Expected Losses, Unexpected Costs?*

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Abstract

This paper examines the real effects of banks switching to an expected credit loss (ECL) framework under IFRS 9. I identify the cross-bank variation in the ECL transition from banks' mandatory reconciliation disclosures about the day-one impact of the accounting change. I find evidence that the ECL rules deteriorate the credit landscape for risky and opaque borrowers, i.e., small- and medium-sized enterprises (SMEs). Affected banks reduce lending to SMEs by a relative 23 percent and switch to corporate lending and non-loan assets. Consistent with a decline in credit supply—rather than in credit demand—SMEs that work with affected banks receive less funding, conditional on applying for a loan. I also observe that in their contracts with SMEs, affected banks increase interest rates and collateral requirements, while reducing loan amounts and maturities. Despite these costs, my inferences do not imply that the ECL paradigm is socially undesirable.

JEL classification: G21, G28, G38, M41

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1. Introduction

Many observers identified the delayed recognition of credit losses as contributing to the Great Recession and thus called for action to improve loan loss provisioning practices (e.g., G20 [2009]; Beatty and Liao [2011]; Bushman and Williams [2012]; IMF [2015]; IAASB [2016]; Cohen and Edwards [2017]). In response, accounting standard setters around the globe have implemented new rules that require banks to incorporate forward-looking and longer-term inputs in their estimation of credit losses (IASB [2013]; FASB [2016]). Under the international accounting regime, such an expected credit loss (ECL) framework was introduced by IFRS 9 in 2014, effective beginning in 2018 (IASB [2014]).

The ECL framework aims to improve banks' credit risk management, increase the transparency of banks' asset quality and risk positions, and allay procyclicality through earlier recognition of credit losses. However, the ECL method also requires banks to recognize expected future losses upfront while not permitting them to recognize expected future benefits. These potentially asymmetric treatments could incrementally distort credit conditions for risky and opaque borrowers, such as small- and medium-sized enterprises (SMEs) (Berger and Udell [1995]). Accordingly, the goal of this study is to analyze the impact of the ECL rules on banks' behavior, focusing on the SME loan contracting landscape. Using bank-level, borrower-level, and contract-level samples that capture European banks' lending decisions, I report evidence on the adverse effects of the new rules on SME credit access.

When IFRS 9 took effect on 1 January 2018, banks published two sets of parallel financial statements—one laying out the position on 31 December 2017, and one showing the position a day later. This clean and mandatory presentation captures the one-off impact of the new rules (e.g., Horton and Serafeim [2010]). I hand-collect these transitional disclosures to assess the heterogeneity in the severity of the ECL transition. I observe that the accounting change triggers a 13% increase in the loan loss allowance of the average bank in my sample. The cross-bank variation in this accounting effect is also substantial—the jump in allowance is over 20% (40%) for the top quartile (top decile) of the sample.

In my empirical analysis, I define ‘affected banks’ as those for which the ECL transition triggered an above-median increase in loan loss allowance. Hence, my tests compare in a difference-in-differences sense affected banks’ SME lending to that of other banks—which also transition to the ECL framework but exhibit modest (i.e., below-median) increases in their loan loss allowance. By exploiting the heterogeneity in the ECL treatment, this empirical approach offers two advantages. First, it does not require a non-European control group, which would be susceptible to a variety of concurrent economic and regulatory developments. Second, this approach better captures the loan-loss provisioning aspect of IFRS 9, as this standard introduced other new rules, such as those pertaining to hedge accounting and classification of financial assets.

My sample spans from 2015 to 2019.[1] The models I use include bank and time fixed effects as well as time-varying bank characteristics, such as size, capital, and profitability. I also account for banks’ nonperforming exposures, risk-weighted assets and the risk calculation method banks use for regulatory capital purposes (e.g., internal ratings-based vs. standardized approach), and note that banks’ allowance and capital calculation for regulatory reporting purposes remains both separate from financial reporting and stable throughout the sample period (Section 2.3).

I study more than 100 banks covered by the European Banking Authority’s (EBA) Transparency Exercise. I focus on this particular sample of significant banks because the EBA data contains a breakdown of loan portfolios, which allows me to distinguish banks’ SME lending from their lending to corporations. In these bank-level tests, I find that affected banks, relative to other banks, decrease lending to small businesses. This decline occurs in an unrestricted sense (a marginal effect of 24% in logged amounts) as well as in the form of a portfolio reallocation (a marginal drop of 23% relative to other exposures). Further, my estimates are stronger among small banks, consistent with regulators’ views predicting that smaller entities would have more difficulties than large banks in implementing the new rules (e.g., EBA [2016]). In contrast, I observe similar effects across banks with high and low capital constraints.

[1] I exclude 2017 to minimize the confounding effect of banks’ transitioning efforts in the year of implementation; however, my findings hold, if not get stronger, if my sample includes observations from this year.

Additional tests suggest that part of the SME funds are reallocated to corporations, for which the application of the ECL model could be less onerous and less costly. However, a more significant shift occurs towards nonlending holdings, which include interbank and repo activities, sovereign and regional government debt, securitization and covered bonds, as well as other investments in financial securities. This observation lends support to the argument that the ECL approach makes traditional lending costlier and other assets more attractive. It also dovetails nicely with the rise of financial disintermediation and the growth in sophisticated investors' demand for bank loans in Europe (Fletcher [2019]).

I also perform borrower-level analyses to explore my research questions through the lens of SMEs. To do so, I rely on the banking relationship information provided by Bureau van Dijk's Amadeus Bankers and examine a sample of about 71,000 borrower-years. Following prior work, I assume that switching banks is prohibitively costly for small businesses and that these borrowers would be exposed to the benefits and costs passed on to them by their relationship banks—especially in the short term (Rajan [1992]). Consistent with this narrative, I find that SMEs that work with affected banks issue less debt than other SMEs in the same industry and country.

Although the tests described above use industry-time and country-time fixed effects, they may be susceptible to lingering concerns relating to credit demand and endogenous matching between banks and borrowers (Acharya and Ryan [2016]; Schwert [2018]). Accordingly, I expand the borrower-level evidence by drawing insights from an ECB Survey that aims to disentangle credit supply from credit demand (Ferrando et al. [2017]; Ertan et al. [2019]). My inferences indicate that, among the SMEs that *did* apply for a loan, 'affected borrowers' experience a decline in credit access (i.e., loan approval rates). Moreover, among the SMEs that *did not* apply for a loan, affected borrowers are more likely to state that they refrain from applying due to fear of rejection, high interest costs, or onerous collateral requirements. In sum, these findings provide support for the idea that the ECL approach has distorted the credit landscape for small businesses.

The firm-level tests above require certain assumptions regarding linking banks to borrowers. Further, they do not directly speak to contractual clauses like interest costs, contract maturities, and loan amounts. Accordingly, in my last set of tests, I analyze more than 215,000

SME loan contracts. This data comes from the European DataWarehouse, which collects contract-level information from European banks on their securitized portfolios under the ECB's Loan-level Disclosure (LLD) Initiative (see Ertan et al. [2017] for details). The key finding from this sample is on the price of loans: I find that conditional on the riskiness of the borrower, interest rates go up in the SME credit contracts made by affected banks in the post-ECL period. Additionally, I observe a decrease in loan amounts. This inference deserves attention because, aside from shedding light on intensive margins, it is indicative of a decline in the supply of credit, i.e., a leftward shift in the supply curve.[2] Furthermore, I find a drop in loan maturities as well. This is consistent with the ECL approach making provisioning for longer-maturity loans more challenging (e.g., banks need to estimate lifetime credit losses for riskier or impaired loans). As with the borrower-level tests, the main effects are stronger for—and at times entirely driven by—small borrowers.[3]

This paper connects to three strands of the literature. First, I contribute to the debate on credit loss recognition, the cornerstone concept of accounting for banks (Beatty and Liao [2014]; Ozili and Outa [2017]). The ECL framework under IFRS 9 (as well as its U.S. counterpart, CECL, or current expected credit losses) is the product of a tenacious process that has received a great deal of attention from practitioners (see Section 2). On the academic side, prior work does provide compelling evidence that good accounting—in particular, good provisioning—practices result in better outcomes for banks and borrowers alike (e.g., Beatty and Liao [2011]; Bushman [2016]; Balakrishnan and Ertan [2018]; Granja [2018]; Leuz and Granja [2018]). However, to the best of my knowledge, there is a paucity of research on the real costs and benefits of forward-looking provisioning (Bushman and Williams [2012]). This paper aims to fill this gap in the literature and to inform the theory and practice of banking (Gorton and Winton [2003]; Jimenez et al. [2017]).[4]

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[2] Loan prices could go up due to an increase in demand or a reduction in supply. In contrast to my supply-based arguments, the finding on increasing loans costs could also be explained by a rightward shift in the demand curve. This alternative explanation, however, would also predict an *increase*—not *decrease*—in loan amounts.

[3] In addition to the contracting credit-supply effects of ECL, I also find evidence that compliance costs rise and information quality declines for affected banks, which is consistent with the ECL approach increasing the complexity of credit loss calculations and giving banks more discretion in making them (See Online Appendix).

[4] In doing so, I also respond to the calls by Bushman and Williams [2012], who state, *"to investigate implications of discretion in loan loss provisioning for risk taking, ideally we would directly compare the incurred loss model with specific alternatives. However, this is not possible as such alternatives have not yet been implemented."*

From a policy standpoint, my conclusions are timely and relevant even outside the IFRS domain, especially in the U.S., which is transitioning to the CECL framework beginning in 2020.

My second contribution is to the broader literature that studies the economic effects of accounting rules, disclosure practices, and capital requirements (e.g., Daske et al. [2008]; Breuer et al. [2017]; Balakrishnan and Ertan [2018]; Gropp et al. [2019]; Shroff [2019]). One innovative aspect of this study is that I observe and measure the cross-bank variation in the effect of a uniform and significant accounting change. This firm-level heterogeneity allows me to establish a tighter connection between the accounting impact and the real outcomes (e.g., Daske et al. [2013]). My work also responds to calls to explore the spillover effects and unintended consequences of regulation (e.g., Leuz and Wysocki [2016]), as well as calls to address some of the fundamental identification concerns inherent in the line of work on banking and credit markets, such as the joint determination of credit supply and credit demand (e.g., Acharya and Ryan [2016]; Dou et al. [2018]; Balakrishnan and Ertan [2019]; Ertan et al. [2019]).

Finally, my paper extends the body of work on small-business financing (e.g., Berger and Udell [1995]). In particular, my conclusions in the context of the ECL transition relate to the challenges large institutions face in making loans to informationally opaque, small companies (Berger et al. [1999]). This insight should be of particular interest to policymakers and regulators since the new provisioning rules could adversely affect bank-dependent SMEs and have implications for economic growth (Beck, Demirgüç-Kunt, and Maksimovic [2005]; Rice and Strahan [2010]; Carbó-Valverde, Rodríguez-Fernández, and Udell [2016]).

While I offer evidence on the costs of adopting expected losses, I note that my conclusions do not invalidate the objective of the ECL framework. The driver of the new rules was the desire to minimize procyclicality, and what I observe in the data is not inconsistent with this outcome. In this sense, it is unclear whether the new rules have triggered a decline in social welfare (Jimenez et al. [2013]). Indeed, in the longer run, the ECL approach could prove more useful and reliable for bank stakeholders and in turn, make funds more readily available or cheaper for small businesses. The ultimate test for this paradigm will be the long-term and down-cycle resilience of the banking sector.

2. *Institutional Background*

2.1 LOAN LOSSES AND THE PATH TO IFRS 9

Banks make loans to households, small businesses, and large corporations, and they are exposed to the repayment risks of borrowers. If debtors cannot pay back their loans (and if the realizable value of the collateral proves insufficient), banks will face credit losses and write off the defaulting accounts. Accounting deals with this problem before the write-offs take place definitively by requiring banks to set aside loan loss provisions in order to absorb such credit losses. Until recently, accounting rules—governed by IAS 39 under the international financial reporting framework—followed an "incurred-loss approach." This system required banks to recognize a credit loss on a loan only if there is objective evidence of a loss event, such as a missed payment.

Under the incurred-loss arrangement, provisioning is essentially backward-looking; banks take action based on what happened in the immediate past rather than what they expect to happen in the near future. This framework potentially exacerbated procyclicality—as long as the economic sun was shining, banks were effectively encouraged to lend aggressively. When the boom in the mid-2000s ended and borrowers started defaulting, the rules required lenders to make provisions against the now-defaulting loans. This led banks to turn off the taps to maintain capital adequacy, worsening the crisis all around and contributing to the most severe credit crunch in recent history.[5]

Following the global financial crisis, the incurred credit loss model's response to credit losses was blamed for being too little, too late (e.g., De Haan and Van Oordt [2018]). This accounting detail was so important that it was explored and addressed not only by bank regulators and managers but also by political leaders (G20 [2009]). These criticisms and calls for improvement have brought about a worldwide shift to a different method to deal with credit losses—the expected credit loss (ECL) framework. The new rule prepared by the international

[5] For prior work focusing on how financial intermediaries transmit shocks to the real sector in general, see, for example, Chodorow-Reich [2013] and Christensen et al. [2019].

accounting standard setters was introduced by IFRS 9 Financial Instruments.[6] This standard, which was adopted in 2014 and took effect in 2018, aims to solve the weaknesses of the incurred-loss method by providing a new framework, under which banks create provisions based on their anticipation that credit risk will increase significantly, well before a loan goes into arrears.[7]

2.2 THE EXPECTED LOSS FRAMEWORK UNDER IFRS 9

IFRS 9 requires using current, past, and future information both to detect significant increases in risk and to measure expected loss. The critical inputs banks use in their models and analyses include the probability of default (PD) and loss given default (LGD).[8] The concept of ECL is the weighted average of credit losses where the weights are the respective default risks. This particular feature constitutes a considerable departure from the incurred-loss framework, especially in the context of performing loans. For performing assets without incurred losses, the ECL approach uses various inputs over a pre-specified future period, which leads to quicker recognition of loan losses. Banks use forward-looking information in scenario analyses, in which the estimate of expected loss is measured as the weighted average of the parameters generated under different scenarios (e.g., neutral, positive, and negative) pertaining to the macroeconomy. The broad range of relevant macroeconomic inputs includes GDP growth, interest rates, and unemployment conditions, as well as equity, commodity, and property prices.[9]

IFRS 9 impairment rules divide financial instruments into three groups according to the stage of credit quality deterioration. Stage 1 includes financial assets without a significant increase

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[6] IFRS 9 is a financial reporting regulation that applies to banks and nonbanks alike. However, it has disproportionately affected banks, and this paper explores banks only. Therefore, the implications of the new provisioning rule for the receivables of nonfinancial firms are beyond the scope of my discussions.

[7] IFRS 9 has three main pillars: (1) a forward-looking impairment model—the ECL approach, (2) classification and measurement of financial assets, and (3) hedge accounting. As major issuers of loans, banks are most affected by IFRS 9's new impairment rules. In this paper, I focus on the new impairment rules under IFRS 9.

[8] LGD is an estimate of the loss arising upon default. It is effectively the expected gap between the contractual cash flows and expected cash flows.

[9] In addition to these estimates and assumptions, banks can include some degree of management overlay in their calculations. This notion aims to reduce the ECL volatility on the income statement and allowances for credit loss on balance sheet in future periods by recognizing a buffer (additional ECL) at the initial set-up of provisions compliant with IFRS 9, especially during the initial implementation phase.

in credit risk. These instruments require a 12-month ECL calculation; i.e., the lender takes into account expected losses arising from default events that are possible within 12 months after the reporting date. At each reporting date, a bank must assess the changes in the credit risk of a loan since its inception and continuously update its loss provision.[10]

When the credit risk of a performing loan has increased significantly since its initial recognition, it is classified as Stage 2. IFRS 9 does not define the trigger events that entail a significant increase in credit risk; this assessment, which may be qualitative as well as quantitative, is left to the management.[11] The impairment allowance for Stage-2 financial assets is measured as the lifetime ECL, i.e., expected losses resulting from all possible default events through the expected life of the loan.[12]

In contrast to these performing assets, Stage-3 instruments have objective evidence of impairment (e.g., defaults). Impairment allowance for these assets is also measured for the lifetime of the loan.[13] The impact of Stage-3 assets should be relatively small since the incurred-loss

[10] As with previous accounting practices, banks estimate provisions individually for heterogeneous loans (like corporate credit) and at the portfolio level for homogenous loans (like residential mortgages).

[11] For example, a loan that is past due by over 30 days is deemed to experience a significant increase in credit risk. However, banks need to take into consideration a variety of developments to assess a significant increase in credit risk using qualitative and quantitative criteria. The relevant developments include but are not limited to news about significant financial difficulty on the part of the borrower; a breach of contract, such as a late payment or default; and other indicators that suggest the increasing likelihood that the borrower will enter into default or go bankrupt. News from the capital markets also matters, in that banks need to monitor the public market performance of their borrowers' bonds. For instance, Commerzbank states, "*In order to determine the existence of a significant increase in credit risk at 1 January 2018 that has not been reflected in published credit ratings, the Group has additionally reviewed any changes in bonds' yields and, where available, CDSs prices, as well as press reports and regulatory information available on the issuers*."

[12] The concept of "significant increase in credit risk with respect to the initial recognition" is an example of the "relative model" of IFRS 9. The main criterion that guides the classification into Stages 1 and 2 is not actually represented by the absolute level of the debtor's credit quality, but by the variation in this level relative to the moment when the credit was first booked to the financial statements. The application of this model may mean that several relationships with the same counterparty are classified into different stages (1 or 2), based on the different levels of credit quality at the moment of the first recognition of each relationship. Moreover, there is a completely different accounting treatment for so-called impaired POCIs (impaired purchased or originated financial assets). These assets, which typically constitute a tiny fraction of a bank's loan portfolio, are measured at fair value, and their income recognition is made by applying the credit-adjusted affected interest rate. These considerations are not within the scope of my paper.

[13] Aside from the amount of provisions, the main difference between Stage 2 and Stage 3 is that interest income is recognized based on the gross carrying amount for Stage-2 loans (and of course Stage-1 assets), while it is recognized based on the net carrying value for Stage-3 assets.

approach already accounted for these assets. The transitional impact of the new rules is driven mainly by 12-month expected losses on performing Stage-1 loans and the lifetime losses on Stage-2 loans (which have deteriorated since origination).

