Expected Losses, Unexpected Costs? Evidence from SME Credit Access under IFRS 9*

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Abstract

This paper examines lending effects of European banks switching to an expected credit loss (ECL) model under IFRS 9. I find evidence that ECL transition deteriorates the credit landscape for SMEs as risky, opaque, and bank-dependent borrowers. Post ECL, Affected banks have reduced SME lending by 16–20 percent. Banks' financial reporting objectives and implementation difficulties explain these findings, while regulatory capital adequacy concerns seem less relevant. Additional tests performed at the borrower and loan-contract levels indicate rising interest rates and collateral requirements and declining loan amounts and maturities for SMEs that do business with affected banks. Echoing these findings, further survey evidence suggests that affected SMEs receive less credit, conditional on applying for a loan.

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1. INTRODUCTION

Many observers identified the delayed recognition of credit losses as contributing to the Great Recession and called for action to improve loan loss provisioning practices that had relied on the incurred credit losses (ICL) impairment model (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 forward-looking impairment models that use statistical methods and additional evidence (e.g., more comprehensive and specific credit and macroeconomic information) to calculate allowances for potential loan losses (IASB (2013), FASB (2016)). This includes "reasonable and supportable" information about past events, current conditions, and forecasts of future outlook. The IASB introduced its expected credit loss (ECL) model as a pillar of IFRS 9 in 2014, effective beginning in 2018 (IASB (2014)).

This paper explores the effect of banks' ECL adoption on their borrowers, specifically small and medium-sized enterprises (SMEs).[1] SMEs are both under-researched and distinct; they are not scaled-down versions of their larger corporate counterparts (Beck, Demirgüç-Kunt, and Martinez-Peria (2008)). Research findings about large, public corporations cannot be extrapolated to SMEs because of the constraints they face, such as those related to growth, product diversification, and financing (Cressy and Olofsson (1997)). In addition, SMEs have distinct economic importance: In Europe and the U.S., for instance, they represent more than 99% of companies in nonfinancial sectors, account for more than two-thirds of total nonfinancial employment, and generate more than half of total gross value added. Since SMEs receive most of their external financing through bank loans, banks largely enable SMEs' critical contributions to economic growth and social welfare

[1] The European Commission defines SMEs as entities with up to 250 employees and with up to €50 million in assets or €43 million in annual sales.

(Beck, Demirgüç-Kunt, and Levine (2005), Beck and Demirgüç-Kunt (2006)). Conversely, impaired lending to these entities could restrain investment, employment, and economic growth.

Ex ante, the effect of the ECL model on SME credit access is not obvious. On the one hand, the ECL framework aims to improve banks' credit risk management, increase the transparency of their asset quality and risk positions, and allay procyclicality through earlier recognition of credit losses. If achieved, these goals could enhance SMEs' bank credit access (Rajan and Zingales (2003), Granja (2018), Balakrishnan and Ertan (2019)). On the other hand, the ECL model's requirement that bank financial statements recognize expected future losses upfront burdens banks' reported performance and ultimately may burden their regulatory capital adequacy. Moreover, the ECL model requires expending significant resources in meeting requirements to periodically evaluate and disclose information on their entire loan portfolio. These challenging aspects of ECL could reduce the relative attractiveness of loan-making, especially to risky and opaque borrowers, such as SMEs, as such activities would require relatively large allowances.[2]

In addition, SMEs depend on banks and their established bank relationships; they cannot switch lenders easily, and are exposed to shocks and associated costs their relationship banks pass on to them (Rajan (1992)). As a result of this dependence and stickiness, banks largely determine SMEs' credit conditions; and banks' use of the ECL method could be especially consequential for SMEs. All these factors combine to make this economically important group of borrowers suitable and valuable to study in the context of ECL (Berger and Udell (1995), Cassar, Ittner, and Cavalluzzo (2015), Harrison and Sigee (2017)). Overall, I examine the changes ECL adoption precipitates in the SME bank-borrowing landscape.

[2] Heightened allowances under ECL would be more pronounced for SME loans as these assets are riskier on average than the rest of the loan portfolio. In the sample I study, for example, the NPL ratio is 6.5 percentage points for SME loans compared to 3.3 percentage points for other loans. Furthermore, it is tougher for banks to provision for SME loans accurately and efficiently because of the lack of information about these entities.

The bulk of my empirical analysis relies on a difference-in-difference framework, which defines "affected banks" in two ways. The homogeneous definition compares banks that adopt the ECL model for financial reporting purposes to those that do not. This choice offers an objective and conventional classification of banks into treatment and control groups. However, it is also susceptible to concerns that IFRS and non-IFRS banks are different from one another and could be subject to distinct economic trends and regulatory developments. To alleviate these issues, I also adopt a heterogeneous approach, approximating the economic distance between the use of ICL and ECL models for each IFRS bank at the moment of transition. For this group, treatment banks are coded as those with an above-median increase in loan loss allowances (corresponding to a 12% rise). The heterogeneous design assumes that the day-one jumps reflect ECL's economic impact to a reasonable degree. To ensure robustness, I employ both approaches.

The bank-level sample I study spans from the end of 2014 to the end of 2019. The models I use include bank and time fixed effects and time-varying bank characteristics, such as size, capital, profitability, and riskiness. In these tests, I study 80 nationally significant banks from 21 countries covered by the European Banking Authority's (EBA) Transparency Exercise. I focus on this particular sample of banks because the EBA data contains a detailed breakdown of loan portfolios, which allows me to distinguish banks' lending to SMEs from their lending to corporations. In these entity-level tests, I find that affected banks, relative to other banks, decrease lending to small businesses.[3] Quantitatively, these declines are about 2.3–2.9 percentage points, which correspond to 15–20% marginal effects (relative to sample averages of about 15 percentage points).

Greater provisions, holding all else constant, should not deteriorate the cash flows from a loan; hence, one immediate question is why and how affected banks reduce SME lending after

[3] Throughout the paper, I use SMEs and small businesses interchangeably.

switching to the ECL model. Several mechanisms could work singularly or simultaneously to decrease SME lending and explain the observed baseline results. First, banks could shy away from making risky loans due to financial reporting concerns. This is because although rising loan-loss provisions under ECL do not hurt banks' cash flows, they do reduce current earnings and likely introduce volatility to financial reporting (PwC (2017)). Post ECL, SME lending would be costlier for banks that are more concerned about reported performance. In support of this argument, I find stronger results for banks with external financing constraints and for banks with higher executive pay-performance sensitivity (Beatty, Ke, and Petroni (2002), Bergstresser and Philippon (2006)).

Second, the ECL model requires that banks create provisions for all loans, which is a complex undertaking that makes banks' lending and forecasting harder, especially for loans made to opaque borrowers like SMEs. To address implementation challenges, banks must also expend nontrivial employee hours and cash payments to external experts and auditors. Consistent with perspective view, I observe that the main effect is more pronounced for small banks.

Third, sharp increases in loan-loss allowances could hurt banks' regulatory capital, inducing them to reduce making risky loans. My findings provide little support for the capital adequacy narrative. In particular, the main effects are mostly similar across banks, whether they are more capital-constrained or less capital-constrained. I interpret this finding as evidence that regulatory capital adequacy is not a primary channel for (and objective of) banks' lending decisions post ECL. This is consistent with the fact that the incremental effect of the ECL model on regulatory capital would be phased in over a five-year period rather than incorporated immediately.

I also conduct tests at the borrower and loan levels to better account for demand-side confounds. These granular analyses are also crucial for understanding substitution and spillover dynamics (Berg, Reisinger, and Streitz (2020)). On a sample of 227,000 borrower-years, I find that SMEs that work with affected banks are less likely to issue debt than other borrowers in the same industry and country. In the cross-section, I find the main effects to be more pronounced for smaller and less transparent borrowers, which is in line with riskiness and opacity worsening SME credit outlook under the ECL regime. These higher-resolution borrower-level inferences also suggest that SMEs are not able to offset the credit lost from their relationship banks, implying real effects.

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)). To mitigate these, I draw insights from an ECB credit access survey (Ferrando, Popov, and Udell (2017)). My inferences indicate that, among the SMEs that applied for a bank loan, 'affected borrowers' experience a decline in loan approval rates. In sum, these findings support the idea that the ECL implementation has distorted the credit landscape for small businesses.

The firm-level tests referenced above do not directly address contractual clauses such as interest costs, contract maturities, and loan amounts. To investigate these areas, I analyze more than 300,000 SME loan contracts in my last set of tests. The key finding from this sample is on the price of loans: conditional on borrowers' riskiness, interest rates rise in the SME credit contracts made by affected banks in the post-ECL period. I also observe a decrease in loan amounts. This inference deserves attention because, in addition to shedding light on intensive margins, it indicates a decline in the supply of credit (i.e., a leftward shift in the supply curve).[4] In addition, I find a drop in loan maturities, which is consistent with the argument that the ECL model makes provisioning for longer-maturity loans more challenging. As with the borrower-level tests, the main effects are more pronounced for (and at times entirely driven by) small borrowers (DeYoung et al. (2015)).

[4] Loan prices could rise 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 be explained by a rightward shift in the demand curve. This alternative explanation, however, would also predict an *increase*—not *decrease*—in loan amounts.

