Bank reporting of Loan Loss Provisions under IFRS9: implications for security analysts

ABSTRACT. The introduction of the IFRS9 forward-looking principle-based Expected Credit Loss (ECL) model, replacing the IAS39 Incurred Credit Loss (ICL) model, is known by practitioners to have been a game changer both for banks and capital market participants. Using an international sample of banks reporting under IFRS from 2012 to 2020, we investigate the implications of reporting Loan Loss Provision (LLP) based on the ECL model for security analysts' LLP forecasts. We find that reporting of LLP based on the ECL model both increases the accuracy and decreases the dispersion of analysts' LLP forecasts. In cross sectional test, we also find that the higher accuracy and lower dispersion of analysts' LLP forecasts under IFRS9 mainly holds in the case of banks exhibiting a richer information environment and low-risk profile. Overall, these findings provide evidence that the shift from the ECL to ICL model brings about convergence between analysts' and CEOs' expectation of banks' future credit loss.

Keywords: Loan loss provision, expected credit loss, incurred credit loss, IFRS 9, security analysts

1. Introduction

Credit losses in the banking sector plays a central role in the evaluation of risks and stability of banks, and thus have substantial significance, not only for banks but also regulators and market participants. While loans represent banks' largest asset class, loan loss provisions are the largest expense in banks' income statements (Beatty and Liao, 2011, 2014). As a result, credit losses are often the primary reason behind bank failures (Ahmed *et al.* 1999; Gebhardt and Novotny-Farkas 2011).

The former IFRS-based loan loss accounting standards (IAS39) prescribed using the "incurred loss" model (thereafter, the ICL model), in which only actual incurred losses (not anticipated losses) were accounted for in Loan Loss Provisions (thereafter, LLP). This model delays the recognition of expected future losses during economic downturns such as the 2008 Global Financial Crisis (Barth and Landsman, 2010; Beatty and Liao, 2011; Bushman and Williams, 2012; Kanagaretnam et al., 2009). A criticism to this model is that the ICL model leads to inadequate provisioning for loan losses, especially anticipated losses, during good times, so that during bad times higher charges against regulatory capital occur once these losses are realised (Laeven and Majnoni, 2003). Available evidence suggests that although reported LLP increased dramatically (Archaya and Ryan, 2016; Shaffer, 2010), it was still inadequate as compared to outside LLP estimates (Laux and Leuz, 2010). In response to calls from investment practitioners, bank regulators and accounting standard setters, the accounting for loan loss provisioning moved from the ICL model to an Expected Credit Loss model (thereafter, the ECL model), following the enforcement of IFRS9.

The ECL model introduces more judgment into the loan loss provisioning as banks must account for potential credit loss right at the time of loan origination – a radical change as compared to the IAS39 prescriptions. Extant literature provides evidence on economic implications of the shift from a backward-looking to a forward-looking model of loan loss provisioning. For instance, Gomaa *et al.* (2019) documents that management's forward-looking information based on the ECL model increases both the amount and adequacy of banks periodic reserves decisions, and more engagement in earnings management. Recently, Kim *et al.* (2021) find that using forward-looking LLP significantly increases loan loss recognition timeliness relative to the historical approach. Similarly, Oberson (2021) shows that the shift to the forward-looking approach improves the timeliness of loan loss provisioning, and managers their discretion offered by the flexibility under the ECL model to smooth earnings more aggressively. In addition, he shows that LLPs become more relevant for credit default swaps (CDS) pricing after IFRS 9 enforcement. In another related study, Beatty and Liao (2015) show that analyst' forward-looking LLP forecasts are more accurate in predicting future LLP than time series-based forecasts based on historical information, suggesting that analysts have a comparative advantage, and their knowledge production is informative to equity participants. Finally, Wheeler (2021) develops a measure of lifetime ECL and finds that bank's stock prices reflect the discrepancy between this measure and the reported measure based on the ICL model.

Although the extant literature on LLP provides evidence on implications of the shift to the ECL model, it is yet to examine the effect of reporting LLP based on the ECL model for security analysts' LLP forecasts. Our paper aims at filling this research gap.

In this paper we investigate the implications of reporting LLP based on the ECL model (following IFRS9 enforcement) for analysts' LLP forecast. This research is particularly relevant for several reasons. First, LLP is the largest bank accrual, and thus accounting for expected credit losses (vs incurred losses based on IAS 39 prior to IFRS 9 enforcement) is considered as a game changer for banks. Second, IFRS 9 was intentionally enforced to assist producing relevant and useful financial information about financial assets/liabilities that facilitates assessment of the amounts, timing, and uncertainty of the bank's future cash flows. Finally, security analysts' forecasts of accounting numbers have been documented to play an important role in facilitating assessment of the amounts, timing, and uncertainty of firms' future cash flows.

Using an international sample of banks reporting under IFRS from 2012 to 2020, we find that the reporting of LLP based on the ECL model both increases the accuracy and decreases the dispersion of analyst LLP forecasts. This finding could be because of an important reason. Following the observed reduction in the level of disagreement among analysts regarding a bank's expected credit loss in the future, a bank CEO could potentially manipulate the reported LLP with an intention to be seen less different from analyst forecasts, and this results in a convergence between CEOs' and analysts' expectation of future credit loss. Since CEOs' intention to engage in LLP manipulation is not directly observable, we further test our hypotheses in four situational scenarios, where CEOs have greater flexibility and opportunities to engage in LLP manipulation – namely, Small vs. Large banks, banks with High vs. Low bid-ask spread, banks with Low vs. High analyst coverage and High vs. Low risk-taking banks. Interestingly, we find that in all these situational scenarios, our primary finding as to higher forecasts and accuracy lower dispersion mainly holds when the bank information environment is richer (i.e., large banks, banks with low bid-ask spread and covered by more analysts) and banks with lower risk profile (i.e., banks with low NPL proportion). These findings rule out the argument that the observed improvement in analyst forecast properties is merely driven by CEOs' manipulation of LLPs.

