THE EFFECTS OF THE ADOPTION OF IFRS 9 ON THE COMPARABILITY AND THE PREDICTIVE ABILITY OF BANKS' LOAN LOSS ALLOWANCES

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Abstract: This research investigates how the adoption, in 2018, of the IFRS 9 standard has affected banks' loan loss provision and allowance disclosures. This constitutes one of the first post-implementation tests of this new standard. Overall, we found that the introduction of IFRS 9 has translated into a moderate loss for banks on the day of the adoption, with significant differences between rich and poor countries. Following the adoption of IFRS 9, sovereign credit ratings have gained greater influence on loan loss allowances, while the influence of impaired loans has been eroded; we posit that this is largely due to the recourse to expected credit loss models – which give considerable weight to credit ratings – to measure provisions. Our results suggest that the heterogeneity of provisioning practices has increased with the switch to IFRS 9, which has altered the comparability of provisions across banks. The association of LLAs with short term loan losses remains close, which contradicts their forward-looking character, unless we deny the effect of economic cycles.

Keywords: IFRS 9, Loan Loss Allowances, Expected Credit Losses, Sovereign Rating.

Résumé: Cet article a pour objet d'identifier les effets de l'adoption, en 2018, de la norme IFRS 9 sur les dotations et les provisions pour pertes de crédit divulguées par les banques. Il constitue l'un des premiers tests de post-implémentation de la nouvelle norme. Nos résultats montrent que l'adoption de la norme IFRS 9 a entrainé, lors de son application, une perte modérée pour les banques, avec des différences notables entre pays riches et pauvres. Les notes souveraines des pays où sont basées les banques ont vu leur influence sur les provisions augmenter, alors que celles des prêts non performants a diminué. Nous attribuons cela à l'utilisation des modèles d'espérance de perte de crédit pour le calcul des provisions, qui accordent un poids important à la notation financière. Nos résultats suggèrent que, suite à l'adoption de la norme IFRS 9, l'hétérogénéité des méthodes de calcul des provisions a augmenté, ce qui a altéré la comparabilité des provisions entre banques, L'adoption de la norme IFRS 9 n'a pas eu d'effet notable sur la relation étroite entre les provisions et les perte sur créances irrécouvrables à court-terme; ceci remet en question le principe de vision à long terme des provisions sous IFRS 9.

Mots-clés: IFRS 9, provisions pour créances douteuses, pertes de crédit attendues, notation souveraine.

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1. Introduction

On 24th July 2014, the International Accounting Standards Board (IASB) replaced the IAS 39 standard with the IFRS 9 Financial Instruments, which became effective on 1st January 2018. The new standard recognizes provisions on financial instruments on an expected credit losses (ECL) basis instead of on the incurred losses approach used by IAS 39. For the IASB's Financial Crisis Advisory Group, the delayed recognition of losses was one of the primary weaknesses of IFRS, which contributed to the loss of confidence in the financial system during the 2007–08 financial crisis (IASB 2009). As well as that, some studies advocate that delay in the provisioning of loan losses (Bushman and Williams 2015), as well as for the limited discretion left to bank managers under IAS 39 (Beatty and Liao 2014), prevented bank managers from anticipating long losses and building sufficient buffer of loan loss allowances (LLA) to absorb them.

The adoption of forward-looking provisioning rules offers bank managers a higher degree of discretion in recognizing and measuring loan loss provisions (LLP). Under the incurred loss approach, provisions are based on the availability of evidence that a loss has occurred; by contrast, the forward-looking provisioning is based on losses that are expected to be incurred over a longer time horizon. The computation of expected credit losses implies a higher degree of judgment than the measurement of provisions based on incurred losses. ECL relies on three parameters: exposure at default (EAD), probability of default (PD), and loss given default (LGD). While clear rules guide the measurement of EAD, there is no universally accepted model to measure PD and LGD. As noted by the European Banking Authority (EBA, 2017, 4), "*the application of IFRS 9 also requires the use of judgement in the ECL assessment and measurement process, which could potentially affect the consistent application of IFRS 9 across credit institutions and the comparability of credit institutions' financial statements*".

For most banks, adopting this new standard translated into an incremental cost that was recognized upon adoption of the new standard on 1st January 2018 (so-called Day One). Indeed, the first post-implementation tests conducted in the year following the adoption of IFRS 9 by the European Banking Authority (EBA 2018) and by Ernst and Young (E&Y 2018) indicated that the adoption of the new standard resulted, for most banks, in an increase in loan loss allowances (LLA) that was recorded on Day One, which translated into a reduction of shareholders' equity and regulatory capital ratio. However, other post-implementation studies noted that the negative Day One impact was followed by an overall reduction in loan loss provisions (LLP) in 2018 and a lower LLA on 31st December 2018.

Increased discretion for bank managers raises the issue of the quality of the financial information. As stated in the IFRS revised conceptual framework (IASB 2018), the purpose of financial reporting is to provide useful financial information to investors, lenders, and other creditors. The comparability of financial information disclosed to third parties is one characteristic that can enhance its quality. Regarding provisioning, it implies that the coverage of impaired loans by provisions obeys the same rules for all banks. Otherwise, investors would be misled in assessing the bank's credit risk exposure. The usefulness of provisions disclosed in financial reports also depends on their ability to predict future loan losses, a key element for investors and lenders whose decisions are based on cash flow projections. This question is closely related to the pro-cyclicality of provisions, which accounting standard setters aim to reduce with the adoption of the IFRS 9 standard. Reduced pro-cyclicality means that LLP will not increase in times of negative economic trend or decrease when the economy rebounds. The objective of forward-looking provisions is to anticipate losses over a long-term horizon, which implies a weaker linkage with short term credit losses.

This study investigates the effects of the adoption of IFRS 9, first by analyzing its impact on banks' capital and, second, by assessing its effect on the quality of financial reporting. More specifically, we focus on banks' loan loss provisions and aim to determine whether the IFRS 9 has improved their comparability and ability to predict future credit losses; a related objective is to assess whether IFRS 9 adoption has reduced the pro-cyclicality of provisions.

We selected a sample of 123 banks based in 32 European countries, which all report under IFRS standards. We first conducted a thorough analysis of banks' financial reports from 2014 to 2019, based manually collected information. Consistent with the first post-implementation studies, we found that, for most banks, the adoption of IFRS 9, on January 1st 2018, translated into a loss equivalent to 0.5% of the gross value of their loans, and that the observed reduction in LLA and LLP observed in 2018 is largely due to the de-recognition of loans, resulting from write-offs or sale. This provides evidence that the adoption of IFRS 9 had a negative impact on bank's capital.

We also found a close association between the Day One loss/gain recorded by banks and the sovereign rating of the country where they are based; this is, in our view, one of the most important findings of this research. The association between LLAs and ratings results from the transition from the incurred loss provisioning approach to ECL provisioning methods and the reliance of the ECL models on credit ratings. The computation of ECL relies on multiple parameters, including borrowers' probabilities of default (PD). PDs are largely derived either from borrowers' ratings – published by credit rating agencies (CRA) or internal to banks – or from scenarios analysis, and sometimes from both. CRAs' methodologies indicate that the credit ratings of borrowers are capped by the sovereign rating of their home country or by a sovereign ceiling based on such rating. Hence, there is a strong link between the rating of a company and the sovereign rating of the country in which it is based.

Using an OLS regression model developed by Gebhardt and Novotny-Farkas (2018) on the pre and post Day One periods, we provided evidence that the sovereign ratings has become, following the adoption of IFRS 9, one of the main determinants of the LLAs, while the influence of impaired loans has decreased. The results of the Chow Test (Chow 1960) clearly indicate that a structural change in the determinants of the LLAs after 2018, which we attribute to the adoption of ECL models to measure LLAs. This result has far-reaching implications, as it raises questions on the comparability of information on provisions disclosed by banks.

To test the effect of adopting IFRS 9 on the comparability of LLA across banks, we have included, in the LLAs determination model, categorical variable which capture banks' individual effects. The results show a significant increase in the individual effect in the post Day One period, which we attribute to the increased discretion in the measurement of LLAs allowed by the new standard. We have examined the variation of the ratio of LLA to impaired loans (or coverage ratio) before and after the adoption of IFRS 9, using the Levene Test of equality of variance over the two periods. We detected a significant increase in the dispersion of the coverage ratio after 2018, attributable to an alteration of the link between provisions and impaired loans after Day One. This suggests an increased heterogeneity in the measurement of provisions for a given amount of impaired loans, and, hence, lesser comparability of information on LLAs across banks.

We have investigated whether the adoption of the IFRS 9 standard led to an improvement of the ability of LLAs to predict loan losses over the years. The results indicate that the association between LLAs and one-year-ahead charge-offs has remained unchanged after Day One, which implies that the predictability of credit losses over the short term has not been altered by the recourse to forward-looking ECL models to measure LLAs. Though this does not necessarily mean that LLAs do not predict long term losses; however, accepting this hypothesis would imply that the amount of one-year-ahead charge-offs is equal or close to the amount of charge-offs recognized several years later, which does not seem realistic. In fact, testing the improvement of the ability of LLAs to predict long-term losses requires observations over a longer period, and so researchers will have to wait a few more years.