This paper connects to and builds on several 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), Wheeler (2019)). Prior work provides compelling evidence that effective accounting and provisioning practices precipitate 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, the real costs and benefits of more comprehensive and forward-looking provisioning, such as that required by the ECL model, remain an empirical question (Bushman and Williams (2012)). Speaking to this gap in the literature, this paper can inform the theory and practice of banking (Gorton and Winton (2003), Jiménez et al. (2017)). From a policy standpoint, my conclusions are timely and relevant within and beyond the IFRS domain, considering the implementation of CECL, which began in 2020.[5]

The paper also contributes to the broader literature that studies the economic effects of accounting rules, disclosure practices, and regulation (e.g., Daske et al. (2008), Breuer, Hombach, and Mueller (2017), Costello, Granja, and Weber (2019), Shroff (2020), Mahieux, Sapra, and Zhang (2020)). The evidence that my results are stronger for smaller banks connects to studies showing that information technologies have resulted in consolidation in the banking industry (Berger (2003)), and it connects to studies documenting that large lenders rely primarily on transaction lending (Berger et al. (2005)). My work also responds to calls to explore the spillover effects and unintended

[5] On this note, the insights of this paper are relevant because the COVID-19 pandemic and the ensuing government guarantees could affect and confound empirical inferences regarding the assessment of the ECL method from March 2020. As Albertazzi et al. (2020) detail in their ECB paper, European governments introduced guarantees of 70-100% of loans made during the pandemic. These guarantees, the authors elaborate, would curb loan loss recognition, as they would transfer potential losses to governments. Zamil (2020) expands this perspective by exemplifying the following extraordinary support measures taken in IFRS jurisdictions during the pandemic: 1) "Banks can accrue interest on payments that have been deferred;" 2) "Use of payment deferral program should not automatically lead to a migration of loans to stage two;" and 3) "in use of forward-looking information in determining ECL provisions, [banks must] consider exceptional circumstances and government support". These bespoke emergency measures, the effects of which likely vary across banks, boost bank earnings and suppress provisions, thereby rendering unattainable a convincing assessment of ECL during the 2020-21 period.

consequences of regulation (e.g., Leuz and Wysocki (2016)). While doing so, I take into account 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, Ryan, and Xie (2018)).

Finally, my paper extends the body of work on small-business financing (e.g., Berger and Udell (1995)). Small businesses are widely viewed as credit-constrained growth engines. Across the world, numerous initiatives (e.g., credit guarantee schemes) aim to support SME access to finance; these initiatives extend beyond attempts to induce banks to increase SME funding (Ertan, Kleymenova, Tuijn (2021)). In this vein, my conclusions on the ECL transition context relate to the challenges institutions face in making loans to small, informationally opaque companies. (Berger, Klapper, and Udell (1999), Jayaraman, Schonberger, and Wu (2019), Dou (2020)). This insight should be of particular interest to policymakers and regulators since the new provisioning rules could adversely affect bank-dependent SMEs and present considerable implications for the broader economy (Beck, Demirgüç-Kunt, and Maksimovic (2005), Rice and Strahan (2010)).

The present study offers evidence of declining bank credit access post ECL and speaks to potentially unintended real consequences of this new financial reporting rule. Despite the importance of this takeaway, my paper does not produce an overall assessment of the ECL approach, speak to whether/how this policy has achieved its stated goals, or draw conclusions about ECL's net effect on economic growth and social welfare. A driver of the new rules was the desire to mitigate procyclicality, and what I observe in the data is not inconsistent with this outcome (also see, for example, Chen et al. (2022), Kim et al. (2021), Jiménez et al. (2017)). In the longer run, the ECL model could make funds more readily available or cheaper for small businesses. The ultimate test for this paradigm will be the long-term performance and down-cycle resilience of the banking sector.

2. INSTITUTIONAL BACKGROUND

2.1 Incurred and Expected Credit Losses

Banks make loans to households, small businesses, and large corporations, exposing themselves to repayment risks. If debtors cannot repay their loans (and if the realizable value of the collateral proves insufficient), banks face credit losses and write off the defaulting accounts. Accounting deals with this problem before the write-offs occur definitively by requiring banks to set aside loan loss provisions to anticipate and absorb such credit losses. Until recently, accounting rules followed an incurred credit losses (ICL) model. This set of rules requires banks to recognize a credit loss on a loan if there is objective evidence (e.g., an event such as a missed payment).

Following the global financial crisis in 2008–09, the ICL model was blamed for being too little, too late: it was considered inadequate in its delayed response to credit losses (e.g., De Haan and Van Oordt (2018), G20 (2009)). The IASB introduced the expected credit losses (ECL) model as part of IFRS 9 Financial Instruments, which sparked a profound shift in how the banking sector addresses credit losses globally.[6] Adopted in 2014 and took effect in 2018, this new impairment rule requires banks to create loan loss provisions based on risk calculations well before a loan goes into arrears. As a result, under the ECL model, creditors are expected to identify and account for expected credit losses at initiation and update the ECL amount periodically to reflect in a timely and accurate manner the changes in the credit risk of the underlying financial instrument.

The ECL model requires using past, current, and future information to assess changes in risk and measure expected losses. The critical parameters banks use in their models and analyses include the probability of default, loss given default, and exposure at default. ECL is the weighted average of credit losses, where the weights are the respective default risks. For risky borrowers and under

[6] IFRS 9 is a financial reporting regulation that applies to banks and nonbanks alike. However, as major issuers of loans, banks are most affected by IFRS 9's new impairment rules, and this paper explores banks only. The implications of the new provisioning rule for nonfinancial firms are beyond the scope of my discussions.

adverse macro scenarios, these parameters lead to larger ECL values.[7] This particular feature is a considerable departure from the incurred-loss framework, especially in the context of performing loans. For such assets without any incurred losses, the ECL model estimates potential losses over a pre-specified future period, which leads to quicker recognition of loan losses.

ECL impairment rules divide financial instruments into three groups according to stages of credit quality deterioration. Stage 1 includes financial assets without a significant increase in credit risk since inception. These instruments require a 12-month ECL calculation: the lender takes into account expected losses arising from default events that it deems possible within 12 months after the reporting date. At each reporting date, a bank must assess the credit quality and changes in the credit risk of an outstanding loan since its inception and continuously update its loss provision.[8]

When the credit risk of a performing loan has increased significantly since its initial recognition, it is classified as Stage-2. The ECL model does not present bright lines to define the trigger events that entail a significant increase in credit risk; this assessment, which may be qualitative and quantitative, is left to the management.[9] 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 loan's expected life).

In contrast to these performing assets, Stage-3 instruments contain objective evidence of impairment (e.g., missed payments). Impairment allowance for these assets is also measured for the

[7] 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) about 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.

[8] As with previous accounting practices, banks estimate provisions individually for heterogeneous loans (e.g., commercial credit) and at the portfolio level for homogeneous loans (e.g., mortgages).

[9] Banks use, qualitatively and quantitatively, a variety of developments to assess a significant increase in credit risk. The relevant developments include but are not limited to news about significant financial difficulty on the part of the borrower, late payments, 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 monitor the public market performance of their corporate borrowers' bonds.

loan’s lifetime. The impact of Stage-3 assets should be relatively small since the incurred-loss model already accounted for these assets. The transitional impact of the ECL model 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).

2.2 A Comparative View of ECL

How does the ECL model compare and intersect with other reporting requirements? This section discusses financial reporting issues under FASB’s Current Expected Credit Losses (CECL) and regulatory reporting considerations related to the Basel framework for bank supervision.

FASB’s CECL is the U.S. version of the ECL model. CECL—initially intended to be a part of a joint convergence initiative between IASB and FASB—became effective in the U.S. in 2020. The primary high-level difference between FASB’s CECL and IFRS’s ECL is that the former requires a lifetime loss calculation for all assets, including those classified as Stage-1 under the ECL model. Banks that report under U.S. GAAP have provided disclosures on the potential and realized impacts of the transition to the CECL model, which were no less than the transition to the ECL model. It will be interesting to learn the extent to which this paper’s findings may carry over to the U.S. setting. On this note, Chen et al.’s (2022) insights suggest that CECL adopters reduce loan growth during the COVID-19 recession relative to non-adopters, while Kim et al. (2022) document that bank CECL rules improve adopting banks’ information production.

Bank supervision rules deserve closer attention in part because they have been followed by the sample banks studied in this paper. This discussion attempts to address distinct dimensions that should not be conflated: (*i*) reforms and changes in bank supervision as a potential confound, (*ii*) banks’ regulatory capital considerations as a potential mechanism contributing to the effect of ECL on SME lending, and (*iii*) the background on loan-loss reporting for regulatory purposes.

Factors and developments relating to bank regulation could confound the baseline effect of ECL. This is an identification concern: it is the idea that changes in the bank regulatory landscape could be the primary driver of my results if these regulatory developments coincide with the timing and treatment assignment of the ECL transition. I note that this concern is largely muted in a difference-in-differences sense because the regulatory landscape has been reasonably stable throughout the sample period and because the sample banks are supervised by the EBA and the same respective national regulators (more on this in Section 4.2).

The implication of banks' regulatory capital reporting on the baseline effect is a distinct notion. Rather than an identification concern, it is the rationale that explores whether the impact of ECL works through banks' regulatory reporting objectives. This viewpoint also deserves attention, as financial reporting changes have a bearing on banks' regulatory reporting, to which banks devote significant attention and resources. I investigate this issue further in Section 4.3.

Regarding the background on provisioning for regulatory purposes, credit-loss allowances computed for the Basel regulatory reporting are distinct from (albeit positively correlated with) those under financial reporting (Novotny-Farkas (2016)).[10] Various stakeholders also highlight significant differences between the details and objectives of the two reporting regimes. PwC, for instance, notes that it is erroneous to assume that banks will be able to use the data and tools they have for regulatory reporting with only minor adjustments.[11] The rationale is that while Basel's expected loss model might be a starting point, banks must significantly adjust the models they use for regulatory reporting

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[10] The difference arises for several reasons. The Basel framework is based on a 12-month horizon (see BCBS (2006)), whereas accounting standards consider the entire lifetime of a loan (under IFRS, this requirement applies to Stage-2 and Stage-3 buckets). Furthermore, whereas IFRS-9 requires that banks use "reasonable and supportable forecasts of future economic conditions when measuring expected credit losses" (IFRS 9 para. 5.5.17), regulatory calculations are based on long-run average default rate (e.g., BIS (2015), BIS (2017), Frykström and Li (2018)).