2.3 A COMPARATIVE VIEW OF THE IFRS 9 ECL FRAMEWORK

How does the ECL framework of IFRS 9 relate to and work with other reporting requirements in the European banking landscape? This section provides a comparative discussion of two such methods: FASB's Current Expected Credit Losses (CECL) and Basel's loan loss allowance calculation.

FASB's CECL is effectively the U.S. version of the ECL framework. CECL—which was initially intended to be a part of the IASB's and FASB's convergence initiative—is scheduled to be implemented in the U.S. beginning in 2020. The primary high-level difference between FASB CECL and IFRS ECL is that the former requires a lifetime loss calculation for all assets, including those that are classified as Stage 1 under the IFRS method.[14] Banks that report under US GAAP have been providing disclosures on the potential impact of the transition to CECL, which could be at least as significant as that of IFRS 9. For instance, JPMorgan Chase estimates that the accounting change will trigger a $5 billion (or 35%) increase in its loan loss reserves.[15] It will be interesting to see the extent to which the insights of this paper carry over to the U.S. setting.

Bank supervision rules, especially the Basel III Accord, deserve closer attention because they require a certain kind of ECL approach and because they have been followed by the European banks studied in this paper. In addition to the fact that expected losses that banks must calculate per IFRS 9 are separate from the regulatory expected loss, institutionally speaking, there are two critical distinctions between Basel and IFRS ECL: measurement horizon and cyclicality assumptions. Basel's PD estimates are based on a 12-month time horizon through the economic

[14] To this point, Financial Times's coverage of practitioners' views suggests that the 12-month element of the IFRS 9 ECL requirements creates added complexities and opportunities for mismanagement and, thus, that lifetime ECL provisioning for all cases is a better way to address these issues. Source: https://www.ft.com/content/d6f1fc76-5334-11e5-8642-453585f2cfcd.

[15] See: https://www.jpmorganchase.com/corporate/investor-relations/document/jpmc-2019-firm-overview.pdf.

cycle, and the LGD is computed using a downturn assumption. However, the ECL model estimates PD over a lifetime horizon (for Stage-2 and Stage-3 loans) and at a specific point in time in the economic cycle. In this framework, LGD is calculated based on a neutral scenario (e.g., BIS [2015]; BIS [2017]; Frykström and Li [2018]).

I should underscore that even though Basel rules require a variant of expected credit losses, observers continue to expect that IFRS 9's impairment rules will have an immense effect on banks (Novotny-Farkas [2016]).[16] PwC, for instance, argues that it is erroneous to think that banks will be able to use the data and tools they have for regulatory reporting with only minor adjustments.[17] In this view, while Basel's expected loss model is a starting point, to comply with the new accounting rules, banks must significantly adjust the models they use for regulatory reporting purposes.

In addition to these institutional insights, from an empirical standpoint, two observations provide further support for my claim that IFRS 9 triggers substantial changes in banks' dealing with loan loss provisioning, conditional on the existing regulatory practices. First, the ECL transition under IFRS 9 should not impact banks if they have already adopted this approach for regulatory reporting purposes. As will be discussed later, my findings suggest otherwise. Second, I verify that 98.5% of banks in my sample report under Basel III.[18] This observation allays any lingering concerns about the confounding effects of the Basel rules by ensuring that the regulatory reporting behavior of the sample banks is stable and up to date throughout the sample period.

[16] Another important implication of the IFRS ECL framework is its effect on capital adequacy. These requirements are to be phased in through 2023, even though most banks had disclosed these effects as of 2018.

[17] PwC also emphasizes, *"Even banks already applying the most sophisticated regulatory capital approaches will likely need to make a number of adjustments, many of which will require more data and new models. Also, obtaining data on the credit risk of a loan at the date the loan was first recognised (that will be needed to assess whether there has been a significant increase in credit risk) may be challenging when that date was many years ago."* Source: https://www.pwchk.com/en/hkfrs/hkfrs-news-oct2016.pdf.

[18] I obtain this bank-year-level information from SNL Financial (Field #225203). All of my inferences remain quantitatively similar if I remove the 1.5% of banks that report under Basel II.

2.4 REACTIONS TO IFRS 9 AND BANK DISCLOSURES

IFRS 9 is widely viewed as the biggest accounting change in the banking sector, and has received substantial attention from regulators, auditors, bankers, analysts, and others (Bischof and Daske [2016]).[19] These commentators recognize that the provisioning requirements for banks' impairment processes were lax (De Haan and Van Oordt [2018]). But observers also point out that IFRS 9 may deteriorate financial statement comparability, may be overly susceptible to subjectivity, and may result in unexpected incremental costs (Harrison and Sigee [2017]).

Regulators have recognized the significance of IFRS 9 (mainly its ECL pillar) and employed several inputs relating to the ECL transition. For instance, the EBA's 2018 stress test incorporates the effects of the IFRS 9 transition on the tested banks. Also, bank regulators have disclosed their assessment of the effects of the new accounting rules for loan loss recognition. For instance, ahead of the changes, the EBA published several documents on the negative day-one impacts of IFRS 9 (e.g., EBA [2016]; EBA [2017]). Supervisors have attempted to gauge the impact on the banking sectors more qualitatively as well. An ECB survey conducted in 2017 shows that most of the surveyed banks had only draft plans to transition to IFRS 9, in spite of the imminent implementation deadline of January 2018. Among other things, the surveyed banks reported experiencing problems with data quality, availability of historical data, assessment of credit risk, and capacity needed to implement IFRS 9.[20] Consequently, there has been an emphasis on collaboration between bank regulators and bank auditors (Cohen and Edwards [2017]; PRA [2019]).[21]

Bank auditors point out significant challenges in the ECL framework. They remark that firms must consider a wide range of scenarios in calculating loan losses and that this task is

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[19] PwC states, "*IFRS 9, the new financial instruments standard, is well recognised as being a big change in accounting by banks, in some cases* ***the biggest such change in living memory****. This is largely due to IFRS 9's requirements in the area of loan loss impairment and the introduction of the expected loss model. The new rules will generally result in earlier recognition of losses compared to today's incurred loss model*" (emphasis added). See also the overviews provided by Deloitte [2016] and EY [2017].

[20] Source: https://www.dnb.nl/en/news/dnb-nieuwsbrieven/nieuwsbrief-banken/newsletter-banks-august-2017/index.jsp.

[21] See Balakrishnan et al. [2019] for a broader take on the benefits of auditors' involvement in bank supervision.

especially difficult presently in light of Europe's uncertain economic environment. According to auditors, the majority of banks lack clarity on how to implement the new regulation and what impact it will have on their business.[22] Audit professionals also underscore potential problems with comparability across financial statements, as the enhanced room for managerial judgment could lead to structurally different assessments of future prospects by different institutions.[23] In addition to the Big Four, international audit regulators and organizations also provide perspective and guidance on ECL (e.g., IAASB [2016]; IFIAR [2016]).

The ECL provisioning model would considerably alter banks' financial statements; unsurprisingly, banks too have raised concerns regarding the implementation of the ECL framework. Bankers have viewed IFRS 9 as an enormous task and admitted they were short on information.[24] Bankers have also expressed reservations about the manipulation of the ECL rules.[25] At times, even the central premise of IFRS 9—the goal of reduced procyclicality—has been questioned by banks in their official disclosures.[26]

The ECL concept has received academic attention and scrutiny as well. For instance, Hronsky [2010] argues that no factual evidence corroborates that the accounting treatment of loss provisioning is a direct cause of procyclicality. Rather, procyclicality results from the banking regulatory framework, not the accounting framework. In this sense, the application of IFRS 9 may improve the timing of banks' loan portfolio analysis, but introduces subjectivity and complexity without directly addressing procyclicality. Reitgruber [2014] points out that the ECL model has significant shortcomings related mostly to the requirement that financial institutions integrate

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[22] Source (KPMG): https://www.ft.com/content/26dfb19c-60a4-11e6-b38c-7b39cbb1138a.

[23] Source (Deloitte): https://www.ft.com/content/50f7aea2-1291-11e4-93a5-00144feabdc0.

[24] Source (HSBC): https://www.reuters.com/article/banks-regulations-ifrs9-idUSL8N1BY40M.

[25] For example, in the case of [Swiss] mortgages, which typically have three-year terms and are regularly refinanced, banks could take that three-year period as their 'lifetime' exposure.

[26] For instance, Nordea Group states in its first annual report post IFRS 9: "*Impairment calculations under IFRS 9 requires more experienced credit judgement by the reporting entities than was required by IAS 39 and a higher subjectivity is thus introduced. The inclusion of forward looking information adds complexity and makes provisions more dependent on management's view of the future economic outlook.* ***It is expected that the impairment calculations under IFRS 9 will be more volatile and pro-cyclical than under IAS 39, mainly due to the significant subjectivity applied in the forward-looking scenarios***" (emphasis added).

forward-looking data into their credit loss models. Abad and Suarez [2017] also raise concerns about the country-cyclicality premise of the ECL framework.

In keeping with the concerns above, the application of ECL may not only fail to yield the desired results, but may also aggravate scenarios in which banks face shortcomings in their required capital coverage ratios, as well as accentuate pro-cyclicality and its impact upon banks' profitability and capital deployment. These concerns are echoed in the research report by Harrison and Sigee [2017]. The authors contend that the new ECL rules—their initial impact aside—would be *more* corrosive to bank capital in a downturn.

Researchers have also explored other aspects of IFRS 9's ECL approach. Gaffney and McCann [2018] assert that provisioning levels may rise sharply if a large share of performing loans falls into the newly defined Stage-2 category, which may harm banks' profitability. Delgado-Vaquero et al. [2019] make suggestions for estimating PDs for unrated companies under IFRS 9. Finally, Loew et al. [2019] study the initial implementation effects of IFRS 9. In addition to presenting extensive descriptive evidence, the authors also assess the impact of the first-time adoption of IFRS 9.[27]

3. Empirical Predictions and Research Design

The move from IAS 39 to IFRS 9 triggers a significant initial increase in provisions for many banks at implementation. This change could induce banks to revisit their lending decisions, especially to risky and opaque borrowers, which are associated with comparatively higher and/or more complicated ECL estimates, respectively. The rules penalize banks but do not reward them for making such loans, in that banks cannot earn their way through. In response, banks could cut down on lending to such risky and opaque entities (e.g., small businesses) in order to shrink the

[27] The following papers explore topics related to forward-looking provisioning as a broad concept: Bushman and Williams [2015]; Laeven and Majnoni [2003]; Fillat and Montoriol-Garriga [2010]; Bouvatier and Lepetit [2012]; Huizinga and Laeven [2012]; Bikker and Metzemakers [2005]; Ozili and Outa [2017]; and Gebhardt and Novotny-Farkas [2011].

"expected loss" basis on which their capital requirements are calculated. Since loan amounts are jointly determined with loan prices, banks might also increase the interest rate for such borrowers.

Another dimension to consider is loan maturities and collateral. Under IFRS 9, the potential loss on loans to safe businesses needs to be calculated for 12 months ahead. But for lending propositions that could experience a significant increase in credit risk, potential losses need to be calculated for the lifetime of the loan, with consequent repercussions on the required provisions. Under such circumstances, the cost of longer maturities would also go up disproportionately, and collateral requirements would likely rise. While shorter maturities reduce the complexity and severity of lifetime loss calculations, heightened collateral requirements minimize LGD estimates and thus, the amount of lifetime loss calculations.

Meanwhile, shareholders and debtholders of banks could be bearing the additional compliance costs in various ways. Moving from an incurred-loss model to the ECL framework requires banks to forecast scenarios of macroeconomic conditions and assemble them into the risk parameters in their credit models. In contrast, the incurred-loss approach relies on a relatively objective loss event. The forward-looking element of the ECL model thus requires substantial modeling efforts and considerably higher managerial judgment.[28] To comply with the new rules, banks need to make nontrivial expenditures on auditors, consultants, and modeling experts, in addition to diverting full-time personnel to the IFRS 9 transition efforts.[29]

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[28] For example, Santander UK plc provides the following information in its 2018 Annual Report: "*Ensuring appropriate application and embedding of IFRS 9 is a significant area of judgement given its technical complexity, the number of judgments needed, and their potential impact. Determining the appropriateness of credit provisions is also highly judgmental, requiring management to make a number of assumptions. ... Our Risk Methodology team developed our ECL impairment models, and all material models are independently reviewed by our Independent Validations Team. ... The models are sensitive to changes in credit conditions, and reflect various management judgements that give rise to measurement uncertainty in our reportable ECL as set out above. ... Board Audit Committee reviews and challenges the appropriateness of the estimates and judgements made by management.*"

[29] Banks often acknowledge the issue of compliance costs. For instance, UniCredit states in its 2018 Annual Report, "*the Board of Statutory Auditors notes that, compared to the previous year, the costs of the services assigned to the External Auditors increased, net of inflation, by €518,000, in consideration of the supplemental fees requested by the External Auditors following the introduction of the new IFRS 9 principle*."

3.1 MEASUREMENT OF THE IMPACT OF THE ECL TRANSITION

This paper's goal is to present initial evidence on the real effects of the ECL approach. To do so, I need to measure a form of cross-bank variation in the effect of the new rules—e.g., a group of banks that are affected by the regulation and another group of banks that are not affected by the regulation but are otherwise similar to the affected banks. This issue is challenging in the setting I study because almost all large banks in Europe report under IFRS and thus must transition to the ECL framework.[30]

One could address this challenge by using banks that have implemented IFRS 9 (e.g., European and most Asian banks) as a treatment group and by constructing a control group of banks that have not gone through such a change (e.g., American banks). The alternative is to explore the intensity of the regulation's impact within the group of transitioning banks. For three reasons, I choose the latter approach. First, the potential sample period (the 2010s) is associated with dramatic changes in the banking landscape across different geographies (Putnis [2016]). This would render a comparison of European banks to American banks—even a difference-in-differences analysis—vague and uninformative due to concurrent economic trends, developments, and regulations. Second, the experiment in question, IFRS 9 implementation, involves changes other than transitioning to the ECL framework, such as new rules for the reclassification of assets and liabilities as well as significant modifications to hedge accounting. This institutional complexity creates an attribution conundrum. Even if one found a control group that is not susceptible to any confounding effects, it would be difficult to identify which specific aspect of IFRS 9 is responsible for the observed results.[31] Third, my analyses require detailed information

[30] A handful of banks covered by the EBA Transparency Exercise are private entities that choose to report under local GAAP. In my empirical analyses, I take the ECL transition impact as zero for these banks. My conclusions are robust to excluding these entities from my sample.

[31] To be sure, IFRS 9 implementation coincides with a number of other rules and regulations in Europe, which is all the more reason to conduct a geographically constrained investigation. In my review of banks' reports and disclosures, I have also examined other concurrent changes. I do not observe a particular trend coinciding with the ECL transition intensity. For instance, IFRS 15 is relevant to banks, but it is less significant in magnitude, it does not correlate with the new impairment rules, and it mainly affects banks' commission income and income from other activities.

on banks' lending behavior, including portfolio-level outcomes and even specific credit clauses. I have access to such comprehensive data for European banks only.

The essential task in my measurement approach is to figure out a way to create an 'intensity' variable that can accurately compare one European bank that adopts IFRS 9 in 2018 to another European bank that also adopts IFRS 9 in 2018. To create such a variable, I use banks' IFRS 9 transition disclosures as well as interim and annual reports post adoption. Per IAS 8, all banks that transition to IFRS 9 are required to provide a reconciliation between IAS 39 (31 December 2017) and IFRS 9 (1 January 2018).[32]

The Online Appendix (OA1) presents several examples of these disclosures and illustrates the basis of my measurement. For instance, the ECL transition increases Barclays Group's loss allowance (for loans) from £4.65 billion to £7.11 billion, whereas the same movement is from €23.95 billion to €25.95 billion for Banco Santander. Accordingly, I assign an impact value of 54.0% (=2.51/4.65) to Barclays and an impact value of 8.4% (=2.00/23.95) to Santander.[33] In my sample of banks, I find an average impact effect between 12.50% and 13.36%. For context, in its study of 49 European banks, EBA [2017] estimates that IFRS 9 would trigger an average increase of 13% in loan loss reserves. While the sample I use is different (and more than twice as large), the similarities in these estimates are reassuring.

Overall, I contend that these day-one disclosures offer a plausible and relatively clean way to capture the intensity of the ECL transition because banks' portfolios on both dates are fundamentally identical, and the increase in loan loss allowance is driven entirely by the transition to the ECL model from the incurred-loss framework. Other benefits of this approach are that regulators have used or referred to similar metrics (e.g., EBA [2017]) and that the transition effects are public information.

[32] Banks with non-December fiscal year-ends adopted the new rules within 2018. This group constitutes a very small fraction of my sample, and its exclusion does not affect my findings.

[33] The impact values for the remaining banks in the Online Appendix OA1 are 26.6% (=990/3,727) for Sabadell, 8.1% (=271/3,345) for Allied Irish, 7.7% (=100/1,299) for Iccrea, and 30.0% (=2,336/7,785) for HSBC.

That being said, I acknowledge that this choice is not without noise. For example, it is possible that the banks that were going to be most affected by the ECL framework changed their lending behavior during the transition years, i.e., before IFRS 9 took effect. Indeed, IFRS 9 received a great deal of attention prior to its implementation, and a variety of European regulatory bodies participated in the IASB's due process (Bischof and Daske [2016]). Table 1 presents a timeline of the IFRS 9 implementation.

My work addresses this concern in three ways. First, I note that this measurement error—absent any systematic confounds or biases—should work against finding significant results. Second, my tests exclude observations that belong to the year 2017, which is plausibly the most intense transition period (Hendricks et al. [2019]). Third, I expect that such measurement errors distort the *magnitude* of the ECL impact, rather than the relative *rankings* of banks. Thus, instead of using the ECL impact as a continuous variable, I create an indicator variable called *Affected bank*, which switches on for banks that experience an above-median increase in their loan loss reserves, purely due to the switch to expected loan loss provisioning. This classification choice refrains from making any numerical assumptions; it states merely that banks that belong to the *Affected bank* category were more intensely affected by transitioning to the ECL framework.[34] In additional robustness tests, I examine the effects of using decile ranks and a continuous variable. I also provide a comparison of affected banks and other banks (See Online Appendix).

