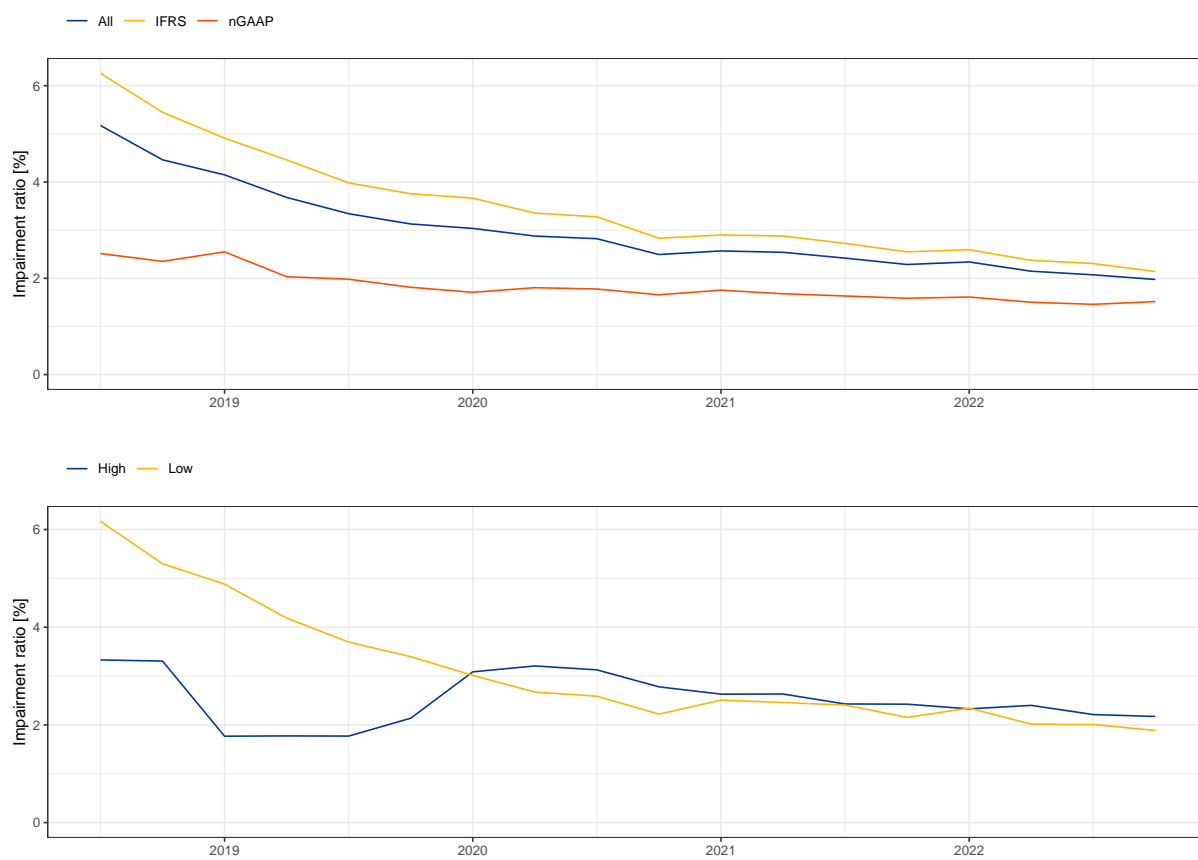
Note: This figure plots the evolution of aggregate provisioning ratios for the banks in our sample, split either by the accounting approach (upper panel) or the bank's CET2 ratio (lower panel, top versus bottom half of banks).

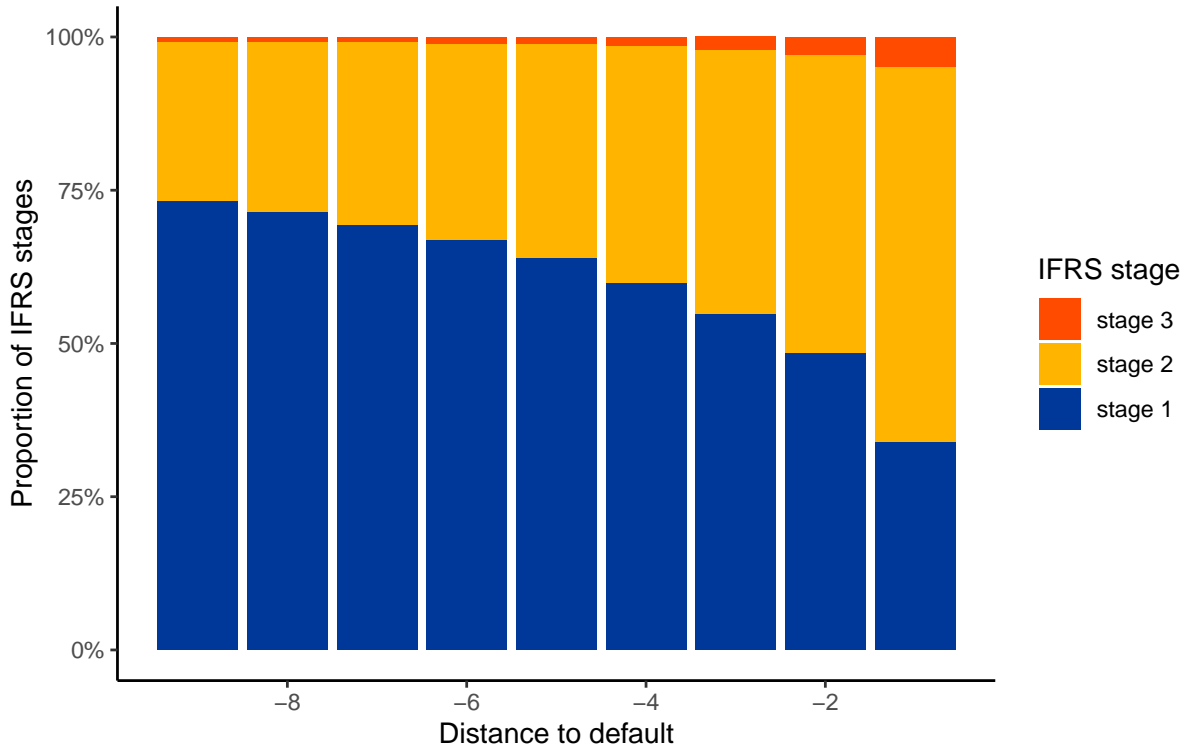**Figure 5:** Share of IFRS 9 loans in different stages
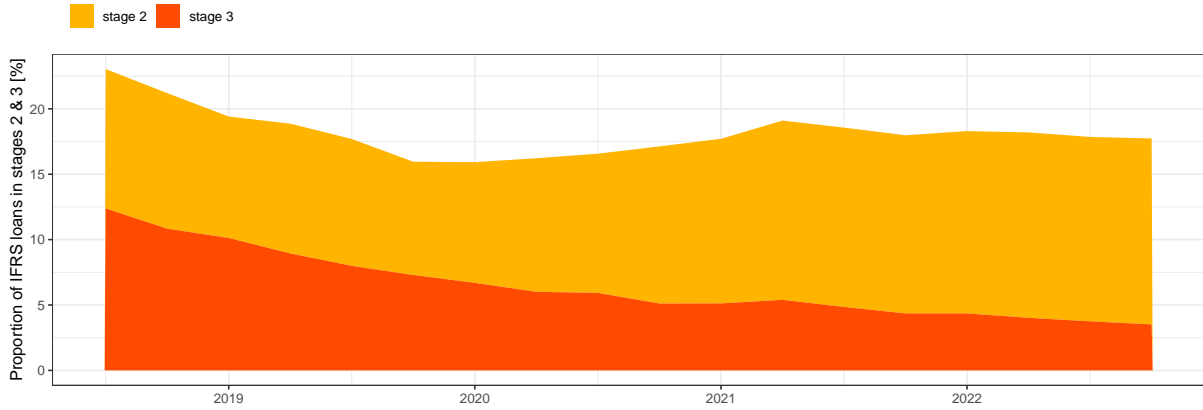
Note: This figure plots the evolution of the aggregate share of IFRS 9 loans in different stages over our sample horizon. The figure shows the percentage of loans in stages 2 and 3, where remaining loans are in stage 1.