[11] PwC also emphasizes the following point: "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.

to comply with the new impairment standard and model. At any rate, if ECL did prompt entail a meaningful change in banks' provisioning practices, one would not find significant empirical results.

2.3 Reactions to ECL and Bank Disclosures

Banks' switching from ICL to ECL is widely viewed as the biggest accounting change in the banking sector in recent history; and has received substantial attention from regulators, auditors, bankers, analysts, and others (Bischof and Daske (2016)).[12] Bank regulators have incorporated the ramifications of IFRS 9 in the 2018 Stress Tests and disclosed their assessment of ECL's impact on loan loss recognition. Ahead of the changes, the EBA published several documents on the effects of ECL (e.g., EBA (2016), EBA (2017)). Supervisors have also attempted to gauge ECL's implications more qualitatively. For example, an ECB survey conducted in late 2017 shows that most banks had only draft plans to transition to IFRS 9 and the ECL model, despite the imminent implementation deadline of January 2018. Among other things, the surveyed banks reported experiencing problems with data quality, historical data availability, credit risk assessment, and capacity needed to implement ECL.[13] Consequently, there has been an emphasis on greater collaboration between bank regulators and bank auditors (Cohen and Edwards (2017), PRA (2019), Balakrishnan et al. (2021)).

Bank auditors have argued that banks would and do face significant challenges applying the ECL framework. According to audit professionals, most banks lack clarity on ECL implementation and its imminent impact on their business.[14] Auditors also underscore potential problems with comparability across financial statements, as the enhanced room for managerial judgment could lead

[12] PwC (2017) 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 (2017b). Likewise, the American Bankers Association (2019) has called CECL the "most sweeping change to bank accounting ever."

[13] https://www.moodysanalytics.com/regulatory-news/aug-30-dnb-issues-banking-newsletter-for-august-2017

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

to structurally different assessments.[15] In addition to the Big Four, international audit regulators and organizations also provide perspective and guidance on ECL (e.g., IAASB (2016), IFIAR (2016)).

In keeping with the ECL model's potential to impact banks' operations and reporting practices, banks, too, have raised concerns regarding its implementation. Bankers have viewed IFRS 9 as an enormous task and admitted they were short on information.[16] They have also expressed reservations about the potential manipulation of ECL requirements. Even the central premise of IFRS 9—the goal of reduced procyclicality—has been questioned by banks in their official disclosures.[17] An S&P survey conducted weeks before the ECL implementation presents valuable insights into bankers' perceptions of the challenges faced by the European banking sector.[18] Bankers indicated five categories of challenges and costs: capital and income volatility, reconsideration of product line-up and elimination of unprofitable options, data and modeling endeavors, systems infrastructure investments, and sheer cash costs associated with the initial transition.[19]

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. The author also highlights that ECL introduces subjectivity and complexity without directly addressing procyclicality. Abad and Suarez (2017) also

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

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

[17] For instance, Nordea's post-ECL annual report reads: "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…*" (emphasis added).

[18] https://www.spglobal.com/marketintelligence/en/news-insights/blog/ifrs-9-implementation-top-five-concerns.

[19] The following PWC note echoes the survey takeaways: "This standard will be very challenging to apply, in particular for financial institutions. Currently, most entities do not collect the amount of credit information required by the standard. Entities will need to significantly modify their current credit and information systems in order to gather the required information. Management will need to build new models to determine both 12-month and lifetime ECL. This will require complex judgements (for example, definition of default, definition of low credit risk and behavioural life of revolving credit facilities). It is expected that the implementation process will require a significant amount of time before an entity will be in a position to comply with the requirements of the standard."

raise concerns about the counter-cyclicality premise of the ECL framework. Reitgruber (2014) points out that the ECL model has significant shortcomings related mainly to the requirement that financial institutions integrate forward-looking data into their credit loss models. According to Harrison and Sigee (2017) the use of ECL could be *more* corrosive to bank capital in a downturn.

Researchers have also attempted to explore other aspects of IFRS 9's ECL model. Gaffney and McCann (2019) 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. Loew, Schmidt, and Tiel (2019) study the initial implementation effects of IFRS 9. In addition to presenting extensive descriptive evidence, the authors also assess the first-time adoption impact for IFRS 9. López-Espinosa, Ormazabal, and Sakasai (2021) present evidence that ECL provisions have better predictive ability than ICL provisions. Kim et al. (2021) document enhanced loan loss recognition timeliness post ECL. Examining the U.S. experience, Chen et al. (2022) find that pre-pandemic CECL adopters reduced loan growth during the subsequent recession relative to non-adopters.

3. OVERVIEW OF PREDICTIONS AND MEASUREMENT

This paper aims to provide insights into the impact of ECL implementation on small businesses. How and why would ECL adoption affect the SME credit landscape, and with what consequences? Several potential consequences and explanations exist. The use of the ECL model could prompt an increase in bank lending to small businesses. ECL aims to enhance financial stability by introducing forward-looking provisioning practices, to improve banks' credit risk modeling practices, and to increase the relevance and usefulness of financial-reporting information (IFRS 9 para. 1.1). These goals and ensuing improvements could lead banks to increase the supply of credit to the economy, including small businesses. In terms of potential mechanisms, this outcome could be achieved, especially if the aforementioned improvements help banks obtain more funds or decrease their funding costs (DeYoung et al. (2015); Granja (2018); Balakrishnan and Ertan (2019)).

Another possibility is that banks' willingness to make SME loans could decrease post ECL, especially in the short-to-medium term, because banks might find this activity less attractive under the new regime. The main reason behind this prediction is that the ECL model significantly increases provisions for many banks and is associated with heightened direct costs. This transitional change and its longer-term implications could induce banks to revisit their loan-making decisions in general—and lending to risky and opaque borrowers, such as SMEs, in particular. This is because under ECL, risky entities, even if performing well, are associated with greater provisions than their safer counterparts. (By comparison, under ICL, risky and safe borrowers receive equal loan-loss provisions of zero unless objective evidence demonstrates they are nonperforming.) The increased provisions can hamper financial reporting performance, introduce volatility to financial statements, and burden banks' capital adequacy. In response to these challenges, banks may curb lending to risky and opaque entities like SMEs in order to shrink expected losses.

To capture ECL's effects on SMEs, one needs to measure a form of cross-bank variation in the impact of the new rules (i.e., the treatment and control groups). The conventional approach has a straightforward binary nature. In the ECL setting, this approach requires that IFRS banks be coded as treatment and non-IFRS banks as control.

As an alternative, I consider a heterogeneous classification that explores the intensity of the regulation's impact within the group of transitioning banks. This option could be valuable for two main reasons. First, comparing IFRS banks to non-IFRS banks—even in a difference-in-differences sense— may be problematic due to concurrent economic trends, developments, and regulations. Second, IFRS 9, in particular, involves changes other than ECL implementation, such as new rules regarding fair values and hedge accounting. This institutional complexity might create an attribution conundrum. Namely, under the traditional homogenous approach, one may be unable to identify which specific aspect of IFRS 9 adoption is responsible for the observed results.[20]

The challenge with the heterogeneous design is to create an "intensity" variable that can accurately compare one European bank that adopted IFRS 9 in 2018 to another European bank that also adopted IFRS 9 in 2018. To overcome this challenge, I presume that the economic distance between the ICL-ECL models varies across IFRS banks; even though the ECL adoption is homogeneous, the degree of the challenges it presents to banks is complex and heterogeneous. To proxy for the bank-specific ICL-ECL distance, I use the day-one accounting jump in allowances from banks' mandatory transitional disclosures (Horton and Serafeim (2010)). Appendix A illustrates the basis of my measurement by using two examples. The ECL transition increases Barclays's loan-loss allowance from £4.65 billion to £7.11 billion; and Santander's from €23.95 billion to €25.95 billion. Accordingly, I assign an impact value of 53.9% (=2.51/4.65) to Barclays and 8.4% (=2.00/23.95) to Santander.

I acknowledge that the heterogeneous approach is not without limitations. For instance, heterogeneous treatment banks possibly have different portfolio characteristics and risk management than heterogeneous control banks. The crucial point (and assumption) here is that these inherent differences do not drive the outcome variable in the absence of ECL adoption.[21] Namely,

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[20] 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 on an otherwise similar set of banks. In my review of banks' reports and disclosures, I do not observe a significant trend in reporting regulation 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' commissions and other income.

[21] However, these inherent bank characteristics that lead to the ICL-ECL difference do become a problem if they affect SME lending due to specific shocks that coincide with ECL adoption. For example, it is a concern if my treatment banks happen to be more exposed to credit cards, and non-ECL credit-card shocks occurring in 2017/2018 could lead the researcher to mistakenly attribute the decline in affected banks' SME lending to ECL adoption rather than the shock on the credit card business. Even though the ECL setting does not permit a staggered design, I make several attempts to mitigate this issue (Appendix C).

the heterogeneous definition needs to make an assumption about plausible exogeneity rather than plain random assignment (which is desirable but unattainable).

One caveat worth mentioning here is that the day-one jumps in loan-loss allowances may reflect some banks' spring-loading of reserves (using the flexibility in accounting rules)—not the true economic impact. In the European ECL experience, banks' disclosed transition figures are consistent with bank supervisors' pre-transition estimates. This observation seems to support the day-one jumps reflecting the economic effect of transition.[22] This is because supervisors' assessments here would capture the economic impact more so than bank-specific accounting discretion in ECL calculations. This notion is also in line with Gee et al.'s (2022) empirical assessments—CECL day-1 impacts are decision- and value-relevant. This being said, it remains possible that banks' accounting discretion systematically shapes (or at least contributes to) transition values.[23] For these reasons, I rely on both homogeneous and heterogeneous approaches.