This paper contributes to the literature on ECL based provisioning. First, it constitutes a post-implementation test of the impact of the mandatory adoption of IFRS 9 on banks' shareholders' equity. Second, it provides evidence of the limitations of the IFRS 9 standard, particularly the effect of increased discretion on the comparability of provisions, a key determinant of the quality of financial reporting. We show that, as a result of ECL provisioning, LLAs are now closely linked to sovereign credit ratings, which might translate into increased pro-cyclicality of provisions. We show that the IFRS 9 did not affect the ability of LLAs to predict short term loan losses, which is contrary to expectations, given the long term-time horizon of provisions under the new standard; this provides further evidence that IFRS 9 did not resolve the pro-cyclical nature of provisions.

2. Institutional background

2.1. The IFRS 9 Standard

The IFRS 9 introduces substantial changes relative to the IAS 39. The first change leads to re-classification and a change in measuring certain financial assets. Under IFRS 9, banks' financial assets are reclassified into three categories based on the business model of the assets: amortized cost (AC), fair value through other comprehensive income (FVOCI), and fair value through profit and loss account (FVP&L). The IAS 39, by contrast, focuses on how the entity intends to realize individual assets in classifying financial assets. Provisions for credit losses are recorded on AC and FVOCI assets.

Banks also have to disclose their financial assets by breaking them down according to the degree of credit risk they are exposed to. The new standard introduces three credit risk exposure levels, based on the assessment of the risk of default: Stage 1, Stage 2, and Stage 3. Financial instruments in Stage 3 include impaired assets. Stage 2 are assets for which a significant increase in credit risk (SICR – credit risk being associated with the risk of default) has occurred. Both the 30 and 90 days' overdue assets can be rebutted in exceptional circumstances. Other assets (less than 30 days overdue) are classified as Stage 1.

The measurement of provisions for credit losses is based on expected losses, rather than on incurred losses, as was the case under IAS 39. The adoption of the forward-looking approach for the recognition and measurement of provision is seen as the major change brought by the new standard, as it responds to the critics on the delayed provision recognition addressed to the IAS 39 standard. At initial recognition, the bank shall measure the LLA for that financial instrument at an amount equal to the 12-month ECL; If the credit risk on that financial instrument has increased significantly since initial recognition, then the bank shall measure the LLA for a financial instrument at an amount equal to the lifetime ECL. For impaired loans the bank shall measure the LLA at an amount equal to the lifetime EC and shall calculate the interest revenue based on the gross carrying amount adjusted for the loss allowance.

Provisions for credit risk are recognized for all assets classified as AC and FVOCI; total provisions are disclosed separately for each stage (stages 1, 2, and 3). An important difference with IAS 39 is that credit loss provisions apply to an extended set of financial instruments. Under the IFRS 9 standard, credit loss provisions are also recognized for committed but undisbursed loans and credit facilities and debt securities at FVOCI. More importantly, provisions are also recognized on performing assets (stages 1 and 2), while they concerned impaired assets only under IAS 39.

2.2. The ECL models

In an IMF study, Gross et al. (2020) have presented an overview of the various types of models used to compute EC. To summarize, ECL is obtained by: (a) identifying scenarios in which a loan or receivable defaults; (b) estimating the cash shortfall that would be incurred in each scenario if a default were to happen; (c) multiplying that loss by the probability of the default happening; and (d) summing the results of all such possible default events. The measurement of the ECL is based on three parameters: the exposure at default (EAD), the probability of default (PD), and the loss given default (LGD), measured as a percentage of the amount in default):

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

ECL is computed on a lifetime horizon for stage 2 and 3 assets, but over twelve months for Stage 1 assets[2]. PD is generally obtained from credit rating agencies (CRA) or the bank's internal models. These parameters are tied to economic projections assuming various scenarios. These typically include a baseline scenario, and more pessimistic and optimistic scenarios. A probability of occurrence is generally attached to each scenario.

The recourse to ECL to measure provisions might reduce the homogeneity of financial reporting rules on loan loss provision across banks. Though banks are broadly aligned in their application of certain key areas of IFRS 9 impairment modeling judgments, there is, according to Deloitte (2019), evidence for divergences between banks on the modeling of ECL. Such divergence raises questions about the comparability of provisions across banks [3]. As highlighted by Pricewaterhouse Coopers (PWC 2017), the IFRS 9 standard does not set a prescriptive method for computing ECL. Banks can establish their own rules within the risk management and reporting policies. In an extensive post-implementation survey of the IFRS 9 adoption, the European Systemic Risk Board (ESRB 2019) pointed out the insufficient standardization of ECL models, and its consequences on the increased discretion it leaves to banks in the measurement of provisions. The question of the heterogeneity of ECL models had already been raised concerning the second version of the regulatory capital ratio proposed by the Basel

[2] The CECL approach retained by the FASB – to be implemented in 2021 in the US – requires lifetime expected credit losses to be held for all loans, including Stage 1.
[3] Main divergences concern the threshold for significant increase in credit risk (which determines whether an asset should be classified in Stage 2 or 3), the definition of macro-economic scenarios and the application of sensitivity analysis.

Committee for Banking Supervision (BCBS). The European Banking Authority (2017) noted that the guidance provided by the BCBS (2015) on the computation of ECL included several judgmental factors that might affect the comparability of ECL assessment across banks. The same limitation remains when ECL is used for accounting purposes. Judgmental factors introduce a higher degree of heterogeneity in the measurement of LLAs and LLPs under the ECL approach versus the incurred-loss model.

3. Literature review and hypotheses

3.1. Existing literature

3.1.1. Expected impact of the adoption of IFRS 9

When the IFRS 9 standard was first established, accounting standard setters – the IASB and European Financial Reporting Advisory Group (EFRAG) – expected the change in provisioning methods to have a negative impact on banks' earnings and on their regulatory capital, which would oblige them to either increase capital or reduce the credit risk of financial instruments. First, on Day One, the implementation of IFRS 9 was expected to increase LLAs for most banks. As noted by O'Hanlon et al. (2015), this immediate reduction of the carrying amount was expected to give rise to Day One losses. Provisions for performing assets classified in Stages 1 and 2 are recorded in addition to those that are recognized as impaired. These additional provisions trigger an accounting loss on the day of the transition from IAS 39 to IFRS 9, which is recorded in the bank's retained earnings for the fiscal year 2018. Also, re-classifications of financial assets according to the business model impact banks' capital; as it involves a remeasurement of the financial asset, which can affect the banks' capital favorably or unfavorably.

Thus, the transition to IFRS 9 implies an overall negative impact on banks' shareholders' equity and banks' regulatory capital, all other things being equal. Several pre-implementation studies conducted by Humblot (2018) and the EBA (2017) demonstrated that the transition to IFRS 9 would have a negative impact on retained earnings on Day One due to the recognition of higher LLAs resulting from their computation based on ECL; thus, the transition leads to a reduction in the Basel capital ratio. In one of the first studies on the impact of the adoption of IFRS 9 on banks' earnings and capital, Deloitte (2019) found that implementing the new standard would increase LLAs on 1st January 2018. However, the study's authors noted that the negative Day One impact on regulatory capital was not substantial because of the favorable effect of the re-classifications and remeasurements of assets allowed under IFRS 9. This study also noted that the LLPs recognized in 2018 decreased; this unexpected finding is explained by the significant increase in write-offs made by banks that year, which translated into a decrease in Stage 3 loan exposure. Another post-implementation test released by the EBA (2018) confirmed that the impact of IFRS 9 adoption negatively affected the bank's regulatory capital ratios, but this effect was not significant. The findings were consistent with EBA's pre-implementation test based on a questionnaire sent to banks in 2018. These results concur with a study from E&Y (2018) based on the first-quarter financial statements, which shows that the overall increase in LLAs on Day One was relatively low for banks. The study provides evidence of the favorable impact on banks' capital of asset re-classification (loans transferred from amortized cost to fair value through P&L, which do not need allowances) required by the new standard and of loan write-offs made by banks in 2018 simultaneously to the transition to IFRS 9 in 2018.

3.1.2. ECL models and sovereign credit rating

As mentioned above, PD is one of the three key parameters in ECL computation. This parameter was first introduced in the Basle 2 Accord in 2003, when risk weight based on ECL was introduced. In the approach recommended by the Basle Committee, PDs are derived from credit ratings assigned to borrowers. The text recommended that banks that do not have the technical capacity to compute PDs of their borrowers have recourse to the ratings published by credit rating agencies (CRA), which creates a close link between the ratings published by CRAs and PD. As shown by Almeida et al. (2016), the 'big three' CRAs (Fitch, Moody's, Standard and Poors') apply the concept of sovereign ceiling. This rule imposes that every rated entity's rating in a given country is capped by a rating equal to or close to the rating assigned to the state, or 'sovereign rating'[4]. Sovereign ceilings are made public for all countries where private or public issuers are rated by the CRAs – such sovereign ceilings have been assigned to all European countries by the three major CRAs.

Banks are not obliged to recourse to PDs used to calculate their regulatory capital ratio to compute ECL retained for provisions. However, using different methods for computing PDs would be inconsistent, and would certainly merit some justification. Besides, such computation requires significant technical and information input, and is generated by the same teams – generally, banks have a risk management unit in charge of this type of calculation. Hence, we can posit that loan loss provisions under IFRS 9 depend on sovereign ratings assigned by CRAs. If verified, this result would likely have implications on the pro-cyclicality of provisions.