Figure 6: Evolution of provisioning ratios around default events
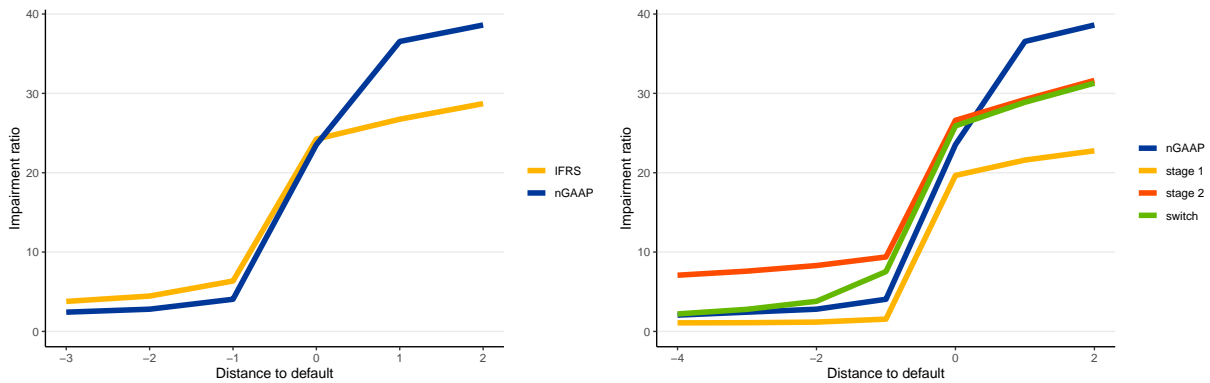

Note: This figure shows the evolution of weighted average provisioning ratios around default events, where the left panel separates loans according to their accounting approach. The right panel additionally separates IFRS 9 loans into those that were consistently in stage 1 ahead of the respective default event, those that switched from stage 1 to stage 2 in the four quarters ahead of default, and those that were consistently in stage 2 throughout this period. The data set is an unbalanced panel.

**Figure 7:** Share of IFRS 9 loans in different stages ahead of default

Note: This figure plots the evolution of the aggregate share of IFRS 9 loans in different stages ahead of the quarter in which the loans default. The data set is an unbalanced panel.

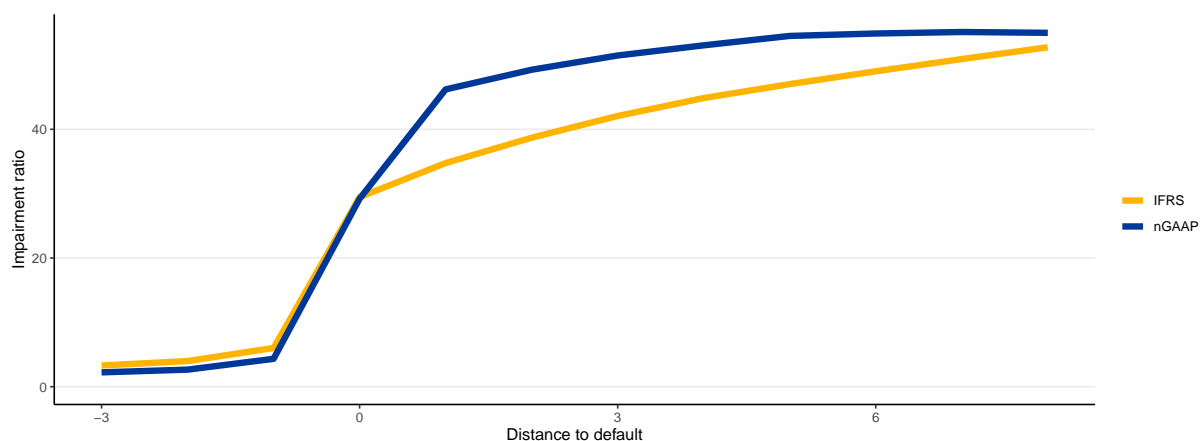**Figure 8:** Provisioning ratio around default by accounting framework: regression
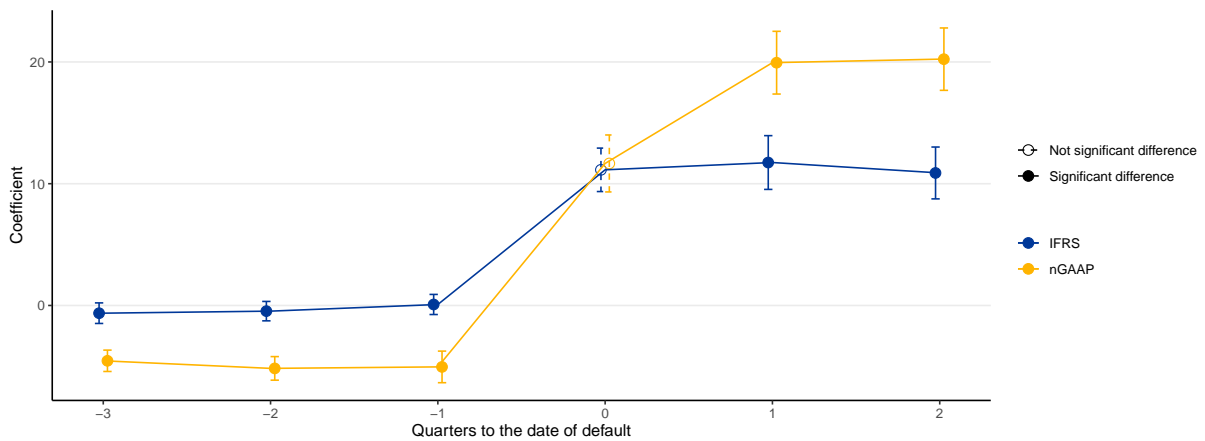
Note: This figure shows the regression coefficients for δ_h in Equation 2, distinguishing loans by the accounting framework. The sample includes all firm-bank pairs reporting a default and without missing values in the interval between [-3; +2] quarters around default. The x-axis reports the distance in quarters to the quarter in which the bank starts reporting default. The vertical lines report the 90% confidence interval. Solid (dashed) confidence interval if the Wald-test for difference of the coefficients is (non)-significant at the 10% level.

