# Determinants of credit risk provisioning in uncertain times – the role of bank conditions and accounting standards

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#### 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 using granular loanlevel data from the euro area's credit register. The results indicate that provisions under the new standard are higher and more responsive to shocks, but the majority of provisioning still occurs at the time of default, and the provisioning dynamics around default events are similar under IFRS 9 and under pre-existing national accounting standards. We also find that bank characteristics, such as capital headroom, have a significant impact on provision-ing ratios, particularly for loans under IFRS 9, which may suggest that banks have more discretion to adjust provisioning under the new approach.

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

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## 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 further destabilise the financial system. Given the implications for bank solvency and financial stability, determinants of bank provisioning have long been studied by academics and policy makers 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'. They 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. The resulting underestimation of future losses implied a lack of transparency and significant hidden risks in the financial system. To address these issues, newly developed Expected Credit Loss (ECL) approaches such as the International Financial Reporting Standard 9 (IFRS 9) take a more forward-looking approach. They require provisions to be based on estimated future credit losses, expected to be varied over time as credit risk evolves and usually obtained from dedicated provisioning models operated by banks themselves. While the new approaches were supposed to enhance transparency by inducing more timely and accurate loss recognition, their implementation soon triggered discussions on potential side effects (see, e.g., European Systemic Risk Board 2017, Basel Committee on Banking Supervision 2021). 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, potentially inducing procyclical effects. Specifically, increased provisioning reduces bank capital, potentially leading banks to reduce credit supply in order to preserve their capital ratios and avoid breaching capital requirements. This can deprive firms and households of necessary financing during economic downturns, exacerbating the crisis. Second, there were fears that the reliance on internal models and the discretion afforded to banks in estimating expected losses could induce more dispersion in provisioning practices, potentially conflicting with the objective of enhanced transparency. In

particular, less capitalised banks could be tempted to underestimate expected losses, to reduce provisioning needs and thus preserve capital.

In this paper, we investigate how the implementation of IFRS 9 has affected euro area banks' provisioning behaviour in the most recent period, characterised by the macroeconomic shocks induced by the COVID-19 pandemic and the outbreak of war in Ukraine. We use granular data from AnaCredit, the European corporate credit register, to identify determinants of provisioning ratios in a sample of around 60 million quarterly loan observations. Importantly, some banks in the euro area continue to rely on national Generally Accepted Accounting Principles (nGAAP) for determining their credit risk provisions, which provides us with natural control group for banks using IFRS 9. Moreover, thanks to the granularity of our data set, we can study how bank and loan characteristics affect provisioning levels and dynamics for loans issued by different banks to the same borrower in the same period. 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).

Our findings indicate that some features of IFRS 9 seem to be working as intended: 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 default. As a result, provisioning dynamics around credit risk shocks are rather similar between loans using IFRS 9 and those using nGAAP. Somewhat in contrast with expectations, this suggests that the new approach may have limited implications in terms of financial system procyclicality. 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 that could influence the regressions.

We also find evidence that IFRS 9 has altered the role of discretion in accounting practices. Bank-specific variables such as the headroom on top of regulatory capital requirements affect provisioning ratios for both IFRS 9 and nGAAP loans. Specifically, we find that banks with less capital headroom 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 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. In this way, the new approach may have fostered stronger divergence in accounting practices across banks, where the implications of this in terms financial stability are *a priori* ambiguous. On a positive side, flexibility can smooth the potential procyclical impact of the ECL approach when the economy weakens: poorly capitalised banks can avoid a jump in provision 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 further down the road.

Finally, we use the energy price shock in early 2022 to study provisioning patterns around macroeconomic shocks. While provisions for IFRS 9 loans are generally higher than those for nGAAP loans, the dynamics around the shock are similar for the average loan under the two approaches. However, we 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. Additionally, banks with more capital headroom increased their provisioning across the board, while those with less excess capital adjusted less and in a more targeted manner, focusing on firms that are more exposed to the shock. Thus, accounting discretion and capital management motives seem to affect not only the overall level of provisioning, but also the distribution of provisions across a bank's borrowers.

Our paper contributes to a growing literature that examines 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, Plosser and Santos 2018, or Behn et al. 2022). 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.<sup>1</sup> We add to this literature by examining the performance of accounting risk models since the outbreak of the pandemic. To the best of our knowledge, our paper is the first to empirically assess whether the recent shift to expected credit loss 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, Huizinga and Laeven 2019, Blattner et al. 2020).<sup>2</sup> 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), or by analysing the effects of forward-looking elements of the previous incurred loss approach (Beatty and Liao 2011, Bushman and Williams 2012). 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 policy makers.

The remainder of this paper is organised as follows: In Section 2, we briefly describe institutional arrangements and discussions surrounding the introduction of expected credit loss 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 The introduction expected credit loss accounting

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

<sup>&</sup>lt;sup>1</sup>On the role of accounting discretion during the global financial crisis, see also Balasubramanyan et al. (2017). <sup>2</sup>The role of fair value accounting has also been examined in this context (e.g., Laux and Leuz 2010, Xie 2016).

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 (Financial Stability Forum 2009). The more 'forward-looking' ECL approach was supposed to enhance transparency and promote more timely and accurate recognition of losses by considering not only realised but also expected credit risk losses (Cohen and Edwards 2017). 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 or our paper, and the similar Current Expected Credit Losses (CECL) standards in the US.<sup>3</sup> The final version of IFRS 9 was published in July 2014. The standard became effective and replaced the previously applicable International Accounting Standard 39 (IAS 39) in January 2018. In the European Union, application is mandatory for consolidated financial statements of public companies that are listed in any Member State. Other companies (e.g., unconsolidated or non-listed entities) have the option to apply IFRS 9 but may also resort to national Generally Accepted Accounting Principles (nGAAP). The latter explains why our sample includes both IFRS 9 and nGAAP loans.<sup>4</sup>

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 1 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 12-month expected credit risk loss, defined as the product of the one-year ahead probability of

 $<sup>^{3}</sup>$ As noted by Domikowsky et al. (2015), some national accounting frameworks contained forward-looking elements even before the introduction of IFRS 9, e.g., discretionary elements in the German standards or the well-known dynamic provisioning elements in the Spanish framework (on the latter, see Jiménez et al. 2017). Our empirical analysis acknowledges the existence of such national specificities but relies on the observation that IFRS 9 is generally *more* forward-looking than national approaches.

<sup>&</sup>lt;sup>4</sup>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.

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.<sup>5</sup> 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.<sup>6</sup>

Overall, the transition from nGAAP to IFRS 9 and forward-looking ECL introduces three key modifications to provisioning practices: (i) it induces higher ex ante provisioning by resorting to expected credit losses (either 12-months ahead or full lifetime); (ii) it makes provisioning more responsive to changes in credit risk, potentially leading to procyclicality; and (iii) it increases the role of internal models to estimate credit risk, potentially leading to more discretion in provisioning practices. 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. 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.

#### 2.2 Possible procyclicality and support measures during the pandemic

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

<sup>&</sup>lt;sup>5</sup>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.

<sup>&</sup>lt;sup>6</sup>The shorter provisioning horizon for stage 1 loans distinguishes IFRS 9 from CECL in the US, since the latter requires banks to provision for expected lifetime credit risk losses from loan origination onward.

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 (Financial Stability Forum 2009). However, concerns that certain features of IFRS 9 itself might 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, 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). These concerns were aggravated by the possibility of so called "cliff effects," where a large number of exposures are suddenly moved to stage 2 or stage 3 and subjected to full lifetime provisioning (recall Figure 1), resulting in a sudden increase in overall provisioning.

