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Limitations of Implementing an Expected Credit Loss Model

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November 2022

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1 Introduction

The regulation of bank reporting shapes bank transparency and constitutes a key input to prudential supervision (e.g., Ryan 2017; Beatty and Liao 2014). This is exemplified by international bank regulators and the G-20 having attributed the turmoil of the 2008 financial crisis to the delayed recognition of loan losses by financial institutions. In their view, banks failed to build a sufficient level of reserves during good times ('too little, too late') and were thus forced to significantly adjust their asset values late during the crisis when their equity had already been depleted with little capacity to absorb additional losses (e.g., G20 Financial Stability Forum 2009). In response to the political pressure, international regulators fundamentally changed the reporting standards for loan loss recognition. Both in the US and internationally, new rules introduce a forward-looking approach to loss provisioning that builds on expected rather than actually incurred credit losses.[1] To determine expected credit losses, banks estimate internal models that quantify future default events of their borrowers.

The consequences of the use of forward-looking information in loan loss recognition for overall bank stability depend on how banks exert their discretion in estimating future default events and how they adjust their lending when some loans require higher loss recognition. We examine these two effects in this paper because they impact bank stability in opposite directions. On the one hand, the recognition of expected credit losses, if appropriately estimated, can result in higher reserve requirements very early during a downturn (compared to the late recognition of incurred losses). In anticipation of earlier and higher loss recognition, banks will then have incentives to reduce the credit risk in the first place and lend to less risky borrowers (Mahieux, Sapra, and Zhang 2022; Bushman and Williams 2012). If such a change in lending lowers the amount of required loss recognition during a downturn, banks' resilience to an economy-wide crisis is enhanced. On the other hand, banks face competitive pressure and have incentives to strategically use the discretion that is inherent in the generation of any forward-looking information (Rajan, Seru, and Vig 2010). Banks can thus use this discretion to systematically underestimate future credit losses during good times (e.g., Moyer 1990; Beatty, Chamberlain, and Magliolo 1995). In this case, forward-looking credit provisions could even contribute to deteriorate banks' resilience during a downturn. This would be the case if banks are forced to adjust for actual losses as well as strategically underreported provisions at the same time during a downturn. In this paper, we investigate how the introduction of forward-looking provisions impact banks' (strategic) reporting of the forward-looking provisions as well as banks' lending behavior. Understanding banks' reaction to these new rules allows us to assess in how-far the IFRS 9 reform contributed to banks' ability to absorb

[1] The new US rules became effective in financial year 2020 with the Financial Accounting Standards Board (FASB)'s Update 2016-13 of Topic 326. The International Accounting Standards Board (IASB) developed IFRS 9 in parallel. The standard became applicable from 2018 onwards.

shocks during a downturn.

To address this question, we exploit the institutional details surrounding the implementation of IFRS 9 by German banks to study how banks determine their expected credit losses under the new rules. The German banks which are required to file IFRS reports (i.e., affected banks) started to implement the new loan loss provisioning standards in 2016.[2] The German setting offers the advantage of detailed loan-level data being available through the credit register by Deutsche Bundesbank, the German central bank which also bears the responsibility for banking supervision at the national level. Most importantly for our research design, the credit register includes information on the internal risk assessment and the ratings that banks assign to their borrowers.[3] We use this information to determine the classification of all loans and, thus, the required loss provisioning according to the new standards.

While previous literature has studied the informational effects of differences between expected and incurred credit loss models (e.g., Harris, Khan, and Nissim 2018; López-Espinosa, Ormazabal, and Sakasai 2021; Wheeler 2021), it is important to also understand the implications of forward-looking reporting requirements for bank behavior, both in the reporting and lending. Evaluating the quality of a loan in a forward-looking manner, and estimating these future credit losses, is not only a function of 'hard' and easily verifiable information but also of 'subjective' and less verifiable information. Since banks have to recognize higher provisions for a given loan once they expect a negative credit event, the new rules provide incentives to ignore information that results in such an event (Holmstrom and Milgrom 1991; Rajan, Seru, and Vig 2015). The complexity involved in the assessment of future credit events and the difficulty to verify subjective information impede the detection of such behavior by auditors and supervisors, making the correct application of the new rules hardly enforceable. Banks are thus likely to endogenously adjust their behavior to the new reporting standards (see Behn, Haselmann, and Vig 2022 for a similar set-up on regulatory capital requirements). This has implications for the regulatory debate about the optimal design of loan loss recognition rules. As argued by Glaeser and Shleifer (2001), coarser regulation can be the optimal regulatory choice and dominate more sophisticated forms of regulation, such as an expected credit loss model, especially in the presence of enforcement constraints as they are common in the international environment of IFRS-adopting banks.

The new IFRS 9 rules rely on a three-stage classification of all loans. All new loans are classified on 'stage 1'. The required loss provision for these loans only needs to cover expected credit losses over the

[2]Under German accounting law, banks are required to file IFRS reports if they have any debt or equity securities listed on a regulated market.

[3]The largest banks in our sample determine their capital requirements under the internal rating based (IRB) approach. They use these ratings for this purpose. However, all other banks which operate under the standard approach (SA) are also required to report the same internal ratings in their supervisory filings.

12-month horizon and, in practice, the resulting loss recognition is almost negligible. Once a loan experiences a significant deterioration in credit risk (as reflected in its internal rating), the loan is transferred to 'stage 2' and the required loss provision needs to cover all expected credit losses over the loan's remaining lifetime. In practice, this transfer leads to a considerable increase in the provision (on average, by a factor of approx. eight). The third stage of the new impairment model comprises all loans for which an actual loss event had become observable such that the loss has already incurred. 'Stage 3' loans are thus exactly equivalent to the loans for which a bank already had to recognize loss provisions under the former standards. Therefore, the main change in loan loss recognition clearly comes from the classification of a loan on 'stage 2'. These loans did not trigger any loss recognition before, but result in a large and economically meaningful increase in loan loss provisions under the new rules.

If a bank had incentives to avoid the substantial loss recognition for stage 2 loans and thus minimize the capital requirements, a bank would seek to decrease its exposure to these loans. For such a management of its loan portfolio, a bank has at least two options. First, managers could decide to reduce the actual holdings of the loans that are most likely to be classified on stage 2. Note that this does not necessarily imply a decrease in a bank's overall risk because, with the accounting criteria rather than the fundamental risk determining the classification, the lending adjustments could be confined only to borrowers near the accounting thresholds leaving riskier borrowers unaffected. It is an open question which business the bank enters into instead. Second, managers could avoid any real adjustment of their loan portfolios and systematically adjust the internal risk assessment (i.e., the ratings) of borrowers, and again especially those with loans close to being transferred to stage 2. Given the complexity of internal risk models, previous research has documented substantial leeway for banks in this regard.

We begin our analysis by using the data from the Bundesbank credit register and the 3-stage definition of IFRS 9 to assign each loan of both the affected and unaffected banks to the three impairment stages. Our descriptive evidence clearly shows that affected banks substantially decreased their share of stage 2 loans by 3 percentage points during the implementation of the new loss provisioning rules. Our empirical strategy allows us to identify the underlying reasons for this trend. First, we examine whether affected banks changed their loan classifications based on internal ratings systematically during this period, relative to unaffected banks. These unaffected banks continue to apply local reporting standards which did not change at this time and do not require a similar use of forward-looking information about expected loss events. For our empirical identification, it is important that, due to cross default clauses, the internal rating models are independent of any loan-specific factors and only assess the credit risk of the borrower. Changes in loan characteristics can, therefore, not explain the divergence in the risk assessment of an identical borrower by the two groups of banks. In our basic research design, we exploit this overlap in the loan portfolios of the two groups, i.e., those borrowers which are in lending relationships with at least one bank from our treatment and control group each. We find that, during the implementation period, an affected bank's probability to classify a loan to the *same* borrower on stage 2 decreases by 7.27 percentage points relative to the risk assessment by banks from the control group. This accounts for half of IFRS-adopting banks' stage 2 loans in the pre-period and reduces the intended effect of new loan loss provisions by around 24 percent.

We refine this identification strategy by taking advantage of a specific feature of the reporting standard. The new rules introduce a cliff effect around the investment grade cut-off. All loans that have an internal rating at the investment-grade level remain on stage 1 irrespective of any changes in their rating. However, any loan that is downgraded below the investment-grade status immediately becomes a stage 2 loan, thus requiring a substantial increase in loan loss provisions. Therefore, we test whether differences in the ratings of the same borrower are homogeneous across all rating notches or clustered around the investment-grade cut-off, where the potential benefit from avoiding the higher loss recognition (through a transfer to stage 2) is most pronounced. This latter pattern shows up very clearly in our results. We find the largest differences between the internal ratings of affected and unaffected banks for an identical borrower right around the investment grade cut-off. The farther away a rating notch is from this point, the smaller does the difference become. The pattern is very consistent with the strategic adjustment explanation because this exact cut-off does not have any other direct implications for determining regulatory capital requirements. Further, the results show that the rating differences tend to come from the avoidance of downgrades, which are easier to manage than upgrades of loans already on stage 2. An additional test shows meaningful differences in the cross-section of loans, suggesting that the differences in the internal risk assessments vary with the magnitude of required loss provisions and the bank's reporting incentives in the predicted direction. Specifically, the differences are more pronounced for loans with higher maturity or borrower exposure, but less pronounced for well-capitalised banks. Note that the loan-level specifications allow for the inclusion of bank $\times$ time fixed effects which systematically controls for differences among affected and non-affected banks.

In the next step, we investigate whether banks change their lending relationships during the implementation of the new loss provisioning standards and thus optimize the accounting classifications of their loans. We do not find evidence that affected banks become more likely to end lending relationships classified as stage 2 at the announcement date, again compared to banks in our control group. Instead, these banks significantly reduce their exposure to borrowers at high risk of stage 2 downgrade in future periods. More precisely, the probability to terminate a lending relationship with a high-risk stage 1 borrower is 11.2 percentage points higher for affected than non-affected banks. Examining the heterogeneity of this effect along the entire range of credit risk ratings shows that the exit rate is increasing in magnitude with greater borrower risk. These extensive margin results are consistent with banks having shifted their loan portfolio towards relatively less risky borrowers compared to non-affected banks. We therefore conclude that the lending adjustments following implementation of the new loss provisioning rules do mitigate some of the adverse impact arising from banks' strategic readjustments to internal risk assessments.