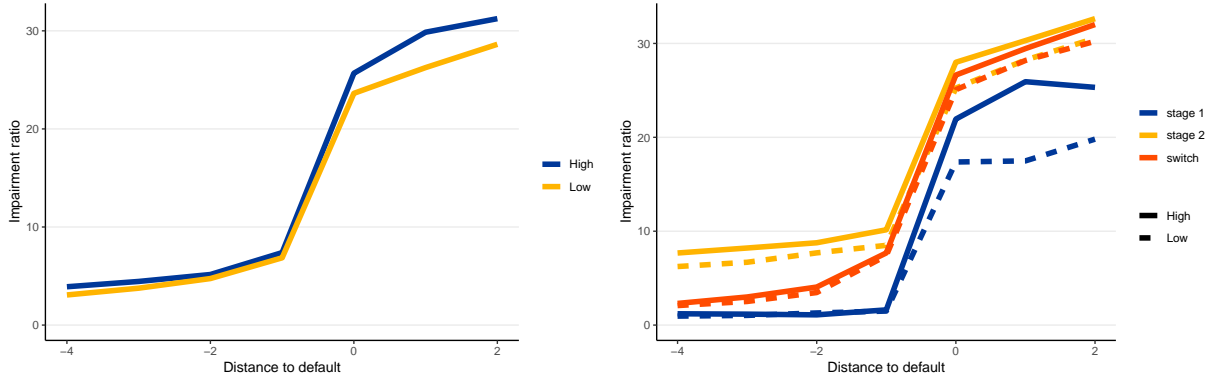**Figure 9:** Provisioning ratio around default – excluding the pandemic
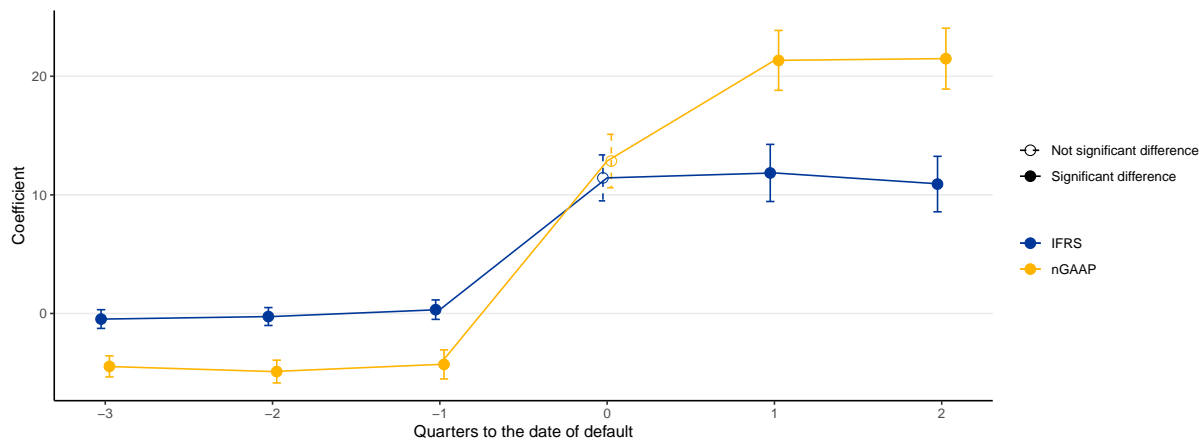
Note: This figure replicates the estimation shown in Figure 8, excluding loans that defaulted during the imminent phase of the pandemic (2020-Q2 to 2020-Q4). For the remaining observations, the sample includes all firm-bank pairs reporting a default and without missing values in the interval between [-3; +2] quarters around default. The x-axis reports the distance in quarters to the quarter in which the bank starts reporting default. The vertical lines report the 90% confidence interval. Solid (dashed) confidence interval if the Wald-test for difference of the coefficients is (non)-significant at the 10% level.

**Figure 10:** Evolution of provisioning ratios around default events – long window

Note: This figure shows the evolution of weighted average provisioning ratios around default events, separating loans according to their accounting approach and extending the time horizon after the default event when compared with Figure 6. The data set is an unbalanced panel.

**Figure 11:** Aggregate provisioning ratios for loans in different stages

Note: This figure shows the evolution of weighted average provisioning ratios around default events for IFRS 9 loans, where the left panel differentiates between banks with above vs. below median capital headroom. The right panel additionally separates IFRS 9 loans that were consistently in stage 1 ahead of the respective default event, those that switched from stage 1 to stage 2 in the four quarters ahead of default, and those that were consistently in stage 2 throughout this period. The data set is an unbalanced panel.

Figure 12: Provisioning ratio around default by capital headroom: regression
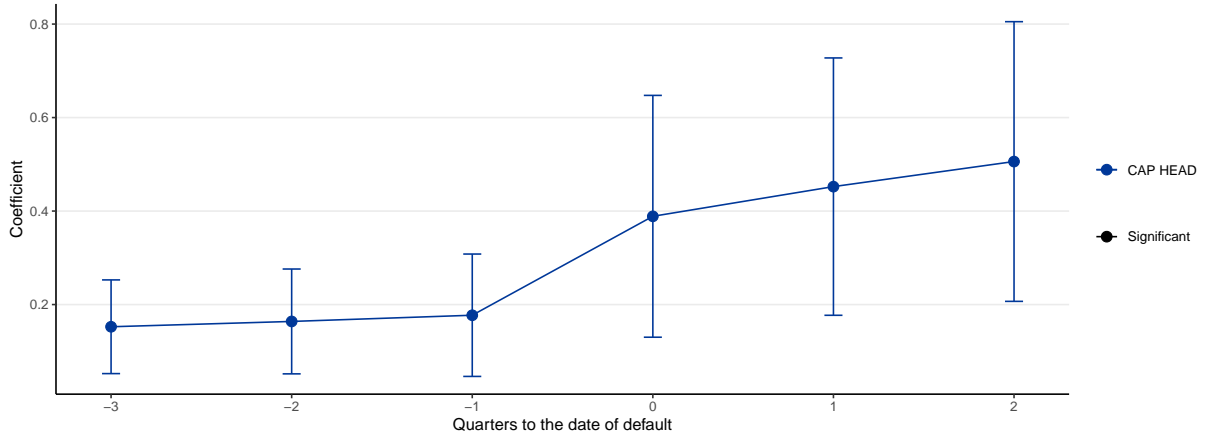
Note: This figure shows the regression coefficients for δ_h in Equation 2, distinguishing loans by the bank's capital headroom. The sample includes all firm-bank pairs reporting a default and without missing values in the interval between [-3; +2] quarters around default. The x-axis reports the distance in quarters to the quarter in which the bank starts reporting default. The vertical lines report the 90% confidence interval. Solid (dashed) confidence interval if the coefficient is (non-)significant at the 10% level.