The shock of the pandemic in early 2020 occurred while banks were still transitioning to IFRS 9 and concerns about possible 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 2 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. Besides these direct measures, 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.

Conceptually, the impact of these support measures on observed provisions could have gone in different directions and is likely to have varied across measures, across banks, and over time. On the one hand, guidance on avoiding excessive procyclicality and public support measures like moratoria and state guarantees are likely to have reduced provisioning needs, particularly for loans under IFRS 9, depending on how individual banks interpreted the guidance. However, 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 based on all relevant information (see Figure 2). Hence, it is likely that any impact of the guidance on banks' provisioning behaviour was strongest in 2020. On the other hand, the possibility to add back the provisions to CET1 capital may have had a more neutral effect or may even have encouraged IFRS 9 banks to provision more actively, since the impact of higher provisions on regulatory capital ratios was neutralised. Regardless of the specific impact, it is important to account for all these support measures in our empirical analysis, and as we will explain in Section 4, we do this in several ways.

#### 2.3 Role of discretion in accounting practices

Besides potential procyclicality, a second concern in relation to accounting standards relates to the discretion afforded to banks with respect to the recognition of losses. 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. Put simply, banks could be provisioning 'as much as they can afford' given current earnings and 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 principles in this respect, ultimate provisioning needs heavily depend on banks' interpretation of the standards, their modelling approaches and the assumptions taken. As pointed out by the European Systemic Risk Board (2017), the flexibility entailed in the new standard might have tempted some institutions 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). While we are not aiming for an ultimate judgment on the desirability of discretion in accounting practices from a financial stability perspective, our empirical setup allows 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-Q2. 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 19 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.<sup>7</sup> 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 impairment amount, the maturity, and whether the loan benefits from a COVID-related public credit guarantee and/or moratorium.<sup>8</sup> 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 impairment 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

<sup>&</sup>lt;sup>7</sup>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).

<sup>&</sup>lt;sup>8</sup>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).

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 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 impairment ratio (or provisioning ratio, as the terms "impairments" and "provisions" are used interchangeably throughout the paper) is defined as the ratio of impairments over the sum of impairments and the carrying amount. From AnaCredit we also extract information on borrower size (four buckets indicating large, medium, small or micro enterprises)<sup>9</sup>, country of residence and 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 62,536,680 loans in our data set, while Panel B shows the correlation matix for the loan-level variables. As expected, given the holistic nature of AnaCredit, the loans differ massively in size and maturity. About 13 percent of them benefited from public credit guarantees schemes and 1 percent from moratoria put in place during the COVID-19 pandemic. Moreover, about 4 percent of the loans are in default, while the provisioning ratio stands 2.5 percent on average but exhibits large heterogeneity (standard deviation of 10 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 90 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.<sup>10</sup> 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 account for 82 percent and 89 percent of IFRS 9 and nGAAP loans, respectively.<sup>11</sup>

 $<sup>^{9}</sup>$ As defined in the Recommendation 2003/361/EC or the European Commission

<sup>&</sup>lt;sup>10</sup>In very few cases (less than 1 percent of the data set), a bank has both IFRS 9 and nGAAP loans with the same borrower in the same quarter. In such cases, the aggregation is performed at the bank  $\times$  firm  $\times$  quarter  $\times$  framework level.

<sup>&</sup>lt;sup>11</sup>The two categories belonging to different accounting approaches, they are not directly comparable.

#### 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 of Table 2, while Panel B shows the correlation matrix. The table shows that banks typically have capital headroom (CAP HEAD) on top of their regulatory requirements, although there is substantial heterogeneity (the standard deviation is around 5 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.<sup>12</sup> For this reason, we perform 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 eliminates any 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  $\times$  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.<sup>13</sup> 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.<sup>14</sup> Descriptive statistics for the measure are provided in Table 3, which shows that

 $<sup>^{12} \</sup>rm We$  classify banks according to the most frequent accounting framework in their corporate credit portfolio.  $^{13} \rm See \ https://www.oecd.org/industry/ind/TiVA-2021-industries.pdf.$ 

<sup>&</sup>lt;sup>14</sup>For more details, see https://www.ecb.europa.eu/pub/economic-bulletin/focus/2022/html/ecb. ebbox202201\_04~63d8786255.en.html.

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 ample variation that allows to identify the impact of the energy shock on provisions.

## 4 Estimation strategy

We perform various regressions to assess how accounting standards and bank characteristics have affected provisioning behaviour during our sample period. In a first step, we use the entire quarterly loan data and investigate general determinants of provisioning behaviour by estimating the following equation:

$$Imp_{b,f,t} = \alpha_{f,t} + \beta X_{b,f,t-1} + \gamma Z_{b,t-1} + \epsilon_{b,f,t}, \qquad (1)$$

where b denotes the bank, f the firm, and t the quarter. The dependent variable is the loanlevel impairment ratio in a given quarter.<sup>15</sup> 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 residual maturity, 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 (Targeted Longer-Term Refinancing Operations (TLTROs) over total assets). The regression includes firm × quarter interactions,  $\alpha_{f,t}$ , which control for any observed and unobserved heterogeneity across firmquarters 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). Finally, to account for potential correlation, standard errors in all our regressions are double clustered at the firm × quarter and bank level, unless indicated otherwise.

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 provi-

<sup>&</sup>lt;sup>15</sup>To mitigate the impact of potential outliers, all our variables are winsorised at  $2.5^{th}$  and  $97.5^{th}$  percentiles.

sioning behaviour during our sample period. However, we need to look at provisioning dynamics in order to assess whether IFRS 9 has induced a shift in behaviour around credit risk shocks. Hence, in a second step, we restrict the sample to firms that defaulted during our sample period, and estimate equations of the following type:<sup>16</sup>

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

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 loan defaults in h quarters and zero otherwise. Depending on the specification,  $W_{b,f}$  is a dummy variable that either indicates the accounting framework (IFRS 9 vs. nGAAP), or whether the bank's capital headroom is below or above the sample median. Thus, by estimating Equation 1 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.

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). 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. 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  $\times$  quarter interactions helps to control for additional direct or indirect support measures that may have been implemented at the country- or firmlevel. Fifth, 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 Section 2.2), we note that the differentiation between well- and less capitalised banks should be unaffected,

<sup>&</sup>lt;sup>16</sup>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.

since both types of banks benefitted from the support measures in an equal manner.<sup>17</sup> Finally, as we will explain now, we conduct an additional test on a period that is less affected by the support measures adopted during the pandemic, exploiting the energy price shock that hit the European economy after 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.<sup>18</sup> 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:

$$\Delta Imp_{b,f} = \alpha_f + \theta W_{b,f} \times E_f + \zeta W_{b,f} + \beta X_{b,f} + \gamma Z_b + \epsilon_{b,f}, \tag{3}$$

with  $\Delta Imp_{b,f}$  the change in impairment ratio at bank-firm level between 2022-Q1 and 2022-Q2,  $E_f$  the sectoral energy dependence measure described in Section 3.3, and all other variables defined as before. As before,  $W_{b,f}$  is a dummy variable 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 adjust provisions in response to the energy shock in a generally stronger (coefficient  $\zeta$ ) and/or in a more risk-sensitive (coefficient  $\theta$ ) manner.

## 5 Determinants of provisioning behaviour

#### 5.1 Determinants of provisioning ratios during our sample period

Figure 3 plots the evolution of aggregate provisioning ratios during our sample period. 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 2.3 percent for loans under IFRS 9, compared

<sup>&</sup>lt;sup>17</sup>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. <sup>18</sup>For further discussion, see chapter 2.3 of the ECB's Financial Stability Review (November 2022): https:

<sup>//</sup>www.ecb.europa.eu/pub/financial-stability/fsr/html/ecb.fsr202211~6383d08c21.en.html#toc13.