We contribute to prior literature in accounting and banking in three ways. First, we expand the literature on the effectiveness of regulation that is relying on precise, yet internal and thus hardly enforceable information. Glaeser and Shleifer (2001) show that coarser regulation can be preferable in situations where the precise targeting of a rule would require such an extensive supervision that strict enforcement would become prohibitively costly. This applies to many settings in banking and accounting. For prudential regulation under Basel II, Behn, Haselmann, and Vig (2022) document managerial opportunism in the assignment of risk weights based on internal ratings of bank loans that are costly to verify for bank supervisors. Similarly, for the financial reporting of banks and insurers, there is robust evidence on how managers systematically exploit their discretion in recognizing impairment losses (e.g., Vyas 2011; Huizinga and Laeven 2012; Bushman and Williams 2012; Bierey and Schmidt 2017; Beatty, Chamberlain, and Magliolo 1995) or estimating fair values (e.g., Hanley, Jagolinzer, and Nikolova 2018; Hodder and Sheneman 2022), especially when the fundamental characteristics of the underlying assets are hardly observable. We complement this evidence by showing that a similar trade-off applies to the reliance on expected credit losses in the regulation of loan impairments. While forward-looking estimates of credit defaults result in timelier and more precise loss recognition, these estimates are the results of internal models that rely on subjective expectations by managers and are thus much costlier to verify than the coarse estimates under an incurred loss model. Our findings underscore that managers systematically take advantage of the frictions in the enforceability of internal credit loss estimates, consistent with their reporting incentives.

Second, we contribute to the literature on the relation between banks' loan loss impairments and bank lending. Prior evidence suggests that delayed loss recognition is associated with greater risk in banks' loan portfolios and, consequently, higher reductions in bank lending during economic downturns (e.g., Beatty and Liao 2011; Bushman and Williams 2015; Wheeler 2019; Sehwa Kim 2022; Huber 2022), while timely fair value accounting does not produce such a procyclicality in bank lending (e.g., Xie 2016; Laux and Rauter 2017). Our evidence is generally consistent with these findings, as we document an association between the shift to a timelier reporting of expected credit losses and a reduction in bank lending to non-investment grade borrowers, i.e., a general decline in overall risk. However, the simultaneous increase in the opportunistic under-reporting of expected credit losses could still lead to a severe tightening in credit supply during a downturn when these losses become observable. This effect can reinforce the horizon effect documented by Chen, Dou, Ryan, and Zou (2022), which can explain even greater lending procyclicality under an expected credit loss model. In fact, the European Central Bank's decision not to strictly enforce the recognition of expected credit losses at the beginning of the downturn during the Covid-19 pandemic is consistent with banks having underestimated their loan losses and, thus, failing to provide a sufficient level of loss reserves at the onset of the crisis.[4] Even under an expected credit loss model, a general blanket adjustment of loan losses, such as in dynamic provisioning (Jiménez, Ongena, Peydró, and Saurina 2017), could thus prove beneficial for purposes of prudential regulation.

Third, we also speak to the broad debate on the overall effects of the introduction of the expected credit loss model under IFRS 9 as well as the current expected credit loss (CECL) model under US GAAP. Early evidence tends to be consistent with informational benefits of the expected credit loss model that manifest in timelier loss recognition (López-Espinosa, Ormazabal, and Sakasai 2021; Sehwa Kim, Seil Kim, Kleymenova, and R. Li 2022), at least if the underlying estimation model is well defined (Harris, Khan, and Nissim 2018; Lu and Nikolaev 2022). Other evidence points to consequences for bank lending (Ertan 2021; Morais, Ormazabal, Peydró, Roa, and Sarmiento 2020). We triangulate this evidence by offering loan-level analyses from a tight setting where we can use within-borrower variation in the lender's reporting standard. The results corroborate concerns about managers' opportunistic use of the reporting discretion inherent in forward-looking loss recognition. At the same time, banks also tend to forgo certain lending relationships which can result in a decrease in their overall risk-taking. This behavior implies consequences for the real activities of borrowers that are now facing credit constraints.

2 Institutional Background

2.1 The Regulation of Loan Loss Provisioning

The G-20 as well as international bank regulators identified the lack of timely loan loss recognition ('too little, too late') as one key problem of prudential supervision during the 2008 financial crisis (G-20 2009; Financial Stability Forum 2009). Under this view, delayed recognition of loan losses contributes to procyclicality of lending, thus aggravating the impact of the crisis. In response to this criticism and the G-20 initiative, accounting standard-setters adopted a more forward-looking approach to loan loss provisioning. In the US, the Financial Accounting Standards Board (FASB) issued a new standard in June 2016 (ASU 2016-13). The new rules, being effective since December 2019, require the recognition of current expected credit losses and eliminate the probability threshold that precluded early loss recognition before.

In a similar spirit, the International Accounting Standards Board (IASB) proposed the relevant regulation for companies outside the US as part of the new standard for financial instruments accounting (IFRS 9).

[4] See the European Central Bank (2020)'s letter to significant institutions from April 1, 2020.

The standard introduces an expected credit loss model that replaces the existing incurred loss model. The IASB proposed the final version of IFRS 9 on July 24, 2014. The European Union finally adopted the new standard on November 22, 2016 (Regulation 2016/2067/EU). Initially, there was considerable opposition against the new regulation and thus uncertainty about the final decision of the EU (e.g., Hashim, W. Li, and O'Hanlon 2016). The main concern was the proximity of the new measurement rules to a full fair value accounting. The controversy peaked in early September 2015, when UK pension funds and financial analyst associations publicly campaigned against IFRS 9 adoption in the EU.[5] Some of the uncertainty was resolved when the European Financial Reporting Advisory Group (EFRAG), an official advisory board to the EU that is involved in the adoption of any new IFRS standard, decided to recommend the adoption of IFRS 9 on September 15, 2015. German auditors confirmed in private interviews that, following this decision and other signals from EU legislators (e.g., during the December hearing in the EU Parliament), European banks started to prepare for the implementation of the new regulation from late 2015 onwards.[6] The transition period for IFRS 9 adoption ended in 2017; all listed companies in the EU were mandated to apply IFRS 9 for financial years beginning in 2018. We present a detailed timeline of the adoption period in Table A1 in the Appendix.

Provisioning rules under the former incurred loss model - referred to as IAS 39 - were fairly plain (e.g., Spooner 2007). Under this model, loan loss provisions were recognized once a loan experienced an observable loss event (e.g., a past-due event or a renegotiation). In this case, the required loan loss provision equaled the present value of the loss given the observed event. Under the expected loan loss model, a bank classifies its loan portfolio into three different stages. Upon origination or purchase, a bank uses stage 1 for this loan (with very limited exceptions for loans that already have very low credit quality at this point). The loan loss provisions for these stage 1 loans include expected credit losses for a 12-month horizon. In practice, provisions for stage 1 loans are thus calculated as 12-month PD * LGD * EAD. All loans with an internal or external rating at an investment-grade level remain on stage 1 over their entire lifetime, and so do non-investment grade loans that do not experience any significant deterioration of the borrower's credit risk. On average, these stage 1 loans comprise 79.3% of European banks' loan portfolios but only account for 10.4% of their total loan loss provisions.[7]

[5]The Financial Times documents this controversy; e.g., September 9, 2015, p. 24; September 3, 2015, pp. 8, 12. Right at this time, the Institute of Chartered Accountants in England and Wales (ICAEW) described IFRS 9 as "one of the most debated new accounting standards in history", see Financial Times (2015b).

[6]Consistent with this assessment, Deutsche Bank, Germany's largest bank, reported in March 2016 for the first time that it had formally set up internal processes for IFRS 9 implementation: "The Group has implemented a centrally managed IFRS 9 program sponsored by the Group's chief financial officer and includes subject matter experts on methodology, data sourcing and modelling, IT processing and reporting."

[7]The data comes from a hand-collected sample of 200 banks from 35 countries. 84 of these banks separately disclose their annual loan loss provisions by the stages of the impairment model.

The next category, stage 2, comprises all under-performing loans. These are non-investment grade loans that did experience a significant increase in the credit risk of the borrower (the SICR criterion). Reporting practice defines such a significant increase as a downgrade to non-investment grade status (for a loan that originated with investment grade status) or a downgrade by two or more notches of the internal rating schedule (for a loan that originated with non-investment grade status). Right at this point, when a loan meets one of these two criteria and is transferred to stage 2, the required loan loss provision rises substantially and covers the full amount of expected credit losses over the remaining lifetime of the loan. We depict the resulting cliff effect in Figure 1. In practice, banks apply period-specific PDs (e.g., in buckets of 12-month periods until loan maturity) multiplied by the corresponding LGDs and EADs for the same periods. Thus, this category is the main forward-looking element of the new regulation and comprises 9.1% of European banks' total loan portfolio. Empirically, our own anecdotal evidence from the first-time application by European banks shows that loss recognition for stage 2 loans is greater than for stage 1 loans by a factor of approx. 8.

The observable loss events that were the main input into the loan loss provisioning under the former incurred credit loss model continue to play a role under the IFRS 9 regulation where they trigger a shift to stage 3 of the expected credit loss model. Put differently, stage 3 loans under IFRS 9 represent those non-performing loans for which loss recognition was already required under the former regulation and during the financial crisis. The shift of a loan to stage 3 does not change the loss provisioning, which is identical to stage 2 and requires the recognition of lifetime expected credit losses. Stage 3 classification only prescribes the additional adjustment of interest income for the effect from the credit loss expectations. Therefore, the loan loss provisions on stages 1 and 2, which internal managers derive from their forward-looking loss expectations, constitute the key difference between the new IFRS 9 regulation and the former approach based on an incurred-loss model.

The link between the loan loss recognition and regulatory capital depends on whether a bank computes capital requirements for a loan portfolio based on internal risk parameters (IRBA) or standardized risk weights (SA).[8] Loan loss provisions for SA portfolios directly reduce CET1 (Common Equity Tier 1) capital one-to-one. Loan loss provisions for IRBA portfolios are benchmarked against regulatory expected losses. A shortfall of accounting provisions is additionally deducted from CET1 capital, while a potential excess over

[8]The European Union has introduced a transition option that banks can use to ease the one-time impact of IFRS 9 on regulatory capital (Article 473a of the European Capital Requirements Regulation). When using this option, banks can add back a portion of the additional loss allowance that is attributable to the recognition of expected credit losses to their CET1 capital. The phase-in factor was 95% for the financial year 2018 and gradually decreases to 25% in 2022 before it fully expires. According to Bundesbank data, not a single institution from Germany that had to adopt IFRS 9 opted for the transitional arrangements in financial year 2018 (Deutsche Bundesbank 2019). For our sample, we can thus plausibly assume that the full regulatory capital effect of the new rules for loan loss recognition sets in immediately upon first-time adoption.

regulatory expected losses can be partially added back to tier 2 capital. Regulatory expected losses always cover a 12-month period and rely on through-the-cycle estimates. For loan loss provisions on stage 1, the benchmarking can go in both directions and depends on the model parameters as well as the stage of the economic cycle. For loan loss provisions on stage 2, the comparison of lifetime expected credit losses under IFRS 9 with the regulatory 12-month losses will likely lead to an overhang of the accounting losses with the stage 2 provisions reducing CET1 capital one-to-one. The regulatory treatment thus reinforces the cliff effect and banks' incentive to maintain loans on stage 1 of the IFRS 9 provision scheme.