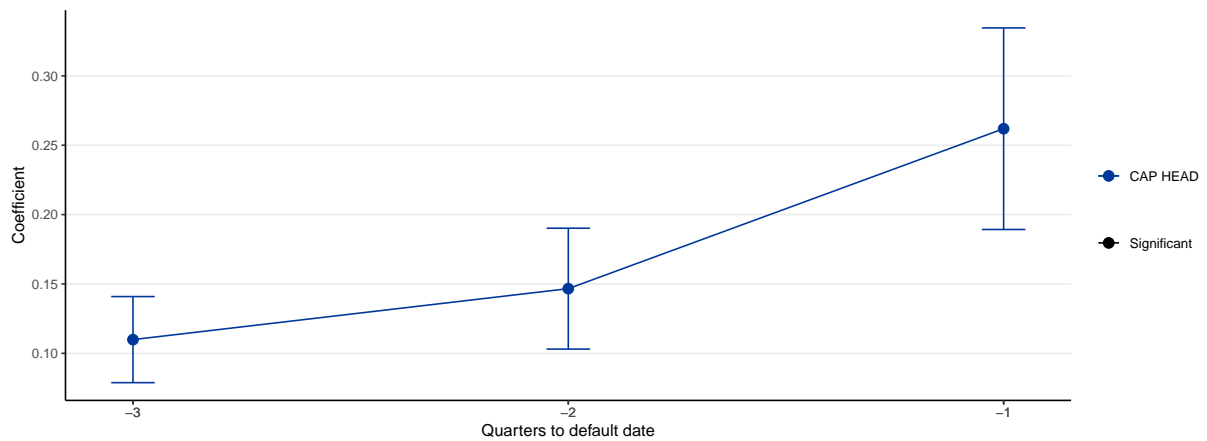**Figure 13:** Provisioning ratio around default by capital headroom (IFRS 9 vs. nGAAP)
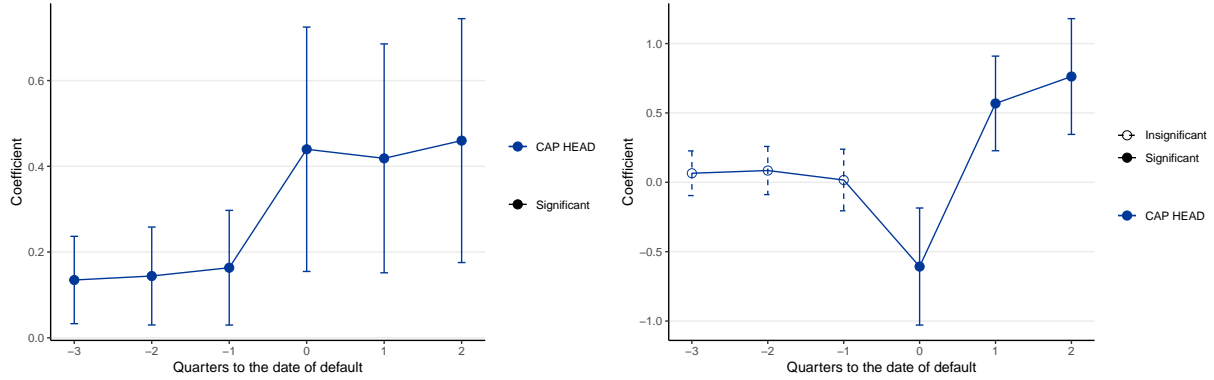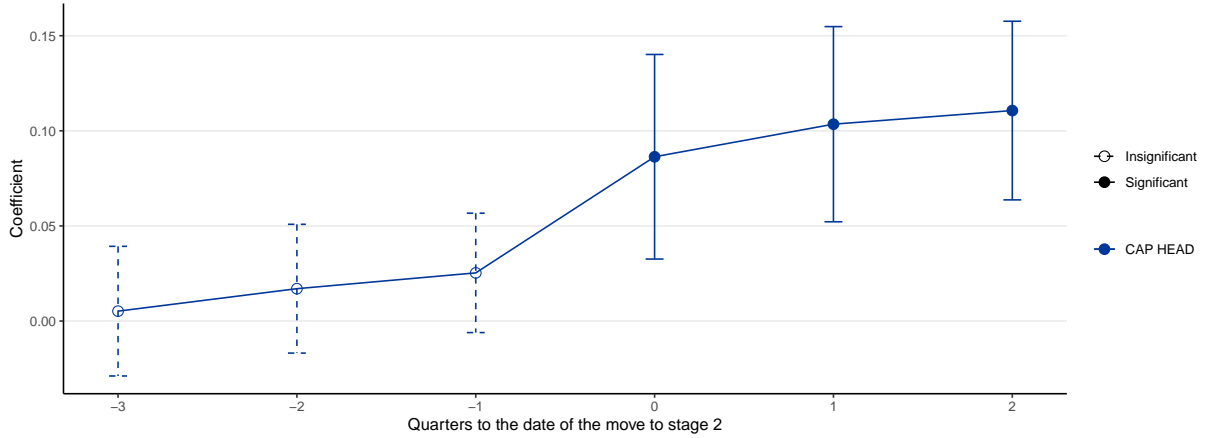

Note: This figure shows the regression coefficients for δ_h in Equation 2, distinguishing loans by the bank's capital headroom and additionally separating the sample into IFRS 9 (left) and nGAAP (right) loans. The sample includes all firm-bank pairs reporting a default and without missing values in the interval between [-3; +2] quarters around default. The x-axis reports the distance in quarters to the quarter in which the bank starts reporting default. The vertical lines report the 90% confidence interval. Solid (dashed) confidence interval if the coefficient is (non)-significant at the 10% level.

Figure 14: Impact of capital headroom on placing a loan in stage 2 ahead of default

Note: This figure shows the regression coefficients for δ_h in Equation 3. The sample includes all IFRS 9 firm-bank pairs reporting a default and without missing values in the three quarters before the event. The x-axis reports the distance in quarters to the quarter in which the bank moves the loan to default. The vertical lines report the 90% confidence interval. Solid (dashed) confidence interval if the coefficient is (non)-significant at the 10% level.

Figure 15: Provisioning ratios around the transition to stage 2: regression

Note: This figure shows the regression coefficients for δ_h in Equation 2, distinguishing IFRS 9 loans by the bank's capital headroom and aligning them around the move to stage 2. The sample includes all firm-bank pairs reporting a move to stage 2 and without missing values in the interval between [-3; +2] quarters around the event. The x-axis reports the distance in quarters to the quarter in which the bank moves the loan to stage 2. The vertical lines report the 90% confidence interval. Solid (dashed) confidence interval if the coefficient is (non)-significant at the 10% level.

Figure 16: Provisioning ratios around the transition to stage 2: regression – excluding the pandemic
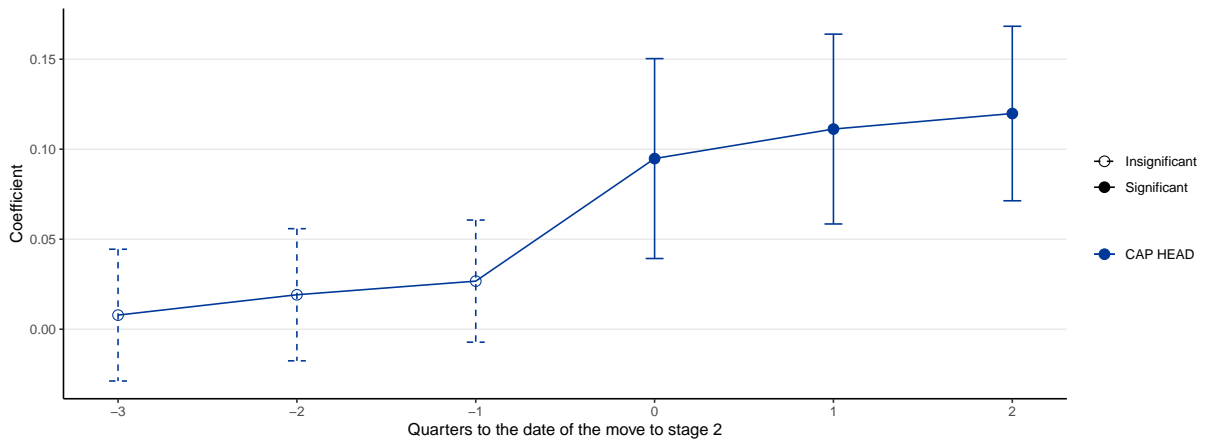
Note: This figure replicates the estimation shown in Figure 15, excluding loans that defaulted during the imminent phase of the pandemic (2020-Q2 to 2020-Q4). For the remaining observations, the sample includes all firm-bank pairs reporting a move to stage 2 and without missing values in the interval between [-3; +2] quarters around the event, excluding the move to stage 2 that occurred in 2020. The x-axis reports the distance in quarters to the quarter in which the bank moves the loan to stage 2. The vertical lines report the 90% confidence interval. Solid (dashed) confidence interval if the coefficient is (non)-significant at the 10% level.