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) ratios in particular.<sup>19</sup> NPL ratios continued to improve throughout the pandemic, but at the same time banks saw an increase in stage 2 provisions (see Figure 4), so that aggregate provisioning ratios stabilised around the levels mentioned above.<sup>20</sup> In the lower panel of Figure 3, we distinguish between banks with low (below median) and those with high (above median) capital headroom on top of their regulatory requirements. Less capitalised banks start off with higher provisioning ratios, because they are – on average – more affected by legacy issues relating to high NPL ratios: in 2018 Q3, banks below the median capital headroom had an average NPL ratio of 5.2%, versus 3.0% for those above the median. 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 (see Section 2.3),

To control for bank, firm and loan characteristics that may exert an impact on observed 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 at the industry  $\times$  location  $\times$  size (column 1) or firm level (column 2). The coefficient estimate in column 2 indicates that provisioning ratios for IFRS 9 loans are on average about 0.34 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

<sup>&</sup>lt;sup>19</sup>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.

 $<sup>^{20}</sup>$ 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 4, aggregate provisioning ratios remained relatively stable also under the (incurred loss) nGAAP approaches, possibly due to the broad set of fiscal and monetary support measures that prevented significant loss materialisation.

in Figure 3 (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 aggregate level. Moreover, the effect is economically meaningful, considering the average provisioning ratio of 2.49 percent during our sample period. We also find that the coefficient estimate for the bank's capital headroom (i.e., the distance between the capital ratio and the overall capital requirement) 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 (5.31 pp) implies a corresponding increase in provisioning ratios of around 0.41 pp. Other bank characteristics have a relatively muted impact on provisioning ratios, whereas loan control variables affect ratios in the expected manner.<sup>21</sup>

In columns 3 to 6 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. For IFRS 9, we can further split the sample into loans in different stages, which we do in Table 5. This additional sample split 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. This is perhaps not surprising, since provisioning ratios are at generally higher levels in the higher 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 stages 1 and 2 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

<sup>&</sup>lt;sup>21</sup>Somewhat surprisingly, the results in column 1 suggest that more profitable banks tend to provision less on average. This effect becomes considerably smaller and statistically insignificant when including firm fixed effects in column 2, suggesting that the results in column 1 may be driven by differences in borrower quality within an industry  $\times$  location  $\times$  size cluster. One possible interpretation of this is that more profitable banks are better at screening their borrowers and therefore lend to firms of slightly higher quality, which would explain both lower provisioning ratios and structurally higher profitability (so that lagging profitability by one period, as we do, would not suffice to fully address potential endogeneity concerns). We further examine this issue in Section 5.3, where we look at provisioning dynamics around a specific credit risk shock.

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 a better capacity of large banks to monitor their loan portfolio. 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. We further examine the dynamics of this heterogeneity in the next subsections.

#### 5.2 Provisioning dynamics around credit risk shocks

#### 5.2.1 IFRS 9 vs. nGAAP

To further investigate how IFRS 9 has affected provisioning strategies and dynamics, we proceed by analysing the evolution of provisioning ratios around credit risk shocks. Focusing on firms that actually defaulted during our sample period, Figure 5 plots weighted average provisioning ratios around the respective default events, separating loans according to their accounting approach. In line with expectations and consistent with previous results, the left panel shows that IFRS 9 loans exhibit higher provisioning ratios ahead of a default event. However, provisioning dynamics are rather similar for loans under IFRS 9 and those using nGAAP. Specifically, a significant cliff effect at the time of default occurs under both approaches, while increases in provisioning ahead of default are small and gradual. Thus, a material cliff effect at the time when IFRS 9 loans would be moved to stage 2 is not detectable at an aggregate level, so that the pattern that emerges is markedly different from the conceptual illustration shown in Figure 1.

To investigate the drivers of this striking difference between conceptual and observed patterns, Figure 6 plots the share of IFRS 9 loans in different stages around default events. 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. The message from this observation is twofold: first, the timing of moving loans to stage 2 varies substantially, so that in each quarter only a small fraction of loans is re-allocated to stage 2. Second, the time period that loans spend in stage 2 tends to be relatively short, at least for a considerable share of the exposures, and many loans do not move to stage 2 at all. Taken together, these two factors explain why pre-default increases in provisioning for IFRS 9 loans remain small and gradual on aggregate, with a substantial jump in provisioning occurring only at the time of default.

The right panel of Figure 5 confirms that loan staging is an important determinant of aggregate provisioning dynamics around default events. It expands on the left panel by separating 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. Not surprisingly, stage 2 loans exhibit the highest provisioning ratios ahead of default, stage 1 loans the lowest, and switcher loans are somewhere in between and gradually catch up with the loans that are consistently in stage 2, with the most pronounced effect occurring only in the quarter immediately ahead of default, however. The patterns indicate 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. Interestingly, aggregate provisioning ratios for loans that are consistently in stage 1 ahead of default are even below the pooled average for nGAAP loans.<sup>22</sup> A possible interpretation for this is that IFRS 9 induces insufficient provisioning for seemingly safe borrowers that are considered unlikely to default by a bank's risk model. In other words, IFRS 9 works well only if banks are able to identify significant increases in credit risk at an early stage, which may not always be easy.

Overall, the descriptive charts indicate that provisioning dynamics around default events are rather similar for IFRS 9 loans and those under nGAAP. To further substantiate the analysis, we estimate Equation 2, thereby assessing dynamics while controlling for bank, firm and loan heterogeneity (see Section 4). Regression coefficients are plotted in Figure 7 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. Differences between the two approaches become statistically insignificant and even reverse signs after the default event. These patterns hold in a series of robustness checks. First, one could be concerned that support measures implemented during the pandemic are biasing the results, and that pre-default differences in provisioning between IFRS 9 and nGAAP loans might have been larger in their absence. As explained in Sections 2.2 and 4, some of the measures may indeed

 $<sup>^{22}</sup>$ As explained in Section 2.1, some national accounting approaches also contain forward-looking or precautionary provisioning features, which explains why provisioning under nGAAP is positive ahead of default.

have induced lower provisioning under IFRS 9, although the impact is likely to vary across measures and banks and probable to have become much less pronounced as of late 2020. To control for the impact of support measures, we re-estimate Equation 2 while excluding the imminent phase of the pandemic (2020-Q2 to 2020-Q4). As shown in Figure 8, results are very similar for the adjusted sample. Second, one could be concerned about structural differences between banks using IFRS 9 and those using nGAAP. To control for such differences in a systematic manner, we apply propensity score matching and replicate the charts on the matched sample of banks.<sup>23</sup> Again, observed patterns are similar to those in the full sample (see Figure 9). Taken together, the findings in this subsection suggest that initially higher provisioning under IFRS 9 slightly reduced the magnitude of the jump in provisioning at the time of default, but nevertheless a substantial cliff effect remains also under the new approach.

#### 5.2.2 Low vs. high capital headroom

We next examine whether provisioning patterns around default events depend on banks' capital headroom, to gauge the impact of accounting discretion. The left panel of Figure 10 plots weighted average provisioning ratios around default events, this time distinguishing between banks with above and below median capital headroom. Focusing on the sample of firms that defaulted during our sample period, aggregate provisioning ratios for differently capitalised banks are close to each other ahead of the respective default event. However, banks with higher capital headroom book higher provisions after the default, in line with a "provision as much as you can afford" strategy.