The contribution of this study is twofold. First, while the nascent literature on loan loss provisioning under IFRS 9 has documented implications of LLP reporting based on the ECL model in various contexts, such as banks' periodic reserves decisions, earnings management, CDS pricing, and stock price reactions as compared to the ICL model, the implications for analysts' forecasts has not been studied. To the best of our knowledge, this is the first academic paper that investigates whether and how ECL-based LLP reporting affects the properties of security analysts' forecasts. Our study also contributes to the literature on security analysts' LLP forecasts. This is the first study that documents an improvement in the properties of security analysts' LLP forecasts in view of IFRS 9 enforcement, providing evidence that the shift to the ECL model enriches analysts' information environment.

The rest of the paper is structured as follows. Section 2 reviews the existing literature, section 3 develops testable hypotheses. Section 4 presents the research design and the data used. Section 5 presents and discusses the empirical results.

2. Literature Review

Our focus is on commercial banks' loan loss provisions (LLP), which is the periodic expense account for banks' estimated uncollectible loans. It is related to the Allowance for Loan Losses (ALL) account, a contra asset account netted against the gross amount of loans on the balance sheet. ALL is reduced by net charge-offs, the actual net losses charged off against loans, and replenished through recognition of the current period's LLP.

2.1. IAS 39 and its problems

IAS 39 *" Financial Instruments: Recognition and Valuation "* was introduced in 1998 and effective from 2001. To many, it was deemed as one of the most complex standards because it deals with financial products. It brings together the classification of all financial assets and liabilities as well as derivatives in a company's balance sheet. More specifically, it covers financial instruments such as investment, equity, debt and derivative instruments, and assets and liabilities held for financial purposes. The outcomes of IAS 39 were major for reporting entities- noticeably so for banks- with the standard establishing rules on accounting principles and valuations of the financial products mentioned above.

IAS 39 presented several obligations that impacted the presentation of a company's financial report. The main points addressed by this standard was the recognition of financial assets at fair value, stricter rules for hedge accounting, and the requirements to report losses on the bank loan portfolios when they materialized, the so-called "incurred loss" model. Under this approach, credit losses were recognized only in the presence of evidence of impairment loss. The only elements considered are then past events and present events having an impact on the depreciation.

Initially, when a loan is accounted for, there is no need to record credit losses because the interest rate is supposed to cover all the losses of the loan. However, the economic value of the loan should be adjusted over its lifetime due to the estimated change in its probability of default and interest rate.

The losses incurred are calculated as follows:

$$EL_t = PD_t(I_t) \text{ x } LGD_t(I_t) \text{ x } dr$$

EL_t is the estimate of expected losses, $PD_t(I_t)$ is the sum of the default probabilities, $LGD_t(I_t)$ is the default loss and dr is the discount rate.

The probability of default is the probability that a debtor will not be able to repay his debt.

The peculiarity of the credit loss estimation model under IAS 39 is that it only takes into account credit risks when there is definite evidence of the loss incurred at the balance sheet date. If a future event is expected after the balance sheet date, the loss will not be recognised.

Another important point addressed by IAS 39, and one of its main objectives, is to provide greater transparency. It aims to make financial institutions clearer. Transparency in financial reporting is the extent to which financial reporting reveals the underlying economic aspects of an entity in a way that is easily understandable to those who use financial reporting (Barth, Schipper,2008). Transparency is promoted by improving the comprehensibility of data contained in financial reports. While the adoption of IAS 39 improves the quality of information provided in the accounting of banks in the United States (Duh, Hsu, Alves, 2012), IAS 39 does not representatively show the financial reality of banks in Asia (Finch,2010). This standard has sparked much debate, the most important being its involvement in the economic crisis of 2007-2008. The ICL model can result in pro-cyclical lending where banks lend more in good times, but less in bad times when their capital adequacy ratios are compromised by large loan loss accruals, thereby worsening the economic downturn (Beatty and Liao, 2011; Hodder et al., 2014). These criticisms were heightened shortly after the Global Financial Crisis.

It had twelve amendments or revisions since and was designated as one of the main culprit for the 2007 crisis, blamed for reporting losses too late. Empirical evidence on the benefits of IAS39 were mixed at best, as some had considered it incomplete or too complex (e.g. Camfferman 2015).

On March 19, 2008, in a discussion paper entitled "*Reducing complexity in Reporting Financial Instruments*", the IASB reported that the various users of IAS 39 found the standard too complex, was not taking into account the management intention, was lacking transparency, and did not anticipate possible market events related to the depreciation of assets. All this questioning of IAS 39, accentuated by the fact that the standard was seen as an accelerator of the GFC, led the IASB to work on the creation of IFRS 9.

2.2. The transition to IFRS 9

The IASB developed IFRS 9 in three phases, dealing separately with the classification and measurement of financial assets, impairment and hedging. Other aspects of IAS 39, such as scope, recognition, and derecognition of financial assets, have survived with only a few modifications. The IASB released updated versions of IFRS 9 as each phase was completed or amended, and, as each phase was finished, entities had the opportunity of adopting the updated version. The final standard was issued in July 2014 with implementation for years beginning on or after January 1, 2018 and earlier adoption permitted. The new standard contains major changes from the old standard on financial instruments IAS 39. These changes concern the classification, measurement and hedge accounting requirements. The implementation of IFRS 9 impacted many entities, including the banking sector.