Figure 17: Impact of IFRS on provision ratios during the COVID pandemic
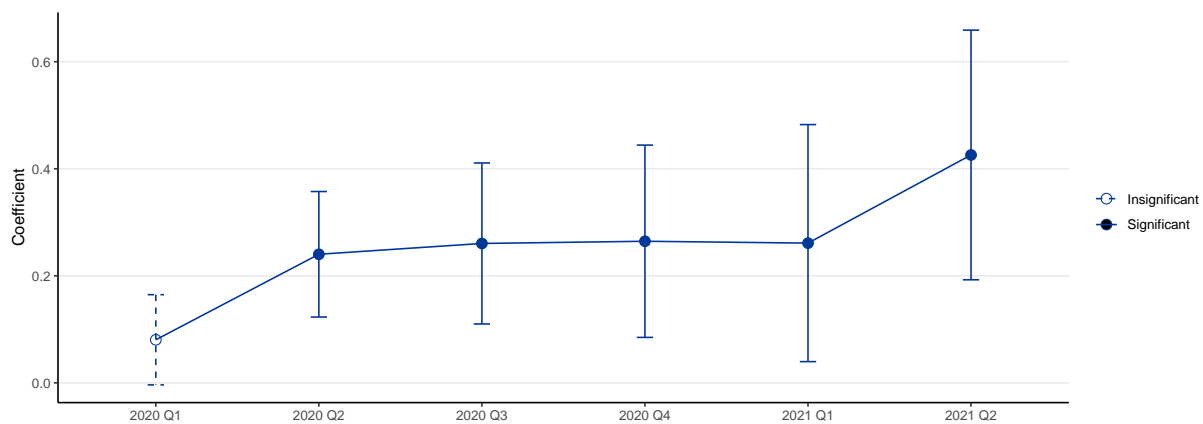
Note: This figure reports the coefficient of the IFRS 9 dummy in the estimation of Equation 4. The vertical lines report the 90% confidence interval. Solid (dashed) confidence interval if the coefficient is (non)-significant at the 10% level.

Figure 18: Change in provisioning ratio during the COVID-19 pandemic by capital headroom
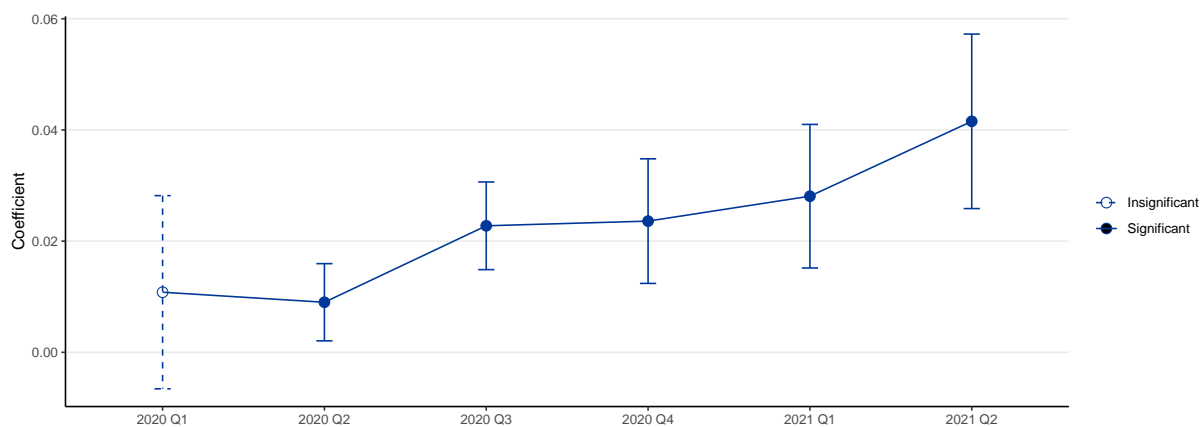
Note: This figure reports the coefficient for the capital headroom variable in the estimation of Equation 4. The vertical lines report the 90% confidence interval. Solid (dashed) confidence interval if the coefficient is (non)-significant at the 10% level.

Figure 19: Change in provisioning ratio during the COVID-19 pandemic by capital headroom (IFRS 9 vs. nGAAP)
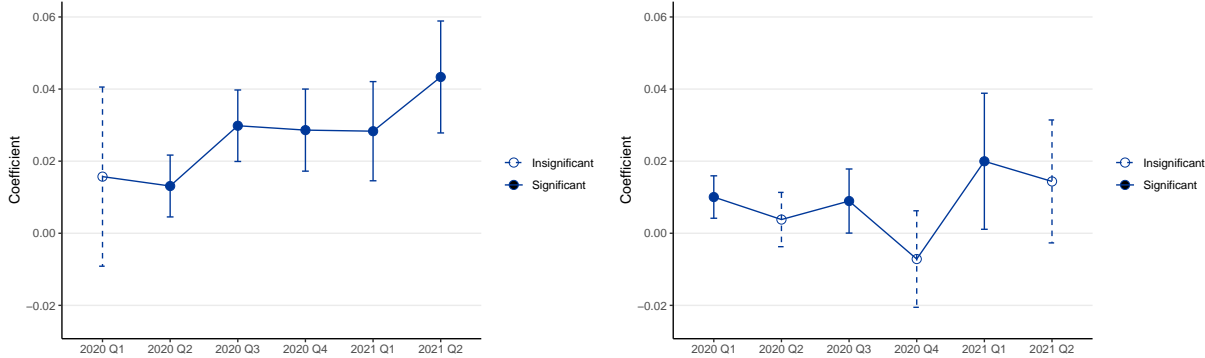
Note: This figure reports the coefficient for the capital headroom variable in the estimation of Equation 4, separating the sample into IFSR 9 (left) and nGAAP (right) loans. The vertical lines report the 90% confidence interval. Solid (dashed) confidence interval if the coefficient is (non)-significant at the 10% level.