4. BANK-LEVEL ANALYSIS: (WHY) DO BANKS REDUCE SME LENDING POST ECL?

I assess the impact of the ECL framework by conducting three sets of empirical analyses: bank-level tests that help examine banks' portfolio decisions (this section), borrower-level tests that shift the focus from the lender to the borrower (Section 5), and contract-level tests that allow me to track individual loan contracts (Section 6). Variable definitions appear in Appendix B.

4.1 Research Design and Data

The bank-level estimation model is as follows:

$$\begin{aligned} \textit{SME lending}_{bt} = {} & \beta_1 \textit{ ECL regime}_t \times \textit{Affected bank}_b + \beta_2 \textit{ ECL regime}_t + \beta_3 \textit{ Affected bank}_b \\ & + \boldsymbol{\Theta}\ \boldsymbol{\textit{Controls}}_{\boldsymbol{bt-1}} + \eta_b + \gamma_t + \varepsilon_{bt}. \end{aligned} \tag{1}$$

[22] 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 similar to my estimates from banks' transitional disclosures.

[23] To be sure, this nuance could affect the interpretation of the results, yet the baseline conclusion that the ECL transition leads to a reduction in SME lending holds.

The dependent variable in these bank-quarter-level tests (*SME lending*) is banks' SME lending as a percentage of total lending. This variable comes from the EBA Transparency Exercise disclosures, which span from December 2014 to December 2019.[24] Toward the end of each year, the EBA releases quarterly information on banks' performing and nonperforming exposures at the asset group level. This breakdown includes traditional lending (e.g., SME, corporate, retail, mortgage) and nonlending activities (e.g., securitization, covered bonds, sovereign bonds, interbank). This data's novel feature is its granularity, allowing the researcher to study SME lending separately from corporate lending.

On the right-hand side, *Affected bank* and *ECL regime* are the two components of the difference-in-differences (DiD) model. *ECL regime* is the "post" variable, which is an indicator that switches on post 2018. *Affected bank* is the "treatment" variable, an indicator with the following two definitions. *Affected bank (homogeneous)* switches on for banks that transition to ECL and remains zero for non-switchers. *Affected bank (heterogeneous)* equals one for banks that experience an above-median increase in their loan loss allowance due to the ECL implementation. The accounting impact on loan loss allowance is inferred using banks' transitional disclosures (Appendix A). ECL banks for which the day-one impact cannot be ascertained are omitted.

The controls vector accounts for time-varying bank characteristics that might change concurrently with the IFRS 9 implementation and affect banks' lending and portfolio allocation decisions. The vector includes the natural logarithm of total USD assets (*Bank size*), the ratio of bank equity to total assets (*Bank capital*), return-on-equity (*Bank profitability*), the ratio of interest income to total assets (*Bank interest income*), interest expense as a percentage of interest-bearing

[24] The data dates for the EBA Transparency Exercise are as follows. Pre ECL (seven data points): 2014-12, 2015-06, 2015-12, 2016-06, 2016-12, 2017-06, and 2017-12. Post ECL (seven data points): 2018-06, 2018-09, 2018-12, 2019-03, 2019-06, 2019-09, 2019-12. As can be seen, the EBA data shifts from semi-annual to quarterly frequency in 2018. I include an equal number of pre and post observations to ensure a balanced sample.

liabilities (*Bank interest expense*), the ratio of risk-weighted assets to total assets (*Bank asset risk*), and the ratio of nonperforming loans to total loans (*Bank NPLs*). In the presence of bank fixed effects (η) and quarter fixed effects (γ), *Affected bank* and *ECL regime* are omitted from the estimation. The data underlying bank controls come from SNL Financial.

Table 1 presents the relevant summary statistics. Panel A explores the homogeneous definition (ECL vs. non-ECL), while Panel B depicts the heterogenous-treatment sample (above-median ECL effect vs. below-median ECL effect). Both panels are broken into two subpanels to present the respective control and treatment groups' statistics separately. The homogeneous sample contains 925 observations from 80 banks. A total of 855 observations come from ECL banks, compared to 70 observations for the control group. In Panel B, these 855 ECL observations are coded as treatment (N=426) and control (N=429).

The statistics in Panel A suggest relatively large differences between treatment and control groups. Non-ECL banks, for which *Affected bank (homogeneous)* equals zero, are more exposed to SMEs, are smaller in size, and hold more capital. This is likely because these non-switching banks, while being significant enough to be subject to the EBA Transparency Exercise, are comparatively smaller than their large and publicly traded counterparts that switch to ECL. Turning to the heterogenous-intensity sample described in Panel B, we observe a greater similarity across the treatment and control groups. While not a necessary condition for the DiD estimation framework, the similarity in observables is reassuring, especially to the extent omitted unobservables are correlated with observables (Altonji, Elder, and Taber (2005)).

4.2 Baseline Findings

Table 2 shows the results of the estimation of Equation 1. Panel A includes the results for the homogeneous treatment approach, and Panel B presents the results for the heterogenous-intensity design. In both panels, column (1) includes time fixed effects only. The models in column (2) contain bank fixed effects, and those in column (3) are also saturated with time-varying bank controls. In both panels, the DiD estimator is negative and significant across all specifications, suggesting a relative decline in affected banks' SME-loan positions.

In Panel A, the coefficient of interest stabilizes around –2.91 percentage points, which translates to 19.7% of the sample mean of SME lending, 14.75 percentage points. The inferences from Panel B are less significant, possibly because this specification relies on within-ECL variation. Quantitatively, the coefficient of interest from the saturated model in column 3 suggests that affected banks decrease SME lending by 2.32 percentage points, which suggests a marginal effect of 16.1%.

An adjusted R-squared of over 0.9 suggests substantial explanatory power for the empirical models, which helps mitigate omitted variable concerns. Relatedly, the coefficients of interest are fairly stable in both panels after the addition of time-varying bank controls (columns 2 and 3). This, too, is an important observation because it adds credibility to the claim that omitted variables, if found and added to the models, would not invalidate the significance of the coefficient of interest, β_1 (e.g., Altonji, Elder, and Taber (2005), Oster (2019)).

Several pieces of additional analyses also indicate that these inferences are reasonably robust. Figure 1 shows the yearly evolution of the treatment effect, which confirms pre-treatment parallel trends along with a sustained decline post ECL. More specifically, the parallel trends in Figure 1 mitigate concerns about banks' strategic anticipation. If banks adjusted their SME lending (or allowances) pre treatment, these would be captured as non-parallel trends pre treatment.[25]

[25] Appendix Table 1 presents additional results pertaining to the effect of omitted bank characteristics on my inferences. The models in this table redefine bank characteristics as above-median dummies and interact these dummies with *ECL regime* (i.e., the post variable). These results do not only continue to obtain significant negative values for the DiD estimator; they also show statistically zero estimates for bank characteristic dummies interacted with *ECL regime*. This is an important observation because it suggests the main effect is driven by treatment banks (be it homogeneous or heterogeneous), rather than by large, risky, or profitable banks.

I also use the 2016–2017 *change* in loan-loss allowances as a placebo treatment variable, which I interact with *ECL regime*. The coefficient on the interaction term is statistically and economically insignificant (untabulated). One would observe otherwise if the results were driven unobservable pre-ECL changes in credit portfolio quality or, perhaps more important, banks' anticipatory provisioning behavior pre ECL.

4.3 Mechanism Tests

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 result. This analysis is essential because it helps answer the natural follow-up question: Why do banks reduce SME lending post ECL? Thus far, my tests hint at the idea of an increase in the relative costliness of SME lending but do not directly explore what these costs entail. Further, this investigation becomes necessary because heightened provisions do not trigger cash outflows. In all, I evaluate three channels, which are neither mutually exclusive nor commonly exhaustive: regulatory capital constraints, implementation costs and difficulties, and financial reporting concerns.

First, banks are subject to various regulations, the most prominent being capital adequacy requirements. While not identical to financial reporting books, regulatory financial statements rely on and are affected by financial reporting, including IFRS updates. As ECL increases loan loss allowances, it reduces accounting and regulatory capital. This mechanism predicts that banks curb SME lending to soften the allowance-driven blow on their regulatory capital. To explore this channel, I split the sample based on capital adequacy, computed as the distance from a bank's Tier-1 capital ratio to its own threshold obtained from the European Systemic Risk Board (ESRB).[26] A greater distance indicates higher capital slack.

Panel A of Table 3 presents the results. I observe an economically and statistically significant DiD estimator for the low-slack group (column 1), which offers capital adequacy concerns as a potential explanation for why banks reduce SME lending. However, the DiD estimator is economically meaningful and statistically borderline insignificant for the high-slack group (column

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[26] The threshold is bank-specific due to bank-specific capital surcharges and buffers, as well as country-specific additions. For banks with a missing threshold, I use 250 basis points as the bank-specific buffer, which is the universally applied capital conservation buffer and also the minimum surcharge in the sample. More details can be found at https://www.esrb.europa.eu/national_policy/systemic/html/index.en.html.

2). Furthermore, I observe larger effects for the high-slack group within the ECL sample (columns 3 vs. 4). I interpret these findings as evidence that capital adequacy does not play a first-order role in banks' SME-lending reductions post ECL.