2.2.1. Classification and measurement of financial assets

The first major change in IFRS 9 dealt with the classification and measurement of financial assets. Classification determines how financial assets are measured in financial statements. The requirements for depreciation and hedge accounting are also based on this classification. Unlike IAS 39, classification under IFRS9 is based on the entity's business model. For debt instruments, the standard takes into account how these assets are managed (the business model test) and their cash flow characteristics (the “SPPI” test), and it is only when both tests pass that the financial asset may be measured at amortized cost. Because these two tests are more stringent than under IAS39, financial assets are now more likely to be measured at fair value. The classification of financial liabilities under IFRS 9 remains the same as in IAS 39.

2.2.2. Depreciation and expected credit loss model

The IASB has sought to address a major concern raised as a result of the financial crisis: the depreciation of financial assets. The credit loss model used under IAS 39 contributed to the delay in the recognition of credit losses. The IASB has introduced a new model of expected credit losses under IFRS 9. The guiding principle of the expected credit loss model is to reflect the general pattern of deterioration or improvement in the credit quality of financial instruments. The amount of expected credit losses is recognized as a provision for losses. The amount of provisioning depends on the extent of the deterioration of the credit since its initial recognition. At each financial reporting period, expected credit losses are recognized, even in the absence of an event involving a change in losses. Reasonable forward-looking information that can be obtained without incurring costs is taken into account when valuing the impairment loss, in addition to current and past events.

Thus, IFRS 9 introduced a forward-looking approach that takes into account more information and better represents the credit value at a given time *t*. This forward-looking approach represents a major challenge for banks. The integration of forward-looking information means that banks moved away from the approach that followed credit loss throughout its cycle, to drift towards a projection of the business cycle of potential credit losses. A method of prospective calculation of the expected credit loss is then used. This method is based on an probability estimate of current and future default*(PD)*,default exposure*(EAD)* and default loss *(LGD)*. The expected losses *(ECL)* are then equal to:

$$ECL = PD \times EAD \times LGD$$

In 2014, the IASB published the elements to be taken into account in order to estimate the losses incurred:

- Credit losses are the present value of all anticipated losses over the entire life of the financial instrument;
- Expected credit losses should reflect an unbiased and weighted amount determined by the assessment of the possible outcomes of the expected loss model;
- When measuring expected credit losses, the entity must identify all possible scenarios. It must consider the risk of whether or not a credit loss occurs, even if the probability of a credit loss is very low;
- Expected credit losses must predict the time value of the money. They must take into account the date of declaration of losses using the effective interest rate;
- In the general approach, companies' financial reports should provide information on past and present events as well as estimates of losses incurred;
- The maximum period to be considered when calculating expected credit losses is the maximum period during which the entity is exposed to credit risk.

IFRS 9 presents 3 different “levels” or “stages” of credit risk:

- Level 1 starts right at loan origination or purchase. Expected credit losses at 12 months are recognised as expenses and a provision for losses is made. The first step serves as an indicator for initial losses on receivables. For financial assets, interest is calculated in relation to the gross book value, without adjustments for losses. For a financial product with a lifespan of more than one year, this process will be applicable as long as there is no deterioration in the quality of the credit until its maturity;
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- Level 2 occurs when a significant increase in credit risk has occurred on an individual or collective basis. An additional provision is then recognised and provisioning is made on the expected losses over the total life of the asset. This step occurs when the debtor defaults during the life of the credit;

- Level 3 occurs when credit losses are incurred due to the deterioration in credit quality or when the asset is impaired. As for the second level, the total life of the credit is taken into account and the recognition will be identical (expected losses and provisions).

Under the accounting framework of IFRS 9, banks must now record provisions for impairment as soon as a financial asset is initially recognised. Therefore, an increase in the credit risk associated with this asset leads to the recognition of additional provisions. This recognition marks a change from IAS 39, which recognized as impairment only credit losses incurred and was based on past quantitative information.

Where the bank considers that the credit risk of a financial instrument has increased significantly compared to its initial recognition, it must record a value adjustment for expected credit losses over the entire life of the financial instrument.

In the event that the credit risk decreases, the financial instrument enters phase 2 and the bank must make the accounting recording of provisions for depreciation.

When an entity uses the expected credit loss model, it must consider:

- basic information available outside of costs or efforts;
- the time value of the money so that expected credit losses are expected at the balancedate.

Although IFRS 9 is very recent and very few results are available regarding this standard, this has not prevented some researchers from focusing on this new standard. The new complex estimation model in IFRS 9 is an improvement over that in IAS 39 because expected credit losses are recognized earlier and are more comprehensive (Günther, 2015). The ECL Model introduced in IFRS 9 allows more information to be taken into account in order to better estimate expected losses (Novotny-Farkas, 2016). In addition, the obligation to disclose information on a more regular basis should increase the transparency of companies and thus improve the quality of the financial market.

Entities must exercise good judgment to take into account available, reasonable and justifiable information about past, present events and forecasts of the future economy in order to correctly estimate expected credit losses.

2.2.3. The impact of IFRS 9 on banks' financial reporting

IFRS 9 had a significant impact on financial reporting in the banking sector and complemented IFRS 7 as regards to the presentation of financial results (PWC 2017). IFRS 7 and IFRS 9 are closely linked, as IFRS 7 impacts the way in which financial reports under the latter must be presented. On the one hand, credit losses must be properly presented in the income statement and in the entity's balance sheet. On the other hand, the risks associated with these credit losses must be presented in the notes of the financial report. Banks subject to IFRS 9 are required to disclose information that explains the basis for their ECL calculations and how they measure ECLs and assess changes in credit risk. They must also provide a reconciliation of the opening and closing ECL amounts and carrying values of the associated assets separately for different categories of ECL (for example, 12-month and lifetime loss amounts) and by asset class. The presentation of risks reflects how the board of directors perceives and measures these risks. Therefore, the use of the expected loss model shall be presented in the financial report notes and the board of management should explain how this model was used to measure their provisions for credit losses.