Figure 20: Impact of capital headroom on placing a loan in stage 2 during the COVID-19 pandemic
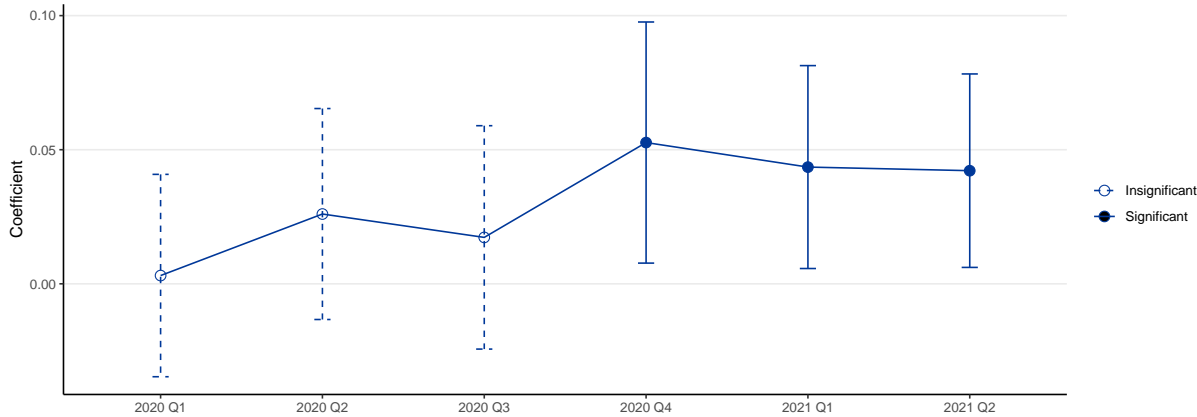

Note: This figure reports the coefficient for the capital headroom variable in the estimation of Equation 5. The vertical lines report the 90% confidence interval. Solid (dashed) confidence interval if the coefficient is (non)-significant at the 10% level.

Table 1: Descriptive statistics – Loan-level data

Panel A: Key characteristics of the distribution							
	Mean	S.D.	Min	Q1	Median	Q3	Max
Credit volume	734310.33	2116803.49	429.48	50159.00	141591.03	448511.00	16148537.51
Provisioning ratio	4.31	15.53	0.00	0.07	0.27	1.01	100.00
Default	6.19	24.06	0.00	0.00	0.00	0.00	100.00
Guarantee	14.40	31.37	0.00	0.00	0.00	0.00	100.00
Moratoria	1.70	11.79	0.00	0.00	0.00	0.00	100.00
Maturity	3.53	4.17	0.00	0.46	2.50	4.65	22.27
Protection ratio	158.04	296.63	0.00	0.00	89.74	174.68	200.00

Panel B: Correlation matrix							
	Credit volume	Provisioning ratio	Default	Guarantee	Moratoria	Maturity	Protection ratio
Credit volume	1						
Provisioning ratio	-0.03	1					
Default	-0.02	0.76	1				
Guarantee	-0.06	-0.08	-0.06	1			
Moratoria	-0.02	-0.03	-0.03	0.02	1		
Maturity	0.16	-0.06	-0.05	0.02	-0.07	1	
Protection ratio	-0.07	0.05	0.04	0.04	0.04	-0.02	1

Panel C: Distribution across accounting classifications						
		IFRS 9			nGAAP	
	Stage 1	Stage 2	Stage 3		General allowance	Specific allowance
# of observations	20,158,194	3,540,303	1,850,027		4,024,453	593,482

Notes: This table reports the descriptive statistics of variables defined at the bank-firm (loan) level for the 30,166,459 loans included in the dataset. Panel A reports key characteristics of the respective variable distributions, where data for credit volumes and maturity are winsorised at the 1% and 99% level. Panel B reports the correlation matrix for the loan-level variables, and Panel C reports the number of observations per accounting framework (IFRS 9 vs. nGAAP). For IFRS 9, it separates observations per credit stage; for nGAAP, it separates observations according to their classification as general or specific allowance, the latter indicating impaired credits.

Table 2: Descriptive statistics – Bank-level data

Panel A: Key characteristics of the distribution								
	Mean	S.D.		Min	Q1	Median	Q3	Max
CAP HEAD	6.70	5.76		0.29	3.57	5.24	7.69	38.68
TA.log	21.45	1.64		18.08	20.49	21.32	22.24	27.04
RWA/TA	53.59	14.06		14.99	45.76	55.27	62.34	88.34
DEP/TA	84.75	10.85		23.69	85.02	88.03	89.73	93.63
RoA	0.26	0.54		−2.12	0.06	0.23	0.50	2.07
CASH/TA	9.15	10.23		0.42	2.46	6.47	11.11	57.45
LOAN/TA	82.47	12.17		29.79	78.28	85.09	90.46	97.63
CB DEPOSITS	1.34	3.85		0.00	0.00	0.00	0.00	19.20

Panel B: Correlation matrix								
	CAP HEAD	log(TA)	RWA/TA	DEP/TA	RoA	CASH/TA	LOAN/TA	CB DEPOSITS
CAP HEAD	1							
log(TA)	-0.09	1						
RWA/TA	-0.28	-0.25	1					
DEP/TA	-0.34	-0.37	0.11	1				
RoA	0.06	-0.01	0.02	-0.1	1			
CASH/TA	0.25	0.2	-0.34	-0.14	-0.04	1		
LOAN/TA	-0.2	-0.26	0.2	0.24	0.09	-0.84	1	
CB DEPOSITS	-0.05	0.34	-0.24	-0.17	0	0.08	-0.05	1

Notes: This table reports the descriptive statistics of variables defined at the bank level for the 23,049 bank-quarter observations in our data set. Variables are winsorised at the 1% and 99% level. Panel A shows key distributional characteristics and Panel B reports the correlation matrix.

Table 3: Descriptive statistics - Energy data

	N	Mean	SD	Min	Q1	Median	Q3	Max
A Agriculture	136	11.42	7.98	1.66	7.41	9.97	13.02	62.82
B-F Industry and Construction	1561	28.54	42.29	1.66	7.67	11.56	20.57	157.99
G-N Services (excl. financial & real estate)	816	11.81	12.60	1.66	4.32	7.45	14.30	95.85

Notes: This table reports the descriptive statistics for the sectoral measure of exposure to energy price developments (see Section 3.3 for a detailed description). Data are winsorised at the 1% and 99% level.

Table 4: Determinants of loan-level provisioning ratios

Model:	All (1)	IFRS 9 (2)	nGAAP (3)
Variables			
nGAAP	-0.5287*		
	(0.2885)		
CAP HEAD	0.0815***	0.0836***	0.0703**
	(0.0240)	(0.0296)	(0.0319)
LOG(TA)	0.1857**	0.2481***	-0.0585
	(0.0784)	(0.0859)	(0.0591)
RWA/TA	-0.0074	-0.0093	-0.0084
	(0.0101)	(0.0136)	(0.0062)
DEP/TA	0.0180**	0.0360***	0.0271***
	(0.0090)	(0.0126)	(0.0066)
ROA	-0.1600	-0.0288	0.0385
	(0.1360)	(0.1584)	(0.2529)
CASH/TA	-0.0679***	-0.1317***	-0.0336***
	(0.0247)	(0.0350)	(0.0129)
LOAN/TA	-0.0210	-0.0740**	0.0150
	(0.0175)	(0.0290)	(0.0115)
CB DEPOSITS/TA	-0.0781***	-0.0751***	0.0416
	(0.0219)	(0.0282)	(0.0330)
Maturity	0.0553	0.0686	0.0012
	(0.0414)	(0.0540)	(0.0158)
Guarantee	-0.0151***	-0.0156***	-0.0185***
	(0.0014)	(0.0015)	(0.0021)
Moratoria	-0.0038**	-0.0035*	-0.0051***
	(0.0018)	(0.0020)	(0.0013)
Credit vol., log.	-0.6143***	-0.7385***	-0.2671
	(0.2009)	(0.2582)	(0.1822)
Protection ratio	-0.0011	-0.0007	0.0003
	(0.0010)	(0.0010)	(0.0051)
Fixed effects			
Firm-Quarter	Yes	Yes	Yes
Fit statistics			
Observations	30,001,022	24,699,885	3,912,655
R^2	0.78063	0.79438	0.65817
Within R^2	0.01217	0.01589	0.00612

Clustered (Firm-Quarter & Bank) standard errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The table shows regression results for Equation 1, estimated on our loan sample covering the period from 2018-Q3 to 2022-Q2. The dependent variable is the quarterly provisioning ratio at the bank × firm level. Explanatory variables are described in Section 4. Bank-level variables variables are lagged by one quarter. All variables are winsorised at 1% and 99%.