2.2 The Implementation of Forward-Looking Provisioning Models

How do bank managers arrive at the credit loss expectations for a given loan? While provisioning under the old reporting standards was only based on observable loss events, the new standard relies on banks' continuous assessment of the credit risk of its borrowers. The determination of loan loss provisions under IFRS 9 demands considerably more information than the previous standard. Since few loans carry an external rating, the new approach relies on banks having set up an internal rating system, similar to the requirements under a model-based capital regulation. According to the IFRS 9 rules, banks have to design these internal rating models such that they estimate the probability that a specific borrower defaults within a certain period (e.g., over the next 12 months). Importantly, these PDs are borrower-specific estimates and their estimation does not consider loan-specific terms. Due to the existence of cross-default clauses, banks should thus arrive at identical estimates and underlying risk factors should equally affect estimates by all banks in the same manner. The fact that these internal ratings are borrower-specific and do not depend on the specific terms of the loan relationship is important for our identification strategy.

In general, banks calibrate their internal risk models on the basis of different portfolios (e.g., portfolios of all large caps and SME borrowers or portfolios of different industries). The rating for a given loan should, however, only depend on the risk of a given borrower and not on the composition of the portfolio that a borrower is assigned to. The most important ingredient of the statistical default models of corporate borrowers is accounting information from financial statements. In addition to these quantitative factors, models can rely on qualitative information such as a firm's management quality or its competitive situation. The complexity of the default models as well as the vast amount of information that serves as input for these models provide banks with opportunity to influence the outcome of these models (see Behn, Haselmann, and Vig 2022). The latter is particularly likely when banks operate in competitive markets and too pessimistic of an assessment leads to an increase in the marginal costs of a loan (i.e., in terms of higher capital requirements).

The adoption of statistical default models is not an innovation of IFRS 9. Banks have also used these models before to estimate PDs for purposes of prudential supervision; for instance, to determine risk-weights under the IRB approach of the Basel framework or for supervisory filings. IFRS 9 extends their use to determine banks' expected credit losses. However, there are differences between the PDs used for financial reporting and for regulatory capital requirements. For one, IFRS 9 requires the use of point-in-time estimates, while the Basel framework relies on through-the-cycle estimates. Another difference comes from the external monitoring of these models. While regulatory default models are annually reviewed by the prudential supervisor, the models used for financial reporting are reviewed by auditors who are supposed to testify the adequacy of the loan loss provisioning.

3 Data and Descriptive Statistics

Our main data source is the German credit register compiled by Deutsche Bundesbank. Deutsche Bundesbank is responsible for the supervision of German banks and collects quarterly data on all loan relationships with domestic clients that have an outstanding volume of at least €1m. The data includes information on the identity of lenders and borrowers, the characteristics of the loan (e.g., volume and collateral), and especially the lender's internal risk assessment (PDs). We add to the data information on bank characteristics that we obtain from the BISTA and GuV databases. These databases include supervisory information about balance sheet and income statement items of German banks collected by Deutsche Bundesbank. We match this dataset with data from the common reporting framework (COREP) on a loan-portfolio level with respect to borrower type and default risk category. This allows us to add borrower characteristics (e.g., LGD and PD) to determine loan loss provisions on the portfolio level and the impact on the equity buffer.

We start the sample selection with the universe of all quarterly observations of lending relationships with corporate clients included in the credit register during the sample period from 2015Q1 to 2018Q4.[9] To achieve a balanced sample and reduce the number of temporary drop-outs when the loan volume fluctuates around the €1m threshold, we only include loans in our sample for which the volume exceeds €2m in at least one quarter of our sample period. Of the 2,120,887 lending relationship quarters, the credit register reports a PD for 829,488 observations.

In the next step, we follow Haselmann, Schoenherr, and Vig (2018) and divide the lending relationships into individual loans because IFRS 9 requires a determination of the expected credit losses and the stage classification at the loan level (not the borrower level).[10] We arrive at 1,313,768 distinct loan quarters and

[9]Our sample period begins in 2015Q1 because the standard information in the Bundesbank's credit register was reorganized at this time and we want to exclude any changes in the composition of the reported loans from our dataset.

[10]We identify a new loan if the loan volume increases. Because the loan volume of credit lines fluctuate over

551 banks. To assess the classification on the IFRS 9 impairment stages, we are able to track the PD data for these loans back to 2008Q1. We use Standard & Poor's SNL Financial database to classify the banks into IFRS (81) and Local GAAP adopters (470).[11] Subsidiary banks are coded as IFRS 9 adopters if the consolidated accounts of their parent entity are prepared in accordance with IFRS 9. None of our sample banks changes its financial reporting standards during our sample period.The matching with data on all bank and loan characteristics used in our main analysis yields a final sample of 1,274,371 loan quarters, of which 1,037,986 relate to IFRS 9 adopters and 236,385 to Local GAAP adopters.

We use the reported PDs from the Bundesbank credit register to assign internal ratings to these loan quarters. For this purpose, we apply a standard 20-notch rating scale from AAA to D with the investment grade threshold between a BBB- and a BB+ rating. We derive the individual mapping from PDs into internal ratings from each bank's Pillar 3 disclosures. These conversion tables remain stable over time. For banks that do not provide any conversion tables in their Pillar 3 reports, we apply the mapping of Deutsche Bank as the German industry leader to generate consistent ratings. Then, we follow industry practice (see above, Section 2.1) and use the internal ratings to classify the loans into the three stages of the IFRS 9 expected credit loss model.[12] More specifically, we proceed as follows:

- *Stage 1*: All loans start in stage 1 at the later of the contract inception (consistent with IFRS 9, para. 5.5.5) or the beginning of our data coverage in 2008Q1 (12% of our sample loans have been originated before this date).
- *Stage 2*: A loan is transferred onto stage 2 if it meets either one of the following two criteria: (i) a loan with an initial rating at the investment-grade level is downgraded to non-investment grade (consistent with IFRS 9, para. 5.5.10), or (ii) a loan with an initial rating at the non-investment grade level is downgraded by more than one rating notch (consistent with IFRS 9, para. 5.5.9). A loan is transferred back (upgraded) to stage 1 when the criteria are no longer fulfilled (consistent with IFRS 9, para. 5.5.7).
- *Stage 3*: A loan is transferred into stage 3 once it experiences a loss event, i.e., its PD is reported at 100% (consistent with IFRS 9, para. 5.4.1).

For purposes of our base regression models, we collapse the data into one observation per loan for the pre-period (2015Q1 to 2015Q4) and the post-period (2018Q1 to 2018Q4) each, using the arithmetic means

time, we assign a new loan only if the amount increases significantly by a third of the outstanding volume.

[11] Under EU Regulation, a bank is required to adopt IFRS if any of its securities are publicly traded on a regulated market. Voluntary IFRS 9 adoption is also possible under local German accounting law.

[12] We conduct three interviews with German bank auditors to confirm that our procedure resembles the actual classification criteria that are applied in practice as closely as possible.

for each period. This procedure gives us 102,693 observations for 2015. Table 1 presents summary statistics for our main sample. We start reporting bank-level statistics in Panel A. To do so, we split our sample banks according to their reporting standards. There are 470 banks under the local GAAP standard that constitute our control group and 81 banks apply the new IFRS 9 standard that constitute the treatment group. IFRS-adopting banks are substantially larger, slightly less capitalized and less profitable than local GAAP banks. They also hold fewer deposits (relative to loans). These differences based on observables give rise to potential inherent differences among treatment and control group banks of our sample. We systematically address these concerns in Section 4.

We report summary statistics of our loan-level data set in Panel B. Given that the IFRS 9 banks are larger, most of our sample loans are from these banks. Overall, our final sample consists of 81,297 loans from IFRS-adopting banks and 21,396 loans from local GAAP banks in 2015Q4. On average, IFRS-adopting banks hold loans with a larger volume and a slightly lower PD. Interestingly, the share of loans with a stage 2 classification is also higher (by approx. five percentage points) for IFRS adopters. We calculate the average share of stage 2 loans at the moment the reform was announced following the methodology described above. Note that we compute the hypothetical stage 2 share given that only IFRS banks were required to comply with the new rules starting in 2018. The volume of loans held by IFRS banks and classified on stage 2 decreases on average from 2015 to 2018. The trend at local GAAP banks is also negative but weaker. The average reported default risk of loans already in stage 2 at the end of the pre-period decreases much more among IFRS than local GAAP banks.

Given that we have classified the loan portfolios of IFRS adopters and our control group banks according to the different stages, we descriptively illustrate how banks reacted to the new reporting standards. Figure 2 shows the share of stage 2 loan volume separately for affected and unaffected banks over time. The graph presents the accumulated change in the loan volume on stage 1 (Panel A) and stage 2 (Panel B) between the announcement and the first-time implementation of the expected credit loss model for loan loss provisioning.[13] Consistent with the incentives that arise from the new standards, we observe a decrease in the relative share of stage 2 loans, setting in right around the announcement of the new loss provisioning models in the first quarter of 2016 and until the initial adoption of the regulation in financial year 2018. Table 2 illustrates these numbers in detail. In the quarter before the announcement the share of stage 2 loans was 13.81% for IFRS adopters and decreased until the adoption date in 2018 to 12.83%. Banks not affected by the new standards actually increased their share of stage 2 loans during the same time period from 8.45% to 9.75%.

[13]We compute the change as the (two-quarter moving average) difference in the loan volume on the respective stage between the current period and 2015Q4 (as our benchmark period right before banks start to implement IFRS 9), with loan volume on each stage scaled by the total loan volume. Thus, we show a trend of the value-weighted average of loans on each stage for both groups of banks during our sample period.

Thus affected banks decreased their share of stage 2 loans relative to control group banks by 2.28 percentage points. This number constitutes a substantial magnitude and makes up for 16.5 percent of the share of stage 2 loans that these IFRS adopters had in their loan portfolio when the standards were announced.