3.1.3. Comparability of provisions across banks

In the IFRS Conceptual Framework (IASB 2018, A25), comparability is defined as "*the qualitative characteristic that enables users to identify and understand similarities in, and differences among, items*". For the IASB, it is one of the characteristics that can enhance financial reporting quality. The need to ensure greater comparability of a bank's financial statements was one reason motivating the mandatory adoption of IFRS in 2005. According to

[4] See Fitch's Country ceiling criteria (2017) for a detailed description of this approach.

the EU, it is a means to "*ensure a higher degree of transparency and comparability of financial statements*"[5]. Surprisingly, the academic literature on the comparability of banks' financial reports is not abundant. Authors generally agree that the adoption of IFRS in 2005 had a positive effect on the comparability of financial reporting. The studies performed by De Franco et al. (2011), Yip and Young (2012), Ahmed et al. (2013), Brochet et al. (2013), and Neel (2017) concluded that the comparability of financial information has improved after 2005. Barth et al. (2012) found that the IFRS adoption led to greater earnings and value relevance comparability between non-US and US firms. Lin et al. (2019) provided evidence that the comparability of accounts of German firms reporting under US GAAP – which is common practice in Germany – improved with adoption of IFRS. They noted, however, that the comparability of financial reports can be altered by the principle-based approach of IFRS, which allows more discretion to banks' management. A comprehensive study undertaken by Institute of Chartered Accountants in England and Wales' Financial Reporting Faculty (ICAEW 2015) concluded that, although the comparability of financial statements benefitted from the mandatory adoption of the IFRS in 2005, there are still differences in financial reporting across EU countries.

Due to the difficulty in measuring comparability of financial reports across firms, researchers have used accounting, analyst and market proxies to assess accounts similarities. To measure comparability, authors observe similarities across firms in the relationship between various accounting amounts and related economic outcome, such as earnings and stock returns, earnings and cash-flows, or accrual and cash flows. Few authors have assessed comparability of financial information on a disaggregated basis. Gebhardt and Novotny-Farkas (2018) have focused on the comparability of banks' disclosures on loan loss provisions across countries and retained a different approach.

[5] Article 1 of the EU Regulation 1606/2002 – the IAS Regulation.

Comparability is assessed through the dispersion of the coverage ratio (LLA to non-performing loans). Based on a study across European countries, these authors found that the application of the incurred loss approach reduced the dispersion of the ratio after 2005. Using a regression model, they also found that country factors have less explanatory power on the coverage ratio after the 2005 adoption of the IFRS, except for countries allowing some form of forward-looking provisioning (Denmark, Portugal, and Spain), which led them to the conclusion that incurred loss provisioning improved the cross-country comparability of banks' financial reports. Their approach differs from most previous researchers in that they use LLA instead of LLP. They justify this choice because auditors and supervisors generally take a balance-sheet perspective, rather than an income statement perspective, when assessing evaluating the adequacy of provisions; Beaver and Engel (1996) and Beck and Narayanamoorthy (2013) also followed this route. Chae et al. (2018, 27) support this conclusion: as they rely on observed change in asset quality, LLA based on incurred losses are better understood by market participants than forward-looking provisions. They posit that "*If forecasts are imperfect or contain idiosyncratic assumptions by risk managers, then comparability may be hindered across banks and time as additional subjectivity confounds the relationship between ALLL* [e.g. allowances for loan and lease losses] *and risk*". In other words, for these authors, the determination of expected losses is based on subjective assumptions from bank managers, which affect the comparability of LLAs. To reflect the underlying credit risk, forward-looking provisions need to be based on perfect projections by bank managers. Over-optimistic assumptions can send biased information to market participants, which need to take this element of subjectivity into account when they assess the risk and value of investments in banks.

3.1.4. *Predictive ability of LLAs*

Quality of information of loan loss provisions can be further enhanced if LLAs allow market participants to predict future credit losses, which are reported as charge-offs in financial statements. Credit losses are generally measured by charge-offs recorded by banks on loans that are considered non-recoverable. Empirical research on the predictability of credit losses aims at finding evidence of an association between credit losses recorded in a given year and indicators of credit risk in the previous years. A key issue is determining which metrics are most relevant to predict credit losses, defined as future loan charged-offs. Liu and Ryan (2006) have demonstrated that NPLs provided a significant estimate of future loan charge-offs. However, NPLs do not consider the collaterals of loans and other protections (e.g., guarantees) taken by banks, in contrast with LLA. The ability of LLAs to predict charge-offs has been examined by Altamuro and Beatty (2010), who found a positive association between the incurred losses provisions and charge-offs, based on a study of the effect of financial reporting quality before and after the 1991 FDICIA[6] in the US. This view is shared by Beck and Narayanamoorthy (2013), who examined the relations between LLAs and future charge-offs before and after the publication of the SEC Staff Accounting Bulletin 102 (SEC 2001)[7], and by Gebhardt and Novotny-Farkas (2018).

The latter showed that the adoption of IAS 39 increased the ability of LLAs to predict future charge-offs. Bushman and Williams (2012) argued that, as incurred losses rely on recent past events, there is a closer association between LLAs and short-term credit losses under IAS 39 than under-provisioning rules allowing more discretion to banks. As highlighted by Basu et al. (2020), under the incurred loans provisions approach, provisions are recognized on credits which, for a large part, will become unrecoverable in the following year, and be written-off.

[6] The Federal Deposit Insurance Corporation Improvement Act (FDICIA), passed in 1991, imposed to US banks increased internal controls requirements.
[7] The Securities and Exchange Commission's (SEC) Staff Accounting Bulletin (SAB) 102 that considers a loan loss allowances methodology as valid when it is able to predict actual subsequent charge-offs.

Hence, there is a strong association between LLAs and one-year-ahead charge-offs. This has been evidenced in LLA determination models used for empirical tests presented in section 3.2.3, most of which include charge-offs among explanatory variables. Some authors, however, have contested the higher predictability power of incurred losses provisions: Marton and Runesson (2017) found that provisions under US GAAP, which integrate a higher degree of judgment, have higher predictive power than provisions under IAS 39.

No research has yet been published on the predictive ability of provisions under IFRS 9. The key issue under the new standard is the time horizon of predictions. Gebhardt and Novotny-Farkas (2018) warned that the objective of LLAs under IFRS 9 is to predict credit losses over the long term, as ECL on Stage 2 and 3 exposures are based on lifetime PDs; hence, the association between LLAs and one-year-ahead NCOs may be altered. The recent implementation of the new standard does not make it possible, as of today, to test the ability of LLAs reported in 2018 to predict long-term NCOs. However, the priority given to long-term prediction implies a weaker link between provisions and one-year-ahead credit losses. Indeed, because of the forward-looking nature of LLAs under IFRS 9, credit losses should be anticipated more in advance, and recognized at the height of the economic cycle. The lag between provisions and actual charge-offs should increase under IFRS 9, as the increase in provisions on newly impaired loans (i.e., loans transferred to Stage 3) following the economic downturn is expected to be significantly lower than under the IAS 39 incurred loss rule. This is an important feature of the new standard, which is expected to reduce the pro-cyclicality of provisions and increase the lag between provisions and losses.

However, a few researchers argue that the new standard might increase the pro-cyclicality of provisions and reduce the forward-looking nature of LLAs, and thus also increase their long-term predictive ability. A report issued in 2017 by the European Systemic Risk Board (ESRB 2017, 31) warned that the ECL provisioning methods "*could have certain pro-cyclical* *effects derived from the cyclical sensitivity of the credit risk parameters used for the estimation of ECLs and from the shifts of exposures between stages".* The ESRB pointed out that using a point-in-time (PIT) credit rating approach to measuring ECL could translate into a higher correlation between provisions and the economic cycle. While the lifetime loss horizon is required to compute Stage 2 and 3 probabilities of defaults (PDs), PDs for stage 1 exposures are computed on a 12-month horizon under IFRS 9; a key difference with CECL rules retained by FASB. This means they are more influenced by PIT conditions than ECL calculated on Stage 2 and 3 exposures. This is also partly the case for Stages 2 and 3, when the remaining maturity of assets is short.

3.2. Hypotheses setting

3.2.1. Descriptive statistics: observed impact of Day One

In prior sections of this paper, we discussed the effects of IFRS 9 and its consequences on financial reporting; especially how the IFRS 9 impacts capital when the bank switches to IFRS9 as of 1st January 2018. We expect a negative impact of implementing IFRS 9 on a bank's capital[8] because the implementation of the ECL-based provisions on unimpaired financial assets translates into losses reported on Day One. We also expect that LLPs reported under IFRS 9 will be higher than LLPs computed under IAS 39 in 2017. However, as noted in E&Y's post-implementation study (2018), banks have written-off a substantial amount of loans in 2018, especially low-quality loans that translated into a reduction in LLPs in 2018. Hence, the increase in LLPs induced by the adoption of IFRS 9 might prove difficult to verify due to the expected reduction in impaired assets in 2018.

[8] This work focuses on capital as reported on the balance sheet and not on regulatory capital. While the information disclosed in the 2018 annual reports is sufficient to assess the effect on shareholders' equity, it does not provide enough details to measure the effect on regulatory capital.

3.2.2. Effect of country factor on Day One impact

We anticipate significant differences in provisioning between banks based in different countries: ECL is expected to be higher for banks based in countries with low credit ratings or weak banking environments. This increased ECL will translate into higher provisioning under IFRS 9 and hence larger Day One losses for countries with a low rating.

As a result of using ECL models for measuring provisions, credit rating has become, with NPL, one of the key variables explaining provisions. We predict a close relationship between sovereign ratings and Day One impact. As mentioned above, credit rating is one of the key parameters used in the computation of PDs. Because borrowers' credit ratings are capped by the sovereign ceiling, we expect a degree of correlation between sovereign ratings and LLAs.