This finding is consistent with two institutional facts. Regulatory capital calculations pre-ECL used a variant of expected losses under Basel. That is, the impact of ECL on the regulatory book is less intense than that on the financial reporting book. Moreover, ECL's incremental impact on regulatory capital would be phased in over five years rather than incorporated immediately (EBA (2017)).[27] Nevertheless, I note that this evidence does not allow one to conclude that banks' regulatory concerns are irrelevant. For one thing, the capital ratio split captures only one of the many aspects of bank regulation. As an example, banks could also be concerned about the uncertainty and volatility ECL adds to risk-weight calculations, which is another regulatory reporting channel that could affect banks' loan-making to small businesses (see, for example, Kim, Kim, and Ryan (2019)).

Second, provisioning for SME loans entails considerable cash costs and implementation difficulties under the ECL regime (DNB (2017), PwC (2017)). In particular, compared to ICL, the ECL framework requires banks to forecast scenarios of macroeconomic conditions and assemble them into the risk parameters in their credit models. Thus, ECL's forward-looking element requires nontrivial expenditures made to auditors, consultants, and modeling experts, in addition to diverting full-time personnel to the ECL implementation efforts.[28] To analyze this channel, I split the sample on bank size, which I view as an all-encompassing proxy capturing overall challenges.

[27] In line with these arguments, the vast majority of European banks computed a regulatory capital impact of up to 25 bps (EY (2017a)). This decline corresponds to 1.23% of the sample average CET-1 ratio; for context, the mean day-one jump in reporting allowance is 14.86%.

[28] These direct costs are not only significant but also largely permanent. Observers point out that banks require effective frameworks for ECL during and after the transition. For example, managers would need to collect and control far larger datasets, which requires sizeable governance and maintenance efforts. Likewise, banks would be investing heavily in new methodologies and models consistent with ECL, which require considerable expertise, commitment, and communication. Finally, strong governance and highly adaptable systems remain key, primarily because banks would be providing reliable results within a short timeframe. Hence, observers conclude that "the

Panel B of Table 3 depicts the estimation results both for the homogeneous-treatment and heterogeneous-intensity samples. My estimates are more pronounced, by an order of magnitude, for small banks than for large banks, consistent with ECL implementation affecting small banks more.[29] Overall, these observations can be interpreted as evidence for the primary role played by transitory challenges, as well as longer-term implementation difficulties and costs associated with ECL (especially in the context of SME lending).[30]

Third, banks' financial reporting objectives could be a valid mechanism. According to this narrative, absent any cash outflows, banks could still opt to decrease funding SMEs because such loans require larger current allowances, hence lower earnings, under ECL. Additionally, observers remark that ECL rules could exacerbate reporting volatility, which remains a concern even if the level of earnings is not affected.[31] One way to get at banks' financial reporting incentives is to look at their external financing frictions and managers' pay-performance sensitivity (e.g., Beatty, Ke, and Petroni (2002), Bergstresser and Philippon (2006)).

The results support the reporting-incentives channel (Panel C, Table 3). The main findings are more pronounced for banks with external financing frictions (i.e., those with an above-median cost of funding pre-ECL) and those with relatively large pay-performance sensitivity. This takeaway dovetails nicely with the message from the broader literature documenting that accounting recognition affects firm behavior (e.g., Barth, Clinch, and Shibano (2003), Hayes, Lemmon, and

costs—before, during, and after transition—associated with achieving all these objectives are likely to be significant, both in terms of direct spend as well as management time." (See Deloitte (2016), KPMG (2016).)

[29] This finding also echoes predictions that smaller banks would face greater difficulties than their larger counterparts in implementing and practicing ECL (e.g., EBA (2016)). Likewise, auditors note that big banks could run sophisticated models unlike typically resource-constrained smaller banks (Ross Roundtable, Accessible here).

[30] Another investigation that could also speak to this cost issue is banks' shifting to nonlending activities. I find that affected banks, rather than engage in traditional lending, switch to nonlending assets, such as sovereign and regional government debt, repo arrangements, and securitization products, among others (Appendix Table 2). This inference is also in line with ECL requirements disincentivizing banks to make loans on the margin.

[31] For example, ICAEW (2020) notes "a major concern with ECL methodology is the susceptibility of ECLs to volatility due to the use of forward-looking information." Similarly, FRC (2020) points out "(ECL's) inherent complexities and its potential to increase earnings volatility compared to the previous accounting standard."

Qiu (2012), Christensen and Nikolaev (2013), Michels (2017)). In summary, financial reporting concerns and implementation difficulties explain the ECL-driven decline in SME lending, while regulatory capital adequacy seems less relevant—at least over the two years post ECL.

5. BORROWER-LEVEL TESTS: CREDIT LANDSCAPE FROM SME PERSPECTIVE

The bank-level analysis provides a link between ECL transition and banks' lending, 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 whether the borrowers of affected banks experience a decline in debt issuance and what types of borrowers feel funding frictions more.

5.1 Realized Credit Issuance Amounts

The borrower-level analysis focuses on SMEs' debt issuance behavior. 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 BvD Amadeus Bankers to identify the links between banks and borrowers, and thus, to assign an ECL-impact score to each borrower.[32] I define *Affected borrower* as an indicator that switches on for firms with a relationship with *Affected bank (heterogeneous)*. I then examine firm-level debt issuance using the following equation.

$$\begin{aligned} \textit{Debt holding}_{it} = {} & \beta_1\, \textit{ECL regime}_t \times \textit{Affected borrower}_i + \beta_2\, \textit{ECL regime}_t \\ & + \beta_3\, \textit{Affected borrower}_i + \boldsymbol{\Theta}\, \boldsymbol{\mathit{Controls}}_{\boldsymbol{it-1}} + \mu_i + \sigma_{ct} + \tau_{kt} + \varepsilon_{it}. \end{aligned} \tag{2}$$

The unit of observation is a firm-year, as per the data frequency in BvD Amadeus Financials, the data source for SME financials. As with the bank-level tests, *ECL regime* switches on for the years 2018 and 2019. *Controls* include firm size, asset tangibility, and profitability. *Debt holding* is

[32] For other papers using Amadeus Bankers data, see, for example, Giannetti and Ongena (2012), Kalemli-Ozcan, Laeven, and Moreno (2018), Duval, Hong, and Timmer (2020), and Berg, Reisinger, and Streitz (2021).

the natural logarithm of total debt. One advantage of this data is its granularity, which allows one to estimate the regression model using country-year and industry-year fixed effects. (As an example, this saturated design compares two Spanish retailers to one another in the same year, where the identifying variation comes from the differential impact on the relationship banks of these borrowers.) This extra step mitigates concerns about time-varying demand confounds at the regional and industry levels, but it also removes from these grids some of the variation attributable to ECL.

Panel A of Table 4 presents the summary statistics. The median borrower has debt of over 1.75 million euros (= exp(14.39)) and profitability (ROE ratio) of 4.9 percentage points. Panels B Table 4 presents the main estimation results. I find that affected borrowers post ECL become less likely to issue debt than their unaffected counterparts (Panel B). Economically, this decline is about 18% (columns 1 and 2). This finding, which looks at SMEs' debt from all sources, suggests that affected SMEs are not able to make up for the lost bank credit.

I expand on this finding by investigating the variation in the main effect by borrower size and by borrower opacity (proxied by whether a borrower reports under local GAAP as opposed to IFRS). The estimates reported in columns (3) through (6) in Panel B suggest that my conclusions are economically more strongly driven by smaller/riskier and opaque borrowers.

5.2 Distinguishing between Supply and Demand: Evidence from SME Credit Access Surveys

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. As noted above, these inferences are useful because they shed light on the cross-section of borrowers. These findings also suggest an indirect yet novel insight that the average affected SME cannot offset the loss in bank funding by using other sources of debt capital.

One concern with the borrower-level tests is that *Affected bank* and *Affected borrower* are susceptible to the impact of confounding fundamentals. 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 address this issue by using confidential microdata from the ECB's Survey on Access to Finance of Enterprises—the most comprehensive SME credit access survey in Europe. The benefit of this dataset is that it captures borrowers' credit access and loan 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)). I run the following model at the SME-half-year level, as per the unit of observation in the survey.

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

SME bank credit access is an indicator variable that switches on for respondents that receive most or all of the credit amount they wanted to get. (The sample consists only of SMEs that reported to have applied for a bank loan in a given survey.) *ECL regime* is a dummy that equals one for observations whose responses pertain to 2018 and 2019. I code *Affected borrower ECB* as an indicator variable for SMEs whose ECL impact score exceeds the sample median.[33] The controls vector includes SME size, age, credit quality, sales growth, and profitability growth.

The sample statistics are presented in Panel A of Table 5. Firms have relatively good access to bank credit, as *SME access to bank credit* switches on for more than three-quarters of the sample (Casey and O'Toole (2014), Ferrando, Popov, and Udell (2017)). Turning to applicant

[33] In the SAFE data, borrower identities are anonymized. To overcome this issue, I match surveyed borrowers following prior work (Ferrando and Mulier (2013), Mayordomo and Rodriguez-Moreno (2018)). First, I bring in the borrower-level impact scores that I obtain for Amadeus borrowers. 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 country-size-grid-level scores to each borrower in the survey. This matching allows me to create a borrower-level intensity score for the survey.

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 3.1%. But, interestingly, they do *not* face the same problem for trade credit (column 2), which further alleviates confounding fundamentals/demand-side concerns. Namely, if affected SMEs got rejected because they were unobservably poorer quality, then a similar deterioration should arise in their access to trade credit.

6. LOAN-LEVEL ANALYSIS: HOW DO ECL RULES AFFECT CREDIT TERMS?

While the borrower-level tests above capture SMEs' financing decisions, these analyses do not directly address the extent to which specific terms of credit change. To improve my analysis along these dimensions, I examine loan-level data from the European DataWarehouse.[34]

I match the originating lender of these loans to my bank-level dataset and estimate the following regression model on credit contracts originated throughout the sample period.