There are basically two potential explanations for this observed pattern. Either IFRS adopters reduced the exposure to their stage 2 loans before the implementation date to economize on the level of their provisions. Alternatively, banks might have managed the classification of their loans to minimize their share of stage 2 loans. While the first explanation would mean that banks actually reduced the share of their risky loans as intended by the reform, the second alternative would mean that banks wold have been able to circumvent the new standards. In the following, we present our empirical strategy to investigate the underlying reasons for the decrease of these type of loans.

4 Methodology

There are alternative explanations for the trend of stage 2 loans that we observed in Figure 2. One is an adjustment of loan ratings to avoid stage 2 classifications. In the first set of analyses, we test whether there is evidence for such a strategic adjustment of internal ratings. Banks could also reduce the overall risk of their loan portfolio which would result in a lower fraction of stage 2 loans. Finally, banks could avoid originating and holding loans at high risk of a stage 2 downgrade, for instance, because the borrower is rated in close proximity to the investment grade threshold. In doing so, they could leave the risk of their portfolio relatively unaffected whilst reducing the share of loans falling into stage 2 during their lifetime. In the second set of analyses, we aim to differentiate among these last two alternative lending explanations.

4.1 Forward-looking loss provisions and internal loan ratings

Our first empirical model tests whether banks systematically adjust their internal ratings to avoid classifications of stage 2 loans before the new reporting requirements are applicable. As illustrated in Section 2.1, the new reporting standards require banks to deduct a considerably higher amount of provisions from their capital, once a loan is classified as stage 2. Consequently, banks subject to the new rules (i.e., affected banks) might adjust internal ratings to avoid a stage 2 classification for a given loan. To test this presumption, we investigate whether loan classifications of the *same* borrower are changed in the period between the announcement and implementation of the reform by affected as compared to non-affected banks. For each loan-quarter in our sample, we define the potential IFRS 9 classification as described in Section 3 in the pre-reform period. Formally, we estimate the following specification:

$$y_{bilt} = \beta_1 IFRS_b + \beta_2 AFTER \times IFRS_{bt} + \alpha_t + \alpha_i + \alpha_b + \beta_3 X_{bt} + \epsilon_{bilt}. \tag{1}$$

The dependent variable, y_{bilt}, is an indicator variable that takes a value of one if loan l from bank b to borrower i is at stage 2 in period t and zero if the loan is at stage 1.[14]

The pre-implementation period is from 2015q1 to 2015q4 and the post-implementation period from 2018q1 to 2018q4. The dummy variable $AFTER$ is equal to one in the post-period and zero otherwise. The indicator variable $IFRS$ takes the value of one for IFRS-adopting banks that are subject to the new regulation and zero otherwise. We collapse the quarterly data into the two periods, using arithmetic means, to avoid problems of serial correlation. We denote time-fixed effects by α_t. Since our specification exploits within-borrower variation between treated and control banks, we include firm fixed effects indicated by α_i. We further saturate our specification by bank fixed effects denoted by α_b and bank controls denoted by X_{bt}. These control variables capture the size (total assets), the profitability (return-on-assets) and the business model of a bank (deposits-to-loan ratio). In all specifications, we cluster the standard errors on a bank $\times$ year level to control for both cross-sectional and time-series dependence of the residuals in our model.

Our coefficient of interest β_2 shows how banks' classification of a stage 2 loan changes from the pre-period to the post-period for affected relative to non-affected banks. It is important to note that the criteria for transferring loans between stage 1 and stage 2 are, as described in Section 2.2, firm-specific and do not depend on any loan-specific characteristics. Thus, if a bank determines a change in the classification of a given borrower, other banks should on average come to the same assessment irrespective of their specific loan terms.[15]

The main identifying assumption is that affected and unaffected banks do not experience different shocks during our sample period that systematically affect their loan classification of identical borrowers. Financial institutions with capital market listings that adopt IFRS tend to be larger in size than other institutions that do not experience a change in their loan loss provisioning standards. If those larger institutions had, for example, experienced a shift towards stricter supervision which affected their risk assessment such a trend could potentially be responsible for a significant coefficient β_2. The institutional particularities of the IFRS 9 reform let us directly address such concerns. By the very specific construction of the rules, a loan

[14]We exclude stage 3 loans from our first analysis to focus on strategic adjustments between stage 1 and stage 2 loans, which is unique to IFRS 9, and avoid potential confounding effects from adjustments between stage 2 and stage 3.

[15]Due to the existence of cross-default clauses, a default with one borrower implies a simultaneous default with all other borrowers. Thus, changes in the probability of default of a loan are always firm-specific and not loan-specific.

has to be classified as stage 2 once a borrower is downgraded from investment grade to non-investment grade (see Section 2.1). Thus, downgrades from a BBB- rating to BB+ mechanically result in a very substantial jump of the required provisions. Right around this threshold, the required provisions increase from an almost negligible amount (for the 12-month horizon on stage 1) to an economically meaningful amount (for the lifetime losses of a loan on stage 2), see Figure 1 for an illustration of this cliff effect. We take advantage of this cliff effect by investigating whether the risk assessment of identical borrowers behaves differently around this threshold for IFRS-adopting banks and our control group. If the difference in risk assessment was most pronounced for these loans, a particular shock to IFRS-adopting banks that comes from differences in prudential supervision would be less plausible to explain the pattern because the distinction between investment grade and non-investment grade status does not play a similarly important role in capital regulation.

In specification 1, a change in the dependent variable y_{bilt} could be either a downgrade (i.e., the indicator switches from 0 to 1) or an upgrade (i.e., the indicator switches from 1 to 0). To obtain more insights on whether potential changes in the loan classification are driven by upgrades, downgrades or a combination of both, we also run our main specification with the dependent variable redefined in the following way: y_{bilt} only takes a value of 1 if the loan is downgraded from a stage 1 to a stage 2 loan, omitting any upgrades from stage 2 to stage 1. This restricted definition allows a clear separation of downgrades from upgrades.[16]

As a final test, we exploit cross-sectional heterogeneity among banks. More specifically, affected banks have stronger incentives to not classify a loan as stage 2 if the loan has a long maturity, the bank has a high exposure to the borrower or the bank's equity ratio is close to its capital requirement. To do so, we limit the sample to IFRS banks and test an interaction of the *POST*-dummy and either the loan or the bank characteristic in specification 2. This test allows to identify within the sample of IFRS banks whether banks change their classification systematically due to the new reporting standards. Thus, we are able to include $bank \times time$ fixed effects in the loan maturity / exposure specification and therefore systematically control for any time-varying differences between affected and non-affected banks. This cross-sectional test allows us to learn about the mechanism at work.

$$y_{bilt} = \beta_2 AFTER \times Characteristic_{ilt} + \alpha_t + \alpha_i + \alpha_b + \alpha_{it} + \alpha_{bt} + \epsilon_{bilt}. \quad (2)$$

[16]We cannot proceed analogously for upgrades since the number of stage 2 loans is rather limited at the end of the pre-period.

4.2 Lending adjustments under forward-looking provisions

An additional strategy to reduce stage 2 provisions is to avoid loans which are highly susceptible to a stage 2 downgrade. These are loans to borrowers rated either close to the investment grade cutoff or in the non-investment grade region (and thus subject to the tighter 2-rating notch criterion). Since these loans have a greater likelihood of being classified as stage 2 over their entire lifetime, this strategy results in a reduction of stage 2 loans. Alternatively (or at the same time) banks could more generally reduce their exposure to borrowers that experienced a negative credit event to reduce their stage 2 provisions. While the latter would clearly be an intended reaction by affected banks (since banks do reduce their exposure to risky borrowers to reduce their provisions), restricting lending to borrowers at high risk of downgrade (solely due to the institutional details of the standard) would primarily be a strategy to circumvent the new rules and potentially inhibit some desirable lending activities. To this end, we investigate banks' lending patterns around the implementation of the reform.

As a starting point, we investigate whether IFRS-adopters reduce the exposures of those loans that have an initial stage 2 classification following the announcement of the reform. We benchmark this against changes in exposure to stage 1 borrowers at high risk of downgrade leaving low-risk stage 1 borrowers as the omitted category. At the intensive margin we estimate Khwaja and Mian (2008) type regressions. At the extensive margin we can test for the probability that an affected bank ends a stage 2 or high-risk stage 1 classified lending relationship compared to a non-affected bank. Since all new loans initially obtain a stage 1 rating, we cannot test whether affected banks are less likely to start a new stage 2 classified loan.

More formally, we test the following specification:

$$\begin{aligned}\Delta Log(Relationship\ Volume)_{bi} = {} & \beta_1 IFRS_b + \beta_2 Stage1\ (High\ Risk)_{bi} + \beta_3 Stage2_{bi} \\ & + \beta_4 IFRS \times Stage1\ (High\ Risk)_{bi} + \beta_5 IFRS \times Stage2_{bi} + \alpha_i + \alpha_b + \epsilon_{bi}.\end{aligned} \tag{3}$$

The dependent variable is the change in the log mean exposure in the lending relationship between bank b and firm i between 2015 and 2018. The indicator variable *Stage2* takes the value of one if the borrower i is classified as stage 2 in 2015q4 by bank b and zero if it is classified as stage 1. Similarly, we define a separate (non-overlapping) indicator for borrowers currently still in stage 1, but at high risk of being downgraded (i.e., rating of BBB or lower). Since ratings are on the borrower and not loan level, we shift from the loan-level to the relationship-level to capture total changes in lending volume. In our fixed-effects specifications we include borrower fixed effects indicated by α_i to control for changes in loan demand. Thus, the coefficients of interest, β_4 and β_5, indicate the change in the volume of the lending relationship between an IFRS-adopting bank and a control group bank for the same borrower.

For the extensive margin, we estimate whether IFRS-adopting banks are more likely to end certain lending relationships after the implementation of the forward-looking loss provisioning models compared to non-affected banks:

$$\begin{aligned} EXIT_{bi} = {} & \beta_1 IFRS_b + \beta_2 Stage1\ (High\ Risk)_{bi} + \beta_3 Stage2_{bi} \\ & + \beta_4 IFRS \times Stage1\ (High\ Risk)_{bi} + \beta_5 IFRS \times Stage2_{bi} + \alpha_i + \alpha_b + \epsilon_{bi}. \end{aligned} \tag{4}$$

The indicator variable *EXIT* is equal to one if the lending relationship between bank b and borrower i is terminated early in the post-period, and zero otherwise.