HYPOTHESIS 1: We predict a close link between the Day One impact and sovereign rating of the country where banks are based.

3.2.3. Increased influence of sovereign ratings on LLA determinants

The literature review suggests that the determinants of LLAs have changed due to the adoption of IFRS 9. It also suggests that sovereign credit ratings greatly influence LLAs under the new standard.

Several empirical studies have found that LLPs can be derived from linear models including the change in NPLs. In an extensive overview of research on the banking industry, Beatty and Liao (2014) have identified nine representative models with different combinations of endogenous and exogenous variables to explain LLPs. Eight of them include NPLs as explanatory variables. However, as demonstrated by Basu et al. (2020), the association between provisions and impaired loans is not linear. This is because of charge-offs: a reduction in impaired loans may follow an increase in the credit loss expectations, leading the bank to charge-off loans. Some researchers have focused on determining LLAs, which are equal to accumulated LLPs at a given date. This route was followed by Gebhardt and Novotny-Farkas (2018); they have retained NPLs, instead of the change in NPLs, as explanatory variables, and included net-charge-offs recorded in the year, as well as the usual control variables.

As their measurement is now based on ECL, LLAs cannot be determined by models including only impaired loans, net charge-offs, and a set of control variables reflecting economic conditions and banks' features. We posit that LLA determination models post IFRS 9 must include credit ratings, which is a key parameter in ECL computation. Given the difficulty of obtaining the rating of all the loans in a banks' portfolio, we use as a proxy the sovereign rating of the country where the bank is based, which is linked to the rating of borrowers (because of the principle of the sovereign ceiling). We anticipate a closer link between ECL and sovereign rating. We have tested the influence of sovereign rating on Day One loss/gain. We also predict a significant effect of sovereign rating on the LLA level in the period following the introduction of IFRS 9, while this effect will be weaker in the years preceding Day One.

HYPOTHESIS 2a: We predict that the LLA determinants have significantly changed with the adoption of the IFRS 9 in 2018.

HYPOTHESIS 2b: We anticipate an alteration of the association between LLAs and impaired loans in 2018, and an increase in the influence of sovereign ratings on LLAs.

3.2.4. Comparability of LLAs pre- and post-Day One

As shown in the literature, under IAS 39, there was a close link between LLAs and impaired loans, which has been verified empirically. The review of recent articles on IFRS 9 has pointed out the lack of standardization of the ECL models used to measure provisions under IFRS 9. This has affected the association between LLAs and impaired loans, which has been verified in several empirical studies. Under IFRS 9, banks use different ECL models, and banks may record different levels of provisions on assets exposed to the same degree of credit risk; the level of LLAs for impaired (Stage 3) loans might differ from bank to banks, while under the IAS 39, the provision measurement rules were more standardized. This will lead to divergences in the coverage of Stage 3 loans by LLAs. The LLA recorded on Stage 1, and 2 loans will also diverge, as they are measured with different ECLs.

We predict that, due to the increased heterogeneity in forecasting models and in designing scenarios to calculate banks' provisions under IFRS 9, the comparability of loan loss provisions across banks was reduced in 2018. Individual factors reflecting banks' own provisioning practices will greatly influence LLAs. As bank managers have more flexibility to measure the provisions needed for a given level of loan impairment, we anticipate a higher degree of dispersion of the ratio of LLA to impaired loans (or coverage ratio) after 1st January 2018 compared to preceding years. We anticipate a high degree of dispersion of the coverage ratio of Stage 1 and 2 provisions relative to loan exposure and lower explanatory power of variables associated with impaired loan in the determination of LLA.

HYPOTHESIS 3a: We predict that individual bank factors will have more influence over LLAs, translating increased discretion allowed to banks for measuring provisions.

HYPOTHESIS 3b: We expect an increased dispersion of the coverage ratio around its mean in the post-IFRS 9 period compared to the pre-IFRS 9 period.

3.2.5. *The ability of LLAs to predict short term credit losses*

Previous empirical studies have provided evidence that the introduction of loan loss provisioning methods based on incurred losses in 2005 has led to improved predictability of short-term credit losses. This is expected to change under IFRS 9. As LLAs are now based on lifetime expected losses (except for Stage 1), LLAs should provide a better prediction of credit losses on a long-term time horizon.

However, a review of recent literature on ECL models raises questions on their actual capacity to reduce pro-cyclicality and provide forward-looking predictions. Suppose we retain the hypothesis that the adoption of IFRS 9 had a limited impact on the forward-looking nature of LLAs and on their capacity to predict long-term credit losses. In that case, the association between LLAs and short-term NCOs should remain intact in the post-IFRS 9 period. No change in the association between LLAs and one-year-ahead charge-offs would be observed following the adoption of IFRS 9.

HYPOTHESIS 4: We anticipate that the ability of LLAs to predict one-year-ahead charge-offs will remain unchanged after the adoption of IFRS 9.

4. Research design, sampling, and descriptive statistics

4.1. Selected sample and descriptive statistics

To test these hypotheses, we manually collected data on 123 European banks having adopted IFRS 9 on 1st January 2018. The data consisted of information extracted from the 2018 financial statements on retained earnings and loan loss reserves as of 31st December 2017 (under IAS 39), as well as LLAs as of 1st January 2018 and 31st December 2018 under IFRS 9 (cost of risk for 2018). LLAs and variations in LLAs were broken down into three categories of financial instruments: financial instruments at amortized cost, financial instruments at FVOCI, and off-balance-sheet commitments. Within each category, we separately collected LLAs for each bucket (1, 2, and 3). In parallel, we collected historical data from 2014 to 2019 on a series of financial indicators used to assess the discretionary element of provisions from the Bank Focus database provided by Bureau Van Dijk and Moody's.

4.2. Methodology

4.2.1. Descriptive statistics and measurement of the Day One impact

We first perform an analysis of data collected based on descriptive statistics to test H1. The amount of LLAs on 1st January 2018 and 31st December 2017 was obtained from the 2018 annual reports, which must disclose the remeasurement of LLA on Day One. We exclude from the Day One remeasurement the changes in LLAs resulting from the de-recognition of loans resulting from sale, transfer, or write-off of loans at end-2017, so that the changes in ECL as of 1st January 2018 are derived from the same loan portfolio as those of 31st December 2017. This allows us to isolate the impact of the change in LLA measurement methods. We compute the ratios of LLA to loans on 31st December 2017 and at 1st January 2018, of the remeasurement on 1st January to gross loan, which provides an assessment of the impact of the transition from IAS 39 to IFRS 9.

Banks are then ranked based on the loss/gain recorded on Day One, and the sovereign rating of the country where they are based is collected. The objective is to observe whether there are significant differences in Day One impact on LLAs between banks based in highly-rated countries and those based in weakly rated countries.

4.2.2. Change in the determinants of LLAs

To measure the country factor's effects, we regress the Day One change in LLAs against the sovereign rating of the country in which the banks are based as of 1st January 2018 and the impaired loans as of 31st December 2017, which is the key determinant of LLAs. We control for other bank's features, including the coverage ratio and the size of the banks (measured through total assets), which are quoted in most research on the determinants of banks' loan loss provisions[9]. As we use least square regression, ratings are transformed into numerical continuous variables, with a score of 21 assigned from Aaa to 1 assigned to C.

$$D1\_ECL_i = \beta_0 + \beta_1 RATING_{ij} + \beta_2 \Delta NPL_i + \beta_3 COVER_i + + \beta_4 LOANS_i + \beta_5 SIZE_i + \varepsilon_i \quad (1)$$

$D1\_ECL_i$ is the change in LLA in bank i due to the adoption of IFRS 9 on 1st January 2018, recorded in retained earnings. The effect of asset re-classification is excluded from the Day One effect. $RATING_{ij}$ is the rating, on 1st January 2018, of the country j where the bank i is based. ΔNPL_t is the slope of Gross NPL to gross loans computed to t from t-5; $COVER_t$ is the amount of LLA by Non-performing loans; $LOANS_t$ is the amount of gross loans on 31st December 2017 scaled to total assets. $SIZE_t$ is the natural logarithm of total assets.

The next step is to assess whether sovereign ratings affect the determination of LLAs, and whether this effect has increased after the adoption of IFRS 9. We have retained the regression model developed by Gebhardt and Novotny-Farkas (equation 2a). In a separate model (2b), we added the sovereign rating to the set of independent variables. In this model, ratings are treated as a categorical variable, *k*, with 21 possible categories (the number of notches in Moody's scale); it takes the value of 1 when the rating of the bank's country is equal to *k*, and 0 for the other categories:

[9] See section on hypothesis setting, Comparability of LLAs.

$$LLA_{it} = \beta_0 + \beta_1 NPL_{it} + \beta_2 NCO_{it} + \beta_3 LOANS_{it} + \beta_4 SIZE_{it} + \beta_5 \Delta GDP_{it} + \beta_6 \Delta UNEMP_{it} + \varepsilon_{it} \quad (2a)$$

$$LLA_{it} = \beta_0 + \beta_1 NPL_{it} + \beta_2 NCO_{it} + \beta_3 LOANS_{it} + \beta_4 SIZE_{it} + \beta_5 \Delta GDP_{it} + \beta_6 \Delta UNEMP_{it} + \beta_i RATING\_FE_{it} + \varepsilon_{it} \quad (2b)$$

where subscript *t* indexes the year, and *i* indexes the bank. Variables are defined as follows: *LLA* is the loan loss allowance scaled by total loans outstanding; *NPL* is the non-performing loans scaled by total loans outstanding; *NCO* is net charge-off; *LOANS* is total loans outstanding scaled by total assets; *ΔGDP* is the change in GDP in year t versus year t-1; *ΔUNEMP* is the change in the unemployment rate in year t versus year t-1. *RATING_FE* is a categorical variable (fixed effects) representing the sovereign rating *k* of the country *j* where the bank *i* is based.