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

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; *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.[35] *Contract term* includes four main clauses: *Interest rate*, *Loan maturity*, *Loan amount*, and *Payment frequency*. *Borrower risk* is the lender's internal LGD estimate on the loan.

[34] This source includes details on SME-loan contracts that are securitized (e.g., Ertan, Loumioti, and Wittenberg-Moerman (2017)). For more information, see https://eurodw.eu/wp-content/uploads/ABS-Market-Coverage.pdf.

[35] The model in Equation 4 does not include borrower fixed effects because firm identities are unknown.

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 under the ECL regime are more expensive than before in a DiD sense. While money is a commodity, SMEs rely on relationship borrowing and are much less able to switch lenders than corporate borrowers (e.g., Petersen and Rajan (1994), Berger and Udell (2006)). Loan maturity is another dimension that might be affected by ECL. 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 lifetime loss calculations are lower in magnitude and easier to make for short-maturity contracts.[36]

A third consideration is the amount of credit. This aspect of loan contracting helps explore the intensive margins, whereas the borrower-level analysis in the preceding section speaks to the extensive margin. Furthermore, this test works as a cross-check for the supply-demand distinction. Namely, if the increasing interest rates were driven by an increase in borrower demand (the alternative explanation), then loan amounts should increase because this explanation predicts a leftward shift in the demand curve. In contrast, if the cost of credit rises as banks' willingness to lend falls (my argument), loan amounts should decrease because this explanation predicts a leftward shift in the supply curve. In addition to loan amounts, I also examine payment frequency. Lenders require frequent payments as an automated way of monitoring the borrower (e.g., Sutherland (2018)). Required payments should become more frequent if affected banks worry more about repayment risk or if lending becomes more transactional post ECL.

[36] In keeping with these results, the European Systemic Risk Board predicted that banks may react to ECL by shortening the maturity of loans and rolling them over more frequently. Source: https://www.esrb.europa.eu/pub/pdf/reports/20170717_fin_stab_imp_IFRS_9.en.pdf

Table 6 reports the relevant summary statistics and estimation results. Panel A shows that affected banks originate about 17% of the sample loan contracts. Over one-third of the sample contracts belong to the post period. The median loan has an interest spread of 3.10 percentage points and a maturity of five years.

Panel B of Table 6 presents the estimation results for the loan-level sample. The estimates in the first two columns suggest a relative increase in the interest affected banks charge their SME borrowers. This figure is about 1.1 percentage points 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 drop of 1.7 years in loan maturity, some 120 thousand euros reduction in loan amounts, and almost three-quarters of an additional payment per year. I note that despite the slight decrease in the sample size, my conclusions hold when controlling for *Borrower risk.*

Another advantage of the loan-level data is that it allows the researcher to explore whether these results are more pronounced for a particular group of borrowers. As in the previous tests and following prior work (e.g., Berger et al. (2005)), I focus on borrower size. Consistent with my previous findings, I observe that loan costs rise, maturities decline, and amounts decrease primarily, if not exclusively, for smaller borrowers (Panel C of Table 6). Overall, my analysis of the loan-level data provides inferences consistent with the paper's main takeaway: banks affected by ECL reduce credit quantities and increase credit costs for small businesses.

7. CONCLUSION

A fundamental construct in the research and practice of bank accounting is loan loss provisions. Since the Global Financial Crisis, standard setters have transformed accounting loan-loss recognition, moving it from the formerly criticized incurred-loss system to an expected credit loss framework. The new model, labeled as ECL under IFRS, requires that provisions are determined in a more forward-looking manner; with the use of a variety of inputs; and for the entire credit portfolio. The aim is to provide a more comprehensive and accurate representation of banks' credit risk and fair value. Nevertheless, the ECL model is also a significant undertaking that is difficult to implement and practice, entailing sizable costs and commitments. Furthermore, provisions under ECL reduce reported performance and induce greater volatility in banks' financial statements. Ultimately, banks could respond to these challenges by altering their real activities, mainly by cutting back on loans or adjusting loan terms for risky and opaque borrowers such as SMEs.

This paper aims to examine the effects of ECL adoption on SME credit landscape. SMEs are an economically important and under-researched group of firms that depend primarily on their relationship banks for external funding. Using bank-level, borrower-level, and contract-level samples that capture banks' lending decisions, I analyze the SME-credit landscape post ECL. I find that the ECL introduction adversely affected the bank credit access of small businesses. The new rules seem to lead to a decline in SME credit amounts and loan maturities while increasing interest costs and collateral requirements for these entities. These inferences provide empirical support for some of the concerns observers have expressed about ECL (Laux (2012), FSB (2019), EBF (2019)).

This paper's in-depth analysis presents a valuable yet partial piece of a mosaic that is necessary to evaluate ECL conclusively. Certainly, more work is needed to ascertain how banks adapt and respond to the new rules in the long term. Furthermore, the main objective of the ECL model is to reduce procyclicality by requiring banks to deal with loan losses that have not yet occurred. To this end, how banks fare in the next down-cycle will be a critical test.

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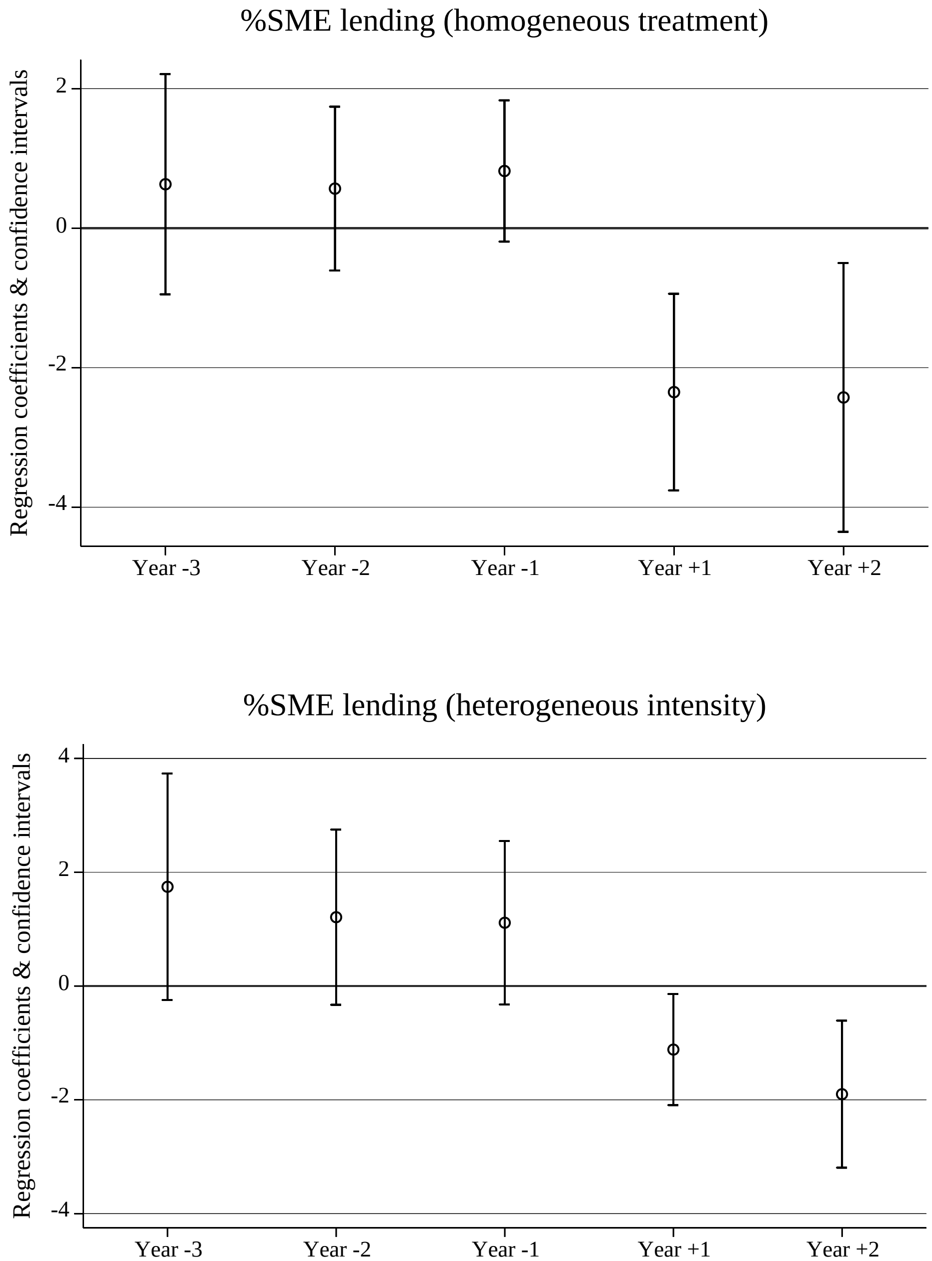
Figure 1. Period-by-period analysis of the effect of the ECL transition on SME lending



This figure presents the conditional evolution of the SME lending difference between treatment and control banks. Each node represents the corresponding DiD estimate from the regressions. Each observation year is separately interacted with *Affected bank homogeneous* (figure on the top) and *Affected bank heterogeneous* (figure on the bottom). The baseline year is 2017.

Table 1. Real Effects of Expected Credit Losses: Bank Lending

This table provides the descriptive statistics for the bank-level sample (excluding degenerate moments for dummy variables). Panels A1 and A2 detail the homogeneous treatment sample (IFRS banks vs. non-IFRS banks). Panels B1 and B2 present the summary statistics for the heterogeneous sample (high-ECL impact vs. low-ECL impact, within the sample of IFRS banks). Variable definitions, including relevant data sources, are in Appendix B.