With IFRS 9, banks have to update their credit risk measures, which were based solely on the probability of default under IAS 39. Now the credit risk is measured over the life of the financial instrument by promoting the implementation of warning signals that can impact it. The enactment of IFRS 9 made the Basel Committee busy regarding the coverage of banks credit risk, credit assessment adjustment framework risk, operational risk framework and leverage ratio. It was already estimated (PWC 2017) that IFRS 9 would increase the amount of bank loan loss provisions and result also in more volatile bank earnings.

2.3. Prior academic findings on LLP bank reporting

2.3.1. Empirical research dealing with the incurred loss model

A wealth of prior research documents the consequences of the ICL model under US GAAP or banks and capital market participants, while may still be enlightening in a IFRS setting. SFAS 5 states that LLP and ALL should be recognised only when it is probable that loans have been impaired at the date of the financial statements and when the amount of losses can be reasonably estimated. Therefore, loan losses should be recognised only when their occurrence is probable. SFAS 5 defines "probable" as a condition where the future event is 'likely to occur'. Recognising that application of the term "probable" in practice requires judgement, and to clarify its intent, the FASB (1999) reiterated that for banks, "probable" does not mean virtually certain, but "probable" is a higher level of likelihood than "more likely than not." In essence, the standards and guidance allowed banks some flexibility in accounting for loan loss accruals. In this vein, prior research documents that banks may manage their earnings via LLP. Prior research shows that banks smooth reported earnings using discretionary loan loss provisioning (Kanagaretnam et al., 2003, 2004) and to anticipate future losses (Bushman and Williams, 2012; Liu and Ryan, 2006), the incurred loss model notwithstanding. Prior research (e.g. Kanagaretnam et al., 2004; Kanagaretnam et al., 2005) also shows that banks use discretionary loan losses to signal expected future earnings changes, which are positively valued by the market. Overall, there is more evidence for smoothing than for signalling (Beatty and Liao, 2014).

2.3.2. Empirical research dealing with the expected credit loss model

Very recent research explored the timeliness of LLP under the IFRS 9 ECL model. Kim *et al.* (2021) examine whether and how the switch to ECL recognition affects the timeliness of banks' provisioning for loan losses. They find that the shift to an ECL model significantly improves loan loss recognition timeliness (LLRT), represented by future change in NPL. The effect is more pronounced for banks that engage in greater risk-taking and record lower loan losses prior to the shift (i.e., less timely LLP) and for banks subject to heavier provisions for underperforming loans after it. Further, the effect of IFRS 9 adoption on enhancing LLRT is more pronounced for banks with proportionately more Stage 2 loans. They also find that the adoption of IFRS 9 extenuates the pro-cyclicality of bank lending and risk-taking. Finally, they find that U.S. banks, which are not subject to IFRS 9, also experience an improvement in LLRT if they have a subsidiary in an IFRS-adopting country.

Oberson (2021) finds that the shift to the ECL model improves the timeliness of loan loss provisioning. Managers also use the greater room for discretion over LLP estimates provided under IFRS 9 to smooth earnings more aggressively, thereby questioning the relevance of LLPs for market participants.

Turning at the incorporation of IFRS 9 info on CDS pricing, the author finds that bank-reported LLPs are more informative for CDS pricing following IFRS9 enactment. Such evidence supports the view that the adoption of IFRS 9 contributed to enhancing the credit-risk relevance of LLPs. Additional tests show that LLPs are more credit-risk relevant for longer CDS maturities than for shorter CDS maturities under IFRS 9, which was not the case under IAS 39. This suggests that bank-reported LLPs contain more forward-looking information under IFRS 9 than IAS 39. Finally, the improvement in the credit-risk relevance of LLPs following the adoption of IFRS9 concentrated amongst banks with weaker pre-IFRS 9 information environments.

Wheeler (2021) find that unrecognized expected credit losses (i.e., expected CL-reported CL) are negatively associated with bank stock prices, consistent with investors being able to obtain information about expected losses that are not recognized in the financial statements. Further, the pricing of these losses is stronger for larger banks, consistent with lower costs of obtaining this information for banks with better information environments. In addition, recorded allowances were less than estimated expected losses, on average, consistent with concerns that implementing the expected loss model may adversely impact regulatory capital adequacy.

Beatty and Liao (2021) finds that analysts' forecasts of loan loss provisions contain information about future changes in nonperforming loans incremental to loan loss provisions for some banks, suggesting that analysts incorporate information about expected losses into their forecasts. Wheeler (2021) also examines whether analysts are a source of information about expected losses for investors. Consistent with Beatty and Liao (2021), the author finds that unrecognized expected losses are associated with analysts' stock price targets, Further, the association between the expected-incurred difference and price is stronger for banks with greater analyst following. These results are consistent with analysts potentially serving as a source of information about expected losses for investors.

Our research builds upon these prior findings and focuses on how the ECL model under IFRS 9 shaped the information environment through the prism of analyst forecasts.

3. Hypothesis Development

Our research question relates to how the extent of a firm's use of the ECL model in measuring LLP enhances or undermines the ability of financial analysts to forecast the firm's future financial performance.

Prior research on analyst behavior shows that an increase in firms' disclosure positively affects analysts' ability to forecasts earnings (e.g. Lang and Lundholm, 1996). Following the enactment of IFRS 9, as seen above banks have to disclose more about the measurement basis for loans classified in Stages 1 (12-month ECL), 2 (Lifetime ECL with EIR calculated on the gross carrying amount) and 3 (Lifetime ECL with EIR calculated on the net carrying amount). Such information was by design not available under IAS39. Hence it is possible that the use of ECL data *improves* analysts' forecasting ability.