We conducted, for both models, a cross-sectional OLS regression for each year of the 2014–2017 period, and computed the R^2. We expect the R^2 to decrease in 2018, as the weaker association between LLAs and impaired loans reduces the model's explanatory power.

Second, the model was run on the whole period, and then separately for the 2014–2017 and 2018–2019 sub-periods. We control for time-series and cross-sectional dependence by robust standard errors clustered by year and by banks.

We expect that, in the 2018–2019 period, the significance of the coefficient associated with impaired loans will decrease, and the coefficient associated with sovereign ratings will increase. In the 2018–2019 period. If these two hypotheses are verified, this would mean that, following the adoption of IFRS 9, it is more difficult to relate the level of LLAs to loan impairment than under the IAS 39 provisioning rules, and that the effect of sovereign rating is more pronounced than before 2018.

To determine whether the changes observed in the determination of LLAs constitute a structural break between the two periods, we have performed a Chow Test using Equation 2b. The Chow Test enables us to compare the same regression model on two separate datasets. It allows us to determine whether there is a structural break between two consecutive sub-periods. The sub-periods subjected to Chow Test are the pre-IFRS 9 era (2014-2017) and post IFRS 9 era (2018–2019), as set in Equation (2c) below:

$$LLA_{it} = \beta_0 + \beta_1 NPL_{it} + \beta_2 NCO_{it} + \beta_3 LOANS_{it} + \beta_4 SIZE_{it} + \beta_5 \Delta GDP_{it} + \beta_6 \Delta UNEMP_{it} + \beta_i RATING\_FE_{it} + \beta_7 IFRS9_t + \beta_8 (IFRS9_t \times NPL_{it}) + \beta_9 (IFRS9_t \times NCO_{it}) + \beta_{10} (IFRS9_t \times LOANS_{it}) + \beta_{11} (IFRS9_t \times SIZE_{it}) + \beta_{12} (IFRS9_t \times \Delta GDP_{it}) + \beta_{13} (IFRS9_t \times \Delta UNEMP_{it}) + \beta_i (IFRS9_t \times RATING\_FE_{it}) + \varepsilon_{it} \quad (2c)$$

The null hypothesis that the post-IFRS 9 regression coefficients equal those of the pre-IFRS 9 models is rejected if the statistic *F* is statistically significant.

Finally, to measure the sovereign ratings and LLAs, we transformed the country rating into a continuous variable noted *RATING*, ranging from 21 (Aaa-rated) to 1 (C-rated) based on Moody's scale. The model is tested separately for the 2014–2017 and the 2018–2019 periods.

$$LLA_{it} = \beta_0 + \beta_1 NPL_{it} + \beta_2 NCO_{it} + \beta_3 LOANS_{it} + \beta_4 SIZE_{it} + \beta_5 \Delta GDP_{it} + \beta_6 \Delta UNEMP_{it} + \beta_7 RATING_{it} + \varepsilon_{it} \quad (2d)$$

where *RATING* is the sovereign rating transformed into a continuous variable.

We expect that the coefficient of *RATING* will increase in the post Day One period, reflecting the increased influence of the sovereign rating over LLAs.

4.2.3. Comparability of loan loss provisions across banks before and after Day One

To determine whether the comparability of the LLAs has been affected by the structural break in LLA models resulting from the adoption of IFRS 9, we first need to identify and measure the bank's specific effect on LLAs. We then determine whether this specific bank effect has increased in the 2018–2019 period relative to the 2014–2017 period. We retained the model used in the preceding test, and included categorical rating and bank variables:

$$LLA_{it} = \beta_0 + \beta_1 NPL_{it} + \beta_2 NCO_{it} + \beta_3 LOANS_{it} + \beta_4 SIZE_{it} + \beta_5 \Delta GDP_{it} + \beta_6 \Delta UNEMP_{it} + \beta_i RATING\_FE_{it} + \beta_i BANK\_FE_{it} + \varepsilon_{it} \quad (3a)$$

where $BANK\_FE_{it}$ is the categorical variable for banks (fixed effects), taking the value of 1 for bank *i* and 0 for other banks.

We expect that the R^2 of Equation (3a) will increase significantly in the 2017–2019 period, and that the coefficient of the *RATING_FE* and *BANK_FE* variables to be significantly different in the 2018–2019 period compared to the 2014–2017 period. To test the difference between the two periods, we conduct a Chow test on Equation (3a). The confirmation that a structural break occurred in the determination of LLAs between the two periods would mean that the factors determining LLAs have changed in 2018, and that unobservable factors specific to banks have gained more influence since the adoption of IFRS 9, and that the association between LLAs and impaired loans has been altered. This makes it more difficult for investors to assess whether the level of LLAs that has been recorded for a given amount of impaired loan is adequate, and whether further provisioning will be necessary.

To obtain evidence that this structural change in the LLAs model is due to the heterogeneity in the measurement of ECL, we used descriptive statistics on the ratio of LLAs to gross Non-performing loans (the so-called Coverage ratio). The distribution and dispersion around the means of this ratio for the period 2018–2019 and 2014–2017 are compared. We use, alternately, the mean-centered Levene Test (Levene 1960) and the median-centered Brown-Forsythe Test (Brown and Forsythe 1974) to test the null hypothesis of the Coverage ratio's equality of variance between the pre-IFRS 9 and post-IFRS 9 periods [10].

We anticipate, for the 2018–2019 years, that the dispersion of the coverage ratio in the 2018–2019 period will be significantly higher than in the 2014–2017 period, reflecting the increased flexibility allowed to banks to measure provisions for a given level of impaired (Stage 3) loan.

4.3. Effect on the ability of LLAs to predict charge-offs over the short-term

To assess the capacity of LLAs to predict one-year-ahead charge-offs, we test the association between LLAs in year N with the ratio of charge-offs reported in year N+1. The test is conducted separately for the 2014–2017 and 2018–2019 periods. For the sake of consistency, we retain a regression model using the same control variables as in the preceding tests.

$$NCO_{it+1} = \beta_0 + \beta_1 LLA_{it} + \beta_2 LOANS_{it} + \beta_3 SIZE_{it} + \beta_4 \Delta GDP_{it} + \beta_5 \Delta UNEMP_{it} + \beta_6 RATING\_FE_{it} + \varepsilon_{it} \quad (4a)$$

Where NCO_{t+1} = Net Charge-offs on t+1;

[10] Levene Test (Levene 1960) for equality of variance is centered at the mean. The Levene' statistic follow a F-Distribution and is computed as follows: $W = \frac{n-K}{K-1} \times \frac{\sum_{k=1}^{K} n_k (\overline{Z_k} - \bar{Z})^2}{\sum_{k=1}^{K} \sum_{i=1}^{n_k} ((Z_k)_i - \overline{Z_k})^2}$, with $(Z_k)_i = |(X|_{Y=k})_i - \overline{X_k}|$ and $\bar{Z} = \frac{\sum_{k=1}^{K} \sum_{i=1}^{n_k} (Z_k)_i}{K}$, and $K \geq 2$ groups. The Brown-Forsythe median-centered test' statistic (Brow and Forsythe 1974) is computed similarly than Levene's statistic with $(Z_k)_i = |(X|_{Y=k})_i - Median\ X_k|$.

To verify the hypothesis of R^2 not different between the two periods, we perform a Chow Test on the model (4a), consistent with the same approach followed for H2 and H3. We expect that the R^2 of the test in the 2018–2019 period will not significantly differ from that observed in 2014–2017, and that the coefficient of the LLA variable will also remain comparable for both periods.

5. Results

5.1. Descriptive statistics

5.1.1. Measurement of the Day One effect

Table 1 provides descriptive statistics of the gains (losses) relative to the adoption of IFRS on Day One relative to banks' gross loans. The data in column 2 (D1 ECL at 01.01.2018) shows the change in ECL on the loan portfolio resulting from the remeasurement of LLAs under the IFRS 9 standard. It shows that the adoption of IFRS 9 translated into an increase in LLAs loss for most banks (113 out of 123), which was equivalent to an accounting loss, as it came as a deduction from retained earnings on 31st December 2017. The average effect was a loss amounting to 0.495% of gross loans; it ranged from 6.434% to –1.157% (the negative sign indicates that the remeasurement translated into a gain for the bank; this was the case for ten banks). Note that the Day One ECL is measured on a comparable loan portfolio basis; details of the effect of re-classification assets between 31st December and 1st January due to IFRS 9 is provided in Table 2, column 3.

TABLE 1
Day One remeasurement of ECL and change in LLAs (N = 123).

	D1 ECL at 01.01.2018	LLAs at 31.12.2017	LLAs at 31.12.2018	LLPs in 2017	LLPs in 2018
Number of observations	123	123	123	123	123
Mean (%)	0.495	4.782	3.923	0.826	0.376
Standard deviation (%)	0.918	6.329	4.937	3.138	0.620
Median (%)	0.203	2.720	2.435	0.233	0.201
1st Quartile (%)	0.063	1.083	0.867	0.026	0.031
3rd Quartile (%)	0.477	6.139	4.592	0.771	0.520
Interquartile Range (%)	0.414	5.055	3.724	0.745	0.489
Maximum (%)	5.277	32.766	25.074	33.784	3.330
Minimum (%)	–1.157	0.069	0.069	–0.943	–0.890
Range (%)	6.434	32.698	25.005	34.727	4.220
Number of neg. effects	113			98	99
Number of pos. effects	10			25	24

Note: ECL are Expected Credit Losses measured at 01.01.2018 relative to Gross Loans; LLA and LLP are Loan Loss Allowance and Loan Loss Provisions, both relative to Gross Loans. ECL, LLA and LLP are expressed in percentage.