To investigate whether discretion plays out differentially in different accounting settings, the right panel of Figure 10 continues to distinguish banks according to their capital headroom but additionally separates loans into those under nGAAP and those under IFRS 9. For the latter, the chart also differentiates between loans consistently in stage 1, those that switched from stage 1 to stage 2, and those that were consistently in stage 2 in the four quarters ahead of default (as in the right panel of Figure 5). Somewhat surprisingly, provisioning ratios of less capitalised banks are higher than those of better capitalised banks for loans under nGAAP, possibly due to differences in borrower or loan quality that are not fully captured in this descriptive analysis (see below for further discussion). In contrast, provisioning ratios of less capitalised banks are always

 $<sup>^{23}</sup>$ See Appendix A for a description of the propensity score matching and the corresponding adjustments.

below those of better capitalised banks for loans using IFRS 9. This difference is particularly pronounced following the default of loans that are consistently in stage 1 ahead of the default event. Hence, while Figure 5 already showed that provisioning for such loans does not fully catch up with stage 2 and nGAAP loans after the default event, Figure 10 illustrates that this provisioning shortfall is driven by less capitalised banks in particular.

Findings on the evolution of aggregate provisioning ratios around default events for IFRS 9 loans are summarised in Table 6, which distinguishes between loans that move directly from stage 1 to stage 3 (Panel A) and those that transition via stage 2 (Panel B). The table confirms that (i) provisioning ratios for less capitalised banks are always below those of better capitalised banks; (ii) there is a substantial share of loans that transition directly from stage 1 to stage 3, which is slightly higher for banks with below median capital headroom (38 percent vs. 36.4 percent for banks with above median capital headroom); (iii) provisioning ratios for loans that are in stage 1 in the quarter ahead of default are substantially lower than those of loans that are in stage 2 at that time (1.9 percent vs. 9.2 percent on average); and (iv) provisioning ratios for the former set of loans remain lower also after the default event, particularly for loans issued by less capitalised banks. In sum, the findings confirm 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.<sup>24</sup>

As in the previous subsection, we complement the descriptive statistics with a regression analysis that controls for bank, firm and loan heterogeneity. Figure 11 presents regression coefficients for a variant of Equation 2 and illustrates that banks with more capital headroom increase provisioning ratios to the same firm in the same period considerably more after default, thus adding to the already existing difference. This resonates with the findings in Section 5.1, which

<sup>&</sup>lt;sup>24</sup>Our findings also suggest that banks may be taking different strategies with respect to the interplay of these two levers. Specifically, there is a negative correlation between the share of a bank's loans that are still in stage 1 in the quarter ahead of default and the average provisioning ratio for the bank's stage 1 loans. That is, there may be a trade-off between a bank's willingness to move a loan to stage 2 and its average provisioning ratio for stage 1 loans. Some banks may prefer to attach low provisions to the average stage 1 loan while putting a lot of effort on identifying loans that experience a significant increase in credit risk and should be moved to stage 2, while other banks may prefer to pre-cautiously attach higher provisions to the average stage 1 loan while putting less effort on identifying stage 2 loans.

showed that differences in capital headroom explain divergences in provisioning particularly in the higher stages of IFRS 9. Indeed, Figure 12 shows that differences between better and less capitalised banks are primarily driven by IFRS 9 loans (left panel), since divergences are considerably smaller and mostly statistically insignificant for loans under national standards (right panel). For IFRS 9 loans, the difference is economically sizable, since better capitalised banks increase provisioning ratios by about 4 pp more than less capitalised banks after a default event.

Focusing on IFRS 9 loans only, we can also investigate divergences relating to loan staging in a more formal manner. First, we re-estimate Equation 2, this time aligning loans around the move to stage 2 rather than the default event. 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. Figure 13 confirms 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. Second, 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.<sup>25</sup>. Results are presented in Table 7 and clearly show that banks with less capital headroom are less inclined to move a specific loan exposure to stage 2. In line with the descriptive analysis, such banks appear to be using all levers available to them to reduce provisioning needs.

Taken together, the findings in this subsection corroborate the assertion that discretionary factors relating to capital management motives affected provisioning behaviour during our sample period. The stronger effects for IFRS 9 loans could be related to more discretion and heterogeneity in banks' modelling approaches under the new accounting framework.

$$Stage2_{b,f} = \alpha_f + \theta W_{b,f} \times E_f + \zeta W_{b,f} + \beta X_{b,f} + \gamma Z_b + \epsilon_{b,f},$$

 $<sup>^{25}</sup>$ More specifically, for all firms for which at least one banks moves its respective loan to stage 2 in at least one quarter, we estimate the following equation:

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 variables are defined as above. We restrict the sample to loans from banks that where lending to firm f before (at least one quarter), at and after (at least one quarter) the time where the first bank moved its exposure to firm f to stage 2. 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 × firm pair.

#### 5.3 The energy price shock in 2022

Our analysis thus far has examined provisioning dynamics around around credit risk shocks at the individual loan level (i.e., defaults and transitions to stage 2). 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), given potential repercussions in terms of systemic risk. For this reason, we now examine provisioning dynamics in the aftermath of the energy price shock resulting from the outbreak of war in Ukraine, which occurred towards the end of our sample period in 2022. As explained in Section 4, the energy price shock strongly affected the import-dependent European economy and corporate sector and represents a considerable increase in credit risk for energy intensive companies in particular. Moreover, when the shock occurred in 2022 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.<sup>26</sup> This latter aspect is the main reason why we focus on this macroeconomic shock rather than the one induced by the pandemic.

Estimation results for Equation 3 are presented in Table 8. To test for divergences in both the dynamics and the overall level of provisioning, the dependent variable is either the change of the provisioning ratio between 2022-Q1 and 2022-Q2 or its level in 2022-Q2. Column 1 shows that provisioning dynamics are similar for the average IFRS 9 and nGAAP loans. 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 intense sectors. Thus, banks' IFRS 9 models seem to be capturing the heterogeneous impact of the shock on firms in the European economy. At the same time, column 2 shows that banks' with more capital headroom increase provisions more than other banks after the shock (positive coefficient on CAP HEAD), but in a less risk sensitive manner (negative coefficient on the interaction term). Again, and consistent with capital management motives, different types of banks take different accounting strategies: banks with sufficient capital headroom seem to increase provisioning ratios

<sup>&</sup>lt;sup>26</sup>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.

in a precautionary manner and across the board, whereas capital constrained banks increased provisions in a more targeted manner according to risk profiles. Thus, accounting discretion and capital management motives seem to affect not only the overall level of provisioning, but also the distribution of provisions across a bank's borrowers. Interestingly, we also observe that more profitable banks increase provisions relatively more, consistent with profit smoothing motives and and a strategy of 'provisioning what you can afford'.<sup>27</sup>

Using the level of the provisioning ratio as a dependent variable, columns 3 and 4 confirm that IFRS 9 loans and loans from banks with more capital headroom exhibit higher average provisioning ratios in 2022-Q2, compared with nGAAP loans and loans from less capitalised banks to the same firm, respectively. Both interaction terms are statistically insignificant, however, indicating that the differential adjustments between Q1 and Q2 of 2022 did not yet result in significant differences in the level of provisioning. Overall, findings for the energy price shock in 2022 confirm that discretionary factors relating to capital management and profit smoothing 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 shock induced by the outbreak of war in Ukraine and related energy price developments.