The 'incurred loss model' of IAS 39 is a model that requires a relatively low level of judgment by preparers compared to alternative models under local GAAP (Marton and Runesson, 2017). Using a similar argument as in Gebhardt & Novotny-Farkas (2011), the expected loss model under IFRS 9 may be rather deemed to be more relevant but less reliable as it relies on loan credit risk internal estimates over the life of the loan, inherently inducing higher judgment and managerial discretion. In addition, the ECL approach may induce the recognition of more transitory items into reported earnings, thus increasing their volatility but also, presumably, reducing their predictability. Hence it is possible that the use of the ECL model *reduces* analysts' ability to forecast earnings and LLP, even when it perfectly reflects the underlying economic volatility, thus rendering reported earnings and LLP a timely representation of underlying economic performance. Indeed, it forces analysts to distinguish between permanent and temporary changes in value to correctly predict future earnings and LLP.

In light of the above arguments, we put forward the following hypotheses:

H1: IFRS9 enforcement affects the accuracy of analysts' LLP forecasts.

H2: IFRS9 enforcement affects the dispersion of analysts' LLP forecasts.

4. Methodology and data

4.1. Dependent variables

We investigate the effect of IFRS9 enforcement on the analysts' forecast properties – namely forecast accuracy and dispersion. We calculate the forecast accuracy (denoted by *ACCURACY*) as the absolute value of the difference between a firm's reported LLP and the most recent analyst consensus LLP forecast available on I/B/E/S summary files before LLP is publicly announced, scaled by total assets and multiplied by "-1". Forecast dispersion (denoted by *DISPERSION*) is calculated as the most recent standard deviation of analysts' LLP forecasts available on I/B/E/S summary files before LLP is publicly announced, scaled by total assets. All variable definitions are outlined in Appendix.

4.2. Independent and control variables

Our independent variable of interest is *IFRS9*, which is a dichotomy that is coded one for firm-year observations in 2018 and subsequent years; and zero otherwise.

We include several control variables based on prior research. To control for the richness of bank information environment, in all our models, we include analyst following (denoted by *ANALYST_COV*). To control for market environment uncertainty, we include the VIX level averaged over the last 3 months of the year (denoted by *VIX*). We control for bank size (denoted by *SIZE*) using the natural logarithm of total assets. To capture the effect of bank financial strength, we include the amount of Tier 1 capital (denoted by *TIER1*). We control for bank financial performance using the net interest income before LLP (denoted by *EARNINGS*). We also control for banks' past Loan Loss Allowance (denoted by *ALL*). All variable definitions are outlined in Appendix.

To test our hypotheses, we run panel regressions using the above variables, while we control for firm and country fixed effects. All the continuous variables are winsorized at the 1% and 99% of their distributions to mitigate the influence of outliers. Standard errors are clustered at the firm level.

4.3. Data collection and statistics

We collect data from Refinitiv. We require that each bank reports under IFRS and be followed by at least three active financial analysts who provide LLP forecasts. After removing missing observations, our final sample includes 1185 bank-year observations on 202 unique banks in 51 countries for the main tests over the 2012-2020 period.

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5. Empirical results and discussion

5.1. LLP forecast accuracy and dispersion

Table 4 presents results from estimating the models that aim at testing the effect of IFRS9 enforcement on the properties of analysts' LLP forecasts. As we observe in column (1), where *ACCURACY* is the dependent variable, *IFRS9* receives a positive coefficient (significant at the 1% level), thus supporting our *H1*. Based on column (2), where *DISPERSION* is the dependent variable, *IFRS9* receives a negative coefficient (significant at the % level), thus supporting our *H2*. These findings are also economically significant. IFRS9 enforcement (*i.e.*, the change of the *IFRS9* variable from 0 to 1) increases (decreases) forecast accuracy(dispersion) by 38% (57%) of its means value.

INSERT TABLE 4 ABOUT HERE

These results suggest that the change from the ICL to the ECL mode, overall, improves properties of security analysts' LLP forecast properties, and results in a convergence between analysts' and bank CEOs' expectations about the bank's future credit loss. Such a convergence could potentially occur because of one important reason. As previously explained, we employed the most recent consensus analyst LLP forecast and the relevant standard deviation available on I/B/E/S summary files *before the LLP is publicly announced*. Given the documented lower disagreement among analysts regarding a bank's expected credit loss in the future (related to *DISPERSION*, as reported in Table 4), the bank's CEO could potentially manipulate the reported LLP with an intention to be seen less different from analyst forecasts.

It is noteworthy that CEOs' intentions are not directly observable. However, there are situations, which would provide CEOs with greater flexibility/opportunities to engage in LLP manipulation. One such group of situations would be where the level of information asymmetry between CEOs and outsiders is high (i.e., firms with poor information environment). Hence, in the following section, we re-test our hypotheses in situational scenarios characterized by high bid-ask spread (vs. low bid-ask spread), being smaller (vs. large banks), and lower analyst coverage (vs. greater analyst coverage). Furthermore, we repeat our tests in the case of high-risk banks (represented by higher proportion of non-performing loans) as opposed to low-risk banks, with the former providing CEOs with higher incentives to engage in LLP manipulation. If the documented improvement in forecast accuracy is driven by the opportunity these scenarios provide, we expect the primary results to hold in situations characterized by greater information asymmetry (i.e., high bid-ask spread, smaller banks, and banks followed by fewer analysts), as well as the case of high-risk banks. This point of enquiry is investigated in the subsequent sub-section.

5.2. The effect of situational scenarios facilitating CEOs' LLP manipulation

5.2.1. Small vs. Large banks

Table 5 presents results of testing the difference between small vs. large banks with respect to the effect of IFRS9 enforcement on analyst forecast properties, where columns (1) and (2) are dedicated to *ACCURACY* and columns (3) and (4) correspond to *DISPERSION*. A bank is categorized as large if its size (represented by total assets) as at end of 2017 is equal to or greater than the sample median; otherwise, it is categorized as small.