Table 1 also shows the ratio of LLAs to gross loans and the ratio of LLPs to gross loans at end-2017 and end-2018. These two ratios decreased in 2018 relative to 2017, which, at first view, might contradict our hypotheses and the pre-implementation studies. However, a detailed analysis of banks' financial reports, summarized in Table 2, indicates that this is attributable to the substantial number of loans that have been written-off by banks in 2018, which represented, on average, 1.202% of gross loans (see column 7). The charge-offs recorded in 2018, which had been mentioned above in the review of post-implementation tests, enabled banks to de-recognize heavily provisioned assets and hence reduce LLAs at year-end 2018.

TABLE 2
Details of changes in LLAs, 31.12.2017 to 31.12.2018 (N = 123).

	LLA at 31.12.2017	Changes: Re-classification	Changes: Measurement of ECL	LLA at 01.01.2018	Loan Loss Provisions	Net Charge-offs	LLA at 31.12.2018
Mean	4.782	–0.187	0.495	5.097	0.376	1.202	3.923
Std. Dev.	6.329	1.111	0.918	6.592	0.620	3.108	4.937
Median	2.720	0.000	0.203	2.977	0.201	0.237	2.435
1st Q	1.083	–0.015	0.063	1.118	0.031	0.016	0.867
3rd Q	6.139	0.000	0.477	6.445	0.520	1.104	4.592
Max.	32.766	2.337	5.277	32.704	33.784	20.288	25.074
Min.	0.069	–9.555	–1.157	0.064	–0.943	–3.658	0.069

Note: Net Charge-offs include effects from consolidation scope's variation and currencies adjustments for which impacts on the amount of Net Charge-offs are negligible. All amounts are expressed in percentage of Gross Loans.

Table 3 shows that the decline in LLAs measured against total assets on 31st December 2018 was concentrated on the riskiest loans: the reduction in Stage 3 loans accounted for 1.071% of gross loans, while the decrease in Stage 1 and Stage 2 loans represented 0.002% and 0.032% of gross loans respectively. Table 3 also shows that the inclusion, as of 1st January 2018, of LLAs on Stage 1 and Stage 2 loans had a minor effect on total LLAs. This means that the 12-month ECL on all loans and the lifetime ECL on loans subject to a significant increase in credit risk only account for a small share of LLAs. These were, in 2018, offset by the decline in LLAs due to the de-recognition of the riskiest assets, which explains the decrease in the average LLA from 5.097% to 3.923% of gross loans throughout 2018. However, though the reduction in Stage 3 assets has a negative impact on LLAs, it is impossible to determine the extent to which the reduction in LLAs throughout 2018 was attributable to the change in the provision measurement method, as the loan portfolios of 31st December and 1st January 2018 are not comparable.

TABLE 3
Average LLA by Stages of Loans as a Percentage of Gross Loans (N = 115).

	Total	Stage 1	Stage 2	Stage 3
LLA at 31.12.2017	4.888			
LLA at 01.01.2018	5.162	0.272	0.448	4.443
LLA at 31.12.2018	4.058	0.270	0.416	3.372
Change 01.01.2018-31.12.2018	–1.104	–0.002	–0.032	–1.071

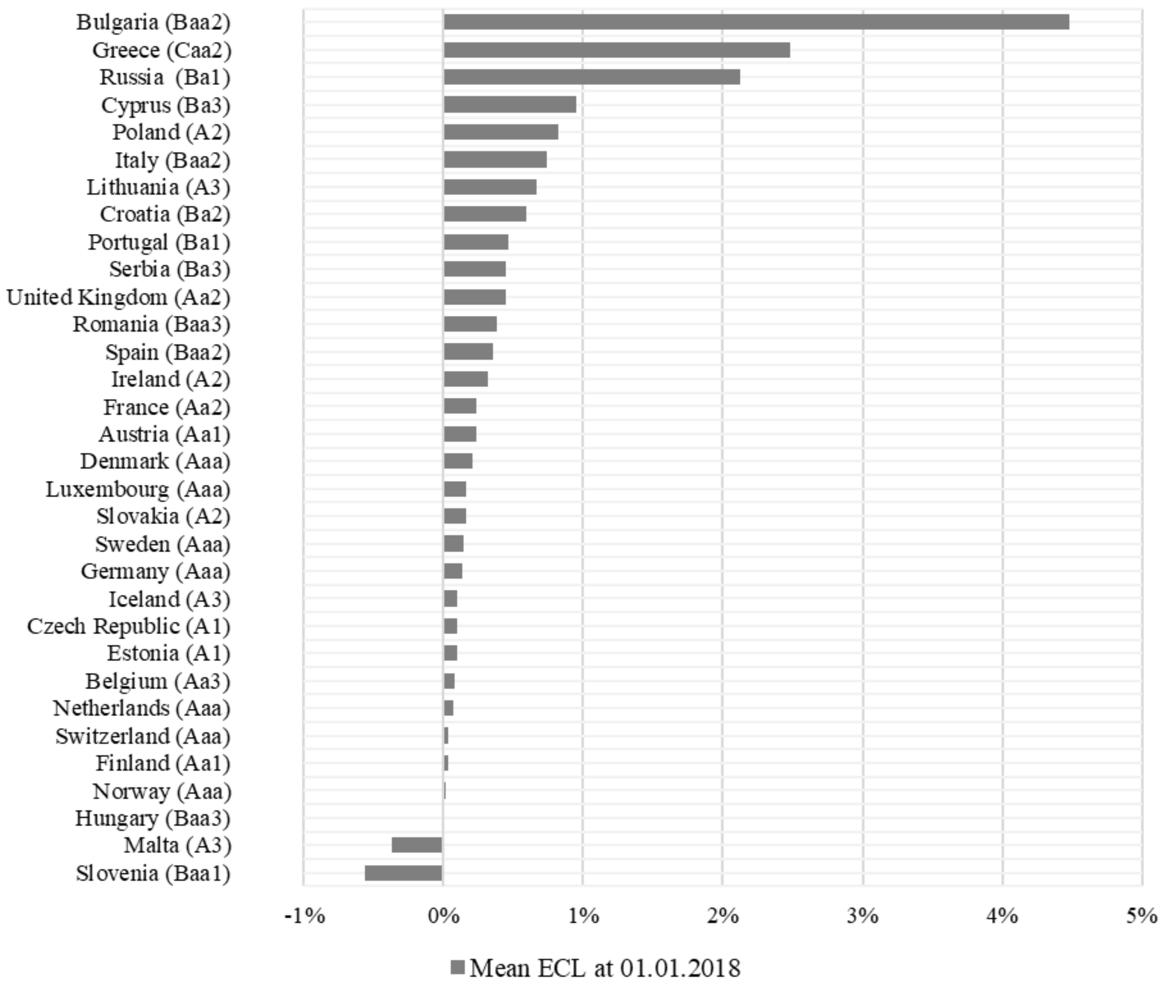
Note: Our total sample includes 123 banks. Eight banks are missing in Table 3 due to the absence of disclosure regarding the ECL stages at loans level in their FY 2018 financial report (five banks disclose ECL by stages for total amortized cost assets only, and three banks did not report ECL by stages for loans on 01.01.2018).

To conclude, the adoption of IFRS 9, on a comparable portfolio basis, has led to a moderate increase in provisions on the day of its implementation (+0.5% of gross loans). This suggests that the ECL based methods lead to higher provisions, which are explained by provisions recognized on unimpaired assets and the extension of assets subject to provisions. However, the increase is not significant, and provisions under IFRS 9 remain, on average, concentrated on the riskiest assets.

These findings are consistent with the pre-implementation studies and the first post-implementation tests conducted by banking authorities and auditing firms, which all concluded that the transition to IFRS 9 would imply a moderate overall loss for banks. This supports the conclusions of the study performed by E&Y (2018), which predicted moderate loss on Day One and a decrease in LLA by December 2018 due to the de-recognition of loans.

5.1.2. The effect of sovereign rating of the Day One change in LLA.

FIGURE 1
Day One Impact on LLA by country



We next present the results of the analysis of Day One by country. Figure 1 depicts the Day One effect, measured by the loss (gains) recorded in retained earnings on Day One, by country (exact numbers are presented in annex 4). Figure 1 clearly shows that banks based in countries with high country ratings have been less impacted by the transition to IFRS 9 than those operating in weakly rated countries.

Three out of five largest D1 ECL to gross loans ratios are recorded in countries rated in speculative-grade ('Ba1' and below on Moody's scale) on 31st December 2017 [Greece (Ca3), Russia (Ba1), and Cyprus (Ba3)], the two others being Bulgaria (Baa2) and Poland (A2), which are emerging countries where corporate ratings are generally low. The countries where the smallest aggregate losses (or gains) were observed are all rated in investment grade, one of them enjoying the highest possible rating (Aaa: Norway) and second highest (Aa1: Finland); two others, Malta and Slovenia, are rated in the middle of the investment-grade scale (A3 and respectively); Hungary (rated Baa3) appears as an outlier, but the sample includes only one bank in this country, which is not representative. More accurate conclusions can be drawn by a regression model covering the whole sample.