The previous specifications allow us to estimate banks' exposure to those borrowers that either carry a stage 2 classification at the announcement date or exhibit a high risk of downgrade. A potential reduction of these types of lending relationships does not necessarily imply a reduction of risky borrowers in banks' portfolios if the lending adjustments are concentrated among borrowers around the investment grade cutoff whilst riskier borrowers remain unaffected. To explore this potential heterogeneity in lending effects, we therefore run our previous intensive and extensive margin regressions separately for each rating class dropping all categorical variables except for the IFRS identifier. The coefficient of interest thus compares lending adjustments between IFRS and LGAAP banks for each borrower credit rating. By focusing solely on credit risk (rather than stage 2 classification), we can also investigate the type of new lending relationships banks start. We substitute an indicator *ENTRY* equal to one if the borrower i in the new lending relationship with bank b has a specific rating r, and zero otherwise (i.e., all other newly initiated lending relationships in the post-period with a different rating) in specification 4. In effect, the outcome variable measures the likelihood that a new borrower is rated at r conditional on a new lending relationship having been established.

Comparing the coefficients of interest of both the extensive margin *ENTRY*/*EXIT* and intensive margin regressions along the entire rating spectrum allows us to distinguish whether IFRS banks' lending adjustments are confined to borrowers just below the investment grade cutoff or extend more broadly to the whole non-investment grade region. While the former would point to a strategy that exploits specific institutional features of the standard without actually reducing the share of risky loans, the latter would be consistent with a decrease in the overall credit risk of banks' loan portfolio. To illustrate this distinction, we plot all coefficients along the rating interval highlighting three separate regions, namely investment grade, cutoff and the non-investment grade rating classes (see Figure 4).

5 Internal Loan Ratings and Loan Classification

A first potential explanation for the patterns shown in Figure 2 can be an adjustment of loan ratings to avoid stage 2 classifications. The estimation of the forward-looking loss provisions are based on the internal rating models. Therefore, our first empirical test addresses the changes in internal loan ratings following the announcement of the IFRS 9 reform.

We examine whether IFRS-adopting banks adjusted loan ratings to avoid a stage 2 classification relative to other banks. We show the results in Table 3, Panel A. First, we focus on banks' classification of their loans into either stage 2 or stage 1. While IFRS adopters do have a significantly higher share of stage 2 loans compared to non-adopters before the announcement, the stage 2 share of IFRS adopters falls by 11.4 percentage points relative to the control group in the period between announcement and implementation of the reform (column 1). In the following specifications, we add firm fixed effects to ensure that our coefficient of interest captures differences in loan classification for the same borrowers by affected and unaffected banks. In column 3, we further saturate our model with bank fixed effects to control for any systematic time-invariant differences among banks. Finally, we add firm × time fixed effects to make sure we compare changes in the classification of loans for the same borrower that has at least one loan from an IFRS adopter and one loan from a non-adopter in column 5. This, our strictest specification focuses only on a subset of borrowers. As already noted, the stage 2 classification is based on PDs that are firm-specific and do not capture recovery rates that might vary from bank to bank. Thus, all banks that are providing loans to a specific firm should arrive at similar PD estimates, even though they may have very different financial contracts with the firm (see Behn, Haselmann, and Vig 2022 for more details). Despite this, IFRS-adopting banks are less likely to assign for *the same borrower* a PD that results into a stage 2 instead of a stage 1 rating. The economic magnitude of this effect is quite substantial. Given that stage 2 loans would have made up about 21 percent of affected banks' loan portfolio at the time of the announcement of the reform. Reducing the classification of stage 2 loans by 7.27 percentage points of all performing loans (see column 5), suggests that the overall share of stage 2 loans was about one third smaller than it should have been. Given stage 2 loans make up about 70 percent of the new provisions from the introduction of IFRS 9, a reduction of the share of stage 2 loans by a third means that the intended effect is about 24 percent lower than it should have been if banks had rated their loans in the same way as non-affected banks. This finding is consistent with banks using their model-based loan loss estimates introduced by the expected credit loss model to avoid loss recognition.

Second, we investigate whether affected banks' classification of stage 3 loans (i.e., loans that experienced a loss event) was affected by the announcement of the new provisioning rules in Table 3, Panel B. Note that the loan impairment rules do not materially change with the introduction of the IFRS 9 regulation.

We employ the same five specifications as in Panel A. The results consistently show that affected banks did not significantly change their stage 3 classification around IFRS 9 adoption relative to non affected banks. This finding undermines our interpretation that the change in the model-based loss estimates around IFRS 9 adoption is attributable to the purposeful avoidance of stage 2 classification, a unique feature of the new regulation that requires particularly high loss recognition, rather than an overall change in rating behavior.

Our main identifying assumption is that affected and unaffected banks do not systematically change their loan ratings due to reasons unrelated to the introduction of the new reporting standards. As explained in Section 4.1 in detail, the institutional particularities of the IFRS 9 reform let us directly address such a concern. By definition of the stage 2 criterion, a loan has to be classified as stage 2 once a borrower is downgraded from investment grade to non-investment grade. Thus, downgrades on the rating scale from BBB- to BB+ are associated with significantly higher provisions. All other migrations by one rating notch from one rating class to another rating class are not associated with an increase in loan provisions. If affected banks' loan rating would have been systematically changed during our sample period, we should observe a similar pattern also among different rating classifications.

We replicate our main specification 1 in Table 4, column (1), but use sample splits to disentangle the effect stemming from the investment grade cut-off. This is a suitable approach because the applicable criterion for stage 2 classification depends solely on the initial rating of the loan, thereby allowing for a clear distinction between the two effects. The coefficient estimate for the interaction term (Post x IFRS) is slightly larger in magnitude compared to the previous estimates from Table 3 as the aggregate effect from both criteria is a weighted average of the individual effects in columns 2 and 4. For the same borrower, there is a significant 7.33 percentage points lower probability that a given loan will end up as stage 2 due to crossing the investment/non-investment grade rating cut-off for affected as compared to unaffected banks. A change in the classification of the dependent variable could be either an upgrade or a downgrade. Both criteria for the IFRS 9 loan classification allow a clear separation in upgrades and downgrades. In column (5), we show the results separately for downgrades, excluding any upgraded loans from the sample. When we compare the downgrades with the other loans that keep their rating status, the coefficient estimate for the interaction term (Post x IFRS) is negative and statistically significant. We observe this relative decrease in the likelihood of a downgrade at a magnitude of 8.03 percentage points for an identical borrower. While we cannot compare this directly to differences in the share of upgraded loans due to data limitations, the size of the coefficient is almost one percentage point larger than the aggregate effect for up- and downgrades. This suggests that banks tend to use the discretion to avoid downgrades in the first place rather than to manage the internal ratings upwards after they had to start recognizing lifetime losses for a loan.

To test whether affected banks' loan rating has systematically changed during our sample period, we generalize this test by running a separate regression for hypothetical cut-offs between any two rating notches in Table 5. We use the transitions between 12 other rating notches from A- to CCC- being as alternative cut-offs. The rating cutoff between BBB- and BB+ corresponds to the actual investment/non-investment grade cutoff. The resulting coefficients show that the significant difference between banks that newly adopt forward-looking loss provisioning and our control banks disappears when we move away by more than one rating notch from the actual threshold and illustrate these findings graphically in Figure 3. For example, if the threshold were between rating notches A- and BBB+ (rather than between BBB- and BB+), the share of loans that hypothetically lost its investment grade status based on internal ratings would remain virtually unchanged for IFRS-adopting banks relative to our control group during the treatment period (statistically insignificant). This finding is inconsistent with a general bias in internal ratings by our treatment banks during the treatment period. The finding further supports that the change in internal ratings is driven by loss avoidance incentives that are tied to the specific rating threshold for investment-grade status which newly induces the cliff effect of a stage 2 classification under the IFRS 9 regulation.

Finally, we systematically control for any differences of affected and non-affected banks by exploiting cross-sectional heterogeneity within banks' loan portfolio. The most salient feature of the new standard is that provisions increase from 1-year to lifetime expected losses once a stage 2 classification is assigned. Thus, the longer the maturity of a loan, the bigger is the difference in the provisions if the classification changes from stage 1 to stage 2. If banks adjust the underlying PDs strategically to manage the level of their provisions, they are incentivized to mostly adjust ratings for long maturity loans. Importantly, this test is based on variation within the loan portfolio of affected banks and thus allows to systematically control for bank heterogeneity (i.e., inclusion of bank $\times$ time fixed effects).

Table 6 presents estimates of specification 2. We limit the sample to affected banks and include bank $\times$ time fixed effects as well as firm $\times$ time fixed effects in columns (2) and (4). In columns (1) and (2) the maturity for each loan is calculated as the remaining maturity of a loan in years at the end of the pre-period (2015q4). This variable is capped at 5.25 years because our sample period ends in 2021q1. The coefficient of the interaction term suggests that a loan with a longer (5 years+) maturity ends up as a stage 2 loan is by 2.36 percentage points less probable. This definition of the dummy variable (High Maturity) ensures that at the implementation date of IFRS 9, the remaining maturity of a particular loan is longer than 3 years.

Similarly, banks' incentives to strategically avoid stage 2 downgrades are more pronounced for borrowers with greater lending exposure. Loans to these borrowers would require a more sizable provisioning increase when transferred from stage 1 to stage 2. In columns (3) and (4) of Table 6 we thus include a dummy for banks' above-median exposure to a borrower at the implementation date (2018q1) and find that loans to these borrowers are 2.81 percentage points less likely to be (re-)classified as stage 2.

We also exploit cross-sectional heterogeneity by banks based on their capitalization. Banks with lower equity buffers have less capacity to make additional provisions. We thus substitute a measure for bank capitalization, i.e. CET 1 Buffer, in specification 2 instead of the loan maturity measure. CET 1 Buffer is the difference between the CET 1 ratio of a bank and the total CET 1 capital requirements. Given that this measure does not vary at the loan level, we cannot include bank $\times$ time fixed effects in this specification. Column (5) of Table 6 illustrates that banks with a higher capital buffer (i.e., above the IFRS median) are more likely to classify a specific loan as stage 2 compared to a low capitalized bank.

Overall, these cross-sectional results yield two important insights. First, banks tend to manage their classification of stage 2 loans precisely then when incentives of doing so are the highest. Second, our previous findings are robust to controlling for systematic biases between affected and unaffected banks.

6 Lending Patterns around the IFRS 9 Adoption

Figure 2 suggested a reduction of stage 2 loans by about 3 percentage points. While previous analysis illustrates that the reduction of stage 2 loan volume presented in Figure 2 is to a large extent explained by rating classifications, some of this trend could also be explained by a reduction of risky loans, or, specifically, those loans prone to a stage 2 downgrade in their remaining lifetime.