As we observe from the comparison of the coefficient for *IFRS9* between columns (1) and (2), this coefficient is positive and attains statistical significance at the 5% level, only in the case of large firms. This finding is consistent with the argument that the accuracy-increasing result documented in Table 4 does not hold in the case of small banks, which are indeed characterized by poorer information environment (and, thus, greater information asymmetry between them and outsiders).

These results, obviously rule out the scenario that the documented convergence between analysts' and CEOs' expected credit loss is merely because of CEOs' act of LLP manipulation. When comparing small and large firms in terms of the effect of IFRS9 enforcement on forecast dispersion, we find that the dispersion-reducing effect previously document exclusively holds for large firms.

INSERT TABLE 5 ABOUT HERE

5.2.2. High vs. Low bid-ask spread

Table 6 presents results of testing the difference between banks with low vs. bid-ask spread with respect to the effect of IFRS9 enforcement on analyst forecast properties, where columns (1) and (2) are dedicated to *ACCURACY* and columns (3) and (4) correspond to *DISPERSION*. A bank is characterized by high bid-ask spread if the mean value of its bid-ask spreads over the last three months preceding the fiscal year as at end of 2017 (BID_ASK_SPREAD is equal to or greater than the sample median; otherwise, it is categorized as low bid-ask spread.

As we observe in columns (1) and (2), the forecast accuracy-increasing effect does occur when the bid-ask spread is high (i.e., when managers have enough flexibility and possibility to engage in LLP manipulation), while the coefficient for *ACCURACY* does not attain any statistical significance at the ordinary levels when the bid-ask spread is low. This again supports the argument that our primary finding is not driven by CEOs' opportunism, which manifests itself in LLP manipulation. Results presented in columns (3) and (4) reveal that in both sub-samples of high and low bid-ask spread, the IFRS9 enforcement reduces that forecast dispersion.

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5.2.3. High vs. Low risk-taking banks

Table 7 presents results of testing the difference between high vs. low risk-taking banks with respect to the effect of IFRS9 enforcement on analyst forecast properties, where columns (1) and (2) are dedicated to *ACCURACY* and columns (3) and (4) to *DISPERSION*. A bank is categorized as risk-taking if its proportion of non-performing loans (relative to total loans) as at end of 2017 is equal to or greater than the sample median; otherwise, it is categorized as low risk-taking.

We find that, in the case of high risk-taking banks (column (2)), the coefficient for IFRS9 does not attain any statistical significance at the ordinary levels, while exclusively for low risk-taking banks (column (1)) IFRS9 enforcement increases the LLP forecast accuracy. This finding is again consistent with the argument that the convergence between analysts' and CEOs' expectation of future credit loss is not merely driven by CEOs' act of LLP manipulation. Similar to Table 6, we again observe that IFRS9 enforcement reduces the forecast dispersion both cases of high-risk and low risk-taking banks.

INSERT TABLE 7 ABOUT HERE

5.2.4. Banks with Low vs. High analyst coverage

Table 8 presents results of testing the difference between banks with high vs. low analyst coverage with respect to the effect of IFRS9 enforcement on analyst forecast properties, where columns (1) and (2) are dedicated to *ACCURACY* and columns (3) and (4) to *DISPERSION*. A focal bank is categorized as high-coverage if the number of LLP estimates related to the bank as at end of 2017 is equal to or greater than the sample median; otherwise, it is categorized as low-coverage.

We find that, in the case of low-coverage banks (column (1)), the coefficient for *IFRS9* does not attain any statistical significance at the ordinary levels, while for high-coverage banks (column (2)), IFRS9 enforcement increases the LLP forecast accuracy. Similar to previous cross-sectional tests, this finding is again consistent with the argument that the convergence between analysts' and CEOs' expectation of future credit loss is not merely driven by CEOs' act of LLP manipulation. Additionally, we again observe that IFRS9 enforcement reduces the forecast dispersion both cases of high covered and low covered banks.

INSERT TABLE 8 ABOUT HERE
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6. Conclusion

The introduction of the Expected Credit Loan Loss model under IFRS 9 was deemed by many practitioners to have been a game changer for banks. This paper analyses how the shift from a incurred loan loss to expected loan loss model affects the properties of analyst forecasts. The importance of this research is particularly pronounced given that the enforcement of IFRS 9 raises additional disclosure needs about the assumptions underlying and the expectations about bank future credit losses.

Using an international sample of IFRS-reporting banks, we show that the passage of IFRS 9 manifests in higher accuracy and lower dispersion of analysts Loan Loss Provision (LLP) forecasts. Further, cross sectional tests suggest that these changes are mainly observed in banks exhibiting a richer environment set and lower risk profile. This latter result rules out the argument that higher accuracy in analyst forecasts is merely driven by managers intentionally adjusting LLP with an intention to report numbers closer to analysts.

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APPENDIX

Variable definition

Variable	Definition	Source
ACCURACY	LLP analyst forecast accuracy, measured as the absolute value of the difference between bank reported LLP and the most recent consensus LLP forecast available on I/B/E/S summary files before LLP is publicly announced, scaled by bank size and multiplied by -1	Refinitiv
DISPERSION	LLP forecast dispersion, measured as the most recent standard deviation of analyst LLP forecasts available on I/B/E/S summary files before LLP is publicly announced, scaled by bank size	Refinitiv
LLP	Bank reported Loan Loss provision deflated by size	Refinitiv
IFRS9	Dummy equal to 1 if year is on or after 2018, and 0 otherwise	Refinitiv
SIZE	Log of bank total assets	Refinitiv
TIER1	Bank Tier 1 Capital Ratio in %	Refinitiv
GSIB	Dummy variable that takes the value of 1 if the bank is a Global Systemically Important Bank (G-SIB) in a given year, and 0 otherwise	FSB website
EARNINGS	Net interest income before LLP deflated by size	Refinitiv
ALL	Lagged loan reserve (loan loss allowance) scaled by size	Refinitiv
ANALYST_COV	Analyst coverage, measured by the number of analyst LLP estimates, the most recent available on I/B/E/S summary files before LLP is publicly announced	Refinitiv
BID_ASK_SPREAD	Daily Bid ask spread averaged over the last three months before fiscal year-end	Refinitiv
VIX	VIX level averaged over the last three months before fiscal year-end	Refinitiv
NPL	Non-performing loan, measures as the amount of non-performing loans scaled by total loans.	