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

<sup>&</sup>lt;sup>27</sup>Changes in provisioning ratios from one quarter to the next may be less affected by the endogeneity issues relating to the level of provisions discussed in footnote 21. Indeed, when we move back to a specification with the level of the provisioning ratio as dependent variable, we obtain once more the already familiar negative relationship between profitability and provisioning ratios, albeit statistically insignificant in this case (columns 3-4).

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 substantial 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 5 and 7) or the evolution of aggregate provisioning patterns during our sample period (Figures 3 and 4). A possible explanation for this is substantial heterogeneity with respect to the timing of moving exposures to stage 2, which implies that only a small fraction of loans is moved in any given quarter (see Figure 6 for an illustration around default events).

We also find some evidence that IFRS 9 may have fostered divergence in accounting strategies across banks, although discretionary elements are also present under national standards. Specifically, provisioning levels appear to be affected by capital management and profit smoothing motives ('provisioning as you can afford'), resulting in substantial heterogeneity in provisioning ratios by different banks even for similar exposures to the same borrower in the same period. 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. Finally, they react generally more strongly to the energy price shock in 2022, consistent with a precautionary increase in provisioning for corporate exposures. However, the increase is less risk sensitive than for less capitalised banks, indicating that the latter adjust provisions in a more targeted manner.

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 (capitalconstrained) banks to maintain the provision 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. In any case, the 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. Assessing the net impact of all factors on financial stability and bank lending behaviour remains a key area for future research.

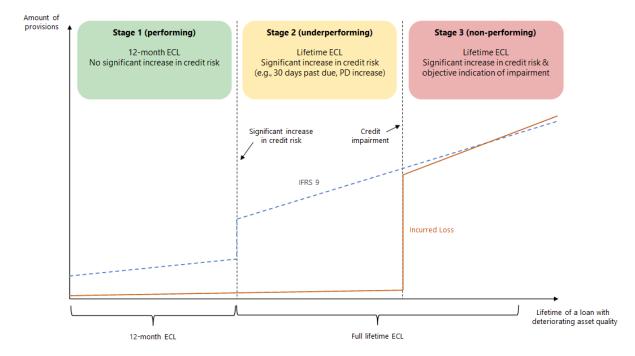
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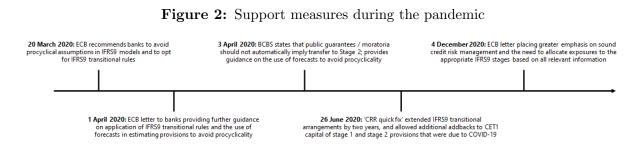
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## Figures & Tables



#### Figure 1: 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.



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

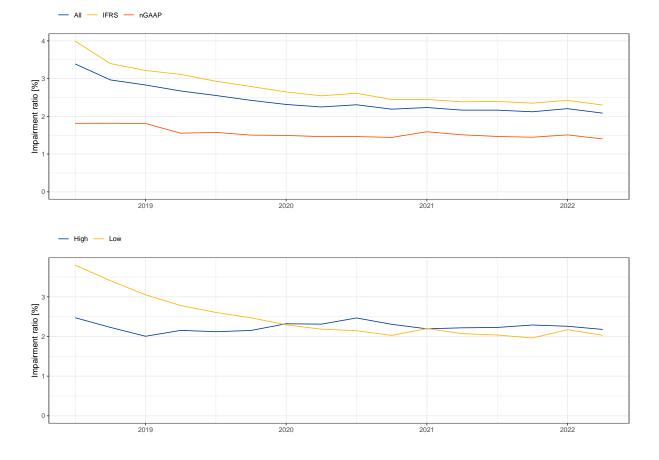


Figure 3: Evolution of aggregate provisioning

*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 capitalisation (lower panel).

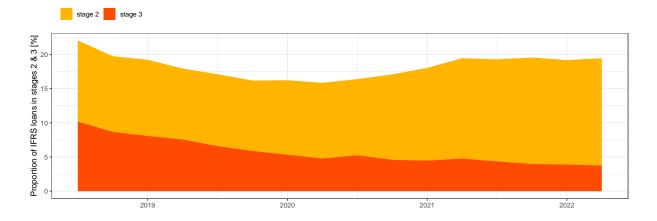
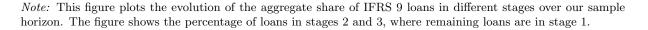


Figure 4: Share of IFRS 9 loans in different stages



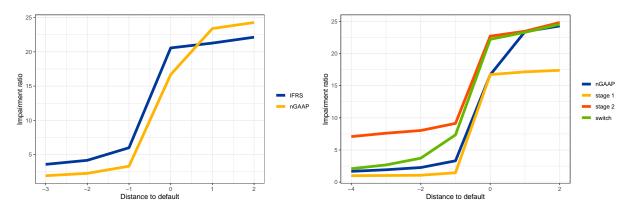


Figure 5: Evolution of provisioning ratios around default events

*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.

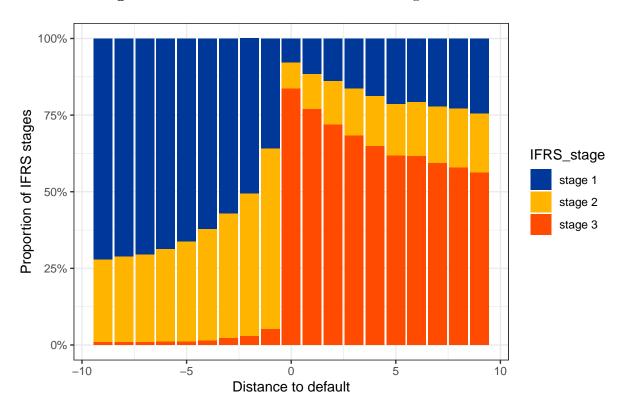


Figure 6: Share of IFRS 9 loans in different stages around default

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

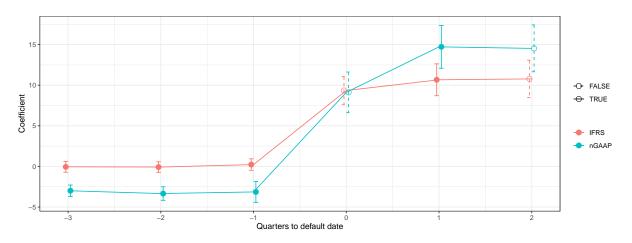


Figure 7: Provisioning ratio around default by accounting framework: regression

Note: This figure shows the regression coefficients of 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 quarter 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.

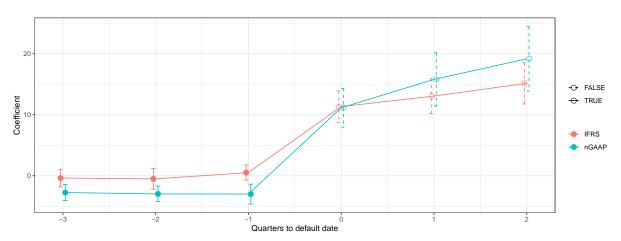


Figure 8: Provisioning ratio around default – excluding the pandemic

*Note:* This figure replicates the estimation shown in Figure 7, 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 quarter 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.

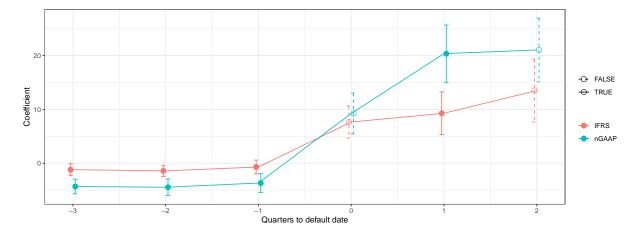


Figure 9: Provisioning ratio around default – propensity score matching

Note: This figure replicates the estimation shown in Figure 7, after applying the propensity score matching described in Appendix A. The estimation includes all firm-bank pairs in the matched sample that report a default and are without missing values in the interval between [-3; +2] quarters around default. The x-axis reports the distance in quarter 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.