In all of the tests, the sample period runs from 2015 to 2019, excluding 2017. I start in 2015 to avoid an excessively long pre-event period and to avoid significant developments relating to the implementation date and method of IFRS 9.[35] These developments include the Basel III transition, as well as other aspects of banks' reporting practices like the EU's Capital Requirements Regulation No. 575/2013 (or CRR). As mentioned above, I remove observations from 2017 to mitigate the concern that banks changed their behavior right before IFRS 9 took effect. (According

[34] It is quite possible that the *Affected bank* category is also susceptible to measurement error, in that it might be missing some of the banks that were heavily impacted by IFRS 9; however, what I need here is for the *Affected bank* indicator to be positively correlated with the true measure of impact.

[35] For Amadeus financials and loan-level information, the year 2019 constitutes a small fraction of the sample, as this data is not yet available. Excluding this year altogether in these samples does not affect my conclusions.

to this concern, whether 2017 belongs de facto to the pre-IFRS 9 period is debatable.) However, I verify that my conclusions hold if I include 2017 in the estimation samples (Online Appendix).

I explore the effect of the ECL framework at the bank level, at the borrower level, and at the individual contract level. In my bank-level and loan-level analyses, the independent variable of interest is a dummy variable denoting banks for which IFRS 9 triggered an above-median rise in their loan loss allowances, i.e., *Affected bank.* In my borrower-level tests, I define the indicator variable *Affected borrower*, which switches on for SMEs with a banking relationship with lenders coded as *Affected bank*.

The disclosures above require hand collection and individual reading and interpretation of bank reports. Furthermore, portfolio-level and loan-level data exist only for the most significant European banks. Thus, instead of examining the entire population of European banks, I limit my attention to banks that go through the EBA's Transparency Exercise. The results of this procedure are released every year, and the pertinent disclosures provide detailed and standardized bank-level data on capital positions, lending and exposure amounts (by segment), and asset quality.[36]

The EBA data come with bank name and legal entity identifiers (LEIs). I measure the ECL impact for each of these banks. I then match this information to SNL, FactSet, Markit, Bureau van Dijk (BvD) Amadeus, and the European DataWarehouse Loan-level Database (variable definitions in Table 2).

3.2 BANK-LEVEL ANALYSIS

The dependent variables in the bank-level tests are banks' portfolio structure (e.g., SME lending, corporate lending). The data for the bank-level portfolio analysis come from the EBA Transparency Exercise. Toward the end of each year, the EBA releases half-yearly information on banks' performing and nonperforming exposures at the asset group level. This breakdown includes traditional lending (e.g., SME, corporate, retail, mortgage) as well as nonlending activities (e.g., securitization, covered bonds, sovereign bonds, interbank).

[36] See https://eba.europa.eu/risk-analysis-and-data/eu-wide-transparency-exercise.

In these tests, I control for a vector of bank controls, including size, capital, profitability, risk-taking, risk measurement method, and loan intensity. The source for these variables is SNL Financial. The regression model is as follows.

$$Bank\ lending_{bt} = \beta_1\, ECL\ regime_t \times Affected\ bank_b + \beta_2\, ECL\ regime_t + \beta_3\, Affected\ bank_b + \boldsymbol{\Theta}\ \boldsymbol{Controls_{bt-1}} + \eta_b + \gamma_t + \varepsilon_{bt} \quad (1)$$

The dependent variables of interest capture banks' lending decisions. The main metrics of SME lending are *SME lending (log)* and *SME lending (% assets)*.[37] The former is the natural logarithm of outstanding credit to small businesses, and the latter is the ratio of a bank's SME lending to its total exposures.[38] *SME lending (log)* captures the amount of lending in a relatively unrestricted sense, while *SME lending (% assets)* conveys insights from a portfolio allocation perspective. In additional tests, I use two similar dependent variables: (1) corporate lending, and (2) other lending, which includes banks' mortgage and retail positions. These variables are defined as corporate loans (and mortgage & retail loans) divided by total loans. Moreover, to shed light on banks' nonlending activities, I examine banks' total exposures minus corporate lending, SME lending, retail lending, and mortgage lending. Hence, the nonlending figure includes banks' positions in the interbank market, sovereign and regional government debt, securitization and covered bonds, and other financial instruments alike. As before, I proxy for nonlending activities in an unrestricted fashion (*Nonlending activities log*) as well as relative to the bank's total exposures (*Nonlending activities % assets*).

On the right-hand side, *Affected bank* and *ECL regime* are the two components of the difference-in-differences model. *ECL regime* is the "post" variable, which is an indicator that switches on for 2018H1, 2018H2, and 2019H1. *Affected bank* is the "treatment" variable, which is an indicator that equals one for banks that experience an above-median increase in their loan

[37] In my discussions of the regression variables, I drop the subscripts to avoid clutter.

[38] The EBA provides data on banks' exposures. Since SME loans are virtually never hedged (e.g., DeYoung et al. [2015]), lending and exposures are quite similar if not identical.

loss allowance due purely to the implementation of the ECL approach. Online Appendix OA1 includes examples of such disclosures.

The controls vector attempts to account for time-varying bank characteristics that might be changing concurrently with the IFRS 9 implementation and might be affecting banks' lending and portfolio allocation decisions. The vector includes the natural logarithm of full-time bank employees (*Bank size*), the ratio of bank equity to total assets (*Bank capital*), return-on-equity (*Bank profitability*), the ratio of loans to total assets (*Bank loan intensity*), an indicator denoting whether the bank measures asset risk weights using the internal-ratings-based approach (*Bank risk method*), and the ratio of risk-weighted assets to total assets (*Bank asset risk*).[39] In addition to these variables, which come from SNL Financial, I also control for the natural logarithm of banks' exposures (*Total exposures log*) and their quality (*Nonperforming exposures %*), which come from the EBA. All bank-level controls are lagged by one period. Since the time dimension of the dependent variable is a half-year, SNL-based bank-level controls, which are calculated at the bank-year level, pertain to the previous year. Namely, for observations from 2018H1 and 2018H2, bank controls are calculated as of the end of 2017. In the presence of bank fixed effects (η) and half-year fixed effects (γ), *Affected bank* and *ECL regime* are omitted, respectively, from the estimation.

3.3 BORROWER-LEVEL ANALYSIS

I conduct two sets of borrower-level tests. First, I examine the debt issuance behavior of small businesses. As in my identification of affected banks above, I need a way to compare borrowers to one another in terms of their exposure to the ECL regime. To do so, I rely on prior literature that highlights the importance and rigidity of relationship lending for small businesses (e.g., Petersen and Rajan [1994]; Berger and Udell [1995]; Berger and Udell [2002]). Accordingly, I use the BvD Amadeus Bankers dataset to identify the links between banks and borrowers, which

[39] I opt to use employees rather than total assets as a measure of bank size because the employees-based measure is institutionally better linked to traditional commercial-bank lending (Schildbach [2017]). At any rate, my measure of total exposures from EBA gets at such a dollar-based size metric.

allows me to assign an ECL-impact score to each borrower.[40] For instance, a given Amadeus borrower receives a score of 8.4% if its relationship bank is Santander in the above example.

I define *Affected borrower BvD* as an indicator that switches on for companies that have a relationship with *Affected banks* (i.e., banks that experience an above-median reduction in their loan loss reserves due to accounting remeasurement). I then examine firm-level debt issuance using the following equation.

$$\begin{aligned} \textit{Debt issuance}_{it} = \beta_1\, \textit{ECL regime}_t \times \textit{Affected borrower BvD}_i + \beta_2\, \textit{ECL regime}_t \\ + \beta_3\, \textit{Affected borrower BvD}_i + \boldsymbol{\Theta}\, \boldsymbol{\textit{Controls}}_{\boldsymbol{it-1}} + \mu_i + \sigma_{ct} + \tau_{kt} + \varepsilon_{it} \end{aligned} \qquad (2)$$

The unit of observation is a firm-year, as per the data frequency in BvD Amadeus Financials, the data source for SME financials. *ECL regime* switches on for years 2018 and 2019. *Controls* include firm size and leverage. In the construction of this sample, to minimize data errors, I exclude companies that do not appear in the ECL period and those with zero leverage.

Debt issuance is the yearly change in net debt, as a percentage of year-ago total assets. This variable can be computed for a large sample, and growth in net debt is a sensible way to capture firms' borrowing behavior without the noise caused by refinancing choices. However, this proxy has two limitations. First, it is based on realized credit figures, which could be driven by supply effects (e.g., banks' willingness to make loans), as well as demand effects (e.g., borrowers' investment opportunities). Although firm (μ), country-year (τ), and industry-year (σ) fixed effects mitigate demand-side confounds, there may still be lingering concerns. Second, *Debt issuance* captures all types of credit, not necessarily bank debt. Even though bank credit constitutes the majority of external financing for SMEs, this choice remains susceptible to error. I attempt to address both issues by examining surveys of SMEs' credit access conditions, which I discuss below.

In my second borrower-level test, I rely on confidential microdata from an SME credit access survey conducted by the ECB—the Survey on Access to Finance of Enterprises (SAFE). The benefit of this SME-level dataset is that it captures borrowers' credit access and loan

[40] If a borrower is associated with more than one bank, I take the maximum score of IFRS 9 impact.

applications, rather than realized borrowing amounts, which might be confounded by concurrent local economic trends and demand factors (e.g., Acharya and Ryan [2016]; Ryan [2018]; Balakrishnan and Ertan [2019]).

The SAFE data includes information on whether the borrower has applied for bank financing, and if this is the case, details on the outcome of the application. To mitigate confounding demand effects, I focus on a sample that consists only of SMEs that report having applied for a bank loan within the past six months of the survey. I then estimate the following model at the SME-half-year level, as per the unit of observation in the SAFE dataset.

$$\begin{aligned} \textit{SME access to bank credit} \quad &= \beta_1 \, \textit{ECL regime}_t \times \textit{Affected borrower ECB}_i + \beta_2 \, \textit{ECL regime}_t \\ &+ \beta_3 \, \textit{Affected borrower ECB}_i + \boldsymbol{\Theta} \, \boldsymbol{Controls}_{it-1} + \tau_k + \gamma_t + \varepsilon_{it} \qquad (3) \end{aligned}$$

SME access to bank credit is an indicator variable that switches on for respondents that receive most or all of the credit amount they applied for. *ECL regime* is a dummy that equals one for observations whose responses pertain to 2018 and 2019.[41]

The drawback of the SAFE data is that borrower identities are not known. Hence, I approximate the heterogeneity in surveyed borrowers using Amadeus. First, I bring in the borrower-level impact scores that I obtain for Amadeus borrowers above. Second, I average these scores within each country and four size brackets. I choose four size brackets because the survey defines sales as an ordinal variable that equals 1 if annual sales are less than €2 million, 2 for sales between €2 and 10 million, 3 for sales between €10 and 50 million, and 4 for sales over €50 million. Third, I assign these approximated country-size-grid-level scores to each borrower in the survey. (See Ferrando and Mulier [2013] for a similar procedure.) This matching allows me to create a borrower-level intensity score for the survey. To give an example, if Spanish firms with annual sales between €10m and €50m have an average impact score of 7%, this becomes the value of the synthetic impact variables in the SAFE data of the Spanish borrowers with annual sales between

[41] The periods in the ECB SAFE data are labelled as waves. My investigation uses waves 14 (2015) through 21 (2019). I exclude wave 18 since the responses in this period fully pertain to SMEs' credit access in 2017. Again, my inferences are not sensitive to this exclusion.

€10m and €50m. Finally, I code *Affected borrower ECB* as an indicator variable for SMEs whose triangulated ECL impact score is greater than the sample median.

In addition to SMEs' access to bank credit, I explore two additional dimensions using the same specification as in Equation 3. First, on a sample of SMEs that did not apply for a bank loan (i.e., a completely different sample), I study the reasons for the lack of application. *Latent demand* is an indicator variable that equals one for respondents who state that they refrained from making a loan application because (*i*) they thought they would get rejected, (*ii*) they feared interest costs would be too high, (*iii*) they thought collateral requirements were too onerous, or (*iv*) they worried about reduced control of their company. This variable remains zero if there is no latent demand, i.e., if the respondent states that the SME did not apply for a loan because it was not necessary. This investigation allows me to explore the credit demand spectrum more comprehensively. For context, other datasets used by prior work—including credit registry records that track loan applications—are unable to shed light on latent demand.

Second, I examine SMEs' views on contractual clauses by analyzing their views on loan amounts (*Amount*), interest costs (*Interest*), maturity structures (*Maturity*), and collateral requirements (*Collateral*). Each of these variables equals one if the respondent reports an increase, zero if the respondent reports no change, and minus one if the respondent reports a decline. A positive coefficient on *ECL regime* × *Affected borrower ECB* implies an increase in the corresponding dependent variable, which could be viewed as an improvement (a deterioration) of the credit landscape for amounts and maturities (for interest costs and collateral requirements).

3.4 CONTRACT-LEVEL ANALYSIS

While the borrower-level tests above capture SMEs' financing decisions, these analyses do not speak directly to the extent to which specific terms of credit change. Furthermore, the fact that the bank-level tests in Equation 1 rely on stock figures, rather than flow figures, makes it difficult to identify the changes in banks' contracting behavior cleanly. To improve my examination along these dimensions, I collect loan-level data from the European DataWarehouse. This source includes details on individual SME-loan contracts as long as these loans belong to SME-loanbacked securities that are pledged as collateral to the Eurosystem by originator banks in their repo operations (e.g., Ertan et al. [2017]).

The advantage of this data source is that it provides extensive information on the loans made to SMEs.[42] The caveat is that the data pertains only to securitized loans. I focus on a recent time period, and the difference-in-differences framework should remove the noise in the measurement. Nevertheless, the inferences from this analysis should be viewed with caution from an external validity perspective (see Ertan et al. [2017] and Neilson et al. [2018]).

I match the originating lender of these loans to my dataset of banks and estimate the following regression model on a sample that includes credit contracts originated throughout the sample period.[43]

$$\begin{aligned} \textit{Contract term}_j = {} & \beta_1\, \textit{ECL regime}_t \times \textit{Affected bank}_b + \beta_2\, \textit{ECL regime}_t + \beta_3\, \textit{Affected bank}_b \\ & + \theta\, \textit{Borrower risk} + \eta_b + \sigma_{ct} + \tau_{kt} + \varepsilon_j \end{aligned} \tag{4}$$

In this model, each observation is an individual loan (j). *Affected bank* and *ECL regime* are indicators; *Affected bank* switches on for banks whose estimated ECL transition impact is above the median (for context, this corresponds to a 10.5% increase). *ECL regime equals* one for loans made in 2018 and 2019. I control for bank fixed effects as well as borrower country-year (σ) and borrower industry-year (τ) fixed effects to account for the demand-side factors that could confound my inferences.[44] *Contract term* includes four main clauses: *Interest rate*, *Loan maturity*, *Loan amount*, and *Payment frequency*. *Borrower risk* is the lender's internal loss given default estimate on the loan.

My narrative predicts that applying the ECL model to SME loans is costly and that banks could pass these costs on to borrowers. Accordingly, I test whether affected banks' loan contracts

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[42] The loan-level data include about 2 million distinct SME loans from 54 active and 136 redeemed/amortized ABS deals. For each loan, the dataset includes more than 100 mandatory and voluntary fields. For details, see https://eurodw.eu/wp-content/uploads/ABS-Market-Coverage.pdf.

[43] In these tests, the ECB LLD data include several lenders that are not covered by the EBA Transparency Exercise. For completeness, my analysis includes the loans originated by these entities; thus, I calculate the ECL impact for these banks as well. However, the tenor of my conclusions is not sensitive to this sample choice.

[44] The models in Equations 3 and 4 do not include borrower fixed effects because firm identities are unknown.

under the ECL regime are more expensive than before in a difference-in-differences sense. I should highlight that while money is a commodity, SMEs heavily rely on relationship borrowing and that their ability to switch lenders is much smaller than that of corporate borrowers (e.g., Petersen and Rajan [1994]; Berger and Udell [2006]).

In addition, I expect to find a decline in the maturity of loans. This is because banks are required to estimate the lifetime loss of a loan once there is evidence of a significant increase in credit risk or outright impairment. This detail assigns a relatively large premium for long-maturity loans, since measuring lifetime losses is cheaper and easier for a two-year loan than for a twenty-year loan.

A third consideration is the amount of credit. This aspect of loan contracting is useful for two reasons. First, it helps to explore the intensive margins, whereas the borrower-level analysis in the preceding section speaks to the extensive margin. Second, this test works as a cross-check for the supply-vs.-demand distinction. Namely, if the increasing interest rates were driven by an increase in borrower demand (the alternative explanation), then loan amounts should go *up*, because this explanation predicts a leftward shift in the demand curve. In contrast, if the cost of credit rises because banks' willingness to lend falls (my argument), loan amounts should go *down*, because this explanation predicts a leftward shift in the supply curve.

Finally, I examine payment frequency. Lenders often require frequent payments as an automated way of monitoring the borrower (Srinivasan [2014]; Sutherland [2018]). Required payments should become more frequent if affected banks enhance their monitoring efforts or if lending becomes more transactional post ECL.

4. *Empirical Results and Discussion*

Consistent with the high-level goal of my paper—to understand the real effects of forward-looking provisioning—I focus my tests on the evolution of lending and contracting. I assess the effects of the ECL framework by conducting three sets of empirical analyses: bank-level tests that help examine banks' portfolio decisions, borrower-level tests that shift the focus from the lender to the borrower, and contract-level tests that allow me to track individual loan contracts.

4.1 BANKS' LENDING AND PORTFOLIO DECISIONS: BANK-LEVEL ANALYSIS

The objective of my bank-level analysis is to shed light on banks' portfolio decisions. The empirical predictions I detail in Section 3 pertain to a particular type of loan, SME credit, since this type of lending becomes more complicated and expensive under an ECL regime.