Table 1. Summary statistics (N=1185)

	Mean	Std. Dev.	p25	Median	p75
ACCURACY	-9.072	21.602	-6.624	-2.192	-.707
DISPERSION	5.388	12.368	.235	1.172	4.458
LLP	.005	0.007	.001	.003	.007
IFRS9	.396	0.489	0	0	1
SIZE	10.892	1.633	9.683	10.713	12.081
TIER1	14.783	3.645	12.306	14.4	16.7
GSIB	.067	0.251	0	0	0
EARNINGS	.299	0.268	.15	.217	.333
LLA	-.474	2.453	-.262	-.129	-.062
ANALYST_COV	2.131	0.930	1.609	2.303	2.89
VIX	16.867	5.113	13.207	15.52	21.573
BID_ASK_SPREAD	0	0.003	0	0	0

Table 2. Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) ACCURACY	1.00											
(2) DISPERSION	-0.55*	1.00										
(3) LLP	-0.12*	0.13*	1.00									
(4) IFRS9	-0.02	-0.07*	0.00	1.00								
(5) SIZE	-0.36*	0.44*	-0.24*	0.03	1.00							
(6) TIER1	0.12*	-0.15*	0.12*	0.15*	-0.20*	1.00						
(7) GSIB	-0.14*	0.29*	-0.10*	0.00	0.50*	-0.06	1.00					
(8) EARNINGS	-0.13*	0.17*	0.32*	0.08*	0.01	-0.20*	0.03	1.00				
(9) LLA	0.04	-0.03	-0.15*	-0.01	-0.01	0.04	0.02	-0.33*	1.00			
(10) ANALYST_COV	-0.18*	0.34*	-0.15*	-0.08*	0.68*	-0.09*	0.30*	0.03	0.01	1.00		
(11) VIX	-0.09*	0.02	0.09*	0.59*	0.01	0.09*	0.00	0.08*	0.02	-0.04	1.00	
(13) BID_ASK_SPREAD	0.00	-0.01	-0.01	0.00	-0.01	-0.03	-0.01	0.03	-0.02	-0.05	0.01	1.00

Variable definitions are outlined in Table I

Table 3. Sample composition by country. The two columns indicate the country sample mean and median balance sheet size in €mln.

Country	N	Mean	Median
Argentina	2	8040	8040
Australia	46	365751	523693
Austria	12	183512	199899
Bahrain	3	7719	7519
Brazil	4	331891	333626
Canada	58	434317	445081
Chile	26	45640	44799
China	9	709241	786325
Colombia	12	44544	44625
Cyprus	2	21318	21318
Czech Republic	9	23181	31641
Denmark	31	149791	35129
Egypt	7	12005	11946
Estonia	3	3227	3032
Finland	3	10326	10573
France	17	1534436	1529294
Germany	12	1040501	1336698
Greece	24	74427	69677
Hong Kong	11	95508	90226
Hungary	6	46988	43979
Iceland	2	7751	7751
Ireland	22	90911	108920
Israel	14	77589	74604
Italy	28	212694	41890
Jordan	12	22199	10064
Kenya	23	3653	3299
South Korea	38	181791	150993
Kuwait	46	29331	18418
Lebanon	18	26642	27638
Lithuania	1	2031	2031
Malaysia	59	59896	42473
Morocco	7	23964	22621
Netherlands	9	611321	395623
Nigeria	19	15385	15675
Norway	68	43008	13079
Oman	36	10897	7954
Poland	47	31136	26270
Portugal	8	77971	76142
Qatar	51	45411	23567
Romania	12	12912	11720
Russia	22	192562	194707
Saudi Arabia	72	42785	40575
Singapore	23	278651	269292
Slovenia	2	16870	16870
South Africa	31	68039	66920
Spain	39	495465	338623
Sweden	30	248034	272149
Switzerland	4	669359	866926
Taiwan	33	42409	45786
United Arab Emirates	58	56488	33508
United Kingdom	70	708326	600311

Table 4. The effect of IFRS9 enforcement on analyst forecasts properties

Controls for firm and country included but not shown. Standard errors shown are clustered by firm.

Variables	(1) DV: ACCURACY	(2) DV: DISPERSION
IFRS9	3.443	-3.067
	(2.80)***	(-4.01)***
TIER1	0.278	-0.185
	(0.88)	(-0.96)
SIZE	-9.426	4.996
	(-2.92)***	(1.97)*
EARNINGS	-0.417	8.022
	(-0.07)	(1.97)**
LLA	-0.875	2.498
	(-0.40)	(1.69)*
ANALYST_COV	-0.609	2.275
	(-0.45)	(2.36)**
VIX	-0.570	0.200
	(-3.87)***	(3.23)***
Constant	98.963	-54.864
	(2.84)***	(-2.02)**
#obs	1185	1185
#banks	202	202
Adjusted R-sq.	0.41	0.44

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Cross-sectional tests based on bank size (*SIZE*).

The sample is sliced to form "Small vs. Large" sub-samples based on the median bank balance sheet size as at end of 2017. Controls for firm and country included but not shown. Standard errors shown are clustered by firm.