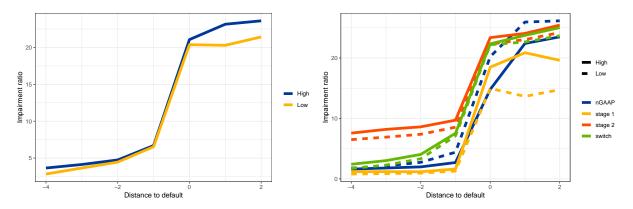


Figure 10: Aggregate provisioning ratios for loans in different stages

*Note:* This figure shows the evolution of weighted average provisioning ratios around default events, where the left panel differentiates between banks with above vs. below median capital headroom. The right panel additionally separates nGAAP loans and 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.

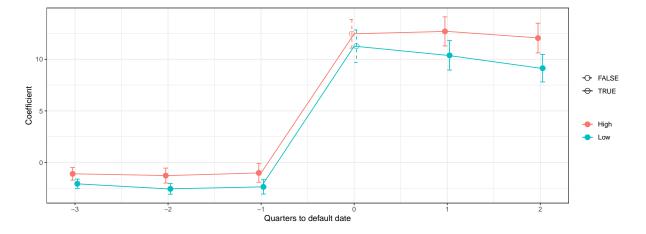


Figure 11: Provisioning ratio around default by capital headroom: regression

*Note:* This figure shows the regression coefficients of 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 quarter 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.

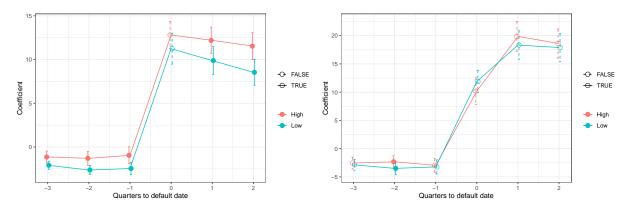


Figure 12: Provisioning ratio around default by capital headroom (IFRS 9 vs. nGAAP)

Note: This figure shows the regression coefficients of 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 quarter 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.

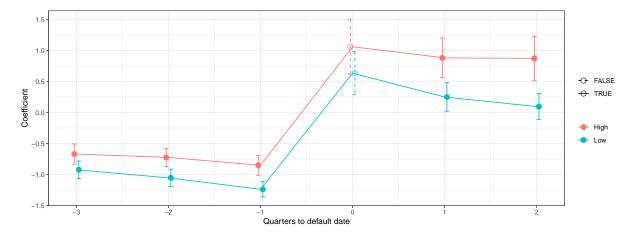


Figure 13: Provisioning ratios around the transition to stage 2: regression

Note: This figure shows the regression coefficients of 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 quarter 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 Wald-test for difference of the coefficients is (non)-significant at the 10% level.

Panel A: Key chara	acteristics of	the distributi	on				
	Mean	S.D.	Min	Q1	Median	Q3	Max
Credit volume	398,466.7	818,181.6	9,130.0	44,548.0	111,654.8	310,881.6	4,260,878.8
Provisioning ratio	2.6	10.0	0.00	0.04	0.19	0.83	100.00
Default	4.4	20.6	0.0	0.0	0.0	0.0	100.0
Maturity	5.6	4.8	0.12	2.18	4.17	7.51	19.45
Guarantee	13.3	31.7	0.0	0.0	0.0	0.0	100.0
Moratoria	1.2	9.9	0.0	0.0	0.0	0.0	100.0
Panel B: Correlatio	on matrix						
		Credit volume	Provisioning ratio	Default	Maturity	Guarantee	Moratoria
Credit volume		1.00					
Provisioning ratio		-0.01	1.00				
Default		0.00	0.69	1.00			
Maturity		0.16	0.02	0.01	1.00		
Guarantee		-0.08	-0.06	-0.05	-0.11	1.00	
Moratoria		-0.01	-0.02	-0.02	-0.09	0.02	1.00
Panel C: Distributi	on across aco	counting class	ifications				
			IFRS 9			nGA	AAP
		Stage 1	Stage 2	Stage 3		General allowance	Specific allowance
# of observations		44,698,975	7,074,824	2,744,482		7,170,866	847,533

 Table 1: Descriptive statistics – Loan-level data

*Notes:* This table reports the descriptive statistics of variables defined at the bank-firm (loan) level for the 62,536,680 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 2.5% and 97.5% 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.

Panel A: Key	characteristics	of the distrib	oution					
	Mean	S.D.		Min	Q1	Median	Q3	Max
CAP HEAD	6.6	4.7	-	1.0	3.6	5.4	7.9	24.0
LOG(TA)	21.3	1.6		18.4	20.3	21.2	22.1	25.5
DEP/TA	85.3	8.5		50.3	85.1	88.0	89.7	92.7
RW	44.7	10.7		21.5	37.6	45.0	51.4	71.4
ROA	0.3	0.4		-0.8	0.1	0.2	0.5	1.4
CASH/TA	8.3	8.5		0.6	2.2	6.1	10.5	38.8
LOAN/TA	83.2	10.6		48.8	78.8	85.4	90.7	96.8
TLTRO/TA	5.3	9.8		0.0	0.0	0.0	7.1	40.0
Panel B: Corr	elation matrix							
	CAP HEAD	LOG(TA)	DEP/TA	RW	ROA	CASH/TA	LOAN/TA	TLTRO/TA
CAP HEAD	1.00							
LOG(TA)	-0.14	1.00						
DEP/TA	-0.32	-0.36	1.00					
RW	-0.23	-0.15	-0.03	1.00				
ROA	0.10	-0.06	-0.12	0.03	1.00			
CASH/TA	0.14	0.21	-0.17	-0.16	-0.04	1.00		
LOAN/TA	-0.12	-0.26	0.23	0.00	0.10	-0.82	1.00	
TLTRO/TA	-0.16	0.31	-0.04	-0.08	-0.07	0.04	-0.02	1.00

 Table 2: Descriptive statistics – Bank-level data

*Notes:* This table reports the descriptive statistics of variables defined at the bank level for the 22,453 bank-quarter observations in our data set. Variables are winsorised at the 2.5% and 97.5% level. Panel A shows key distributional characteristics and Panel B reports the correlation matrix.

Table 3: Descriptive statistics - Energy data

	N	Mean	SD	Mir	n Q1	Median	Q3	Max
A Agriculture	136	11.42	7.98	1.66	5 7.41	9.97	13.02	62.82
B-F Industry and Construction	1561	28.54	42.29	1.66	5 7.67	11.56	20.57	157.99
G-N Services (excl. financial & real estate)	816	11.81	12.60	1.66	6 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 2.5% and 97.5% level.