Panel A of Table 3 presents the relevant summary statistics. The sample contains a total of 623 bank-half-years from 108 distinct banks. The median threshold classifies 44% of the sample banks as affected.[45] SME lending constitutes some 10.2% of total exposures, while the median SME lending is 3.82 billion euros (=$e^{8.248}$). Within the loan portfolio, SME lending accounts for 24.5%, corporate lending for 33.2%, and other lending (retail and mortgages) for 42.2%. For the average bank, nonlending activities are responsible for more than half of the exposures (58.7%). Turning to controls, we see that the median bank has over 6,100 employees (=$e^{8.72}$), a tier-1 capital ratio of 14.1%, and an ROE of 6.1%. Most observations in the sample rely on the internal-risk-based model to measure risk weights. The median bank has a total exposure of about 51.6 billion euros (=$e^{10.852}$), while 2.15% of these exposures are nonperforming. In the Online Appendix, Table OA2.1 presents these statistics separately for affected banks and other banks.

Panels B and C of Table 3 show the results of the estimation of Equation 1. In both panels, column (1) includes half-year fixed effects only. The models in column (2) include bank fixed effects, and those in column (3) are also saturated with time-varying bank controls. In both panels, the difference-in-differences estimator is negative and significant, suggesting a relative decline in the SME-loan positions of affected banks. In Panel B, the coefficient of interest stabilizes around -0.39, which translates to 23% of the sample standard deviation of *SME lending (log)*, 1.726. The inferences from Panel B suggest that this decline is not driven by affected banks reducing their overall lending and shrinking their balance sheets as a whole. Indeed, estimates in this table suggest a decline of over 2% in affected banks' SME positions, relative to their other exposures. For context, the sample standard deviation of SME positions is 8.9%. In terms of dynamic effects, the evidence in Figure 1 suggests the decline in SME lending has not reversed.

[45] This number is not exactly 50% because of banks without a day-one impact value.

As Table OA2.2 shows, my insights are robust to additional tests and alternative specifications: accounting for pre-treatment trends (Panel A and Figure 1), including country-time fixed effects (Panel B), redefining *Affected bank* using decile ranks (Panel C), interacting *ECL regime* with bank characteristics (Panel D), and adding the year 2017 to my sample period (Panel E).

Having provided baseline evidence on the SME-lending effects of switching to the ECL framework, I next explore the cross-bank variation in the main effect with bank size and capital. I report the results in Panels D and E, respectively. My estimates are stronger, by an order of magnitude, for small banks than for large banks. In contrast, the main effect does not vary with banks' capital constraints. Overall, these findings suggest that bank size is an important factor in the implementation of the ECL method and that bank capital slack per se is not a first-order determinant of the reallocation of the loan portfolio under the ECL regime. While the former finding is consistent with the notion that the new rules affect small banks more (e.g., EBA [2017]), the latter suggests capital constraints are not a first-order mediating factor in the ECL transition.

The evidence thus far points to a reduction in SME lending. I expand this finding by investigating what kind of changes occur in affected banks' asset portfolios as a whole. Table 4 presents the results. The estimates in Panel A suggest that holding the loan portfolio constant, banks seem to switch to corporations from SMEs (columns 1 and 2). While banks need to apply the ECL method for these borrowers as well, this type of lending remains relatively inexpensive to continue due to the relatively low risk and relatively high transparency of corporate borrowers. As column 3 shows, there is not a particular trend (in a difference-in-differences sense) in retail and mortgage portfolios.

I also shed light on banks' asset allocation as a whole by examining lending vs. nonlending activities (Panel B of Table 4). It seems like affected banks, rather than engaging in traditional lending, are switching to nonlending assets, such as sovereign and regional government debt, interbank assets and repo arrangements, and securitization and cover bond products. This inference is in line with traditional loan-making operations getting less attractive following the adoption of the ECL rules.

4.2 SME BORROWING FROM RELATIONSHIP BANKS: BORROWER-LEVEL ANALYSIS

The bank-level analysis provides a direct link between the ECL transition and banks' exposures to certain asset classes, but by design, it cannot speak to the borrower side of the story. I next shift my focus to a set of borrower-level tests to shed light on (1) whether the borrowers of affected banks experience a decline in debt issuance, (2) what types of borrowers feel the reduction in loanable funds most, and (3) the extent to which the observed effects are driven by banks' credit supply and willingness to lend, rather than borrowers' changing demand for external financing.

Panel A of Table 5 presents the summary statistics for the Amadeus sample of SME-years. Net indebtedness remains unchanged for the median company, while the average increase in this ratio is a little over 2.28%. Some 37% of borrowers are coded to do business with banks that were affected by the ECL transition.

Regarding the estimation results, I find that debt issuance goes down for affected borrowers post ECL, relative to that of their unaffected counterparts (Panel B of Table 5). Columns (1) and (2) indicate a decline of 1.25–2.44%, which is economically meaningful given the sample standard deviation of *Debt issuance*, 13.23%. One advantage of this data is its granularity, which allows me to estimate the regression model using country-year and industry-year fixed effects (pertaining to the borrower). This additional step allays concern about time-varying demand confounds at the regional and industry level, although it also removes some of the variation that could be attributed to IFRS 9. As column (3) shows, the coefficient of interest does go down to 0.63%; however, the tenor of my inferences remains similar after these exhaustive controls.

I expand on this finding by investigating the variation in the main effect by borrower size. I report these results in Panel C of Table 5. These estimates suggest that my conclusions are economically more strongly driven by small borrowers.[46] Taken together, the results from the borrower-level tests imply a reduction in the borrowing of SMEs (especially the smaller ones) that do business with banks affected by the ECL transition.

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[46] The standard deviation of *Debt issuance* is similar across the large-borrower subsample (12.7%) and small-borrower subsample (13.7%). This suggests larger marginal effects within the small-borrower subsample.

Next, I move to a different dataset that helps me better account for factors related to the demand for credit. The main concern here is that *Affected bank* and *Affected borrower (BvD)* are susceptible to confounding fundamentals, rather than capturing the intensity of the new ECL regulation. If this were the case, the decision to apply for credit should systematically differ across affected borrowers, and the credit approval rates should be no different across affected and unaffected banks. I attempt to illuminate this issue using the European Central Bank's SME surveys.

The controls vector in this specification includes SME size, age, credit quality, sales growth, and profitability growth—all of which are ordinal variables whose detailed definitions appear in Panel B of Table 2. The sample statistics are presented in Panel A of Table 6. Firms have relatively good access to bank credit, as *SME credit access to bank credit* switches on for more than three-quarters of the sample (Casey and O'Toole [2014]; Ferrando et al. [2017]). Turning to applicant characteristics, we see that the median SME in the sample has between 10 and 49 employees, is over 10 years old, and has stable trends of credit quality and profit growth.

Panel B of Table 6 presents the estimation results. As column (1) shows, affected respondents experience a decrease in their access to bank credit by about 2.8%. The results in columns (2) and (3) complement my earlier findings on borrower size. In fact, the main effect is driven entirely by relatively small borrowers (i.e., those with fewer than 50 employees) (column 2). In contrast, there is no change in the larger borrowers' access to bank credit (column 3). In sum, the inferences from the ECB SAFE setting validate my earlier conclusions: borrowers of banks that are most affected by the ECL transition experience a relative reduction in their credit access, even after I hold constant their decision to apply for a bank loan.

Panels C and D of Table 6 explore additional aspects of the credit access challenge SMEs face. In Panel C, I provide economically significant evidence that SMEs that did *not* apply for a loan are more likely to refrain from doing so because of unfavorable borrowing conditions (i.e., fear of rejection, high interest costs, collateral requirements, or reduced control rights), rather than a lack of demand for bank credit. This inference is statistically significant for small firms. An estimate of about 1.1% (column 1) and 3.1% (column 2) are economically meaningful increases in latent demand, relative to the sample mean of this indicator variable, 16.9%.[47]

Complementing this finding and my preceding inferences, the evidence in Panel D indicates that SMEs perceive an overall deterioration in credit conditions. Specifically, affected respondents are more likely to state that interest rates and collateral requirements have risen by 3.8% and 6.0%, respectively. Similarly, for these SMEs, loan amounts and maturities decline by 5.8% and 3.1% in the ECL period. Relative to the respective standard deviations, these estimates correspond to marginal effects of about 10%.

4.3 CHANGES IN SME DEBT CONTRACTING: LOAN-LEVEL ANALYSIS

My final analysis explores individual credit agreements that I obtained from the European DataWarehouse. Table 7 reports the relevant summary statistics and estimation results. Panel A shows that about 16% of the sample loan contracts are originated by affected banks. More than half of the sample contracts belong to the post period. The median loan has an interest spread of 3.24%, has a maturity of five years, and requires monthly repayments of the principal.

The results in the first two columns of Table 7, Panel B suggest a relative increase in the interest affected banks charge their SME borrowers. This figure is about 1.38% with interacted fixed effects that account for trends within the borrowers' countries and industries. The results for the remaining terms are reported in columns (3) through (8). I observe a decline of almost two years in loan maturity, 0.9 log reduction in loan amounts, and 0.77–0.79 more required payments within the year. I note that despite the slight reduction in the sample size, my conclusions hold if I control for the lender's loss given default estimate on the loan (*Borrower risk*). Also, reassuringly, this borrower-level risk variable is positively associated with interest costs and payment frequencies and negatively associated with loan amounts and maturities.

[47] Throughout the paper, the benchmark for my economic magnitudes is the sample standard deviation of the dependent variable. For the dummy variables only, I use sample means as reference point because this is the only nondegenerate moment for them.

One advantage of the loan-level data is that it allows me to explore whether these results are stronger for a particular group of borrowers. As in the previous tests, following prior work (e.g., Berger et al. [2005]), I focus on borrower size. I define the large-borrower subsample as loans made to small-sized or medium-sized borrowers. The small-borrower subsample includes companies that are coded as micro-sized by their respective lenders. Consistent with my previous findings, I observe that loan costs rise, maturities decline, and amounts go down primarily for small borrowers (Panel C of Table 7).[48] Overall, my analysis of the loan-level data provides inferences consistent with the main takeaway of the paper: affected banks reduce the quantity and increase the cost of credit for small businesses.

4.4 OTHER COSTS

Observers suggest that the ECL framework involves substantial costs. In additional analyses, I investigate two other aspects of transitioning to the ECL approach: information imprecision and compliance costs. I report these results from the analysis of these tests and detail inferences in the Online Appendix (OA.3).

I proxy for information imprecision using the ratio of a bank's short-term credit default swap (CDS) spreads to its long-term CDS spreads (Duffie and Lando [2001]). The advantage of this metric is that it isolates the quality of a firm's information environment, conditional on the underlying credit risk. My tests of the CDS setting show a 15% relative increase in the term-structure flatness of affected banks. This inference suggests that investors view ECL provisions as comparatively unreliable or complex, at least in the short to medium term. In a way, these results also expand the conclusions of Bushman and Williams [2012], who argue that the procyclicality-reducing benefits of the ECL may be offset by losses in transparency.

I investigate compliance costs using audit fees. Observers point out that impairment allowance calculations under the ECL framework entail greater flexibility but require significant judgment and hard work (Deloitte [2016]; EY [2017]; Harrison and Sigee [2017]). In keeping with

[48] The sizes of the individual subsamples in Panel C do not add up to the size of the main sample in Panel B, because the borrower size information is missing for a small group of contracts (fewer than 1,000).

the idea that the ECL model requires significantly more effort, I find a relative increase in affected banks' audit fees. I note that these costs may be a lower bound because this estimation omits several other categories of relevant expenditures, such as the full-time employees diverted to the IFRS 9 transition or the external consultants and experts hired for the ECL implementation.

5. *Conclusions*

IFRS 9 introduces fundamental changes to the criteria for impairment procedures, moving the credit loss paradigm from the formerly criticized incurred-loss system to an expected credit loss (ECL) framework. The new rules aim to induce institutions to more accurately reflect the potential for credit loss and asset impairment earlier in the credit cycle and, thus, to provide a more accurate representation of the company's credit risk and fair value. However, the requirements for estimates on future performance and risk could increase the potential for subjectivity, financial statement volatility, and implementation costs. In addition, banks could react to these changes by altering their real activities, mainly by switching away from risky and opaque borrowers such as small businesses. This paper attempts to explore these fundamental issues.

Using bank-level, borrower-level, and contract-level samples that capture banks' lending decisions, I analyze banks' lending behavior and the evolution of credit agreements in the post-ECL period. I find that the introduction of the ECL approach has adverse effects on the credit access of small businesses. For these entities, the new rules seem to reduce credit amounts and loan maturities, while increasing interest costs and collateral requirements. I also observe that the main effects are stronger for smaller banks and smaller borrowers. Overall, my inferences provide empirical support for some of the concerns various observers have expressed about the ECL model (Laux [2012]; FSB [2019]; EBF [2019]; Loew et al. [2019]).

The goal of this paper is to explore the economically important and academically valuable impact of the ECL method (Beatty and Liao [2014]; Bushman [2014]). Nonetheless, many important questions remain for future research. For one thing, my study can explore only the first couple of years of the new system. More work is needed to ascertain how banks cope with the new framework in the longer term. Furthermore, I recognize that the main objective of the ECL approach is to reduce procyclicality by requiring banks to deal with loan losses that have not yet occurred. To this end, a thorough investigation of how banks fare in the next down-cycle will be a critical test. Researchers will then be able to better assess the social value of the ECL approach. In particular, it is critical to ascertain whether the ECL rules improve banks' credit risk modeling (e.g., Bhat et al. [2018]; Bhat et al. [2019]). If the ECL framework (or its U.S. counterpart, CECL) could achieve this, the impact would be profound.

References

Abad, J. and Suarez, J., 2017. Assessing the cyclical implications of IFRS 9: A recursive model. *Working paper*.

Acharya, V.V. and Ryan, S.G., 2016. Banks' financial reporting and financial system stability. *Journal of Accounting Research*, *54*(2), pp.277–340.

Arora, N., Richardson, S. and Tuna, I., 2014. Asset reliability and security prices: evidence from credit markets. *Review of Accounting Studies*, *19*(1), pp.363–395.

Balakrishnan, K., De George, E.T., Ertan, A. and Scobie, H., 2019. Mandatory auditor involvement in bank supervision. *Working Paper*.

Balakrishnan, K. and Ertan, A., 2018. Banks' financial reporting frequency and asset quality. *The Accounting Review*, *93*(3), pp.1–24.

Balakrishnan, K. and Ertan, A., 2019. Bank asset transparency and credit supply. *Review of Accounting Studies*, forthcoming.

Beatty, A. and Liao, S., 2011. Do delays in expected loss recognition affect banks' willingness to lend? *Journal of Accounting and Economics*, *52*(1), pp.1–20.

Beatty, A. and Liao, S., 2014. Financial accounting in the banking industry: A review of the empirical literature. *Journal of Accounting and Economics*, *58*(2-3), pp.339–383.

Beck, T., Demirgüç-Kunt, A.S.L.I. and Maksimovic, V., 2005. Financial and legal constraints to growth: Does firm size matter?. *Journal of Finance*, *60*(1), pp.137–177.

Berger, A.N., Klapper, L.F. and Udell, G.F., 1999. *The ability of banks to lend to informationally opaque small businesses*. The World Bank.

Berger, A.N., Miller, N.H., Petersen, M.A., Rajan, R.G. and Stein, J.C., 2005. Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics*, *76*(2), pp.237–269.

Berger, A.N. and Udell, G.F., 1995. Relationship lending and lines of credit in small firm finance. *Journal of Business*, pp.351–381.

Berger, A.N. and Udell, G.F., 1998. The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle. *Journal of Banking & Finance*, *22*(6-8), pp.613–673.

Berger, A.N. and Udell, G.F., 2002. Small business credit availability and relationship lending: The importance of bank organisational structure. *The Economic Journal*, *112*(477), pp.32–53.

Berger, A.N. and Udell, G.F., 2006. A more complete conceptual framework for SME finance. *Journal of Banking & Finance*, *30*(11), pp.2945–2966.

Bhat, G., Lee, J.A. and Ryan, S.G., 2019. Using loan loss indicators by loan type to sharpen the evaluation of banks' loan loss accruals. *Working paper*.

Bhat, G., Ryan, S.G. and Vyas, D., 2018. The implications of credit risk modeling for banks' loan loss provisions and loan-origination procyclicality. *Management Science*, *65*(5), pp.2116–2141.

Bikker, J.A. and Metzemakers, P.A., 2005. Bank provisioning behaviour and procyclicality. *Journal of International Financial Markets, Institutions and Money*, *15*(2), pp.141–157.

BIS (2015). Basel Committee on Banking Supervision: Guidance on credit risk and accounting for expected credit losses.

BIS (2017). Basel Committee on Banking Supervision: Standards. Regulatory treatment of accounting provisions—interim approach and transitional arrangements.

Bischof, J. and Daske, H., 2016. Interpreting the European Union's IFRS endorsement criteria: The case of IFRS 9. *Accounting in Europe*, 13(2), 129–168.

Bouvatier, V. and Lepetit, L., 2012. Provisioning rules and bank lending: A theoretical model. *Journal of Financial Stability*, *8*(1), pp.25–31.

Breuer, M., Hombach, K. and Müller, M.A., 2017. How does financial reporting regulation affect firms' banking?. *Review of Financial Studies*, *31*(4), pp.1265–1297.

Bushman, R.M., 2014. Thoughts on financial accounting and the banking industry. *Journal of Accounting and Economics*, *58*(2-3), pp.384–395.

Bushman, R.M., 2016. Transparency, accounting discretion, and bank stability. *Economic Policy Review, Issue Aug*, pp.129–149.

Bushman, R.M. and Williams, C.D., 2012. Accounting discretion, loan loss provisioning, and discipline of banks' risk-taking. *Journal of Accounting and Economics*, *54*(1), pp.1–18.

Bushman, R.M. and Williams, C.D., 2015. Delayed expected loss recognition and the risk profile of banks. *Journal of Accounting Research*, *53*(3), pp.511–553.

Carbo-Valverde, S., Rodriguez-Fernandez, F. and Udell, G.F., 2016. Trade credit, the financial crisis, and SME access to finance. *Journal of Money, Credit and Banking*, *48*(1), pp.113–143.

Casey, E. and O'Toole, C.M., 2014. Bank lending constraints, trade credit and alternative financing during the financial crisis: Evidence from European SMEs. *Journal of Corporate Finance*, *27*, pp.173–193.

Christensen, H.B., Macciocchi, D., Morris, A., and Nikolaev, V.V., 2019. Financial shocks and corporate investment activity: The role of financial covenants. *Working paper.*

Chodorow-Reich, G., 2013. The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *Quarterly Journal of Economics*, *129*(1), pp.1-59.