	Panel A1. Homogeneous Treatment (Affected Bank = 1, N = 855)					Panel A2. Homogeneous Treatment (Affected Bank = 0, N = 70)				
	Mean	stdev	p10	p50	p90	Mean	stdev	p10	p50	p90
SME lending (% assets)	14.412	8.542	4.237	12.827	26.691	18.920	13.275	0.271	19.536	41.166
SME lending (log)	23.540	1.367	21.748	23.552	25.323	22.651	1.670	19.905	22.954	24.339
Bank size (log)	25.590	1.493	23.687	25.541	27.862	24.834	0.452	24.379	24.953	25.673
Bank capital (%)	7.366	2.811	4.618	6.859	11.581	11.337	9.991	3.461	7.236	31.881
Bank profitability (%)	6.190	6.426	1.035	6.750	12.554	2.911	2.154	0.079	2.469	5.922
Bank interest expense (%)	1.205	1.103	0.311	0.919	2.445	1.633	1.053	0.129	1.866	2.913
Bank interest income (%)	2.466	1.206	1.395	2.078	4.147	2.267	0.587	1.610	2.225	2.984
Bank asset risk (%)	37.286	12.114	23.626	36.101	52.832	37.061	19.538	14.947	28.597	71.589
Bank NPLs (%)	3.503	3.525	0.589	2.382	8.018	0.677	0.519	0.197	0.485	1.547

Bank level

	Panel B1. Heterogeneous Treatment (Affected Bank = 1, N = 426)					Panel B2. Heterogeneous Treatment (Affected Bank = 0, N = 429)				
	Mean	stdev	p10	p50	p90	Mean	stdev	p10	p50	p90
SME lending (% assets)	14.221	9.042	3.624	14.049	27.089	14.602	8.020	6.571	12.457	26.451
SME lending (log)	23.677	1.190	21.818	23.915	25.214	23.404	1.511	21.247	23.409	25.532
Bank size (log)	25.778	1.406	24.190	25.847	27.665	25.403	1.555	23.657	25.240	27.924
Bank capital (%)	7.095	2.607	4.730	6.114	11.508	7.635	2.978	4.563	7.138	12.434
Bank profitability (%)	6.118	6.044	0.589	6.554	11.946	6.261	6.790	1.035	6.847	12.985
Bank interest expense (%)	1.189	1.066	0.331	0.868	2.372	1.222	1.139	0.287	0.980	2.516
Bank interest income (%)	2.430	1.109	1.457	2.078	4.160	2.502	1.295	1.380	2.077	4.147
Bank asset risk (%)	35.798	13.010	23.535	33.676	55.917	38.764	10.970	23.939	38.302	51.634
Bank NPLs (%)	3.031	3.585	0.452	1.843	7.289	3.972	3.405	0.953	2.782	9.044

Table 2. Bank-level Tests of SME Lending: Main Results

This table describes an empirical analysis of the ECL regime from the banks' perspective. Panel A includes estimation results for the homogeneous treatment sample (IFRS banks vs. non-IFRS banks). Panel B presents the results for the heterogeneous treatment sample (high-ECL impact vs. low-ECL impact, within the sample of IFRS banks). Variable definitions, including relevant data sources, are in Appendix B. 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. SME lending: IFRS banks vs. non-IFRS banks

	(1)	(2)
	SME lending (%)	*SME lending (%)*
Affected bank homogeneous	-2.384*	-2.911***
× ECL regime	(-1.94)	(-3.28)
Bank size		5.531**
		(2.21)
Bank capital		0.842***
		(2.71)
Bank profitability		0.006
		(0.17)
Bank funding costs		1.025
		(0.97)
Bank interest income		-1.011
		(-1.03)
Bank asset risk		0.007
		(0.07)
Bank NPLs		-0.055
		(-0.32)
Observations	925	925
Adjusted R-squared	90.9%	91.5%
Time FE	Y	Y
Bank FE	Y	Y

Panel B. SME lending: IFRS banks with high impact vs. IFRS banks with low impact

	(1)	(2)
	SME lending (%)	*SME lending (%)*
Affected bank heterogeneous	-2.541***	-2.317**
× ECL regime	(-2.77)	(-2.61)
Bank size		5.227**
		(2.14)
Bank capital		0.614*
		(1.89)
Bank profitability		0.025
		(0.78)
Bank funding costs		1.001
		(0.97)
Bank interest income		-0.787
		(-0.78)
Bank asset risk		0.007
		(0.08)
Bank nonperforming loans		0.041
		(0.26)
Observations	855	855
Adjusted R-squared	89.9%	90.4%
Time FE	Y	Y
Bank FE	Y	Y

Table 3. Bank-level Tests of SME Lending: Cross-sectional Results on the Mechanisms

This table describes an empirical analysis of the expected credit loss regime from the banks' perspective. The tests depicted in this table rely on sample splits. In Panel A, the sample split is conducted on the capital slack, calculated as the bank's reported capital minus all the relevant bank-specific capital surcharges obtained from the European Systemic Risk Board. (Treatment and control groups are separately split into high and low subsamples to ensure consistent sample sizes.) In Panel B, the sample split is performed on total assets. The sample split in Panels C is carried out within the ECL group (i.e., heterogeneous intensity sample) due to the lack of availability of this data for non-IFRS banks. The median of the resulting distribution is used to split the sample. Pay-performance sensitivity information comes from Capital IQ, computed as the CEO's variable compensation as a percentage of total compensation as of 2017. All previous controls include the full controls vector in Table 2. Variable definitions appear in Appendix B. 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. Cross-sectional variation in the main results with regulatory capital constraints

	(1)	(2)	(3)	(4)
	Low slack	High slack	Low slack	High slack
	Affected bank: *Affected bank homogeneous*		Affected bank: *Affected bank heterogeneous*	
	SME lending (%)	*SME lending (%)*	*SME lending (%)*	*SME lending (%)*
Affected bank × ECL regime	-2.912***	-2.345	-1.583*	-3.219**
	(-3.66)	(-1.49)	(-1.73)	(-2.07)
Observations	460	456	425	421
Adjusted R-squared	95.4%	91.1%	95.6%	88.9%
All previous controls	Y	Y	Y	Y
Bank and Time FE	Y	Y	Y	Y

Panel B. Cross-sectional variation in the main results with bank size

	(1)	(2)	(3)	(4)
	Large Bank	Small Bank	Large Bank	Small Bank
	Affected bank: *Affected bank homogeneous*		Affected bank: *Affected bank heterogeneous*	
	SME lending (%)	*SME lending (%)*	*SME lending (%)*	*SME lending (%)*
Affected bank × ECL regime	-2.253	-4.226***	-1.726*	-2.687*
	(-1.47)	(-3.78)	(-1.78)	(-1.72)
Observations	464	461	429	426
Adjusted R-squared	96.7%	88.1%	96.2%	87.3%
All previous controls	Y	Y	Y	Y
Bank and Time FE	Y	Y	Y	Y

Panel C. Cross-sectional variation with external financing frictions and pay-performance sensitivity

	(1)	(2)	(3)	(4)
	Low external financing frictions	High external financing frictions	Low pay-performance sensitivity	High pay-performance sensitivity
	SME lending (%)	*SME lending (%)*	*SME lending (%)*	*SME lending (%)*
Affected bank × ECL regime	-1.272	-2.682**	-2.601	-4.317***
	(-1.44)	(-1.99)	(-1.03)	(-3.09)
Observations	465	444	256	286
Adjusted R-squared	93.1%	83.7%	92.1%	88.6%
All previous controls, Bank and Time FE	Y	Y	Y	Y

Table 4. Borrower-level Tests of SME Borrowing: Evidence on Realized Credit Amounts

This table describes an empirical analysis of the expected credit loss regime from the borrowers' perspective. 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). Panel B presents the estimation results. *Affected borrower* is an indicator variable that switches on for borrowers that do business with affected banks. *ECL regime* is an indicator variable that equals one for periods 2018 and 2019. The dependent variable is *Debt holding*, the natural logarithm of bank debt. Panel B also reports results from subsample analyses based on size and opacity cuts (columns 3 through 6). The size cut is made at the median of total assets. Opaque includes companies whose reporting practice is 'Local GAAP' and transparent others (i.e., IFRS). T-statistics shown 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
Affected borrower	0.382					227,756
ECL regime	0.306					227,756
Debt holding (log)	11.645	6.225	0.000	14.390	16.819	227,756
Borrower size (log)	16.929	0.989	15.817	16.799	18.169	227,756
Borrower tangibility (%)	97.571	8.532	95.092	99.961	100.000	227,756
Borrower profitability (%)	6.501	10.193	-2.347	4.943	18.890	227,756

Panel B. Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample		Small	Large	Opaque	Transparent
	Debt holding	*Debt holding*	*Debt holding*	*Debt holding*	*Debt holding*	*Debt holding*
Affected borrower × *ECL regime*	-0.185**	-0.186**	-0.189*	-0.102	-0.244***	0.036
	(-2.12)	(-2.50)	(-1.73)	(-0.98)	(-3.02)	(0.20)
Affected borrower	-1.079***					
	(-9.40)					
Observations	227,756	227,756	114,853	112,903	186,016	41,740
Adjusted R-squared	17.0%	77.3%	76.5%	78.6%	76.8%	78.9%
Borrower characteristics	Y	Y	Y	Y	Y	Y
Borrower industry-year FE	Y	Y	Y	Y	Y	Y
Borrower country-year FE	Y	Y	Y	Y	Y	Y
Borrower FE	N	Y	Y	Y	Y	Y