	А	All		RS	nGAAP		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	
Variables							
D(nGAAP)	$-1.460^{***}$	$-0.3441^{**}$					
	(0.3565)	(0.1522)					
Maturity	0.0514	0.0254	0.0676	0.0267	-0.0300***	$0.0084^{**}$	
	(0.0442)	(0.0181)	(0.0528)	(0.0237)	(0.0052)	(0.0036)	
Guarantee	-2.986***	-1.298***	-3.063***	-1.338***	-1.127***	-1.011***	
	(0.2811)	(0.0935)	(0.3034)	(0.0998)	(0.1524)	(0.1192)	
Moratoria	$-1.923^{***}$	-0.0049	$-2.021^{***}$	0.0054	$-0.6986^{***}$	0.0018	
	(0.3828)	(0.2035)	(0.4379)	(0.2226)	(0.1228)	(0.1250)	
CAP HEAD	$0.0753^{**}$	$0.0773^{***}$	$0.0715^{*}$	$0.0731^{***}$	$0.0537^{***}$	$0.0842^{***}$	
	(0.0379)	(0.0188)	(0.0433)	(0.0208)	(0.0202)	(0.0135)	
LOG(TA)	-0.1025	0.0298	-0.1825	0.0551	-0.0076	-0.0056	
	(0.0974)	(0.0537)	(0.1549)	(0.0782)	(0.0673)	(0.0406)	
DEP/TA	-0.0088	0.0076	-0.0240	0.0041	0.0127	$0.0207^{***}$	
	(0.0158)	(0.0074)	(0.0268)	(0.0133)	(0.0091)	(0.0040)	
RW	0.0052	-0.0141*	0.0020	-0.0163	0.0030	-0.0116***	
	(0.0145)	(0.0073)	(0.0241)	(0.0120)	(0.0059)	(0.0032)	
ROA	-0.8437***	-0.1470	-0.8380**	-0.0508	-0.8900***	-0.4562***	
	(0.2709)	(0.1426)	(0.3540)	(0.1778)	(0.1130)	(0.0724)	
CASH/TA	-0.0587**	-0.0325*	-0.0604	-0.0412*	$-0.0170^{*}$	-0.0223***	
	(0.0292)	(0.0168)	(0.0458)	(0.0246)	(0.0097)	(0.0062)	
LOAN/TA	-0.0026	-0.0090	0.0060	-0.0159	-0.0044	-0.0040	
	(0.0227)	(0.0088)	(0.0404)	(0.0167)	(0.0066)	(0.0034)	
TLTRO/TA	$0.0216^{*}$	-0.0196***	$0.0261^{*}$	-0.0189***	-0.0098	-0.0114***	
	(0.0121)	(0.0055)	(0.0137)	(0.0063)	(0.0061)	(0.0034)	
Fixed-effects							
ILS-Quarter	Yes		Yes		Yes		
Firm-Quarter		Yes		Yes		Yes	
Fit statistics							
Observations	62,536,680	62,536,680	54,518,281	54,518,281	8,018,399	8,018,399	
$\mathbb{R}^2$	0.03437	0.90970	0.03456	0.91270	0.03395	0.90066	
Within $\mathbb{R}^2$	0.00950	0.00576	0.00993	0.00583	0.00434	0.00924	

 Table 4: Determinants of loan-level provisioning ratios

Double clustered (Firm  $\times$  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  $\times$  firm level. Explanatory variables at the loan level include a dummy variable indicating the accounting framework, the residual maturity of the loan in years, and the fraction of the loans covered by COVID-19 related guarantee schemes or credit moratoria. Explanatory variables at the bank level include the bank's capital headroom (defined as the distance between the CET1 ratio and the overall capital requirement), the total assets in logarithm, the deposit ratio, the risk weight density, the return on assets, the ratio of cash over total assets, the ratio of loans over total assets, and the ratio of TLTRO loans over total assets. Banking variables are lagged by one quarter. All variables are winsorised at 0.5% and 99.5%.

	stag	ge 1	stag	ge 2	stage 3		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	
Variables							
Maturity	-0.0047	-0.0035	$0.2666^{***}$	$0.1960^{***}$	-0.2278	-0.3031	
	(0.0060)	(0.0051)	(0.0653)	(0.0257)	(0.2200)	(0.1939)	
Guarantee	-0.2318***	-0.3101***	-2.827***	-2.606***	-19.66***	-14.06***	
	(0.0521)	(0.0367)	(0.6507)	(0.2401)	(2.012)	(1.432)	
Moratoria	0.0926	0.0582	1.008	1.004**	-14.04***	1.442	
	(0.1333)	(0.0888)	(0.7709)	(0.5087)	(3.544)	(2.868)	
CAP HEAD	0.0391	0.0313**	$0.1856^{**}$	$0.1354^{***}$	$0.6926^{***}$	$0.8098^{***}$	
	(0.0326)	(0.0146)	(0.0870)	(0.0439)	(0.2629)	(0.2300)	
LOG(TA)	$-0.1852^{*}$	-0.1170**	-0.4591*	-0.3479**	1.616	2.240***	
	(0.0975)	(0.0534)	(0.2396)	(0.1760)	(1.027)	(0.8605)	
DEP/TA	-0.0188	-0.0056	-0.0522	-0.0267	-0.0143	0.3099**	
	(0.0173)	(0.0079)	(0.0507)	(0.0325)	(0.1693)	(0.1553)	
RW	-0.0135	-0.0065	-0.1166***	-0.0920***	-0.2186	0.0907	
	(0.0094)	(0.0049)	(0.0394)	(0.0312)	(0.2060)	(0.1640)	
ROA	-0.0513	0.0358	-0.1881	0.3906	-2.191	-1.662	
	(0.0876)	(0.0477)	(0.3718)	(0.3547)	(2.892)	(2.112)	
CASH/TA	-0.0052	0.0046	-0.0564	-0.0099	-0.2428	$-0.5946^{*}$	
	(0.0163)	(0.0125)	(0.1047)	(0.0572)	(0.3707)	(0.3307)	
LOAN/TA	0.0076	0.0035	0.0209	-0.0221	0.2889	0.0794	
	(0.0151)	(0.0084)	(0.0919)	(0.0367)	(0.3440)	(0.3361)	
TLTRO/TA	0.0023	-0.0041	-0.0205	-0.0220*	-0.1569*	-0.3970***	
	(0.0038)	(0.0029)	(0.0191)	(0.0122)	(0.0813)	(0.0874)	
Fixed-effects							
ILS-Quarter	Yes		Yes		Yes		
Firm-Quarter		Yes		Yes		Yes	
Fit statistics							
Observations	44,698,975	44,698,975	7,074,824	7,074,824	2,744,482	2,744,482	
$\mathbb{R}^2$	0.06728	0.81089	0.14174	0.94288	0.16528	0.91993	
Within $\mathbb{R}^2$	0.00889	0.00784	0.04947	0.03087	0.04100	0.06333	

Table 5: Determinants of loan-level provisioning ratios – IFRS 9 stages

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-Q2. The dependent variable is the quarterly provisioning ratio at the bank  $\times$ firm level. Explanatory variables at the loan level include a dummy variable indicating the accounting framework, the residual maturity of the loan in years, and the fraction of the loans covered by COVID-19 related guarantee schemes or credit moratoria. Explanatory variables at the bank level include the bank's capital headroom (defined as the distance between the CET1 ratio and the overall capital requirement), the total assets in logarithm, the deposit ratio, the risk weight density, the return on assets, the ratio of cash over total assets, the ratio of loans over total assets, and the ratio of TLTRO loans over total assets. Banking variables variables are lagged by one quarter. All variables are winsorised at 0.5% and 99.5%.