Variables	(1) Small DV: ACCURACY	(2) Large DV: ACCURACY	(3) Small DV: DISPERSION	(4) Large DV: DISPERSION
IFRS9	0.668	4.597	-0.036	-4.198
	(1.13)	(2.52)**	(-0.09)	(-3.88)***
SIZE	-1.631	-15.634	-0.333	8.391
	(-1.17)	(-3.01)***	(-0.34)	(2.05)**
EARNINGS	-6.220	5.860	3.139	6.146
	(-2.91)***	(0.60)	(2.67)***	(1.09)
TIER1	-0.033	0.448	0.031	-0.453
	(-0.39)	(0.73)	(0.48)	(-1.27)
LLA	-3.279	1.611	1.009	1.800
	(-6.52)***	(0.50)	(2.64)**	(0.79)
ANALYST_COV	-0.746	-0.934	1.648	2.877
	(-0.63)	(-0.41)	(2.42)**	(1.54)
VIX	-0.009	-0.890	0.030	0.319
	(-0.21)	(-3.75)***	(1.39)	(3.31)***
Constant	15.327	179.661	-0.100	-96.863
	(1.25)	(2.89)***	(-0.01)	(-2.03)**
#obs	391	722	391	722
#banks	71	112	71	112
Adjusted R-sq.	0.32	0.39	-0.00	0.40

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Cross-sectional tests based on bid-ask spread (*BID_ASK_SPREAD*).

The sample is sliced to form Low vs. High information asymmetry sub-samples based on the median bid-ask spread as at end of 2017. Controls for firm and country included but not shown. Standard errors shown are clustered by firm.

Variables	(1) Low DV: ACCURACY	(2) High DV: ACCURACY	(3) Low DV: DISPERSION	(4) High DV: DISPERSION
IFRS9	5.355	1.980	-4.109	-1.721
	(2.67)***	(1.27)	(-3.38)***	(-2.69)***
SIZE	-8.341	-10.398	7.651	2.463
	(-1.43)	(-2.99)***	(1.48)	(1.70)*
EARNINGS	1.935	-3.392	9.987	4.170
	(0.21)	(-0.43)	(1.67)*	(1.26)
TIER1	0.126	0.315	-0.256	-0.035
	(0.20)	(0.83)	(-0.71)	(-0.16)
LLA	-2.315	0.695	4.442	0.545
	(-0.73)	(0.24)	(3.11)***	(0.49)
ANALYST_COV	-3.205	1.240	4.555	0.533
	(-1.42)	(0.67)	(2.48)**	(0.66)
VIX	-0.680	-0.476	0.184	0.212
	(-3.26)***	(-2.14)**	(1.67)*	(2.72)***
Constant	95.316	105.035	-87.057	-26.758
	(1.52)	(2.82)***	(-1.58)	(-1.68)*
#obs	547	630	547	630
#banks	91	107	91	107
Adjusted R-sq.	0.43	0.34	0.44	0.38

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7. Cross-sectional tests based on bank risk taking (*NPL*).

The sample is sliced to form Low vs. High risk-taking sub-samples based on the median proportion of non-performing loans (*NPL*) as at end of 2017. Controls for firm and country included but not shown. Standard errors shown are clustered by firm.

Variables	(1) Low DV: ACCURACY	(2) High DV: ACCURACY	(3) Low DV: DISPERSION	(4) High DV: DISPERSION
IFRS9	5.523	3.146	-3.328	-3.654
	(2.90)***	(1.48)	(-2.84)***	(-2.60)**
SIZE	-13.794	-10.044	6.905	4.661
	(-2.32)**	(-3.19)***	(1.44)	(1.80)*
EARNINGS	13.290	-4.022	-2.034	9.348
	(0.83)	(-0.64)	(-0.37)	(1.59)
TIER1	-0.181	0.408	0.060	-0.476
	(-0.36)	(0.80)	(0.25)	(-1.34)
LLA	25.424	-0.288	-8.706	1.710
	(1.13)	(-0.16)	(-0.67)	(0.99)
ANALYST_COV	-2.481	-1.333	2.961	2.340
	(-1.08)	(-0.72)	(1.69)*	(1.52)
VIX	-0.902	-0.450	0.331	0.219
	(-3.21)***	(-2.14)**	(2.98)***	(2.20)**
Constant	169.064	99.177	-85.667	-44.449
	(2.36)**	(2.86)***	(-1.57)	(-1.53)
#obs	505	480	505	480
#banks	76	80	76	80
Adjusted R-sq.	0.39	0.42	0.33	0.49

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8. Cross-sectional tests based on analyst coverage (*ANALYST_COV*).

The sample is sliced to form low-high sub-samples based on the median analyst coverage as at end of 2017. Controls for firm and country included but not shown. Standard errors shown are clustered by firm.

Variables	(1) Low DV: ACCURACY	(2) High DV: ACCURACY	(3) Low DV: DISPERSION	(4) High DV: DISPERSION
IFRS9	-0.730	5.856	-0.035	-4.928
	(-0.53)	(3.69)***	(-0.09)	(-4.58)***
SIZE	0.276	0.100	0.086	-0.437
	(1.03)	(0.19)	(1.10)	(-1.27)
EARNINGS	-1.700	-17.624	-1.315	9.732
	(-0.81)	(-3.09)***	(-1.24)	(2.18)**
TIER1	-5.575	7.218	2.481	10.511
	(-2.18)**	(0.71)	(2.43)**	(1.62)
LLA	-0.901	-1.063	0.885	3.051
	(-0.30)	(-0.37)	(1.98)*	(2.15)**
ANALYST_COV	0.440	-6.263	1.555	2.465
	(0.39)	(-1.54)	(2.09)**	(1.02)
VIX	0.063	-1.068	0.055	0.294
	(0.58)	(-4.41)***	(1.70)*	(2.69)***
Constant	8.766	223.582	9.314	-111.708
	(0.44)	(3.23)***	(0.93)	(-2.09)**
#obs	486	678	486	678
#banks	88	105	88	105
Adjusted R-sq.	0.19	0.42	0.00	0.42

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$