We first test whether IFRS-adopting banks reduce their exposures of stage 2 loans following the announcement of the reform. Estimates of Equation 3 are shown in Table 7, columns 1 and 2. IFRS-adopting banks do not significantly change the volume of their existing lending relationships at stage 2 compared to their low-risk stage 1 borrowers and relative to the control group. In columns 3 and 4 of Table 7, we present the estimates of Equation 4, where we test whether banks end stage 2 loan relationships prematurely with a higher probability than low-risk stage 1 relationships relative to non-affected banks. Consistent with the effect along the intensive margin, we find only a modest and insignificant increase in the exit rate for stage 2 lending relationships among IFRS-adopting banks. This is independent of the inclusion of borrower and bank fixed effects as shown in column 4. Since new loans are always classified at stage 1 according to the stage definitions, we cannot observe changes in entry rates of new stage 2 lending relationships.

Next, we consider lending adjustments to borrowers whose loans are currently classified as stage 1 but which face a high risk of downgrade because they are rated either near the investment grade cutoff or are subject to the tighter 2-rating notch criterion. For IFRS banks these loans have a higher marginal cost attached in terms of future provisioning potential. At the intensive margin, the interaction between $Stage$ 1 ($High\ Risk$) and $IFRS$ in Table 7 shows that affected banks reduce their exposure to borrowers at high risk of stage 2 (re-)classification (columns 1 and 2). While this effect is not robust to the inclusion of fixed effects, results at the extensive margin reveal a significantly higher exit rate for lending relationships with these borrowers in either specification. Affected banks have a 7.7% and 11.2% higher probability of terminating relationships with high-risk stage 1 borrowers in the post-period (columns 3 and 4).

In summary, affected banks do not (significantly) reduce their exposure to those loans that carry a stage 2 classification at the announcement date, but instead respond most strongly in their lending activities to the potential risk of future stage 2 downgrade. Given that this downgrade risk is determined either by the proximity to the investment grade cutoff or an initial credit rating within the non-investment grade region, a reduction of these types of loans does not necessarily imply a (meaningful) decrease in the riskiness of banks' loan portfolios if the lending restrictions are concentrated in the former group of moderately risky borrowers. To test for this, we compare changes in lending across IFRS and LGAAP banks separately for each credit risk rating.

Figure 4 plots the rating-specific coefficients on the IFRS indicator for changes in lending along the intensive margin (Panel A), early terminations of lending relationships in the post-period (Panel B) and the likelihood that a newly initiated lending relationship is with a borrower of given credit risk rating (Panel C). Each panel graphically distinguishes between the lower-risk investment grade, the moderate-risk cutoff and the higher-risk non-investment grade region. Panel A shows that affected banks significantly reduce their exposure to borrowers rated just below the investment-grade cutoff relative to the control group. The loan volume to borrowers with non-investment grade rating also decreases at similar (albeit statistically insignificant) magnitude. Panel B reveals a more distinct pattern in early terminations of lending relationships. The exit rate rises significantly for borrowers in the cutoff region, then drops in magnitude for those just slightly exceeding the threshold before almost monotonically increasing again with greater borrower risk. This latter observation is very much in line with IFRS banks actually reducing the credit risk of their loan portfolio in response to greater provisioning requirements. For newly originated lending relationships, however, we do find some concentration of effects in the cutoff region (Panel C). IFRS banks are significantly less likely to initiate a loan with a borrower rated BBB or BBB- than LGAAP banks unaffected by the reform. In contrast, lending relationships with non-investment grade borrowers are equally (or slightly more) likely among IFRS banks.

7 Conclusion

The reliance on internal, forward-looking estimates had been an important trend in the design of prudential regulation and reporting standards for financial institutions. The main idea is that banks develop a sophisticated risk management system that serves as a foundation to determine capital requirements and loss recognition. The regulatory intention is that banks build up a sufficient capital buffer before they actually incur the loan losses. While the conceptual support for this regulatory ideal is strong, our findings also show the downsides of the approach. Any regulation that resorts to banks' internal risk assessment is relying on forward-looking information, which, by its very design, is subjective and hardly verifiable. In a competitive market, banks are incentivized to exploit the discretion and strategically minimize loss recognition and, eventually, the capital requirements. We provide evidence on bank behavior consistent with these incentives and document two important consequences of the implementation of forward-looking loan loss recognition. First, banks adjust their internal risk assessment of borrowers, especially for borrowers around provisioning cut-offs, i.e., where the risk of increased loan loss recognition is greatest. Second, banks also cut back their lending to borrowers whose loans are most likely to be in this range of potentially high loss provisions.

The overall effect on bank risk goes in opposite directions and, therefore, the paper does not provide an overall judgment of the new standards for loan loss recognition. We rather complement prior literature, which has shown informational benefits and lending changes upon the adoption of the expected credit loss model, by using loan-level micro-data and within-borrower variation in lending standards to identify economic costs of this approach. It is an open question whether a better design of the reporting standards could effectively reduce these costs and prevent the strategic behavior by banks. In our view, this is very unlikely. Given that banks compete among each other, those banks that assign the most pessimistic assessment to a given borrower have the highest marginal costs (due to the risk-sensitive reporting requirements). Thus, banks do have incentives to favorably assess the underlying risk of the borrowers they decide to lend to. Effective enforcement that would be able to fully counter the resulting bias in the risk assessment of borrowers is notoriously hard to achieve because of the complexity of the rules as well as the subjectivity involved in the use of forward-looking information for the internal risk assessment. As a consequence, any reporting standard that would require the use of forward-looking information will be associated with high enforcement costs and still enable banks to minimize loss recognition. Such a regulatory design will likely fail to establish a more stable financial system.

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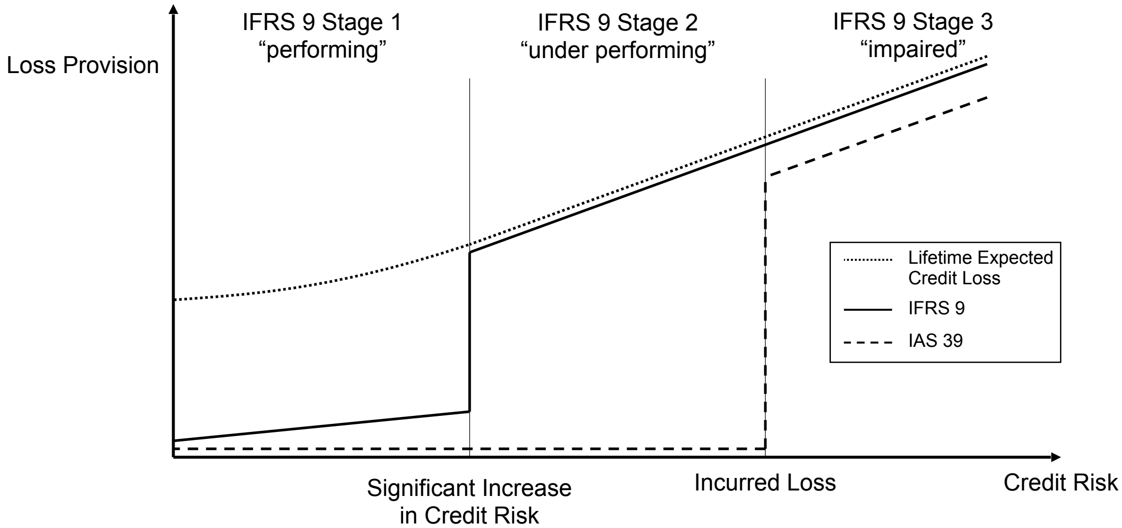
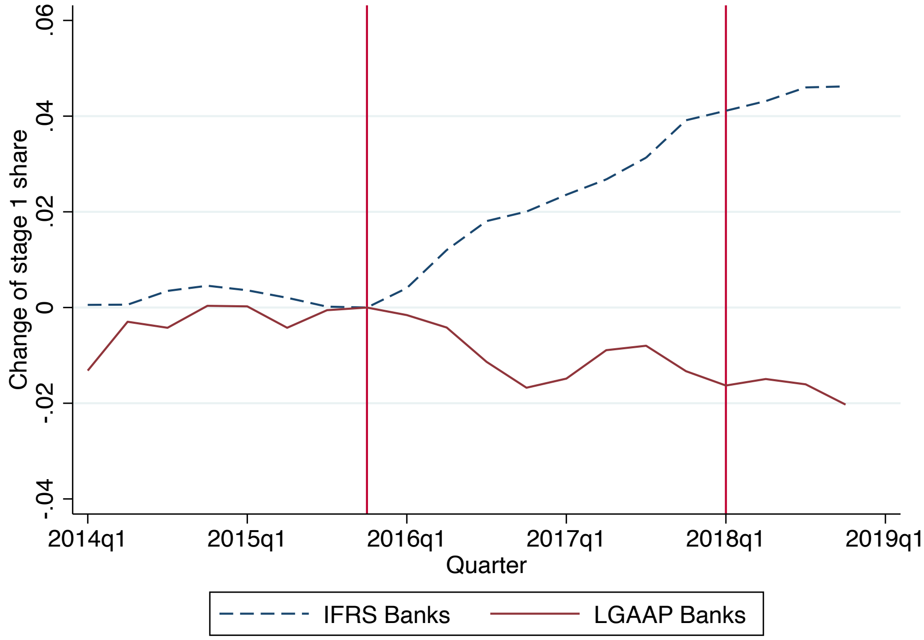


Figure 1: Cliff Effect. The figure presents loan loss provisions depending on the credit risk of a loan under IFRS 9 (solid line) and IAS 39 (dashed line). Under IFRS 9, loan loss provisions jump after a significant increase of credit risk to the lifetime expected credit loss (dotted line). Under IAS 39, loan loss provisions jump when loan losses incur.