Table 5: Determinants of loan-level provisioning ratios – Robustness

Model:	Propensity Score Matching			Banks using both IFRS & nGAAP			Bank-quarter FEs	Controlling by credit type		
	All	IFRS 9	nGAAP	All	IFRS 9	nGAAP	All	All	IFRS 9	nGAAP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Key Variables										
nGAAP	-0.5982***			-3.641***			-2.877***	-0.4539**		
	(0.1880)			(1.103)			(0.4753)	(0.2028)		
CAP HEAD	0.1228***	0.1743**	0.0961***	0.3615*	0.5525*	-0.0835		0.1152***	0.1225***	0.0716***
	(0.0355)	(0.0767)	(0.0266)	(0.1845)	(0.3036)	(0.0593)		(0.0234)	(0.0279)	(0.0263)
Bank control variables	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Loan control variables	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Fixed effects										
Firm-Quarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Quarter-Loan Type							Yes			
Bank-Quarter							Yes			
Fit statistics										
Observations	1,554,100	472,284	807,574	139,542	70,006	36,788	5,944,892	31,625,863	27,203,092	3,200,757
R^2	0.71096	0.74394	0.69732	0.64937	0.70011	0.75516	0.80725	0.85007	0.85435	0.80316
Within R^2	0.02343	0.09081	0.01069	0.07983	0.12392	0.01428	0.02229	0.01189	0.01271	0.01447

Clustered (Firm-Quarter & Bank) standard errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: The table shows robustness tests for the estimation of Equation 1, estimated on our loan sample covering the period from 2018-Q3 to 2022-Q4. The dependent variable is the quarterly provisioning ratio at the bank × firm level. In columns 1 to 3, the sample of banks is built by classifying banks as "IFRS 9" or "nGAAP" according to their dominant accounting framework. Then a Propensity Score Matching selects comparable IFRS 9 and nGAAP banks, using the "nearest neighbor" approach, a caliper of 0.2 and matching on the explanatory variables of Equation 1. In columns 4 to 6, we restrict the sample to banks using both IFRS 9 and nGAAP for at least 20% of their loans each. In column 7, we saturate the specification by including bank × quarter fixed effects. Finally, columns 8 to 10 use an alternative data set aggregating loans at the more granular bank-firm-quarter-*type of loan* level, as described in Section 5.1. Bank-level variables variables are lagged by one quarter. All variables are winsorised at 1% and 99%.

Table 6: Determinants of loan-level provisioning ratios – IFRS 9 stages

Model:	stage 1 (1)	stage 2 (2)	stage 3 (3)
Variables			
CAP HEAD	0.0344	0.1832***	0.5327***
	(0.0230)	(0.0418)	(0.1841)
LOG(TA)	-0.1018*	0.1672	2.688***
	(0.0551)	(0.1105)	(0.5618)
RWA/TA	-0.0153*	-0.0204	-0.0011
	(0.0078)	(0.0194)	(0.1141)
DEP/TA	0.0068	0.0528**	0.1939
	(0.0095)	(0.0215)	(0.1561)
ROA	0.0799	0.1370	-1.220
	(0.0865)	(0.2874)	(1.008)
CASH/TA	-0.0485	-0.1960***	-0.5035
	(0.0340)	(0.0737)	(0.4196)
LOAN/TA	-0.0460	-0.1269**	0.3185
	(0.0304)	(0.0582)	(0.3801)
CB DEPOSITS/TA	-0.0202	-0.1064***	-0.9046***
	(0.0196)	(0.0402)	(0.1904)
Maturity	0.0994***	0.2391***	-0.2705
	(0.0275)	(0.0305)	(0.1971)
Guarantee	-0.0005	-0.0268***	-0.1876***
	(0.0011)	(0.0019)	(0.0194)
Moratoria	-0.0017*	0.0067	0.0087
	(0.0010)	(0.0043)	(0.0166)
Credit vol., log.	-0.7105***	-0.8171***	-1.097***
	(0.1887)	(0.1573)	(0.3828)
Protection ratio	0.0002	-0.0002	-0.0491***
	(0.0005)	(0.0015)	(0.0055)
Fixed effects			
Firm-Quarter	Yes	Yes	Yes
Fit statistics			
Observations	17,893,082	1,252,261	1,332,183
R^2	0.41469	0.52903	0.61709
Within R^2	0.04308	0.03938	0.07579

Clustered (Firm-Quarter & Bank) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The table shows regression results for Equation 1, estimated on the sample of IFRS 9 loans only and split according to stages, covering the period from 2018-Q3 to 2022-Q4. The dependent variable is the quarterly provisioning ratio at the bank × firm level. Explanatory variables are described in Section 4. Bank-level variables variables are lagged by one quarter. All variables are winsorised at 1% and 99%.

Table 7: Determinants of moving a loan to stage 2

Dependent Variable:	Bank reports Stage 2
Variables	
CAP HEAD	0.0333*
	(0.0171)
LOG(TA)	0.5092***
	(0.0843)
RWA/TA	0.0638***
	(0.0134)
DEP/TA	0.0421**
	(0.0180)
ROA	-0.2667*
	(0.1554)
CASH/TA	-0.0244
	(0.0228)
LOAN/TA	-0.0478*
	(0.0253)
CB DEPOSITS/TA	-0.0030
	(0.0218)
Maturity	-0.0263***
	(0.0101)
Guarantee	0.0049***
	(0.0013)
Moratoria	0.0017
	(0.0023)
Credit vol., log.	0.0887***
	(0.0202)
Protection ratio	0.0017***
	(0.0005)
Fixed effects	
Firm	Yes
Fit statistics	
Observations	567,439
Squared Correlation	0.14705
Pseudo R^2	0.11478
BIC	3,381,251.0

Clustered (Firm & Bank) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The table shows regression results for Equation 7, estimated on our loan sample covering the period from 2018-Q3 to 2022-Q4. The dependent variable is a dummy taking the value 1 if bank b moves the loan to firm f to stage 2 at any point. Explanatory variables are described in Section 4. For this regression, all variables are fixed at their value when the first bank moves its loan to firm f to stage 2. All variables are winsorised at 1% and 99%.