Cohen, B.H. and Edwards, G., 2017. The new era of expected credit loss provisioning. *BIS Quarterly Review, March*.

Daske, H., Hail, L., Leuz, C. and Verdi, R., 2008. Mandatory IFRS reporting around the world: Early evidence on the economic consequences. *Journal of Accounting Research*, *46*(5), pp.1085–1142.

Daske, H., Hail, L., Leuz, C. and Verdi, R., 2013. Adopting a label: Heterogeneity in the economic consequences around IAS/IFRS adoptions. *Journal of Accounting Research*, *51*(3), pp.495–547.

De Haan, L. and Van Oordt, M. R., 2018. Timing of banks' loan loss provisioning during the crisis. *Journal of Banking & Finance*, 87, 293–303.

Delgado-Vaquero, D., Morales-Díaz, J. and Zamora-Ramírez, C., 2019. IFRS 9 expected loss: A model proposal for estimating the probability of default for non-rated companies. *Working paper.*

Deloitte, 2016. IFRS 9: Financial Instruments – high level summary.

DeYoung, R., Gron, A., Torna, G. and Winton, A., 2015. Risk overhang and loan portfolio decisions: small business loan supply before and during the financial crisis. *Journal of Finance*, *70*(6), pp.2451–2488.

Dou, Y., Ryan, S.G. and Xie, B., 2018. The real effects of FAS 166/167 on banks' mortgage approval and sale decisions. *Journal of Accounting Research*, *56*(3), pp.843–882.

Duffie, D. and Lando, D., 2001. Term structures of credit spreads with incomplete accounting information. *Econometrica*, *69*(3), pp.633–664.

EBA (European Banking Authority), 2016. European Banking Authority: Report: On results from EBA impact assessment of IFRS 9.

EBA (European Banking Authority), 2017. European Banking Authority: Guidelines on disclosure requirements on IFRS 9 transitional arrangements.

EBF (European Banking Federation), 2019. EBF Answers to the FSB consultation on the evaluation of the effects of financial regulatory reforms on the provision of financing to SMEs.

Ertan, A., Loumioti, M. and Wittenberg-Moerman, R., 2017. Enhancing loan quality through transparency: Evidence from the European Central Bank loan-level reporting initiative. *Journal of Accounting Research*, *55*(4), pp.877–918.

Ertan, A., Kleymenova, A. and Tuijn, M., 2019. Financial intermediation through financial disintermediation: Evidence from the ECB Corporate Sector Purchase Programme. *Working paper*.

EY, 2017. Financial instruments, a summary of IFRS 9 and its effects.

FASB (Financial Accounting Standards Board), 2016. Accounting standards update no. 2016-13, financial instruments-credit losses (topic 326): Measurement of credit losses on financial instruments.

Ferrando, A. and Mulier, K., 2013. Do firms use the trade credit channel to manage growth?. *Journal of Banking & Finance*, *37*(8), pp.3035–3046.

Ferrando, A., Popov, A. and Udell, G.F., 2017. Sovereign stress and SMEs' access to finance: Evidence from the ECB's SAFE survey. *Journal of Banking & Finance*, *81*, pp.65–80.

Fillat, J.L. and Montoriol-Garriga, J., 2010. Addressing the pro-cyclicality of capital requirements with a dynamic loan loss provision system. *Federal Reserve Bank of Boston, Boston MA*.

Fletcher, L., 2019. Hedge fund Cheyne raises €1bn for stressed loan fund. *Financial Times*. June 17, 2019.

FSB (Financial Stability Board), 2019. FSB roundtable on the effects of reforms on SME financing.

Frykström N. and Li, J., 2018. IFRS 9 – The new accounting standard for credit loss recognition. Sveriges Riksbank Economic Commentary.

G20, 2009. London Summit – Leaders' Statement, 2 April.

Gaffney, E. and McCann, F., 2019. The cyclicality in SICR: Mortgage modelling under IFRS 9 (No. 92). European Systemic Risk Board.

Gebhardt, G.U. and Novotny-Farkas, Z., 2011. Mandatory IFRS adoption and accounting quality of European banks. *Journal of Business Finance & Accounting*, *38*(3-4), pp.289–333.

Gorton, G. and Winton, A., 2003. Financial intermediation. In *Handbook of the Economics of Finance* (Vol. 1, pp. 431–552). Elsevier.

Granja, J., 2018. Disclosure regulation in the commercial banking industry: lessons from the national banking era. *Journal of Accounting Research*, *56*(1), pp.173–216.

Granja, J. and Leuz, C., 2018. The death of a regulator: Strict supervision, bank lending and business activity. *Working paper.*

Gropp, R., Mosk, T., Ongena, S. and Wix, C., 2018. Banks response to higher capital requirements: Evidence from a quasi-natural experiment. *Review of Financial Studies*, *32*(1), pp.266–299.

Hendricks, B.E., Neilson, J.J., Shakespeare, C. and Williams, C.D., 2019. Financial reporting and operational decisions in response to proposed regulation: Evidence from Basel III. *Working paper*.

Horton, J. and Serafeim, G., 2010. Market reaction to and valuation of IFRS reconciliation adjustments: first evidence from the UK. *Review of Accounting Studies*, *15*(4), pp.725–751.

Hronsky, J., 2010. IFRS 9, Impairment and procyclicality: Is the cure worse than the disease?. *JASSA*, (4), p.55.

Huizinga, H. and Laeven, L., 2012. Bank valuation and accounting discretion during a financial crisis. *Journal of Financial Economics*, *106*(3), pp.614–634.

IAASB (International Auditing and Assurance Standards Board), 2016. Project to revise ISA 540: An update on the project and initial thinking on the auditing challenges arising from the adoption of expected credit loss models.

IASB (International Accounting Standards Board), 2013. Snapshot: financial instruments: expected credit losses.

IASB (International Accounting Standards Board), 2014. IFRS 9 Financial Instruments.

IFIAR (International Forum of Independent Audit Regulators), 2016. Report on 2015 Survey of inspections findings.

Jiménez, G., Ongena, S., Peydró, J.L. and Saurina, J., 2017. Macroprudential policy, countercyclical bank capital buffers, and credit supply: Evidence from the Spanish dynamic provisioning experiments. *Journal of Political Economy*, *125*(6), pp.2126–2177.

Laeven, L. and Majnoni, G., 2003. Loan loss provisioning and economic slowdowns: too much, too late?. *Journal of Financial Intermediation*, *12*(2), pp.178-197.

Laux, C., 2012. Financial instruments, financial reporting, and financial stability. *Accounting and Business Research*, *42*(3), pp.239–260.

Leuz, C. and Wysocki, P.D., 2016. The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research. *Journal of Accounting Research*, *54*(2), pp.525–622.

Loew, E., Schmidt, L.E. and Thiel, L.F., 2019. Accounting for financial instruments under IFRS 9–First-time application effects on European banks' balance sheets. *Working paper*.

Neilson, J.J., Ryan, S.G., Wang, K.P. and Xie, B., 2018. Asset-level transparency and the (e) valuation of asset-backed securities. *Working paper*.

Novotny-Farkas, Z., 2016. The interaction of the IFRS 9 expected loss approach with supervisory rules and implications for financial stability. *Accounting in Europe*, *13*(2), pp.197–227.

Ozili, P.K. and Outa, E., 2017. Bank loan loss provisions research: A review. *Borsa Istanbul Review*, *17*(3), pp.144–163.

Petersen, M.A. and Rajan, R.G., 1994. The benefits of lending relationships: Evidence from small business data. *Journal of Finance*, *49*(1), pp.3–37.

PRA (Prudential Regulation Authority), 2019. Annual Report.

Putnis, J., 2016. The Banking Regulation. *Londres: Law Business Research*.

Reitgruber, W., 2014. Methodological thoughts on expected loss estimates for IFRS 9 impairment: hidden reserves, cyclical loss predictions and LGD backtesting. *Working paper*.

Rice, T. and Strahan, P.E., 2010. Does credit competition affect small-firm finance?. *Journal of Finance*, *65*(3), pp.861–889.

Ryan, S.G., 2018. Recent research on banks' financial reporting and financial stability. *Annual Review of Financial Economics*, *10*, pp.101–123.

Schildbach, J., 2017. Large or small? How to measure bank size. *Deutsche Bank Research*.

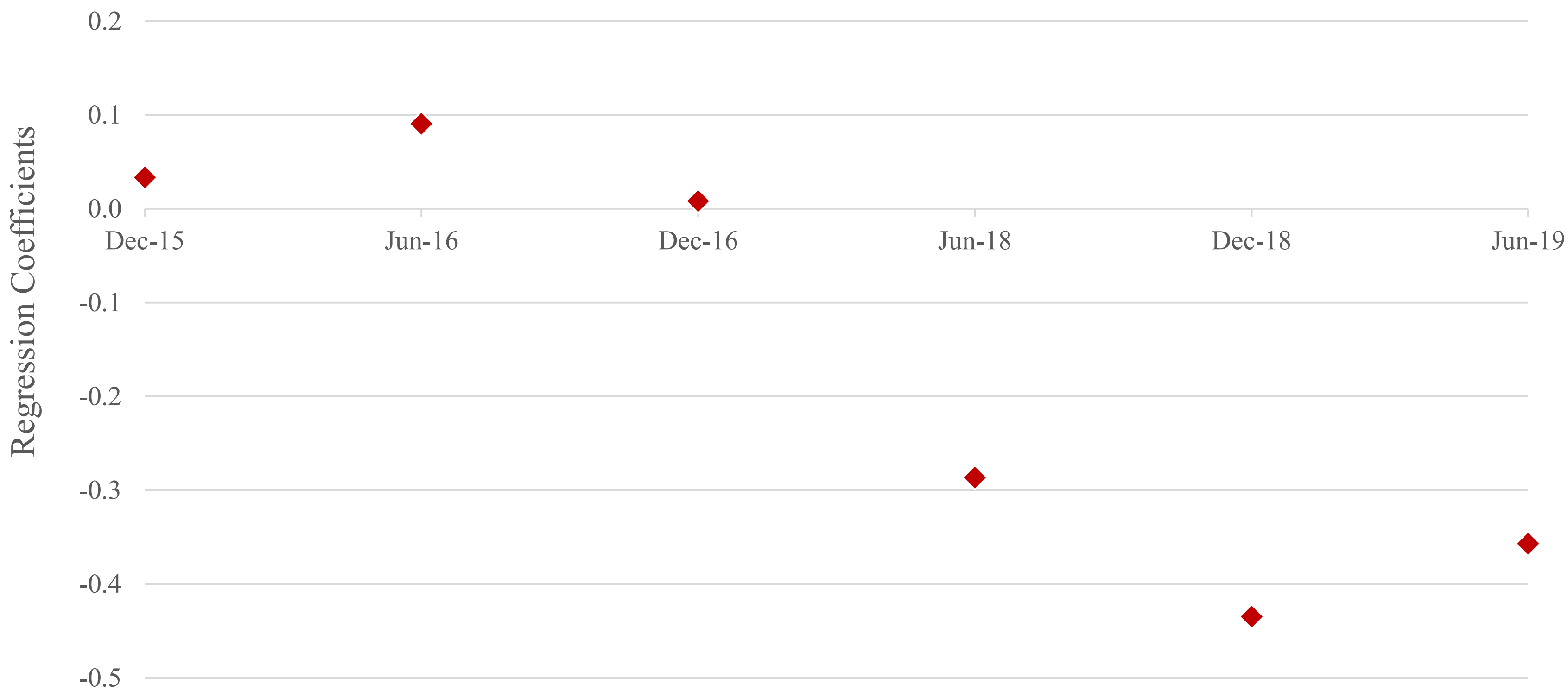
Schwert, M., 2018. Bank capital and lending relationships. *Journal of Finance*, *73*(2), pp.787–830.

Shroff, N., 2019. Real effects of PCAOB international inspections. *The Accounting Review*.

Srinivasan, A., 2014. Long run relationships in banking. *Foundations and Trends in Finance*, *8*(2), pp.55–143.

Sutherland, A., 2018. Does credit reporting lead to a decline in relationship lending? Evidence from information sharing technology. *Journal of Accounting and Economics*, *66*(1), pp.123–141.

Figure 1. Period-by-period analysis of the effect of the ECL transition on SME lending



This figure presents the temporal evolution of the difference in SME lending between *Affected banks* and other banks. Each node represents the corresponding difference-in-differences estimates from the following regression, where the baseline is June 2015:

$$\textit{SME lending} = \beta_1 \text{ Dec-15} \times \textit{Affected bank} + \beta_2 \text{ Jun-16} \times \textit{Affected bank} + \beta_3 \text{ Dec-16} \times \textit{Affected bank}$$
$$+ \beta_4 \text{ Jun-18} \times \textit{Affected bank} + \beta_5 \text{ Dec-18} \times \textit{Affected bank} + \beta_6 \text{ Jun-19} \times \textit{Affected bank} + \boldsymbol{\Theta}\ \boldsymbol{\mathit{Controls}_{bt-1}} + \eta_b + \gamma_t + \varepsilon_{bt}.$$

Table 1. IFRS 9 Timeline

This table illustrates the key developments in the IFRS 9 pronouncement and implementation process. The source is the Institute of Chartered Accountants in England and Wales (ICAEW).

Date	Development
12 November 2009	IASB issues IFRS 9 Financial Instruments covering classification and measurement of financial assets. Originally effective for annual periods starting on or after 1 January 2013 (date later removed).
28 October 2010	IASB reissues IFRS 9 including requirements on financial liability accounting. Originally effective for annual periods starting on or after 1 January 2013 (date later removed).
16 December 2011	IASB issues Mandatory Effective Date and Transition Disclosures (amendments to IFRS 9). Amended effective date to 1 January 2015 (later removed).
19 November 2013	IASB issues IFRS 9 Financial Instruments (Hedge Accounting and amendments to IFRS 9, IFRS 7 and IAS 39). Effective date of IFRS 9 removed.
24 July 2014	IASB reissues IFRS 9 Financial Instruments. Effective for annual periods starting on or after 1 January 2018.
12 September 2016	IASB issues Applying IFRS 9 with IFRS 4 amendments to IFRS 4. Applicable when IFRS 9 is first applied (overlay approach) or for annual periods beginning on or after 1 January 2018 (deferral approach).
21 April 2017	IASB proposes minor amendments to IFRS 9 to aid implementation. Press release issued on 21 April 2017 announcing amendment proposals.
12 October 2017	IASB issues Prepayment Features with Negative Compensation (amendments to IFRS 9). To be applied retrospectively for years beginning on or after 1 January 2019.
26 September 2019	IASB amends IFRS Standards in response to the IBOR reform. News update issued by the IASB on 26 September 2019 announcing amendments to some of its requirements for hedge accounting within IFRS 9, IAS 39 and IFRS 7.

Table 2. Variable Definitions

Panel A depicts the bank-level samples analyzed in Tables 3 and 4, as well as the tables in the Online Appendices OA2 and OA3. The variable definitions in Panel B pertain to the borrower-level tests presented in Tables 5 and 6, and the definitions in Panel C pertain to the loan-level tests shown in Table 7.

Panel A. Bank-level samples

Variable Name	Definition	Data Source
Affected bank	Indicator that equals one for banks with an above-median increase in their loan loss reserves per IFRS 9. The impact is calculated as the signed difference between IFRS 9 loan loss allowances at 01.01.2018 and IAS 39 loan loss allowances at 31.12.2017 divided by the latter.	Bank annual reports and transition disclosures See Online Appendix OA1 for examples.
ECL regime	Indicator equals one for periods from January 2018.	n/a
SME lending (log)	Natural logarithm of €mm SME lending.	EBA Transparency Exercise results.
SME lending (% assets)	SME lending as a fraction of total exposures of the bank.	EBA Transparency Exercise results.
SME lending (% total lending)	SME lending as a fraction of total lending of the bank.	EBA Transparency Exercise results.
Corporate lending (% total lending)	Corporate lending as a fraction of total lending of the bank.	EBA Transparency Exercise results.
Other lending (% total lending)	NonSME and noncorporate lending as a fraction of total lending of the bank.	EBA Transparency Exercise results.
Non-lending activities (log)	Total exposures less retail, mortgage, corporate, and SME lending, in logged form.	EBA Transparency Exercise results.
Non-lending activities (% assets)	Total exposures less retail, mortgage, corporate, and SME lending, divided by total exposures (%).	EBA Transparency Exercise results.
Bank size	Natural logarithm of the number of full-time-equivalent employees working for the company and its subsidiaries.	SNL Financial (field #134875).
Bank capital	Tier-1 capital ratio (%).	SNL Financial (field #248885).
Bank profitability	Return on equity (%).	SNL Financial (field #132006).
Bank loan intensity	The ratio of loans to assets (%).	SNL Financial (fields #132264 and #131923).
Bank risk method	Indicator that equals one for banks that use internal risk-based models.	SNL Financial (field #225205).

Bank asset risk	The ratio of total risk-weighted assets to total assets (%).	SNL Financial (fields #248884 and #132264)
Total exposures (log)	Natural logarithm of total exposures	EBA Transparency Exercise results.
Nonperforming exposures (%)	Nonperforming exposures divided by total exposures (%).	EBA Transparency Exercise results.
CDS spread flatness	Quarterly average 1-year CDS spread divided by 5-year CDS spread.	Markit and SNL Financial.
Audit fees (log)	Natural logarithm of €mm audit fees.	Factset (item ff_audit_fees) and SNL Financial.

Panel B. Borrower-level samples

Variable Name	Definition	Data Source
ECL regime	Indicator equals one for periods from January 2018.	n/a
Affected borrower (ECB)	Indicator that equals one for SMEs, which belong to size decile-country grids that have an *Affected bank* score of above-median.	Bank annual reports and transition disclosures and BvD Amadeus Bankers.
SME access to bank credit	Indicator that equals one if the SME states that it got most or all of the bank credit it applied for.	ECB SAFE (Original question: Q7b_a).
Latent demand	Indicator that equals one if the SME refrained from a loan application for fear of rejection, high interest costs, onerous collateral requirements, or due to reduced control over the firm.	ECB SAFE (Original question: Q32).
Interest	Equals one if the respondent states an increase in interest cost conditions, zero if no change, minus one if decrease.	ECB SAFE (Original question: Q10_a).
Amount	Equals one if the respondent states an increase in amount of credit available, zero if no change, minus one if decrease.	ECB SAFE (Original question: Q10_c).
Maturity	Equals one if the respondent states an increase in loan maturities, zero if no change, minus one if decrease.	ECB SAFE (Original question: Q10_d).
Collateral	Equals one if the respondent states an increase in collateral requirements, zero if no change, minus one if decrease.	ECB SAFE (Original question: Q10_e).
SME size	1 if up to 9 employees, 2 if between 10 and 49 employees, 3 if between 50 and 249 employees, and 4 if over 250 employees	ECB SAFE (Original question: d1_rec).
SME age	1 if up to two years, 2 if between two and five years, 3 if between five and ten years, 4 if over ten years.	ECB SAFE (Original question: d5_rec).