Panel A: Stage 1



Panel B: Stage 2

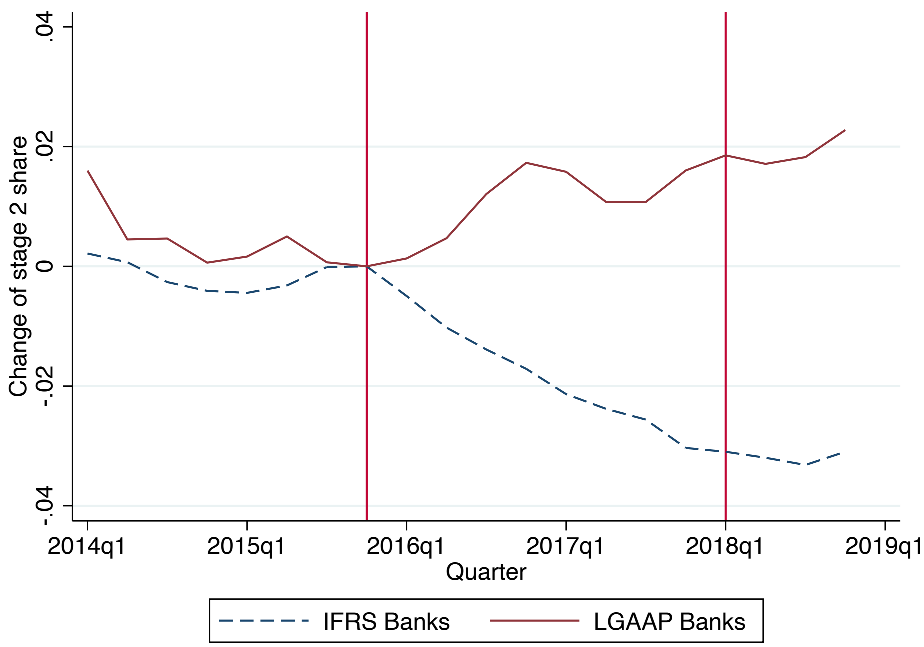


Figure 2: Adjustment of Loan Classification. The figure illustrates the cumulative (two-quarter moving average) change of the share of loans in risk classes over time relative to the share in 2015Q4. Panel A shows the share classified as stage one loans and Panel B the share classified as stage two loans. The dashed line indicates the loan share of the treated IFRS banks and the solid line indicates the loan share of the untreated local GAAP banks. The vertical lines indicate the last quarter before the adjustment period, 2015Q4, and the first quarter of the implementation period, 2018Q1.

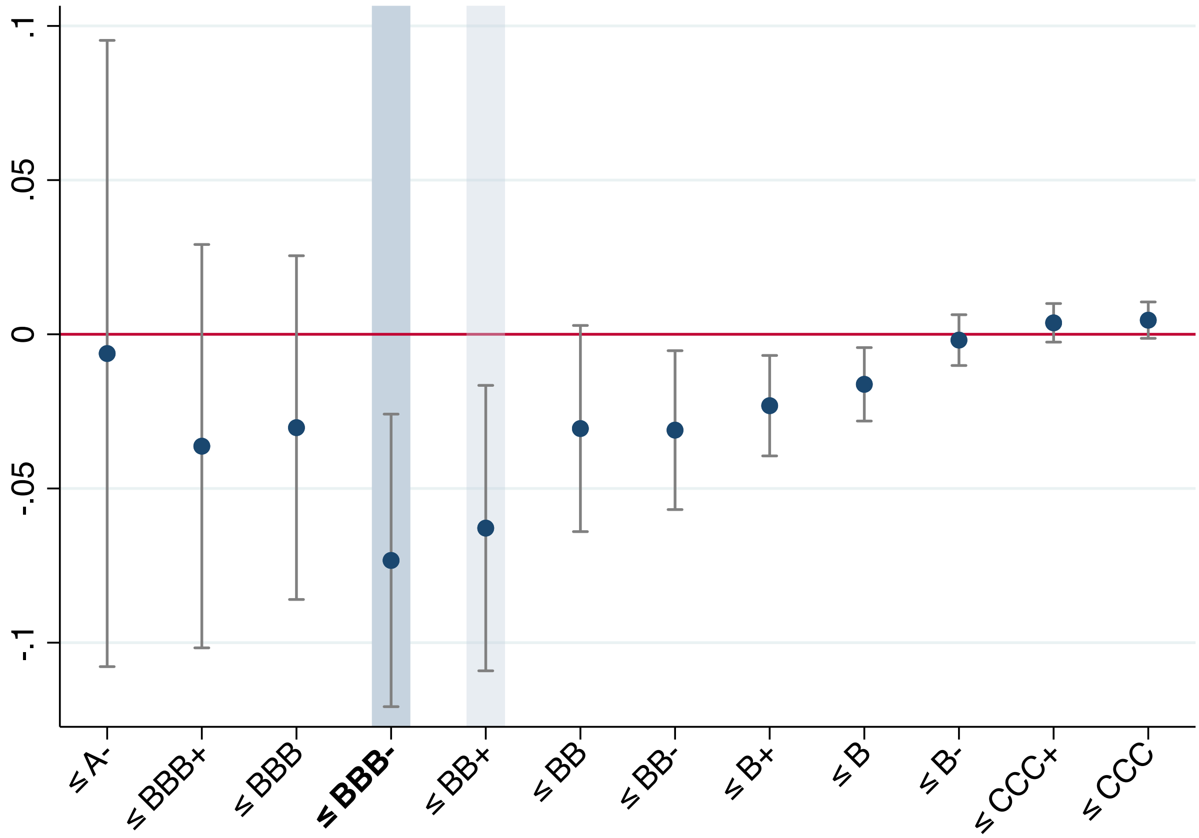
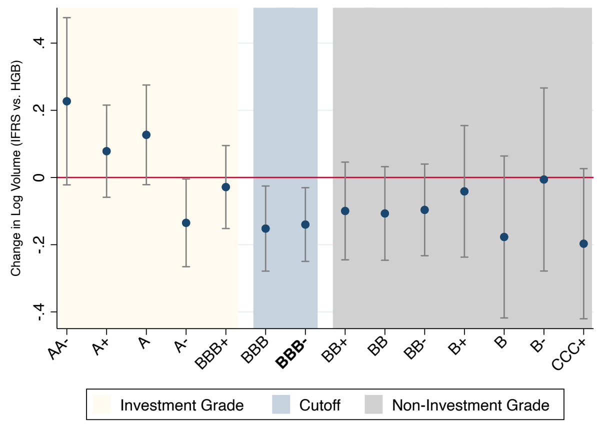
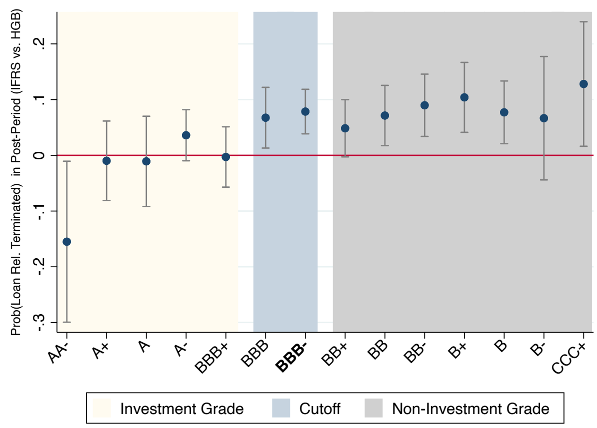


Figure 3: Varying Stage 2 Cutoff. The figure illustrates how the difference-in-differences coefficient would change when the cutoff between investment grade and non-investment grade would move away from the true cutoff between BBB− and BB+ in the regression equation 1. The dot marks the beta coefficient and the vertical interval the 95% confidence interval. The x-axis indicates the hypothetical rating cutoff from A− to CCC. The true cutoff between BBB− and BB+ is highlighted with a blue column. The light-blue column is also affected by the investment grade cutoff since (local GAAP) loans tend to be downgraded by more than one rating notch below the investment grade cutoff.

Panel A: Intensive Margin (IFRS vs. LGAAP)



Panel B: Exit Rate (IFRS vs. LGAAP)



Panel C: Entry Rate (IFRS vs. LGAAP)

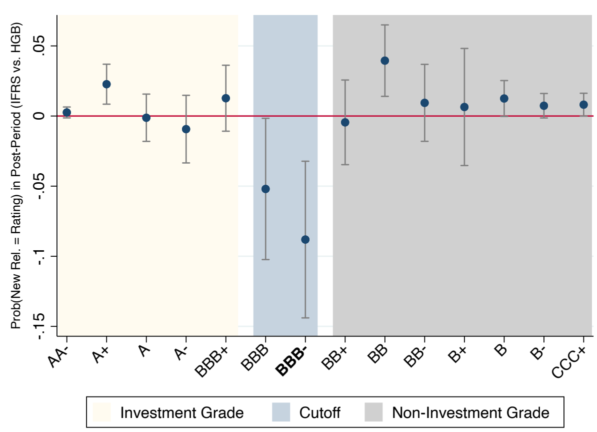


Figure 4: Intensive & Extensive Margin Effects. The figures illustrate how lending effects along the intensive and extensive margin vary by the credit risk rating of the borrower at the end of the pre-period. The dependent variable in Panel B is a binary variable indicating whether the loan relationship has been terminated early in the post-period. Panel C employs a variable measuring the likelihood that a new borrower has a specific rating relative to all other newly initiated lending relationships with different ratings.

Table 1: Summary Statistics. Panel A shows the mean and standard deviation of bank characteristics for financial institutions that are not affected by the new accounting requirements (Local GAAP) and financial institutions that are affected (IFRS). Panel B shows summary statistics for loans held by the two bank groups. The level characteristics are determined at the last quarter of the pre-event period (2015Q4) and the changes are calculated between the end of the pre-event period and the implementation date (2015Q4 - 2018Q1).

Panel A: Bank-level variables	Local GAAP (470 banks)		IFRS (81 banks)	
	Mean	S.D.	Mean	S.D.
Bank assets (in mn. Eur)	1,229	3,080	109,444	162,185
Bank equity ratio	0.063	0.023	0.050	0.028
Bank ROA	0.006	0.004	0.002	0.003
Bank ROE	0.111	0.057	0.049	0.076
Deposit to loan ratio	1.329	0.462	0.971	0.578

Panel B: Loan-level variables	Local GAAP (21,396 loans)		IFRS (81,297 loans)	
	Mean	S.D.	Mean	S.D.
Loan size (in thous. Eur)	2,326	6,924	5,384	19,275
PD – probability of default	0.084	0.253	0.071	0.234
Share stage 2	0.085	0.278	0.138	0.345
Δ Log(loans) stage 2 in 2015	−0.241	0.561	−0.393	0.894
Δ Log(PD) stage 2 in 2015	−0.036	1.210	−0.241	1.362

Table 2: Loan Stage Distribution. The table presents the distribution of loans among stage 1, stage 2 and stage 3. It shows the level of stage shares and differences both between local GAAP- and IFRS-adopting banks and between the end of the pre-period and the implementation date.