Table 8: Impact of the energy price shock in 2022 on provisioning ratios

Dependent Variable:			Δ provisioning ratio			
Period:	2022 Q1 - 2022 Q2		2022 Q1 - 2022 Q3		2022 Q1 - 2022 Q4	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
IFRS	-0.0224	-0.3009***	-0.0058	-0.1027*	-0.0154	-0.2025***
	(0.0537)	(0.1095)	(0.0877)	(0.0608)	(0.1113)	(0.0726)
CAP HEAD	0.0155***	0.0168	0.0139***	0.0163***	0.0162*	0.0174**
	(0.0051)	(0.0135)	(0.0054)	(0.0054)	(0.0096)	(0.0083)
IFRS $\times$ Energy		0.0341**		0.0152*		0.0287**
		(0.0152)		(0.0087)		(0.0138)
Energy $\times$ CAP HEAD		0.0003		-0.0003		-0.0002
		(0.0012)		(0.0008)		(0.0012)
LOG(TA)	0.0152	0.0351	0.0121	0.0122	0.0608*	0.0610**
	(0.0189)	(0.0349)	(0.0258)	(0.0258)	(0.0311)	(0.0310)
RWA/TA	0.0002	-0.0053	-0.0030	-0.0030	-0.0015	-0.0016
	(0.0024)	(0.0044)	(0.0029)	(0.0030)	(0.0037)	(0.0038)
DEP/TA	-0.0002	-0.0039	-0.0036*	-0.0036*	-0.0011	-0.0012
	(0.0018)	(0.0038)	(0.0020)	(0.0019)	(0.0031)	(0.0030)
ROA	0.1134*	-0.0062	0.1011	0.1012	0.0391	0.0394
	(0.0590)	(0.1126)	(0.0641)	(0.0639)	(0.1008)	(0.1006)
CASH/TA	0.0064*	-0.0097	-0.0002	-0.0002	-0.0045	-0.0043
	(0.0035)	(0.0087)	(0.0049)	(0.0049)	(0.0072)	(0.0072)
LOAN/TA	0.0047	-0.0057	0.0033	0.0033	0.0014	0.0014
	(0.0035)	(0.0071)	(0.0063)	(0.0063)	(0.0063)	(0.0063)
CB DEPOSITS/TA	-0.0011	0.0077	0.0059	0.0058	0.0039	0.0039
	(0.0034)	(0.0076)	(0.0040)	(0.0040)	(0.0064)	(0.0063)
Credit vol., log.	-0.0158***	-0.1390*	-0.0839*	-0.0840*	-0.1007	-0.1009
	(0.0061)	(0.0808)	(0.0485)	(0.0486)	(0.0618)	(0.0619)
Protection ratio	-0.0004***	0.0010	0.0002	0.0002	0.0008	0.0008
	(0.0001)	(0.0010)	(0.0005)	(0.0005)	(0.0008)	(0.0008)
Maturity	0.0026	0.0096	0.0071	0.0071	0.0067	0.0067
	(0.0017)	(0.0075)	(0.0054)	(0.0054)	(0.0048)	(0.0048)
Guarantee	-0.0004	-0.0020**	-0.0007*	-0.0007*	-0.0019**	-0.0019**
	(0.0004)	(0.0008)	(0.0004)	(0.0004)	(0.0007)	(0.0007)
Moratoria	0.0001	0.0019**	0.0008*	0.0008*	0.0020**	0.0020**
	(0.0004)	(0.0009)	(0.0005)	(0.0005)	(0.0009)	(0.0009)
Fixed effects						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,612,281	1,404,886	2,548,375	2,548,375	2,415,775	2,415,775
R^2	0.80397	0.79198	0.81477	0.81477	0.82711	0.82712
Within R^2	0.00216	0.00373	0.00266	0.00268	0.00250	0.00254

Clustered (Firm & Bank) standard-errors in parentheses
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Notes: The table shows regression results for Equation 6, estimated on our loan sample covering the period from 2022-Q1 to 2022-Q2 (columns 1 and 2), from 2022-Q1 to 2022-Q3 (columns 3 and 4) and from 2022-Q1 to 2022-Q4 (columns 5 and 6). The dependent variable is the change in provisioning ratio at the bank $\times$ firm level. Explanatory variables are described in Section 4, fixed at their value in 2022-Q1, and winsorised at 1% and 99%.

Appendix

A Propensity Score Matching

Banks using IFRS 9 and those using nGAAP differ in several aspects. Panel A of Table A.1 presents descriptive statistics of key balance sheet and income statement variables for the two groups of banks, along with a Welch test for equality of mean. The two groups differ significantly in almost all dimensions under consideration. To account for these differences in a systematic manner, we run a robustness exercise relying on a Propensity Score Matching (PSM) approach. That is, we match pairs of IFRS 9 and nGAAP banks to obtain two groups of banks with similar characteristics but different accounting frameworks, allowing for a clearer identification of the impact of the latter.

The matching is performed on the vector of bank-level control variables that enters all our regressions. We average these variables across all quarters at the bank-level, resulting in one value per variable for each bank. Additionally, we include the logarithm of the number of observations per bank in the data set as a matching variable. This is necessary to avoid that we match banks with a very different presence in the data set, which would imply that one of the banks would be practically absent and the other practically unmatched in the matched sample, thus defeating the point of the PSM. To implement the PSM, we use the "nearest neighbour" approach and a caliper of 0.2.

Results of the matching are presented in Panel B of Table A.1. The matched sample includes 207 banks in each group. Mean values for all of the variables under consideration come very close to each other, and the Welch test indicates that differences between IFRS 9 and nGAAP banks are no longer statistically significant, except for central banks deposits and marginally for the return on assets. Thus, the PSM successfully controls for differences between treatment and control group that could affect our estimation results presented in Section 5.1.

Table A.1: Comparison of IFRS 9 and nGAAP banks pre- and post PSM

Panel A: Pre PSM

	nGAAP nb	IFRS nb	nGAAP mean	IFRS mean	Welch test
CAP HEAD	1130	454	7.121	8.466	-4.04***
LOG(TA)	1130	454	21.018	21.909	-9.09***
RWA/TA	1130	454	55.776	45.634	13.47***
DEP/TA	1130	454	86.216	79.181	10.84***
ROA	1130	454	0.25	0.34	-3.54***
CASH/TA	1130	454	6.085	13.077	-12.31***
LOAN/TA	1130	454	85.282	79.204	8.89***
CB DEPOSITS/TA	1130	454	0.146	3.448	-17.14***

Panel B: Post PSM

	nGAAP nb	IFRS nb	nGAAP mean	IFRS mean	Welch test
CAP HEAD	207	207	8.83	8.107	1.15
LOG(TA)	207	207	21.327	21.396	-0.37
RWA/TA	207	207	46.189	48.501	-1.54
DEP/TA	207	207	78.285	80.368	-1.55
ROA	207	207	0.388	0.298	1.89*
CASH/TA	207	207	11.184	11.085	0.09
LOAN/TA	207	207	82.46	81.482	0.76
CB DEPOSITS/TA	207	207	0.797	1.916	-3.84***

Sig. Levels: $^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$

Notes: This table reports the descriptive statistics of bank characteristics, averaged over time at the bank level. It separates between IFRS 9 and nGAAP banks. Panel A reports statistics for all banks in the sample. Panel B reports statistics for those banks that remain after performing a Propensity Score Matching (PSM) between IFRS 9 and nGAAP banks. The PSM matches banks on all the variables reported in the table, using the "nearest neighbour" approach and a caliper of 0.2.

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