The association between the Day One effect and sovereign rating is confirmed by the cross-sectional OLS regression between D1 ECL and the determinants of LLAs (equation 1). Results are presented in Table 4; descriptive statistics of the variables are in Annex 4. Two models are tested: one includes the control variables only, while the second includes the sovereign rating of the country where banks are based. The second model has a stronger explanatory power, with an adjusted R^2 of 0.3478 versus 0.2587 in the first model. Most interestingly, the second model shows that the sovereign rating variable is statistically significant (at 1%), and appears as one of the two key determinants of the Day One impact, with the variation in NPL.

TABLE 4
OLS Regression of Equation (1) (N = 123).

	Expected Sign	*D1_ECL$_t$* 1(a)	1(b)
Intercept	?	0.964	2.049**
		(1.288)	(2.510)
RATING$_t$	–		–0.073***
			(–4.658)
$\Delta NPL_{t,t-5}$	+	0.239***	0.178**
		(3.474)	(2.609)
COVER$_t$	–	0.001	–0.002
		(0.314)	(–0.526)
LOANS$_t$	?	0.005	0.002
		(0.912)	(0.349)
SIZE$_t$	?	–0.071	–0.032
		(–1.577)	(–0.705)
Observations		123	123
Adjusted R^2		0.2587	0.3478

Note: Table 4 presents the OLS regression of Equation (1). The numbers in parentheses are t-statistics. We control for cross-sectional dependence by robust standard errors clustered by the bank. D1_ECL LLA change from ECL measurement at Day-one; RATING = Bank's country rating; ΔNPL = Slope of Gross NPL computed to *t* from *t-5*; COVER = Coverage ratio as LLA to Gross NPL; LOANS = Gross loans to total assets; SIZE = Natural logarithm of total assets converted in USD. *t* refers to the end of 2017. All variables are expressed in percentage except RATING and SIZE. *, ** and *** denote statistical significance at a level of 10%, 5%, and 1%, respectively.

The high significance of the sovereign rating in the determination of the Day One impact confirms our initial hypothesis regarding the effect of the ECL based provisioning model. As the computation of ECL relies on borrowers' credit ratings, and given the importance of the sovereign ceiling in determining these indicators, provisions have become increasingly linked to sovereign ratings. This has far-reaching implications for the provisioning policy of banks, which will become increasingly reliant on sovereign ratings.

5.2. Change in the determinants of LLAs and increased influence of sovereign ratings

More evidence on the change which occurred in 2018 is provided in the analysis of the factors determining LLAs. Figure 2 depicts the evolution of the adjusted R^2 of LLA determination models – equations 2a and 2b – over the 2014–2019 period, obtained from cross-sectional regressions. We observe a marked reduction in R^2 of Equation (2a) in 2018 compared to previous years; the R^2 of Equation 2b, for which sovereign rating is added to the set of independent variables, is more stable in 2018. This suggests a structural break has occurred in the determinants of LLAs between 2014–2017 and 2018–2019.

FIGURE 2
Evolution of Ajusted R^2

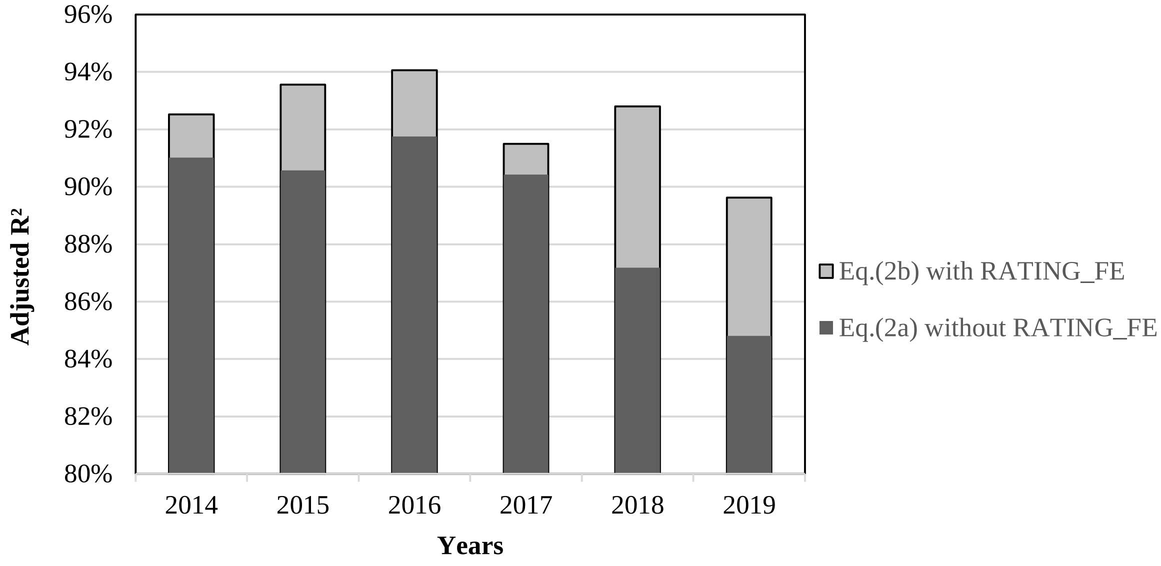


Table 5 presents the results of equation 2(a) and 2(b). The reduction by 4% points in the R^2 clearly shows that the explanatory power of the traditional LLA determination model, based on impaired loans, net charge-offs, and control variables, has decreased in 2018, after the adoption of IFRS 9. By contrast, the R^2 of the model, which includes sovereign ratings, has remained quasi-stable over the period, which provides evidence of the influence of this variable in the determination of LLAs. The incremental impact of *RATING_FE* on R^2 is clearly higher in the post-IFRS 9 period than in the pre-IFRS9 period: it increased by 5.62% in 2018, and 4.81% in 2019, compared to an incremental impact of 1.51%, 2.99%, 2.31%, and 1.07% in 2014, 2015, 2016, and 2017, respectively.

TABLE 5
OLS Regression of Equations (2a) and (2b).

	Sign	LLA_{it}					
		Whole period 2014-2019		Post-IFRS 9 2018-2019		Pre-IFRS 9 2014-2017	
		(2a)	(2b)	(2a)	(2b)	(2a)	(2b)
Intercept	?	2.500***	6.038***	2.282**	10.883***	2.425***	3.444**
		(3.830)	(4.212)	(2.422)	(3.665)	(2.966)	(2.507)
NPL_{it}	+	0.489***	0.448***	0.420***	0.296***	0.510***	0.473***
		(32.821)	(15.312)	(11.204)	(4.333)	(34.182)	(16.455)
NCO_{it}	+	0.143***	0.103**	0.169*	0.134*	0.160**	0.121**
		(2.839)	(2.212)	(1.768)	(1.889)	(2.157)	(2.070)
$LOANS_{it}$	?	–0.012**	–0.017***	–0.012*	–0.019***	–0.013**	–0.012**
		(–2.574)	(–3.738)	(–1.716)	(–2.924)	(–2.086)	(–2.001)
$SIZE_{it}$	?	–0.123***	–0.069	–0.086	–0.066	–0.129***	0.025
		(–3.212)	(–1.634)	(–1.590)	(–1.089)	(–2.701)	(0.528)
ΔGDP_{it}	–	–0.001	0.004	0.024	0.019	–0.001	0.001
		(–0.085)	(0.308)	(1.284)	(0.989)	(–0.072)	(0.073)
$\Delta UNEMP_{it}$	+	–0.007	0.000	–0.001	–0.010	–0.015	0.009
		(–0.691)	(–0.018)	(–0.064)	(–0.857)	(–1.211)	(0.633)
$RATING\_FE_{it}$		No	Yes	No	Yes	No	Yes
Observations		738	738	246	246	492	492
Adjusted R^2		0.8846	0.8979	0.8565	0.9065	0.8974	0.9152

Note: Table 5 presents the OLS regression of Equations (2a) and (2b). The numbers in parentheses are t-statistics. We control for time-series and cross-sectional dependence by robust standard errors clustered by bank and year. LLA = Loan Loss Allowance to Gross Loans; NPL = Gross Non-Performing Loans to Gross Loans; NCO = Net Charge-offs to Gross Loans; LOANS = Gross Loans to Total Assets; SIZE = Natural logarithm of total assets converted in USD; ΔGDP = Year Change in Gross Domestic Product; ΔUNEMP = Year Change in Unemployment Rate; RATING_FE = Bank's country rating according to Moody's rating scale treated as a categorical variable at rating range level (Fixed Effects). All variables are expressed in percentage except SIZE and RATING_FE. *, ** and *** denote statistical significance at a level of 10%, 5%, and 1%, respectively.

The Chow Test results, presented in Table 6, allow us to confirm that a structural break occurred in 2018. The null hypothesis of equality of R^2 between the two periods is rejected at the threshold of 1%. The F test performed on each coefficient shows that the coefficient for dummy variables representing sovereign rating is also significant at 1%. This implies that the structural break between the two periods is caused by the inclusion of the sovereign rating variable. This conclusion is consistent with the results research published by Abrahimi (2020), who studied the effect of IFRS 9 adoption on the determinants of LLPs, and is, to our knowledge, the only academic publication on this topic as of today.

TABLE 6
Chow's Test on Equation (2c) (N = 738).