Table 5. Borrower-level Tests of SME Credit Access: Survey Evidence

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). Panels B and C present the estimation results. *Affected borrower (ECB)* is an indicator variable that switches on for borrowers that are estimated to do business with an *Affected bank (heterogeneous)*. *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. *Bank credit access* 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). *Trade credit access* is an indicator variable that switches on if the surveyed SME applied for trade credit and received most or all of the amount it applied for (Survey question Q7b_b). 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	0.476					7,953
Affected borrower (ECB)	0.457					7,953
Bank credit access	0.815					7,953
Trade credit access	0.825					5,544
SME size	2.480	1.006	1.000	3.000	4.000	7,953
SME age	3.852	0.467	3.000	4.000	4.000	7,953
SME credit quality	2.238	0.632	1.000	2.000	3.000	7,953
SME sales growth	2.326	0.787	1.000	3.000	3.000	7,953
SME profitability growth	2.051	0.824	1.000	2.000	3.000	7,953

Panel B. Survey evidence on SME access to bank loans and trade credit

	(1)	(2)
	Bank credit access	*Trade credit access*
Affected borrower (ECB) × ECL regime	-0.031*	0.008
	(-1.75)	(0.38)
Affected borrower (ECB)	0.029	-0.018
	(1.63)	(-0.58)
SME size	0.058***	0.043***
	(8.12)	(5.30)
SME age	0.048***	0.055***
	(4.24)	(4.35)
SME credit quality	0.062***	0.062***
	(7.99)	(6.39)
SME sales growth	0.008	0.003
	(1.13)	(0.38)
SME profitability growth	0.021***	0.029***
	(3.28)	(3.75)
Observations	7,953	5,544
Adjusted R-squared	0.074	0.046
Country FE, Industry FE, and Time FE	Y	Y

Table 6. Loan-level Tests of SME Lending

This table describes an empirical analysis of the ECL regime using individual loan contracts. 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. The size-based sample split in Panel C is conducted using the European DataWarehouse's borrower category classification for SMEs: Large borrowers include medium-sized enterprises, whereas small borrowers include small-sized and micro-sized borrowers. All variables are defined in Appendix B. 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
ECL regime	0.350					334,251
Affected bank	0.170					334,251
Interest rate (%)	3.456	1.779	1.450	3.100	5.950	334,251
Loan maturity	5.228	4.236	1.000	5.000	10.000	334,251
Loan amount (€000)	101.404	302.025	14.337	32.000	200.000	334,251
Payment frequency	11.162	2.789	12.000	12.000	12.000	334,251
Borrower risk (%)	33.110	15.034	18.000	32.000	54.000	290,075

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	1.141***	1.137***	-1.736***	-1.760***	-118.185***	-119.191***	0.757***	0.747***
	(24.13)	(26.14)	(-9.20)	(-7.77)	(-21.63)	(-19.36)	(10.04)	(10.08)
Borrower risk		0.013		-0.081***		-1.272		-0.006
		(1.01)		(-3.34)		(-1.12)		(-1.08)
Observations	334,251	290,075	334,251	290,075	334,251	290,075	334,251	290,075
Adjusted R-squared	33.2%	26.5%	33.2%	39.8%	8.2%	9.8%	27.4%	28.2%
Bank and Year 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. Variation in the main effect by borrower size

	(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	1.055***	0.137***	-2.290***	-0.058	-43.377***	-73.772***	0.744***	0.148
	(19.97)	(5.32)	(-9.37)	(-0.16)	(-18.17)	(-6.05)	(12.78)	(0.99)
Subsample includes	Small borrowers	Large borrowers	Small borrowers	Large borrowers	Small borrowers	Large borrowers	Small borrowers	Large borrowers
Observations	218,421	114,441	218,421	114,441	218,421	114,441	218,421	114,441
Adjusted R-squared	34.6%	41.2%	17.3%	53.4%	5.4%	15.0%	25.8%	34.8%
Bank and Year 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

Appendix A. 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**

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.

Appendix B. Variable Definitions

Panel A depicts the bank-level samples analyzed in Tables 1, 2, and 3, as well as the tables in Appendix C. The variables in Panel B (Panel C) pertain to the borrower-level tests presented in Table 4 (Table 5). The definitions in Panel D are for the loan-level tests in Table 6.

Panel A. Bank-level analysis

Variable Name	Definition	Data Source
Affected bank (homogeneous)	An indicator that equals one for banks that report under IFRS, thus adopted IFRS 9 in 2018.	SNL Financial, EBA
Affected bank (heterogeneous)	An 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 on 01.01.2018 and IAS 39 loan loss allowances on 31.12.2017 divided by the latter. (Defined for IFRS banks only.)	Bank annual reports and transition disclosures See Appendix A for examples.
ECL regime	Indicator equals one for periods from January 2018.	n/a
SME lending (% assets)	SME lending, as a fraction of total exposures of the bank.	EBA Transparency Exercise results.
Bank size	Total assets in USD (used in the natural logarithm form).	SNL Financial (field #132264).
Bank capital	Total equity divided by total assets (%).	SNL Financial (fields #132385 and #132264).
Bank profitability	Return on average equity (%).	SNL Financial (field #132006).
Bank interest income	Annual interest income as a fraction of total assets (%).	SNL Financial (fields #132450 and #132264).
Bank funding costs	Annual interest expense as a fraction of interest-bearing liabilities (%).	SNL Financial (field #133833).
Bank asset risk	The ratio of total risk-weighted assets to total assets (%).	SNL Financial (fields #248884 and #132264)
Bank NPLs	The ratio of nonperforming loans to total assets (%).	SNL Financial (fields #243681 and #132264)

Panel B. Borrower-level sample (Amadeus)

Variable Name	Definition	Data Source
ECL regime	Indicator that equals one for periods from January 2018.	n/a
Affected borrower (BvD)	Indicator that equals one for SMEs with at least one relationship bank that is coded as *Affected bank (homogeneous)*.	Bank annual reports and transition disclosures, and Bureau van Dijk Amadeus Bankers.
Debt holding	Natural logarithm of total bank debt.	Amadeus Financials (mnemonics *loan* and *ltdb)*
Borrower size	Natural logarithm of total assets.	Amadeus Financials (mnemonic *toas*)
Borrower tangibility	Percentage ratio of total tangible assets to total assets.	Amadeus Financials (mnemonics *ifas* and *toas*)
Borrower profitability	Pre-tax income as a percentage of total assets.	Amadeus Financials (mnemonics *plbt* and *toas*)

Panel C. Borrower-level sample (Survey)

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-country grids that have an *Affected bank* score of above median.	Bank annual reports and transition disclosures and Bureau van Dijk Amadeus Bankers.
SME access to bank credit	Indicator that equals one if the SME got most or all of the bank credit it applied for.	ECB SAFE (Original question: Q7b_a).
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).

Panel D. Loan-level analysis

Variable Name	Definition	Data Source
ECL regime	Indicator that 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 Appendix A for examples.
Interest rate	Percentage credit spread.	ECB Loan-level Data (variable as80).
Borrower risk	Bank's internal estimate of loss given default ratio 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	Loan amount in thousand euros.	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 and as50).

Appendix C. Additional Robustness Tests

Appendix Table 1. Individual interaction terms for bank characteristics

This table describes an empirical analysis of the expected credit loss regime from the banks' perspective. Each control term is defined as a dummy variable, which is included in the regression as a separate regressor as well as an interaction term with the post variable (*ECL regime*). For instance, *High Bank Size* denotes observations with above-sample-median size (as of 2017), and *ECL regime* × *High Bank* is the pertinent interaction term. All other variables are as defined in Appendix B. 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.

	(1)	(2)
	SME lending (%)	*SME lending (%)*
ECL regime × Affected bank homogeneous	-3.587*	
	(-1.90)	
ECL regime × Affected bank heterogeneous		-2.123**
		(-2.42)
ECL regime × High bank size	-0.240	-0.316
	(-0.20)	(-0.26)
ECL regime × High bank capital	-0.780	-0.691
	(-0.98)	(-0.84)
ECL regime × High bank profitability	0.360	0.600
	(0.39)	(0.63)
ECL regime × High bank funding costs	1.613	1.665
	(1.48)	(1.60)
ECL regime × High bank interest income	-1.417	-1.196
	(-1.51)	(-1.41)
ECL regime × High bank asset risk	1.373	1.107
	(1.31)	(1.08)
ECL regime × High bank NPLs	1.057	0.658
	(1.12)	(0.76)
Observations	925	855
Adjusted R-squared	91.2%	90.1%
Uninteracted controls	Y^	Y^
Bank and Time FE	Y	Y

^ subsumed

Appendix Table 2. Evidence on banks' switching to Nonlending assets

This table describes an empirical analysis of the expected credit loss regime from the banks' perspective. *Nonlending assets (%)* is total exposures less retail, mortgage, corporate, and SME lending, divided by total exposures and presented in percentage points. All other variables are as defined in Appendix B. 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.

	(1)	(2)
	Nonlending assets (%)	*Nonlending assets (%)*
ECL regime × Affected bank homogeneous	2.879***	
	(3.38)	
ECL regime × Affected bank heterogeneous		1.451*
		(1.81)
Bank size	-6.753**	-6.636**
	(-2.31)	(-2.25)
Bank capital	-0.561	-0.429
	(-1.27)	(-0.84)
Bank profitability	0.047	0.034
	(1.21)	(0.82)
Bank funding costs	0.239	0.063
	(0.19)	(0.05)
Bank interest income	-0.435	-0.510
	(-0.39)	(-0.44)
Bank asset risk	-0.278*	-0.280*
	(-1.98)	(-1.94)
Bank NPLs	0.318*	0.270
	(1.90)	(1.57)
Observations	891	831
Adjusted R-squared	0.964	0.962
Bank and Time FE	Y	Y