Stage 1	Local GAAP	IFRS	Δ
2015q4	0.9060	0.8363	−0.0697
2018q1	0.8942	0.8529	−0.0413
Δ	−0.0118	0.0166	0.0284
Stage 2	Local GAAP	IFRS	Δ
2015q4	0.0845	0.1381	0.0536
2018q1	0.0975	0.1283	0.0308
Δ	0.0130	−0.0098	−0.0228
Stage 3	Local GAAP	IFRS	Δ
2015q4	0.0094	0.0256	0.0162
2018q1	0.0083	0.0188	0.0105
Δ	−0.0011	−0.0068	−0.0057

Table 3: Loan Classification. Panel A of the table shows how the share in stage two loans changes over time depending on the regulatory requirements of the issuing bank. The dependent variable is an indicator of stage two loans in the sample restricted to loans in stage two and stage one. Stage 2 follows both criteria of significant deterioration in credit quality. In Panel B the dependent variable is the share in stage three loans in the sample of stage 1, 2 and 3 loans. The sample period (2015Q1 to 2018Q4) is divided into the pre-event period (2015Q1 to 2015Q4) and the post-event period (2018Q1 to 2018Q4). We collapse all quarterly observations into a pre- and post-period mean and only consider loans existing in both pre- and post-period to control for any concurrent changes in loan portfolio composition. Bank controls consist of total assets, return on assets and deposit-to-loan ratio. Standard errors are adjusted for bank × year-level clustering and reported in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: Loan Classification between Stage 2 and Stage 1

	Stage 2 vs. 1				
	(1)	(2)	(3)	(4)	(5)
IFRS	0.0730***	0.109***		0.0983***	
	(0.0188)	(0.0276)		(0.0198)	
Post x IFRS	−0.114***	−0.110***	−0.107***	−0.0690***	−0.0727***
	(0.0371)	(0.0233)	(0.0227)	(0.0262)	(0.0164)
Time FE	yes	yes	yes	yes	yes
Firm FE	no	yes	yes	yes	yes
Bank FE	no	no	yes	no	yes
Bank controls	no	no	yes	yes	yes
Firm × Time FE	no	no	no	yes	yes
Adj. R^2	0.008	0.382	0.386	0.421	0.432
Obs.	59534	59534	59534	9290	9290

Panel B: Loan Classification between Stage 3 and Stage 1 and 2

	Stage 3 vs. 1 and 2				
	(1)	(2)	(3)	(4)	(5)
IFRS	0.0116***	0.0022		0.0048**	
	(0.0038)	(0.0044)		(0.0021)	
Post x IFRS	−0.0046	−0.0047	−0.0080	0.0005	−0.0002
	(0.0094)	(0.0062)	(0.0059)	(0.0020)	(0.0017)
Time FE	yes	yes	yes	yes	yes
Firm FE	no	yes	yes	yes	yes
Bank FE	no	no	yes	no	yes
Bank controls	no	no	yes	yes	yes
Firm × Time FE	no	no	no	yes	yes
Adj. R^2	0.003	0.607	0.609	0.828	0.827
Obs.	60954	60954	60954	9371	9371

Table 4: Loan Classification - Investment Grade vs. 2-Rating Notch Criterion. The table shows how the share in stage two loans according to the investment grade criterion changes due to the introduction of IFRS 9. In addition, the movements between stage 1 and stage 2 are also shown for the two-rating notch criterion applicable to non-investment grade loans. The dependent variable in the first four columns is an indicator of stage two loans in the sample restricted to loans in stage 2 and stage 1. Columns 1/2 and 3/4 employ only loans originating within investment- or non-investment grade, respectively. The dependent variable in column 5 excludes any upgrades in loan classification from stage 2 to stage 1. The sample period (2015Q1 to 2018Q4) is divided into the pre-event period (2015Q1 to 2015Q4) and the post-event period (2018Q1 to 2018Q4). We collapse all quarterly observations into a pre- and post-period mean. Bank controls consist of total assets, return on assets and deposit-to-loan ratio. Standard errors are adjusted for bank × year-level clustering and reported in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Stage 2 vs. 1				Downgrade Only
	Investment Grade		Non-Investment Grade		
	(1)	(2)	(3)	(4)	(5)
Post x IFRS	−0.114***	−0.0733***	−0.0988***	−0.0620**	−0.0803***
	(0.0316)	(0.0240)	(0.0249)	(0.0306)	(0.0161)
Time FE	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes
Bank FE	yes	yes	yes	yes	yes
Bank controls	yes	yes	yes	yes	yes
Firm × Time FE	no	yes	no	yes	yes
Adj. R^2	0.525	0.609	0.353	0.451	0.473
Obs.	36513	6342	22862	2346	8197

Table 5: Varying Stage 2 Cutoff. The table examines how the share in stage two loans would change in the post-event period for different hypothetical rating cutoffs between investment grade and non-investment grade. The dependent variable in all specifications is an indicator of stage two loans defined as loans that shift from investment grade to non-investment grade. The first row reports the difference-in-differences regression as in equation 1 with a hypothetical cutoff between the rating A- and BBB+. The regression in each row is estimated using only loans potentially subject to the hypothetical cutoff (i.e., with initial rating at the cutoff or better). Row 4 shows the regression of the true cutoff between BBB- and BB+. The sample period (2015Q1 to 2018Q4) is divided into the pre-event period (2015Q1 to 2015Q4) and the post-event period (2018Q1 to 2018Q4). We collapse all quarterly observations into a pre- and post-period mean. Bank controls consist of total assets, return on assets and deposit-to-loan ratio. The number of observations varies between 1,650 and 9,242. Standard errors are adjusted for bank × year-level clustering and reported in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Dependent variable: Stage 2 vs. 1			
Cutoff (≤ Rating)	Post × IFRS	Standard Error	Adj R^2
A-	-0.0062	0.0507	0.662
BBB+	-0.0363	0.0328	0.694
BBB	-0.0303	0.0281	0.645
BBB-	-0.0733^{***}	0.0240	0.609
BB+	-0.0629^{***}	0.0234	0.587
BB	-0.0306^{*}	0.0169	0.537
BB-	-0.0311^{**}	0.0131	0.553
B+	-0.0231^{***}	0.0083	0.613
B	-0.0162^{***}	0.0060	0.595
B-	-0.0019	0.0042	0.560
CCC+	0.0037	0.0032	0.861
CCC	0.0046	0.0030	0.806

Table 6: Bank and Loan Characteristics of IFRS banks. The table shows how the share in stage two loans of IFRS banks changes over time depending on maturity, total exposure to borrower and CET 1 ratio buffer. The dependent variable is an indicator of stage two loans in the sample restricted to loans in stage two and stage one. High Maturity is a dummy that indicates whether more than 5 years of maturity are remaining at the end of the pre-period. High Borrower Exposure reflects an above-median exposure to the borrower at the implementation date (2018Q1). High CET 1 buffer is a dummy equal to one if the CET 1 ratio buffer of the issuing bank in 2015Q4 is greater than the median CET 1 buffer across all IFRS banks. The sample period (2015Q1 to 2018Q4) is divided into the pre-event period (2015Q1 to 2015Q4) and the post-event period (2018Q1 to 2018Q4). We collapse all quarterly observations into a pre- and post-period mean. Standard errors are adjusted for bank × year-level clustering and reported in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Stage 2 vs. 1				
	Loan Maturity		Borrower Exposure		Bank Capital
	(1)	(2)	(3)	(4)	(5)
Post x High Maturity	-0.0236^{***}				
	(0.0088)				
Post x High Maturity		-0.0275^{***}			
		(0.0095)			
Post x High Borrower Exposure			-0.0281^{**}		
			(0.0124)		
Post x High Borrower Exposure				-0.0268^{**}	
				(0.0127)	
Post x High CET 1 Buffer					0.0157^{**}
					(0.0061)
Bank FE	yes	yes	yes	yes	yes
Firm × Time FE	yes	yes	yes	yes	yes
Bank × Time FE	no	yes	no	yes	no
Bank controls	yes	yes	yes	yes	no
Adj. R2	0.526	0.527	0.527	0.527	0.525
Obs.	42182	42182	42403	42403	40222

Table 7: The table shows how the intensive and extensive margin of lending are adjusted with respect to the IFRS stage 2 (risk) of the borrower. Panel A uses two non-overlapping indicators for borrowers still in stage 1 (but at high likelihood of being downgraded) or borrowers already in stage 2 at the end of the pre-period (stage 1 borrowers with better investment-grade rating are the omitted category). The dependent variable in the first two columns is the change of the log mean volume per borrower (loan) from 2015 to 2018. The dependent variable in the second two columns indicates whether the lending relationship (loan) is terminated early in the post period. Standard errors are adjusted for bank-level clustering and reported in parentheses. * indicates statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	$\Delta Log(Relationship\ Volume)$		EXIT	
	(1)	(2)	(3)	(4)
IFRS	-0.133^{*}		-0.009	
	(0.0745)		(0.0214)	
Stage 1 (High Risk)	0.153^{*}	0.244	-0.020	-0.096^{*}
	(0.0839)	(0.352)	(0.0167)	(0.0514)
Stage 2	-0.120	-0.333	0.077^{*}	0.002
	(0.134)	(0.572)	(0.0430)	(0.0940)
Stage 1 (High Risk) x IFRS	-0.198^{**}	-0.306	0.077^{***}	0.112^{**}
	(0.0934)	(0.353)	(0.0216)	(0.0517)
Stage 2 x IFRS	-0.201	0.028	0.012	0.030
	(0.144)	(0.583)	(0.0468)	(0.0930)
Firm FE	no	yes	no	yes
Bank FE	no	yes	no	yes
Adj. R^2	0.008	0.206	0.007	0.381
Obs.	24605	10751	32950	14081

A Appendix

Table A1: The Adoption of the IFRS 9 Expected Credit Loss Model in Germany.

November 2009	The IASB publishes an Exposure Draft "Financial Instruments: Amortized Cost and Impairments" that proposes a full expected loss model for loans.
March 2013	The IASB publishes a revised Exposure Draft "Financial Instruments: Expected Credit Losses" that limits loan loss recognition to expected credit losses and proposes a three-stage model to distinguish between 12-month and lifetime expected credit losses.
July 2014	The IASB publishes the final standard IFRS 9 "Financial Instruments" that introduces the expected credit loss model based on the three impairment stages.
May 2015	The EFRAG starts its public consultation on its IFRS 9 endorsement advice to the European Union.
September 2015	The Financial Times reports about active lobbying against IFRS 9 by large UK pension funds, several large banks and a Swedish Financial Analyst Society.
September 2015	The EFRAG publishes its final endorsement advice to the European Union that is in unconditional favor of a full IFRS 9 endorsement, including the three-stage expected credit loss model.
December 2015	The European Parliament holds a public expert hearing on the IFRS 9 endorsement where all four invited experts express clear support for the endorsement of the expected credit loss model.
January 2016	**German banks start to actively implement the new model-based impairment rules according to IFRS 9.**
November 2016	The EU officially endorses the IFRS 9 regulation.
January 2018	IFRS 9 becomes effective and banks start to recognize expected credit losses retrospectively for each loan contract based on the new three-stage impairment model.