Table 6:	Aggregate	provisioning	ratios	around	$\operatorname{credit}$	risk	shocks	(IFRS 9	loans)	

Panel A: St	age 1 in the quarter	before default					
	% of loans in stage 1 before default	>1 quarter before moving to default			1 quarter before moving to default	On default	4 quarters after default
Overall	39.8%	1.59			1.60	16.83	17.88
High capital	36.4%	1.82			1.77	18.60	22.14
Low capital	38.0%	1.25			1.41	14.95	13.47
Panel B: Sta	age 2 in the quarter	before default					
	% of loans in stage 2 before default	>1 quarter before moving to stage 2	1 quarter before moving to stage 2	After moving to stage 2	1 quarter before moving to default	On default	4 quarters after default
Overall	60.2%	0.92	1.52	6.93	8.76	22.37	26.14
High capital	63.6%	1.00	1.55	7.20	9.34	22.57	26.29
Low capital	62.0%	0.80	1.50	6.63	7.99	22.34	26.07

Dependent Variable:	D(moved t	to stage 2)
	(1)	(2)
Variables		
CAP HEAD Low	-0.3681**	-0.4039**
	(0.1524)	(0.1597)
Maturity		-0.0027
		(0.0085)
Guarantee		$0.5813^{***}$
		(0.1293)
Moratoria		0.0081
		(0.1567)
TA.log		$0.4635^{***}$
		(0.0600)
RW		$0.0388^{***}$
		(0.0109)
DEP/TA		$0.0265^{**}$
		(0.0116)
RoA		$-0.2024^{*}$
		(0.1085)
CASH/TA		-0.0113
		(0.0174)
LOAN/TA		-0.0087
		(0.0171)
TLTRO		$0.0094^{*}$
		(0.0053)
Fixed-effects		
Firm	Yes	Yes
Fit statistics		
Observations	696,333	696,333
Squared Correlation	0.09634	0.13168
Pseudo $\mathbb{R}^2$	0.07442	0.10263
BIC	4,059,280.2	4,032,488.5

 Table 7: Determinants of moving a loan to stage 2

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

Notes: The table shows regression results for equation 4, estimated on our loan sample covering the period from 2018-Q3 to 2022-Q2. 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 at the loan level include a dummy variable indicating the accounting framework, the residual maturity of the loan in years, and the fraction of the loans covered by COVID-19 related guarantee schemes or credit moratoria. Explanatory variables at the bank level include the bank's capital headroom (defined as the distance between the CET1 ratio and the overall capital requirement), the total assets in logarithm, the deposit ratio, the risk weight density, the return on assets, the ratio of cash over total assets, the ratio of loans over total assets, and the ratio of TLTRO loans over total assets. All variables are taken at their value when the first bank moves its loan to firm f to stage 2. All variables are winsorised at 0.5% and 99.5%.

	Change in Im	pairment Ratio	Impairment F	Ratio (2022-Q2)
	(1)	(2)	(3)	(4)
D(IFRS)	-0.1141	-0.0152	$0.4468^{*}$	$0.4272^{**}$
D(II III)	(0.0712)	(0.0536)	(0.2476)	(0.2063)
CAP HEAD	0.0131	0.0312***	0.1361***	0.1041***
	(0.0101)	(0.0106)	(0.0307)	(0.0293)
$D(IFRS) \times Energy$	$0.0140^{*}$	(0.0100)	-0.0041	(0.0200)
D(II 105) × Ellergy	(0.0081)		(0.0169)	
CAP HEAD $\times$ Energy	(0.0001)	-0.0021*	(0.0100)	0.0038
8		(0.0011)		(0.0034)
Maturity	$0.0155^{***}$	0.0153***	$0.0609^{***}$	0.0612***
	(0.0046)	(0.0046)	(0.0193)	(0.0192)
Guarantee	-0.1459***	-0.1466***	-1.322***	-1.321***
	(0.0464)	(0.0465)	(0.1136)	(0.1140)
Moratoria	0.1380**	0.1319**	0.0556	0.0652
	(0.0624)	(0.0618)	(0.2319)	(0.2329)
$\log(TA)$	0.0726	0.0704	-0.0736	-0.0698
5( )	(0.0474)	(0.0472)	(0.1088)	(0.1090)
RW	0.0074	0.0068	-0.0245*	-0.0234*
	(0.0066)	(0.0066)	(0.0127)	(0.0126)
DEP/TA	0.0040	0.0041	-0.0119	-0.0119
	(0.0063)	(0.0063)	(0.0111)	(0.0110)
RoA	$0.3760^{***}$	$0.3749^{***}$	-0.3784	-0.3757
	(0.1305)	(0.1294)	(0.2992)	(0.2985)
CASH/TA	$0.0197^{***}$	0.0196***	-0.0270	-0.0269
	(0.0071)	(0.0070)	(0.0212)	(0.0211)
LOAN/TA	$0.0118^{**}$	$0.0117^{**}$	-0.0173	-0.0172
	(0.0052)	(0.0051)	(0.0123)	(0.0123)
TLTRO/TA	-0.0019	-0.0021	$-0.0177^{***}$	-0.0174***
	(0.0019)	(0.0018)	(0.0054)	(0.0053)
Fixed-effects				
Firm	Yes	Yes	Yes	Yes
Fit statistics				
Observations	$1,\!398,\!742$	1,398,742	1,501,814	1,501,814
$\mathbb{R}^2$	0.74735	0.74737	0.87521	0.87522
Within $\mathbb{R}^2$	0.00249	0.00254	0.01019	0.01025

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

Notes: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01. The table shows regression results for equation 3, estimated on our loan sample covering the period from 2022-Q1 to 2022-Q2. The dependent variable is the quarterly provisioning ratio at the bank × firm level, in change in columns (1) and (2) and in level in columns (3) and (4). Explanatory variables at the loan level include a dummy variable indicating the accounting framework, the residual maturity of the loan in years, and the fraction of the loans covered by COVID-19 related guarantee schemes or credit moratoria. Explanatory variables at the bank level include the bank's capital headroom (defined as the distance between the CET1 ratio and the overall capital requirement), the total assets in logarithm, the deposit ratio, the risk weight density, the return on assets, the ratio of cash over total assets, the ratio of loans over total assets, and the ratio of TLTRO loans over total assets. All variables are taken at their value when the first bank moves its loan to firm f to stage 2. All variables are winsorised at 0.5% and 99.5%.

# 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 0.01.

Results of the matching are presented in Panel B of Table A.1. The matched sample includes 230 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. Thus, the PSM successfully controls for differences between treatment and control group that could affect our estimation results presented in Section 5.2.

Panel A: Pre	$\mathbf{PSM}$				
	nGAAP	IFRS	nGAAP	IFRS	Welch
	nb	nb	mean	mean	test
Dist. MDA	$1,\!151$	458	7.152	7.814	-2.2**
TA.log	$1,\!151$	458	21.001	21.884	-9.23***
DEP/TA	$1,\!151$	458	86.388	79.977	11.18***
RW	$1,\!151$	458	46.218	41.728	7.45***
RoA	$1,\!151$	458	0.39	0.364	1
LOAN/TA	$1,\!151$	458	85.724	80.991	7.87***
CASH/TA	$1,\!151$	458	5.499	11.407	-11.95***
TLTRO	$1,\!151$	458	3.587	9.314	-8.96***
Nb of obs., log	$1,\!151$	458	4.581	5.91	-11.34***
Panel B: Pos	t PSM				
	nGAAP	IFRS	nGAAP	IFRS	Welch
	nb	nb	mean	mean	test
Dist. MDA	230	230	7.353	7.134	0.48
TA.log	230	230	21.875	21.66	1.47
DEP/TA	230	230	81.73	81.46	0.25
RW	230	230	43.739	43.926	-0.18
RoA	230	230	0.371	0.341	0.67
LOAN/TA	230	230	83.183	83.132	0.05
CASH/TA	230	230	9.327	9.263	0.08
TLTRO	230	230	5.898	5.867	0.03
Nb of obs., log	230	230	5.34	5.174	0.95

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

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 0.01.