SME credit quality	1 if credit quality deteriorated over the past six months, 2 if credit quality remained the same, 3 if credit quality improved	ECB SAFE (Original question: Q11_e).
SME sales growth	1 if sales decreased over the past six months, 2 if sales remained the same, 3 if sales increased	ECB SAFE (Original question: Q2_a).
SME profitability growth	1 if profits decreased over the past six months, 2 if profits remained the same, 3 if profits increased	ECB SAFE (Original question: Q2_e).
ECL regime	1 if profits decreased over the past six months, 2 if profits remained the same, 3 if profits increased	n/a
Affected borrower (BvD)	Indicator that equals one for SMEs with at least one relationship bank that is coded as *Affected bank*.	Bank annual reports and transition disclosures, Bureau van Dijk Amadeus Bankers, and ECB SAFE.
Debt issuance (%)	Change in outstanding debt, as a fraction of lagged total assets.	Amadeus Financials (mnemonics *loan, ltdb, toas)*
Borrower size	Natural logarithm of total assets	Amadeus Financials (mnemonics *toas*, *exchrate2*)
Borrower leverage	Total debt as a percentage of total assets	Amadeus Financials (mnemonics *loan*, *ltdb*, *toas*)

Panel C. Loan-level sample

Variable Name	Definition	Data Source
ECL regime	Indicator equals one for periods from January 2018.	n/a
Affected bank	Indicator that equals one for loans originated by banks that are above the median of IFRS 9 Impact, which is calculated as the signed difference between IFRS 9 loan loss allowances at 01.01.2018 and IAS 39 loan loss allowances at 31.12.2017 divided by the latter.	Bank annual reports and transition disclosures See Online Appendix OA1 for examples.
Interest rate	Percentage credit spread.	ECB Loan-level Data (variable as80).
Borrower risk	Bank's internal estimate of loss given default at initiation.	ECB Loan-level Data (variable as37).
Payment frequency	Number of principal payments required in a year.	ECB Loan-level Data (variable as58).
Loan amount	Natural logarithm of the euro loan amount.	ECB Loan-level Data (variable as54).
Loan maturity	The difference between the stated maturity date and origination date (in years).	ECB Loan-level Data (variable as51, as50).

Table 3. Real Effects of Expected Credit Losses: Bank Lending

This table describes an empirical analysis of the expected credit loss regime from the banks' perspective. Each observation is a bank-half-year. The data sources are the European Banking Authority Transparency Exercise Disclosures and SNL Financial. Panel A provides the descriptive statistics (excluding degenerate moments for dummy variables). Panels B–E present the estimation results. *Affected bank* is an indicator variable that switches on for banks with an above-median increase in their loan loss reserves per IFRS 9. (This impact is calculated as the signed difference between IFRS 9 loan loss allowances at 01.01.2018 and IAS 39 loan loss allowances at 31.12.2017 divided by the latter.) *ECL regime* is an indicator variable that equals one for periods from the first half of 2018. The definition of bank-level control variables is detailed in Panel A of Table 2. The dependent variables used in the tests in Panels B and C are *SME lending (log)* and *SME lending (% assets)*. These variables are respectively defined as the natural logarithm of €mm SME lending and SME lending as a percentage of total exposures. Panels D and E present the results of the subsample analyses that cut the main sample based on bank size (total exposures in euros) and bank capital (the tier-1 capital ratio), respectively. T-statistics presented in parentheses are computed using standard errors robust to within-bank correlation and heteroscedasticity. ***, **, and * denote statistical significance at the two-tailed 1%, 5%, and 10% levels, respectively.

Panel A. Descriptive Statistics

	Mean	Stdev	p10	p50	p90	N
Affected bank	0.437	.	.	.	.	623
ECL regime	0.494	.	.	.	.	623
SME lending (log)	7.942	1.726	5.611	8.248	9.798	623
SME lending (% assets)	10.247	8.935	1.428	8.077	23.029	623
SME lending (% total lending)	24.544	16.444	5.687	21.360	45.567	623
Corporate lending (% total lending)	33.237	21.079	8.964	30.428	60.547	623
Other lending (% total lending)	42.219	21.269	12.877	42.848	69.834	623
Non-lending activities (log)	10.100	1.363	8.479	10.032	12.016	623
Non-lending activities (% assets)	58.696	21.024	31.605	58.405	87.094	623
Bank size (log)	8.857	1.776	6.312	8.720	11.418	590
Bank capital (%)	17.294	15.086	11.268	14.124	23.694	590
Bank profitability (%)	4.363	10.972	-7.941	6.111	13.781	590
Bank loan intensity (%)	58.344	15.768	37.521	59.529	76.449	590
Bank risk method	0.641	.	.	.	.	590
Bank asset risk (%)	44.486	19.057	21.963	43.029	70.704	590
Total exposures (log)	10.747	1.306	9.001	10.852	12.440	590
Nonperforming exposures (%)	4.058	6.143	0.099	2.146	10.415	590

Panel B. SME lending, logged and unscaled

	(1)	(2)	(3)
	SME Lending (log)	*SME Lending (log)*	*SME Lending (log)*
Affected bank × ECL regime	-0.733***	-0.346***	-0.392***
	(-3.28)	(-2.78)	(-3.32)
Affected bank	0.674**		
	(1.98)		
Bank size			0.387**
			(2.08)
Bank capital			-0.004***
			(-3.29)
Bank profitability			0.002
			(1.26)
Bank loan intensity			0.004
			(0.85)
Bank risk method			-0.202
			(-1.24)
Bank asset risk			-0.014**
			(-2.13)
Total exposures			0.621***
			(3.88)
Nonperforming exposures			0.070***
			(3.63)
Observations	623	623	590
Within R-squared	1.9%	4.6%	26.7%
Time FE	Y	Y	Y
Bank FE	N	Y	Y

Panel C. SME lending as a fraction of total exposures

	(1)	(2)	(3)
	SME Lending (%)	*SME Lending (%)*	*SME Lending (%)*
Affected bank × ECL regime	-3.657***	-1.534*	-2.065**
	(-2.89)	(-1.74)	(-2.32)
Affected bank	0.198		
	(0.11)		
Bank size			0.110
			(0.11)
Bank capital			-0.018**
			(-2.62)
Bank profitability			0.006
			(0.48)
Bank loan intensity			0.021
			(0.58)
Bank risk method			-0.407
			(-0.37)
Bank asset risk			-0.056
			(-1.15)
Total exposures			-0.494
			(-0.38)
Nonperforming exposures			0.631***
			(2.99)
Observations	623	623	590
R-squared within	1.9%	1.9%	14.4%
Time FE	Y	Y	Y
Bank FE	N	Y	Y

Panel D. Expected losses and SME lending: The role of bank size

	(1)	(2)	(3)	(4)
	Small Bank	Large Bank	Small Bank	Large Bank
	SME lending (log)	*SME lending (log)*	*SME lending (% assets)*	*SME lending (% assets)*
Affected bank × ECL regime	-0.712***	-0.104	-3.534**	-0.834
	(-3.58)	(-0.94)	(-2.57)	(-0.76)
Observations	292	298	292	298
R-squared within	31.9%	39.7%	21.7%	14.5%
All previous controls	Y	Y	Y	Y
Bank and Time FE	Y	Y	Y	Y

Panel E. Expected losses and SME lending: The role of bank capital

	(1)	(2)	(3)	(4)
	Low Tier1	High Tier1	Low Tier1	High Tier1
	SME lending (log)	*SME lending (log)*	*SME lending (% assets)*	*SME lending (% assets)*
Affected bank × ECL regime	-0.364**	-0.502***	-1.989*	-2.694**
	(-2.55)	(-2.68)	(-1.86)	(-2.02)
Observations	293	297	293	297
R-squared within	38.1%	25.7%	22.7%	15.6%
All previous controls	Y	Y	Y	Y
Bank and Time FE	Y	Y	Y	Y

Table 4. Other Activities

This table presents the results of the tests on the effects of the expected credit loss regime on banks' activities other than SME lending. Each observation is a bank-half-year. The data sources are the European Banking Authority Transparency Exercise Disclosures and SNL Financial. *Affected bank* is an indicator variable that switches on for banks with an above-median increase in their loan loss reserves per IFRS 9. (This impact is calculated as the signed difference between IFRS 9 loan loss allowances at 01.01.2018 and IAS 39 loan loss allowances at 31.12.2017 divided by the latter.) *ECL regime* is an indicator variable that equals one for periods from the first half of 2018. The definition of bank-level control variables is detailed in Panel A of Table 2. The dependent variables are defined as follows. *SME lending (% total lending)* is the bank's SME exposures as a percentage of the sum of SME, corporate, and retail & mortgage exposures. *Corporate lending (% total lending)* is the bank's corporate exposures as a percentage of the sum of SME, corporate, and retail & mortgage exposures. *Other lending (% total lending)* is the bank's retail and mortgage exposures as a percentage of the sum of SME, corporate, and retail & mortgage exposures. *Nonlending activities (log)* is the natural logarithm of a bank's total exposures less retail, mortgage, corporate, and SME lending, *Nonlending activities (%)* is total exposures less retail, mortgage, corporate, and SME lending, divided by total exposures and presented in percentage points. T-statistics presented in parentheses are computed using standard errors robust to within-bank correlation and heteroscedasticity. ***, **, and * denote statistical significance at the two-tailed 1%, 5%, and 10% levels, respectively.

Panel A. Allocation of the loan portfolio

	(1)	(2)	(3)
	SME lending (% total lending)	*Corp. lending (% total lending)*	*Other lending (% total lending)*
Affected bank × ECL regime	-4.272*	5.054**	-0.782
	(-1.74)	(2.20)	(-0.31)
Bank size	0.887	0.880	-1.767
	(0.22)	(0.29)	(-0.36)
Bank capital	-0.009	0.022	-0.013
	(-0.62)	(1.11)	(-0.58)
Bank profitability	0.055*	-0.073	0.018
	(1.68)	(-1.42)	(0.37)
Bank loan intensity	-0.119	-0.017	0.135
	(-0.81)	(-0.14)	(0.99)
Bank risk method	-1.500	4.644	-3.144
	(-0.81)	(1.40)	(-0.99)
Bank asset risk	-0.227	0.323***	-0.096
	(-1.60)	(2.78)	(-0.71)
Total exposures	0.508	-1.827	1.319
	(0.21)	(-0.80)	(0.32)
Nonperforming exposures	1.111***	-0.815*	-0.296
	(3.40)	(-1.97)	(-0.63)
Observations	590	590	590
R-squared within	10.6%	10.7%	1.7%
Bank and Time FE	Y	Y	Y

Panel B. Nonloan assets

	(1)	(2)
	Nonlending activities (log)	*Nonlending activities (% assets)*
Affected bank × ECL regime	0.094*	4.426*
	(1.80)	(1.93)
Bank size	-0.097	-4.663
	(-1.48)	(-1.45)
Bank capital	0.001	0.033
	(1.15)	(1.46)
Bank profitability	0.000	0.006
	(0.73)	(0.19)
Bank loan intensity	-0.002	-0.102
	(-0.92)	(-1.03)
Bank risk method	-0.102	-2.178
	(-1.12)	(-0.70)
Bank asset risk	-0.001	-0.073
	(-0.63)	(-0.78)
Total exposures	1.235***	11.693**
	(10.42)	(2.17)
Nonperforming exposures	-0.018	-1.039*
	(-1.65)	(-1.85)
Observations	590	590
R-squared within	83.1%	24.3%
Bank and Time FE	Y	Y

Table 5. Real Effects of Expected Credit Losses: SME Borrowing

This table describes an empirical analysis of the expected credit loss regime from the borrowers' perspective. Each observation is a borrower-year. The data sources are Bureau van Dijk's Amadeus Bankers and Amadeus Financials. Panel A provides the descriptive statistics (excluding degenerate moments for dummy variables). Panels B and C present the estimation results. *Affected borrower (BvD)* is an indicator variable that switches on for borrowers whose relationship banks experience an above-median increase in the latter's loan loss reserves per IFRS 9. (This impact is calculated as the signed difference between IFRS 9 loan loss allowances at 01.01.2018 and IAS 39 loan loss allowances at 31.12.2017 divided by the latter.) Banks and borrowers are matched using the 2019 vintage of the Amadeus Bankers dataset. *ECL regime* is an indicator variable that equals one for periods 2018 and 2019. The dependent variable is *Debt Issuance (%)*, which is computed as the year-over-year change in total debt as a percentage of lagged total assets. Panel C presents the results of the subsample analyses that cut the main sample at the median based on borrower size (total assets). T-statistics presented in parentheses are computed using standard errors robust to within-borrower correlation and heteroscedasticity. ***, **, and * denote statistical significance at the two-tailed 1%, 5%, and 10% levels, respectively.

Panel A. Descriptive Statistics

	Mean	Stdev	p10	p50	p90	N
ECL regime	0.795	.	.	.	.	71,166
Affected borrower (BvD)	0.369	.	.	.	.	71,166
Debt issuance (%)	2.276	13.232	-8.204	0.000	15.309	71,166
Size	17.167	1.599	15.502	16.884	19.281	71,166
Leverage	24.900	23.695	0.748	18.242	60.238	71,166

Panel B. Main results

	(1)	(2)	(3)
	Debt issuance (%)	*Debt issuance (%)*	*Debt issuance (%)*
Affected borrower (BvD) × ECL regime	-1.254***	-2.443***	-0.629**
	(-5.19)	(-10.51)	(-2.18)
Affected borrower (BvD)	1.129***		
	(7.47)		
Observations	71,166	71,166	71,166
Adjusted R-squared	0.001	0.283	0.285
Time FE	Y	Y	Y
Borrower FE	N	Y	Y
Control for *Size* and *Leverage*	N	Y	Y
Borrower industry-year FE	N	N	Y
Borrower country-year FE	N	N	Y

Panel C. Variation in the main effect by borrower size

	(1)	(2)
	Debt issuance (%)	*Debt issuance (%)*
Affected borrower (BvD) × ECL regime	-0.966**	-0.751*
	(-2.31)	(-1.85)
Subsample includes	Small borrowers	Large borrowers
Observations	35,583	35,583
Adjusted R-squared	0.349	0.272
Time FE	Y	Y
Borrower FE	Y	Y
Control for *Size* and *Leverage*	Y	Y
Borrower industry-year FE	Y	Y
Borrower country-year FE	Y	Y

Table 6. Real Effects of Expected Credit Losses: SME Credit Access

This table describes an empirical analysis of the expected credit loss regime from the borrowers' perspective. Each observation is a borrower-half-year. The data sources are Bureau van Dijk's Amadeus Bankers and the European Central Bank's Survey on the Access to Finance of Enterprises. Panel A provides the descriptive statistics (excluding degenerate moments for dummy variables). As indicated in boldface font, the subsamples include companies that did apply for a loan, those that didn't apply for a loan, and those that respond to questions on loan terms. Panels B, C, and D present the estimation results. *Affected borrower (ECB)* is an indicator variable that switches on for borrowers whose relationship banks experience an above-median increase in the latter's loan loss reserves per IFRS 9. (This impact is calculated as the signed difference between IFRS 9 loan loss allowances at 01.01.2018 and IAS 39 loan loss allowances at 31.12.2017 divided by the latter.) Since the identities of the surveyed SMEs are unknown, the average value of the Amadeus borrowers in the same country and the same sales bracket. In the Amadeus data, banks and borrowers are matched using the 2019 vintage of Amadeus Bankers. *ECL regime* is an indicator variable that equals one for periods from the first half of 2018. This variable is omitted from the estimation model in the presence of time fixed effects. The main dependent variable is *SME access to bank credit*, which is an indicator variable that switches on if the surveyed SME applied for bank financing and received most or all of the amount it applied for (Survey question Q7b_a). *Latent demand* is an indicator variable that switches on if the surveyed SME did not apply for bank financing and stated that the reason for lack of application is fear of rejection, high interest costs, onerous collateral requirements, or reduced control rights, as opposed to a lack of demand (Survey question Q32). *Interest*, *Amount*, *Maturity*, and *Collateral* are ordinal variables that equals one if the respondent states an increase, zero if the respondent states no change, and minus one if the respondent states a decrease in interest costs, loan amounts, loan maturities, and collateral requirements, respectively. These are survey questions, Q10_a, Q10_c, Q10_d, and Q10_e. The definition of SME-level control variables is detailed in Panel B of Table 2. In Panels B and C, the results of the subsample analyses that cut the main sample at the median based on SME size (number of employees). Since this variable is an integer between one and four; the size of the subsamples are not identical. T-statistics presented in parentheses are computed using standard errors robust to within-company correlation and heteroscedasticity. ***, **, and * denote statistical significance at the two-tailed 1%, 5%, and 10% levels, respectively.

Panel A. Descriptive Statistics

	Mean	stdev	p10	p50	p90	N
Applicants						
ECL regime	0.405					9,557
Affected borrower (ECB)	0.601					9,557
SME access to bank credit	0.785					9,557
SME size	2.426	0.991	1.000	2.000	4.000	9,557
SME age	3.839	0.484	3.000	4.000	4.000	9,557
SME credit quality	2.259	0.623	2.000	2.000	3.000	9,557
SME sales growth	2.340	0.774	1.000	3.000	3.000	9,557
SME profitability growth	2.055	0.825	1.000	2.000	3.000	9,557

Panel A. Descriptive Statistics (continued)

	Mean	stdev	p10	p50	p90	N
Nonapplicants						
ECL regime	0.442	.	.	.	.	20,765
Affected borrower (ECB)	0.458	.	.	.	.	20,765
Latent demand	0.169	.	.	.	.	20,765
SME size	1.995	0.987	1.000	2.000	3.000	20,765
SME age	3.785	0.552	3.000	4.000	4.000	20,765
SME credit quality	2.187	0.498	2.000	2.000	3.000	20,765
SME sales growth	2.231	0.747	1.000	2.000	3.000	20,765
SME profitability growth	2.065	0.778	1.000	2.000	3.000	20,765
Overall responses						
Interest	-0.165	0.664	-1.000	0.000	1.000	13,208
Amount	0.147	0.539	0.000	0.000	1.000	13,208
Maturity	0.043	0.390	0.000	0.000	0.000	13,208
Collateral	0.142	0.476	0.000	0.000	1.000	13,208

Panel B. SME credit access: Evidence on companies that *did* apply for bank credit

	(1)	(2)	(3)
	All firms	Small firms	Large firms
	SME access to bank credit	*SME access to bank credit*	*SME access to bank credit*
Affected borrower × ECL regime	-0.028*	-0.058**	0.002
	(-1.66)	(-2.22)	(0.09)
Affected borrower	0.125***	0.020	0.144***
	(3.19)	(0.29)	(3.03)
SME size	0.075***	0.095***	0.036
	(11.24)	(6.71)	(1.58)
SME age	0.038***	0.030**	0.057***
	(3.83)	(2.56)	(3.18)
SME credit quality	0.060***	0.069***	0.049***
	(8.19)	(6.57)	(5.06)
SME sales growth	0.018***	0.005	0.030***
	(2.74)	(0.52)	(3.49)
SME profitability growth	0.018***	0.031***	0.005
	(2.90)	(3.22)	(0.72)
Observations	9,557	4,835	4,722
Adjusted R-squared	11.3%	11.5%	5.6%
Time FE	Y	Y	Y
Country FE	Y	Y	Y
Borrower industry FE	Y	Y	Y

Panel C. SME credit access: Evidence on companies that *didn't* apply for bank credit

	(1)	(2)	(3)
	All firms	Small firms	Large firms
	Latent demand	*Latent demand*	*Latent demand*
Affected borrower × ECL regime	0.011	0.031*	-0.006
	(1.04)	(1.72)	(-0.54)
Affected borrower	-0.007	-0.050	-0.010
	(-0.51)	(-1.25)	(-0.64)
SME size	-0.042***	.	-0.050***
	(-11.45)	.	(-7.08)
SME age	-0.031***	-0.028***	-0.036***
	(-5.60)	(-3.48)	(-4.91)
SME credit quality	-0.014**	-0.018*	-0.012*
	(-2.52)	(-1.68)	(-1.85)
SME sales growth	0.003	0.009	0.001
	(0.66)	(1.00)	(0.19)
SME profitability growth	-0.034***	-0.053***	-0.022***
	(-7.82)	(-6.12)	(-4.63)
Observations	20,765	8,476	12,289
Adjusted R-squared	9.8%	8.9%	7.1%
Time FE	Y	Y	Y
Country FE	Y	Y	Y
Borrower industry FE	Y	Y	Y

Panel D. Survey evidence on loan terms

	(1)	(2)	(3)	(4)
	Interest	*Amount*	*Maturity*	*Collateral*
Affected bank × ECL regime	0.038	-0.058***	-0.031**	0.060***
	(1.64)	(-2.97)	(-2.24)	(3.52)
Affected borrower	0.037	0.040	0.043	-0.026
	(0.77)	(0.95)	(1.33)	(-0.69)
SME size	-0.084***	0.037***	0.015***	-0.041***
	(-9.97)	(5.30)	(3.05)	(-6.61)
SME age	-0.041***	-0.021**	0.001	-0.019**
	(-3.47)	(-2.05)	(0.11)	(-2.02)
SME credit quality	-0.111***	0.120***	0.057***	-0.064***
	(-10.99)	(13.43)	(8.41)	(-8.09)
SME sales growth	-0.009	0.042***	0.021***	-0.007
	(-0.95)	(5.55)	(3.87)	(-1.07)
SME profitability growth	-0.058***	0.019***	0.010*	-0.049***
	(-6.85)	(2.72)	(1.91)	(-7.72)
Observations	13,208	13,208	13,208	13,208
Adjusted R-squared	9.0%	4.3%	1.9%	6.1%
Time FE	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Borrower industry FE	Y	Y	Y	Y

Table 7. Real Effects of Expected Credit Losses: Loan-level Evidence

This table describes an empirical analysis of the expected credit loss regime from the perspective of loan agreements. Each observation is an individual loan contract. The main data source is the European DataWarehouse's Loan-level Data. Panel A provides the descriptive statistics (excluding degenerate moments for dummy variables). Panels B and C present the estimation results. *Affected contract* is an indicator variable that switches on for SME loans contracts originated by banks who experience an above-median increase an increase in their loan loss reserves per IFRS 9. (This impact is calculated as the signed difference between IFRS 9 loan loss allowances at 01.01.2018 and IAS 39 loan loss allowances at 31.12.2017 divided by the latter.) *ECL regime* is an indicator variable that equals one for loans originated from 1 January 2018. The dependent variables are defined as follows. *Interest rate* is the percentage interest charged on the loan. *Loan maturity* is the difference between the loan's stated maturity data and origination date, in years. *Loan amount* is the natural logarithm of the original size of the loan. *Payment frequency* is the number of principal payments required in the contract. *Borrower risk* is the bank's loss-given-default estimate on the individual loan. Panel C presents the results of the subsample analyses that cut the main sample based on SME size: Large borrowers are those that the European DataWarehouse database defines as "medium" or "small," and small borrowers are those that the European DataWarehouse database defines as "micro." T-statistics presented in parentheses are computed using standard errors robust to within-country-year correlation and heteroscedasticity. ***, **, and * denote statistical significance at the two-tailed 1%, 5%, and 10% levels, respectively.

Panel A. Descriptive Statistics

	Mean	Stdev	p10	p50	p90	N
ECL regime	0.432	.	.	.	.	215,365
Affected bank	0.158	.	.	.	.	215,365
Interest rate	3.652	2.017	1.470	3.244	6.250	215,365
Loan maturity	5.681	4.251	2.000	5.000	10.000	215,365
Loan amount	10.549	1.251	9.159	10.342	12.206	215,365
Payment frequency	10.994	3.017	4.000	12.000	12.000	210,590
Borrower risk	35.386	17.418	16.010	32.000	59.000	179,484

Panel B. Main results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Interest Rate	*Interest Rate*	*Loan maturity*	*Loan maturity*	*Loan amount*	*Loan amount*	*Payment frequency*	*Payment frequency*
Affected bank × ECL regime	1.373***	1.382***	-1.870***	-1.928***	-0.897***	-0.909***	0.794***	0.768***
	(14.78)	(17.80)	(-6.26)	(-7.55)	(-30.62)	(-50.74)	(3.45)	(3.36)
Borrower risk		0.023***		-0.094***		-0.017***		-0.004
		(3.77)		(-4.74)		(-6.25)		(-1.55)
Observations	215,365	179,484	215,365	179,484	215,365	179,484	210,590	174,776
Adjusted R-squared	33.2%	27.4%	13.1%	20.1%	15.5%	19.0%	30.5%	31.0%
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Borrower industry-year FE	Y	Y	Y	Y	Y	Y	Y	Y
Borrower country-year FE	Y	Y	Y	Y	Y	Y	Y	Y

Panel C. Cross-borrower variation in the main effect

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Interest Rate	*Interest Rate*	*Loan maturity*	*Loan maturity*	*Loan amount*	*Loan amount*	*Payment frequency*	*Payment frequency*
Affected bank × ECL regime	1.338***	0.103***	-2.736***	0.736	-0.625***	-0.182	0.804**	-0.035
	(8.38)	(4.43)	(-17.02)	(0.71)	(-49.17)	(-1.52)	(3.04)	(-0.13)
Subsample includes	Small borrowers	Large borrowers	Small borrowers	Large borrowers	Small borrowers	Large borrowers	Small borrowers	Large borrowers
Observations	158,533	55,894	158,533	55,894	158,533	55,894	156,683	52,969
Adjusted R-squared	33.9%	41.5%	9.0%	27.3%	11.9%	30.2%	29.4%	35.0%
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Borrower industry-year FE	Y	Y	Y	Y	Y	Y	Y	Y
Borrower country-year FE	Y	Y	Y	Y	Y	Y	Y	Y

Online Appendix for

Expected Losses, Unexpected Costs

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December 2019

OA1. Sample IFRS 9 Transition Disclosures

Banco Santander, 2018 Annual Report (page 454):

b) Reconciliation of impairment provisions from IAS39 to IFRS9

The following table shows a comparison between IAS39 as of 31 December 2017 and IFRS9 as of 1 January 2018 of the impairment provisions of the financial instruments in accordance with the new requirements of IFRS9:

Million of euros

	IAS39 31/12/2017	Impairment impact	IFRS9 01-01-2018
Financial assets at amortised cost	**24,682**	**1,974**	**26,656**
Loans and advances	23,952	2,002	25,954
Debt instruments	730	(28)	702
Financial assets at fair value through other comprehensive income	**-**	**2**	**2**
Debt instruments	-	2	2
Commitments and guarantees granted	**617**	**197**	**814**
Total	**25,299**	**2,173**	**27,472**

Banco de Sabadell, 2018 Annual Report (page 196):

- The reconciliation of asset impairment allowances and the Group's off-balance sheet exposures as at 31 December 2017 recorded in the consolidated annual accounts for 2017, with those recorded in accordance with IFRS 9, on the date of its entry into force, is as follows:

Million euro

Portfolios used in the consolidated annual accounts for 2017 (IAS 39)	Measurement category IAS 39	Portfolios used after the entry into force of IFRS 9	Measurement category IFRS 9	Loss allowance IAS 39 31/12/2017	Remeasurement	Loss allowance IFRS 9 01/01/2018
Loans and receivables		**Financial assets at amortised cost**		**3,733**	**990**	**4,723**
Loans and advances		Loans and advances		3,732	989	4,721
Central banks and Credit institutions	Amortised cost	Central banks and Credit institutions	Amortised cost	5	(1)	4
Customers	Amortised cost	Customers	Amortised cost	3,727	990	4,717
Debt securities	Amortised cost	Debt securities	Amortised cost	1	1	2
Loans and receivables		**Financial assets at fair value through other comprehensive income**		**-**	**3**	**3**
Debt securities	Amortised cost	Debt securities	FV-OCI (*)	-	3	3
Held-to-maturity investments		**Financial assets at amortised cost**		**1**	**-**	**1**
Debt securities	Amortised cost	Debt securities	Amortised cost	1	-	1
Available-for-sale financial assets		**Financial assets at fair value through other comprehensive income**		**6**	**-**	**6**
Debt securities	Available for sale	Debt securities	FV-OCI (*)	6	-	6
Total asset impairment allowances				**3,740**	**993 (**)**	**4,733**
Loss allowances for off-balance sheet exposures				**85**	**8 (***)**	**93**
Total impairment allowances				**3,825**	**1,001**	**4,826**

Allied Irish Banks plc, 2018H1 Interim Report (page 107):

Impairment allowance	31 December 2017 Impairment allowance under IAS 39 or provision under IAS 37 € m	1 January 2018 Reclassification impact € m	Additional IFRS 9 loss allowance € m	Loss allowance under IFRS 9 € m
Loans and advances to customers at amortised cost	3,345	–	271	3,616
Loans and advances to banks at amortised cost	–	–	1	1
Available for sale investments, financial investments at FVOCI[1]	–	–	4	4
Undrawn commitments and financial guarantee contracts	32	–	36	68
Total	3,377	–	312	3,689

Iccrea Banca Spa, 2018H1 Interim Report (page 324):

CHANGE IN IMPAIRMENT LOSS IN SHIFT FROM IAS 39/IAS 37 TO IFRS 9

The following table reconciles the balance of IAS 39 IAS 37 provisions with the balance for the same provisions calculated under IFRS 9, indicating changes by credit risk stage. The table shows an increase in provisions of €99.9 million.

Table 1.1

	(€/millions)
31/12/2017 - IAS 39/IAS 37 provisions	**1,298.9**
Reclassification	-0.3
Increase/reduction in ECL on Stage 1 and 2 exposures	18.4
Increase/reduction in ECL on Stage 3 exposures	81.5
01/01/2018 - IFRS 9 ECL	**1,398.6**

Barclays Holdings plc, Transition Report issued in March 2018 (page 6):

Impairment allowance reconciliations

Reconciliation from IAS 39 to IFRS 9 - financial assets under IFRS 9 subject to an increase in impairment allowance

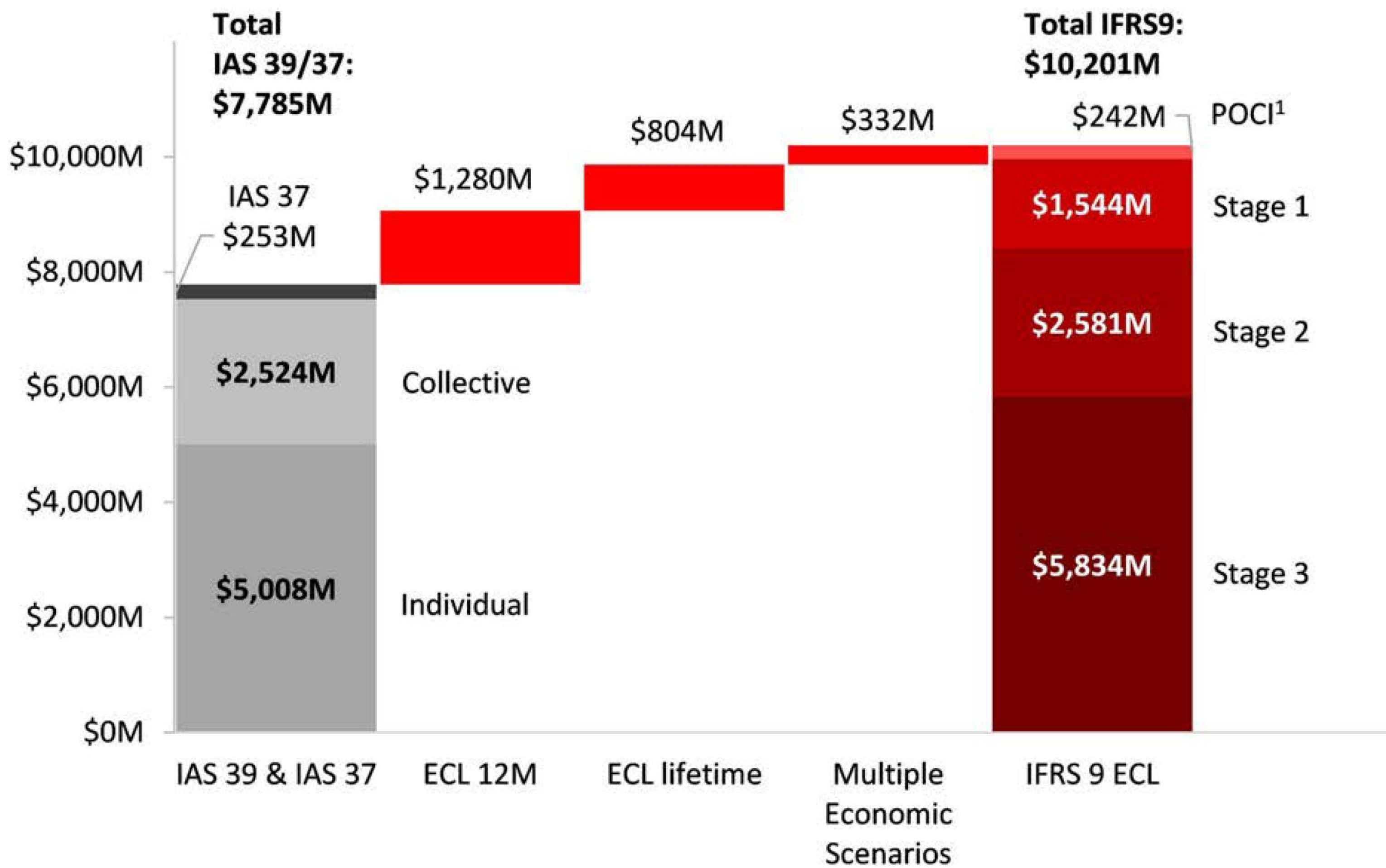
The table below, reconciles the closing impairment allowances for financial assets in accordance with IAS 39 and provisions for loan commitments and financial guarantee contracts in accordance with IAS 37 *Provisions, Contingent Liabilities and Contingent Assets* as at 31 December 2017 and the opening impairment allowances determined in accordance with IFRS 9 as at 1 January 2018.

Reconciliation of impairment allowance and provisions	Impairment allowance under IAS 39 or provision under IAS 37	Reclassification impact	Additional IFRS 9 impairment allowance	Impairment allowance under IFRS 9
	£m	£m	£m	£m
Loans and advances at amortised cost	4,652	(52)	2,508	7,108
Available for sale investments / Financial assets at fair value through other comprehensive income	38	(38)	3	3
Total on-balance sheet	**4,690**	**(90)**	**2,511**	**7,111**
Provision for undrawn contractually committed facilities and guarantee contracts	79	-	341	420
Total impairment and provision	**4,769**	**(90)**	**2,852**	**7,531**

- The introduction of IFRS 9 has increased the total impairment allowance held by Barclays by approximately £2.76bn, from £4.8bn as at 31 December 2017 to £7.5bn as at 1 January 2018, as a result of earlier recognition of impairment allowances.

HSBC Holdings plc, Transition Report issued in February 2018 (page 1):

IAS 39/IAS 37 allowances to IFRS 9 ECL walk



OA2. Additional Robustness Tests

Table OA2.1. Summary Statistics of Affected Banks and Other Banks Presented Separately

This table describes the samples used in the main tests shown in Table 3. Each observation is a bank-half-year. The data sources are the European Banking Authority Transparency Exercise Disclosures and SNL Financial. *ECL transition impact* is the percentage day-one change in banks' loan loss reserves per IFRS 9. (This impact is calculated as the signed difference between IFRS 9 loan loss allowances at 01.01.2018 and IAS 39 loan loss allowances at 31.12.2017 divided by the latter.) *Affected bank* is an indicator variable that switches on for banks with an above-median increase in *ECL transition impact*. *SME lending (log)* and *SME lending (% assets)* are respectively defined as the natural logarithm of €mm SME lending and SME lending as a percentage of total exposures. The definition of bank-level control variables is detailed in Panel A of Table 2.

Panel A. Affected Banks

	Mean	Stdev	p10	p50	p90	N
ECL transition impact	22.599	11.361	11.573	17.899	40.224	260
SME lending (log)	8.116	1.688	5.970	8.365	9.756	260
SME lending (% assets)	9.138	7.278	1.786	6.997	20.816	260
Bank size (log)	9.068	1.817	6.957	8.744	11.494	260
Bank capital (%)	18.224	21.002	11.696	14.351	23.515	260
Bank profitability (%)	5.979	8.341	-1.192	6.567	14.494	260
Bank loan intensity (%)	56.607	17.992	33.555	57.013	76.472	260
Bank risk method	0.642	.	.	.	.	260
Bank asset risk (%)	40.313	18.861	20.216	35.255	67.211	260
Total exposures (log)	10.925	1.346	9.141	10.970	12.885	260
Nonperforming exposures (%)	3.092	3.823	0.100	2.041	7.674	260

Panel B. Unaffected Banks

	Mean	Stdev	p10	p50	p90	N
ECL transition impact	3.228	6.063	-5.243	3.759	9.485	330
SME lending (log)	7.848	1.784	5.178	8.205	10.027	330
SME lending (% assets)	11.132	10.072	1.203	8.739	24.647	330
Bank size (log)	8.691	1.727	6.219	8.659	10.770	330
Bank capital (%)	16.561	7.681	11.013	13.968	23.825	330
Bank profitability (%)	3.090	12.533	-9.589	5.274	13.151	330
Bank loan intensity (%)	59.713	13.639	41.088	61.455	76.449	330
Bank risk method	0.639	.	.	.	.	330
Bank asset risk (%)	47.774	18.589	24.160	47.607	72.399	330
Total exposures (log)	10.607	1.258	8.895	10.700	12.071	330
Nonperforming exposures (%)	4.819	7.398	0.099	2.394	12.513	330

Table OA2.2. EBA Bank Lending Tests Revisited

This table describes an empirical analysis of the expected credit loss regime from the banks' perspective. Each observation is a bank-half-year. The data sources are the European Banking Authority Transparency Exercise Disclosures and SNL Financial. *Affected bank* is an indicator variable that switches on for banks with an above-median increase in their loan loss reserves per IFRS 9. (This impact is calculated as the signed difference between IFRS 9 loan loss allowances at 01.01.2018 and IAS 39 loan loss allowances at 31.12.2017 divided by the latter.) *ECL regime* is an indicator variable that equals one for periods from the first half of 2018. The definition of bank-level control variables is detailed in Panel A of Table 2. The dependent variables used in the tests are *SME lending (log)* and *SME lending (%)*. These variables are respectively defined as the natural logarithm of €mm SME lending and SME lending as a percentage of total exposures. The tests shown in Panel A include a *Pre1* dummy interacted with *Affected Bank*. *Pre1* switches on for observations in 2016. In Panel B, *Affected bank* is replaced (i) by *Affected bank (decile ranks)*, which is calculated as the decile ranks of the estimated day-one impact of the ECL transition, (ii) *Affected bank (continuous)*, which is the estimated day-one impact of the ECL transition. (See OA.1 for examples.) Panel C presents results from regression models that include bank characteristics interacted with the *ECL regime* dummy. The estimates presented in Panel D are based on models that include country-time fixed effects. T-statistics presented in parentheses are computed using standard errors robust to within-bank correlation and heteroscedasticity. ***, **, and * denote statistical significance at the two-tailed 1%, 5%, and 10% levels, respectively.

Panel A. Parallel Trends

	(1)	(2)
	SME lending (log)	*SME lending (% assets)*
Affected bank × ECL regime	-0.376***	-2.277**
	(-3.01)	(-2.28)
Affected bank × Pre period	0.028	-0.362
	(0.33)	(-0.54)
Observations	590	590
Within R-squared	26.7%	14.4%
Time FE	Y	Y
Bank FE	Y	Y

Panel B. Alternative definitions of *Affected bank*

	(1)	(2)
	SME lending (log)	*SME lending (log)*
Affected bank (decile ranks) × ECL regime	-0.058**	
	(-2.41)	
Affected bank (continuous) × ECL regime		-0.010*
		(-1.78)
Bank size	0.427**	0.357*
	(2.19)	(1.88)
Bank capital	-0.004***	-0.005***
	(-4.14)	(-4.58)
Bank profitability	0.002	0.002
	(1.21)	(1.30)
Bank loan intensity	0.003	0.003
	(0.66)	(0.63)
Bank risk method	-0.217	-0.222
	(-1.40)	(-1.44)
Bank asset risk	-0.014**	-0.012*
	(-2.07)	(-1.74)
Total exposures	0.591***	0.612***
	(3.38)	(3.46)
Nonperforming exposures	0.067***	0.067***
	(3.33)	-3.35
Observations	590	590
R-squared within	25.2%	23.1%
Time FE	Y	Y
Bank FE	Y	Y

Panel C. Higher-order interaction controls

	(1)	(2)
	SME lending (log)	*SME lending (% assets)*
Affected bank × ECL regime	-0.352***	-1.971**
	(-2.99)	(-2.24)
Bank size × ECL regime	-0.020	0.028
	(-0.46)	(0.06)
Bank capital × ECL regime	0.001	-0.048
	(0.16)	(-0.77)
Bank profitability × ECL regime	-0.005	0.005
	(-1.38)	(0.14)
Bank loan intensity × ECL regime	0.004	0.022
	(1.31)	(0.74)
Bank risk method × ECL regime	0.155	1.501
	(1.09)	(1.14)
Bank asset risk × ECL regime	0.001	-0.021
	(0.28)	(-0.72)
Total exposures × ECL regime	0.007	-0.300
	(0.12)	(-0.61)
Nonperforming exposures × ECL regime	-0.001	0.114*
	(-0.08)	(1.77)
Observations	590	590
Within R-squared	28.4%	19.2%
Uninteracted controls	Y	Y
Bank and Time FE	Y	Y

Panel D. Country-time Fixed Effects

	(1)	(2)
	SME lending (log)	*SME lending (% assets)*
Affected bank × ECL regime	-0.343***	-2.345**
	(-2.79)	(-2.28)
Observations	590	590
R-squared within	28.1%	22.8%
Country × Time FE	Y	Y
Bank FE	Y	Y

Panel E. Including the year 2017

	(1)	(2)
	SME lending (log)	*SME lending (% assets)*
Affected bank × ECL regime	-0.310***	-1.651**
	(-3.45)	(-2.44)
Observations	776	776
R-squared within	21.9%	12.5%
Time FE	Y	Y
Bank FE	Y	Y

OA3. Other Bank-Level Costs of the ECL Method

As described above, the ECL approach requires significantly more assumptions and complex calculations than the incurred model.[1] Especially in the initial implementation phase of the new standard, banks need to exert immense effort to estimate the status of their loans. For example, a particularly challenging task in the initial ECL calculations is assessing whether the loan has experienced a significant increase in credit risk since inception. Accordingly, I next examine whether affected banks experience a relative increase in information imprecision.

I proxy for informational costs using CDS spreads obtained from Markit and SNL Financial. Using the term structure of a bank's CDS spreads, I define *CDS spread flatness* as the ratio of the one-year CDS spread to the five-year CDS spread. The idea behind this metric is that compared to long-term credit spreads, which are determined by fundamental asset volatility, short-term spreads more strongly reflect the lack of precision in information signals. Put differently, for two firms with identical five-year CDS spreads (and thus identical fundamental credit risk), the one with a higher one-year spread is said to have lower information quality. This measure is motivated by Duffie and Lando [2001] and is used in empirical work such as Arora et al. [2014]. Accordingly, I estimate the following regression at the bank-quarter level.[2]

$$\begin{aligned} \textit{CDS spread flatness}_{bt} &= \beta_1\, \textit{ECL regime}_t \times \textit{Affected bank}_b + \beta_2\, \textit{ECL regime}_t \\ &\quad + \beta_3\, \textit{Affected bank}_b + \boldsymbol{\Theta}\, \boldsymbol{\textit{Controls}}_{bt-1} + \eta_b + \omega_t + \varepsilon_{bt} \qquad \text{(OA1)} \end{aligned}$$

Affected bank and *ECL regime* are defined as above. In the presence of bank (η) and quarter fixed effects (ω), *Affected bank* and *ECL regime* are omitted, respectively, from the estimation. Since the time dimension is a quarter, bank-level controls, which are calculated at the bank-year level, pertain to the previous year. Namely, for observations from 2018Q1–2018Q4, bank controls are from the year of 2017.

[1] Barclays's IFRS 9 transition report describes the issues relating to the ECL approach: "*The measurement of expected credit loss involves increased complexity and judgement, including estimation of probabilities of default, loss given default, a range of unbiased future economic scenarios, estimation of expected lives, and estimation of exposures at default and assessing significant increases in credit risk. Impairment charges will tend to be more volatile, will be recognised earlier and the amounts will be higher.*"

[2] I observe CDS spreads at a daily level. I choose a quarterly frequency (over a semi-annual one) to increase the sample size, especially over the post-ECL period. My conclusions hold if I adopt a bank-half-year specification.

Table OA3.1 describes the sample used in the information precision tests and presents the results. As Panel A shows, the estimation sample includes 636 bank-quarters, which is reduced to 573 observations after I require non-missing data for bank-level controls. Although it has information on only 51 distinct banks, this sample is fairly similar to the one used in the EBA lending tests in Table 3. (The initial sample examined in Table 3 includes 108 banks.) Bank capital and profitability are slightly smaller in the CDS sample, while most banks rely on the IRB approach. *CDS spread flatness* has a mean of about 0.5, which means that the long-term credit spread is twice the short-term spread for the average bank. This variable exhibits little skewness (the median is 0.447) but nontrivial variation, with an interdecile range of almost 0.48.

The estimation results in Panel B of Table OA3.1 lend support to the idea that banks whose provisioning activities are more affected by the new loan loss recognition rules experience a relative increase in their information imprecision. The coefficient on *Affected bank* × *ECL regime* suggests about 0.08 of a decline in *CDS spread flatness*, which constitutes one-third of the sample standard deviation of this variable. Turning to control variables, I observe that banks that use the standardized approach for risk estimation have flatter term structure, as do larger banks.

In untabulated tests, I break the post period into three parts: short term (2018Q1 and 2018Q2), medium term (2018Q3 and 2018Q4), and long term (2019Q1 and 2019Q2). I find similar coefficients across each of the subgroups, which indicates a shift that is relatively stable and long-lived (at least as of 2019Q2). Overall, my inferences from the CDS analysis suggest that the financial markets view the ECL modeling as a factor exacerbating the imprecision of accounting information. However, it is essential to note that markets learn over time, and even 1.5 years might be a relatively short period to claim a structural impact. The evidence I provide might be driven mainly by the *implementation* of ECL, rather than a fundamental shortcoming of ECL relative to the incurred-loss approach. Finally, I should also warn that this test does not allow me to infer whether the apparent reduction in information quality is due to enhanced managerial discretion or to the complexity inherent in measuring expected loan losses.

In addition, IFRS 9 in general and its ECL requirements in particular require banks to make nontrivial real expenditures. I proxy for such compliance and transition costs using audit fees, which I collect from FactSet and SNL Financial.[3] While this measure is a noisy and possibly understated way to capture the direct cash costs of the ECL transition, I view audit fees as the most suitable metric that could work on a large sample. The estimation model is as follows:

$$\begin{aligned} \textit{Audit fees}_{bt} &= \beta_1\, \textit{ECL regime}_t \times \textit{Affected bank}_b + \beta_2\, \textit{ECL regime}_t \\ &\quad + \beta_3\, \textit{Affected bank}_b + \boldsymbol{\Theta}\ \boldsymbol{Controls}_{bt\text{-}1} + \eta_b + \zeta_t + \varepsilon_{bt} \qquad \text{(OA2)} \end{aligned}$$

The unit of observation is a bank-year, per the data frequency in FactSet International and SNL Financial. *Affected bank* and *ECL regime* are as defined in the discussion of Equation 1 above. Again, in the presence of bank fixed effects (η) and year fixed effects (ζ), *Affected bank* and *ECL regime* are omitted, respectively, from the estimation. The control vector pertains to the previous year.

The sample statistics and results of this analysis are presented in Table OA3.2. As Panel A shows, the characteristics of this bank-year sample are quite akin to those of the previous CDS sample. The median payment to auditors is € 6.8 million (= $e^{1.916}$).

As for the estimation results, which I present in Panel B of Table OA3.2, the difference-in-differences estimator has a coefficient of 0.677 after I control for bank and time fixed effects, as well as time-varying bank controls. Given the average value of unadjusted audit fees (€ 25.5 million), this decline is economically meaningful. Overall, my analysis of compliance costs indicates that the banks that are more affected by the ECL transition increase their payments to auditors. This inference is consistent with the idea that more intricate tasks and a thorough transition to a new accounting system require more effort from external parties. It also adds credibility to the findings presented in the earlier tables by clarifying the link between the empirical proxy for the impact of IFRS 9 and accountants' effort.

[3] CDS spreads and audit fees are not kept as readily available historical fields on SNL Financial. I am grateful to the data analysts at SNL Financial for providing me with time-varying versions of these fields.

Table OA3.1. Informational Costs of Expected Credit Losses: Bank-level Evidence

This table describes an empirical analysis of the expected credit loss regime from the banks' perspective. Each observation is a bank-quarter. The data sources are Markit and SNL Financial. Panel A provides the descriptive statistics (excluding degenerate moments for dummy variables). Panel B presents the estimation results. *Affected bank* is an indicator variable that switches on for banks with an above-median increase in their loan loss reserves per IFRS 9. (This impact is calculated as the signed difference between IFRS 9 loan loss allowances at 01.01.2018 and IAS 39 loan loss allowances at 31.12.2017 divided by the latter.) *ECL regime* is an indicator variable that equals one for periods from the first quarter of 2018. The definition of bank-level control variables is detailed in Panel A of Table 2. The dependent variable, *CDS spread flatness*, is defined as the ratio of the quarterly average spread of the one-year CDS contract to that of the five-year CDS contract. T-statistics presented in parentheses are computed using standard errors robust to within-bank correlation and heteroscedasticity. ***, **, and * denote statistical significance at the two-tailed 1%, 5%, and 10% levels, respectively.

Panel A. Descriptive Statistics

	Mean	Stdev	p10	p50	p90	N
Affected bank	0.418	.	.	.	.	636
ECL regime	0.387	.	.	.	.	636
CDS spread flatness	0.503	0.240	0.292	0.447	0.770	636
Bank size	10.015	1.478	8.021	10.001	11.793	573
Bank capital	7.205	2.870	4.509	6.652	11.396	573
Bank profitability	3.035	11.754	-8.790	6.074	12.985	573
Bank loan intensity	57.031	15.673	34.362	58.580	74.962	573
Bank risk method	0.897	.	.	.	.	573
Bank asset risk	41.428	16.671	21.286	41.629	63.947	573

Panel B. Estimation results for information precision

	(1)	(2)	(3)
	CDS spread flatness	*CDS spread flatness*	*CDS spread flatness*
Affected bank × ECL regime	0.089**	0.079**	0.078**
	(2.31)	(2.19)	(2.04)
Affected bank	-0.189***		
	(-3.43)		
Bank size			0.108**
			(2.14)
Bank capital			-0.004
			(-0.45)
Bank profitability			-0.001
			(-0.33)
Bank loan intensity			0.001
			(0.54)
Bank risk method			-0.159***
			(-7.83)
Bank asset risk			-0.001
			(-0.36)
Observations	636	636	573
Adjusted R-squared	0.195	0.746	0.748
Time FE	Y	Y	Y
Bank FE	N	Y	Y

Table OA3.2. Compliance Costs of Expected Credit Losses: Bank-level Evidence

This table describes an empirical analysis of the expected credit loss regime from the banks' perspective. Each observation is a bank-year. The data sources are FactSet International Annual and SNL Financial. Panel A provides the descriptive statistics (excluding degenerate moments for dummy variables). Panel B presents the estimation results. *Affected bank* is an indicator variable that switches on for banks with an above-median increase in their loan loss reserves per IFRS 9. (This impact is calculated as the signed difference between IFRS 9 loan loss allowances at 01.01.2018 and IAS 39 loan loss allowances at 31.12.2017 divided by the latter.) *ECL regime* is an indicator variable that equals one for periods from the first quarter of 2018. The definition of bank-level control variables is detailed in Panel A of Table 2. The dependent variable, *Audit fees*, is defined as the natural logarithm of the audit fees in million euros. T-statistics presented in parentheses are computed using standard errors robust to within-bank correlation and heteroscedasticity. ***, **, and * denote statistical significance at the two-tailed 1%, 5%, and 10% levels, respectively.

Panel A. Descriptive Statistics

	Mean	Stdev	p10	p50	p90	N
Affected bank	0.526	.	.	.	.	116
ECL regime	0.267	.	.	.	.	116
Audit fees (log)	2.166	1.583	0.181	1.916	4.290	116
Bank size	10.093	1.536	8.328	10.001	11.835	111
Bank capital	7.714	3.180	4.783	6.770	12.994	111
Bank profitability	3.488	10.922	-9.246	5.781	13.151	111
Bank loan intensity	54.765	14.304	34.320	56.452	70.889	111
Bank risk method	0.811	.	.	.	.	111
Bank asset risk	43.137	15.839	25.053	42.084	64.257	111

Panel B. Estimation results for audit fees

	(1)	(2)	(3)
	Audit fees (log)	*Audit fees (log)*	*Audit fees (log)*
Affected bank × ECL regime	0.862**	0.657**	0.677*
	(2.40)	(2.21)	(1.70)
Affected bank	0.597		
	(1.25)		
Bank size			-1.337
			(-1.05)
Bank capital			-0.230
			(-0.74)
Bank profitability			-0.008
			(-0.54)
Bank loan intensity			-0.028
			(-0.99)
Bank risk method			.
			.
Bank asset risk			0.115
			(1.37)
Observations	116	116	111
Adjusted R-squared	0.074	0.768	0.794
Time FE	Y	Y	Y
Bank FE	N	Y	Y