IFRS 9 related Variables (H_0: $\beta_{IFRS9} = 0$):	β_i (Post) – β_i (Pre)	F	*p-value*
$IFRS9_t$	10.848	1.747	0.187
$IFRS9_t \times NPL_{it}$	–0.177	5.811**	0.016
$IFRS9_t \times NCO_{it}$	0.013	0.022	0.883
$IFRS9_t \times LOANS_{it}$	–0.007	0.575	0.449
$IFRS9_t \times SIZE_{it}$	–0.091	1.415	0.235
$IFRS9_t \times \Delta GDP_{it}$	0.018	0.566	0.452
$IFRS9_t \times \Delta UNEMP_{it}$	–0.019	1.056	0.305
All IFRS 9 variables clustered (ex. *RATING_FE*):		1.930*	0.074
$IFRS9_t \times RATING\_FE_{it}$ (clustered)		2.599***	0.001
All IFRS 9 variables clustered (H_0: $RSS_{IFRS9} = 0$):		2.921***	0.000

Note: Table 6 presents the coefficients of IFRS 9 related variables from OLS regression of Equation (2c). We control for time-series and cross-sectional dependence by robust standard errors clustered by bank and year. F is Fisher's statistic. IFRS9 is a dummy variable noted 1 for the years 2018 and 2019, 0 otherwise; NPL = Gross Non-Performing Loans to Gross Loans; NCO = Net Charge-offs to Gross Loans; LOANS = Gross Loans to Total Assets; SIZE = Natural logarithm of total assets converted in USD; ΔGDP = Year Change in Gross Domestic Product; ΔUNEMP = Year Change in Unemployment Rate; RATING_FE = Bank's country rating according to Moody's rating scale treated as a categorical variable at rating range level (Fixed Effects). All variables are expressed in percentage except IFRS9, SIZE and RATING_FE. *, ** and *** denote statistical significance at a level of 10%, 5%, and 1%, respectively.

The above analysis leads to the conclusion that, since 2018, the sovereign ratings have gained higher importance in the determination of sovereign ratings. The results of the regression test of Equation (2d), presented in Table 7, enables us to measure the relationship between the sovereign ratings and LLAs before and after the adoption of IFRS 9.

TABLE 7
OLS Regression of Equation (2d).

	Sign	LLA_{it} Whole period 2014-2019	Post-IFRS 9 2018-2019	Pre-IFRS 9 2014-2017
Intercept	?	5.055***	5.462***	4.537***
		(6.722)	(6.094)	(4.749)
NPL_{it}	+	0.449***	0.366***	0.477***
		(22.683)	(8.791)	(23.429)
NCO_{it}	+	0.126***	0.147	0.146**
		(2.608)	(1.530)	(2.063)
$LOANS_{it}$	?	–0.015***	–0.014**	–0.015**
		(–3.310)	(–2.323)	(–2.541)
$SIZE_{it}$	?	–0.074*	–0.003	–0.093*
		(–1.853)	(–0.052)	(–1.897)
ΔGDP_{it}	–	0.001	0.028	0.002
		(0.111)	(1.548)	(0.129)
$\Delta UNEMP_{it}$	+	0.001	0.006	–0.008
		(0.070)	(0.457)	(–0.638)
$RATING_{it}$	–	–0.155***	–0.218***	–0.122***
		(–5.693)	(–5.061)	(–3.955)
Observations		738	246	492
Adjusted R²		0.8917	0.8778	0.9013

Note: Table 7 presents the OLS regression of Equation (2d). The numbers in parentheses are t-statistics. We control for time-series and cross-sectional dependence by robust standard errors clustered by bank and year. LLA = Loan Loss Allowance to Gross Loans; NPL = Gross Non-Performing Loans to Gross Loans; NCO = Net Charge-offs to Gross Loans; LOANS = Gross Loans to Total Assets; SIZE = Natural logarithm of total assets converted in USD; ΔGDP = Year Change in Gross Domestic Product; ΔUNEMP = Year Change in Unemployment Rate; RATING = Bank's country rating according to Moody's rating scale treated as a continuous variable. All variables are expressed in percentage except SIZE and RATING. *, ** and *** denote statistical significance at a level of 10%, 5%, and 1%, respectively.

The coefficient associated with the sovereign rating (transformed into a continuous variable) has doubled in the 2018–2019 period compared to 2014–2017, and remains significant at the 1% level. This means that, following the adoption of IFRS 9, a one-notch downgrade in the rating of the country where a bank is based leads to a 0.218% increase in LLAs relative to gross loans, compared to an increase of only 0.122% before. Simultaneously, the coefficient of impaired loans (*NPL*), the other most significant factor, has been reduced from 0.477 to 0.366, which illustrates the weaker link between provisions and NPLs since 2018, already shown in previous tests.

The untabulated Chow test for comparing coefficients associated with *RATING* for post and pre-IFRS 9 reveals a statistically significant difference in β of –0.096 (p-value = 0.071). The F-statistic is equal to 3.273 (significant at the 1% level, with p-value = 0.071), which indicates that a structural break occurred in the model based on sovereign ratings as a continuous variable, consistent with previous analyses.

5.3. Effect on the comparability of LLAs across banks

5.3.1. Banks' individual effect

To measure the heterogeneity of provisioning rules, we assess the influence of factors specific to banks and not captured in the LLA determination models discussed above. Table 8 indicates that the inclusion of a categorical variable (fixed effects) to capture individual effect for each bank allows an improvement of the R^2 of the model, which increases from 0.97 in the 2014–2019 period to 0.99 in the 2018–2019 period.

TABLE 8
OLS Regression of Equation (3a).

		LLA_{it}		
	Sign	Whole period 2014-2019	Post-IFRS 9 2018-2019	Pre-IFRS 9 2014-2017
Intercept	?	9.454***	5.952	28.418***
		(2.659)	(0.719)	(3.429)
NPL_{it}	+	0.551***	0.382***	0.582***
		(13.701)	(4.954)	(6.502)
NCO_{it}	+	0.003	0.081	0.011
		(0.118)	(1.385)	(0.297)
$LOANS_{it}$	?	–0.021	0.003	–0.088**
		(–1.333)	(0.092)	(–2.087)
$SIZE_{it}$	?	–0.542*	–0.144	–1.904***
		(–1.882)	(–0.198)	(–2.796)
ΔGDP_{it}	–	0.010	0.012	0.014
		(1.216)	(0.865)	(1.483)
$\Delta UNEMP_{it}$	+	–0.009	0.006	–0.007
		(–1.323)	(0.434)	(–0.621)
$RATING\_FE_{it}$		Yes	Yes	Yes
$BANK\_FE_{it}$		Yes	Yes	Yes
Observations		738	246	492
Adjusted R²		0.9672	0.9907	0.9781

Note: Table 8 presents the OLS regression of Equation (3a). The numbers in parentheses are t-statistics. We control for time-series and cross-sectional dependence by robust standard errors clustered by bank and year. LLA = Loan Loss Allowance to Gross Loans; NPL = Gross Non-Performing Loans to Gross Loans; NCO = Net Charge-offs to Gross Loans; LOANS = Gross Loans to Total Assets; SIZE = Natural logarithm of total assets converted in USD; ΔGDP = Year Change in Gross Domestic Product; ΔUNEMP = Year Change in Unemployment Rate; RATING_FE = Bank's country rating according to Moody's rating scale treated as a categorical variable at rating range level (Fixed Effects); BANK_FE = Bank categorical variable noted 1 for bank *i*, 0 otherwise (Fixed Effects). All variables are expressed in percentage except SIZE, RATING_FE and BANK_FE. *, ** and *** denote statistical significance at a level of 10%, 5%, and 1%, respectively.

Although the improvement in R^2 is modest, the Chow Test applied to the new model (Table 9) indicates that the difference in the coefficients of the categorical variables capturing banks' individual effect is significant between the two periods. The F test result for all IFRS9 variables indicates that the structural break observed in the previous versions of the model is also present when banks' individual effect is included. These results lead to the conclusion that, after 2018, factors unique to banks play a more important role in the determination of LLAs, which suggests an increased heterogeneity in provisioning rules.

TABLE 9
Chow's Test on Equation (3b) (N = 738).

IFRS 9 related Variables (H_0: $\beta_{IFRS9} = 0$):	β_i (Post) – β_i (Pre)	*F*	*p-value*
$IFRS9_t$	–19.183	5.232**	0.023
$IFRS9_t \times NPL_{it}$	–0.200	2.985*	0.084
$IFRS9_t \times NCO_{it}$	0.070	1.246	0.265
$IFRS9_t \times LOANS_{it}$	0.091	2.959*	0.086
$IFRS9_t \times SIZE_{it}$	1.760	3.402*	0.066
$IFRS9_t \times \Delta GDP_{it}$	–0.002	0.020	0.889
$IFRS9_t \times \Delta UNEMP_{it}$	0.013	0.539	0.442
$IFRS9_t \times RATING\_FE_{it}$ (clustered)		2.881***	0.000
$IFRS9_t \times BANK\_FE_{it}$ (clustered)		6.509***	0.000
All IFRS 9 variables clustered (H_0: $RSS_{IFRS9} = 0$):		7.252***	0.000

Note: Table 9 presents the coefficients of IFRS 9 related variables from OLS regression of Equation (3b). We control for time-series and cross-sectional dependence by robust standard errors clustered by bank and year. F is Fisher's statistic. IFRS9 is a dummy variable noted 1 for the years 2018 and 2019, 0 otherwise; NPL = Gross Non-Performing Loans to Gross Loans; NCO = Net Charge-offs to Gross Loans; LOANS = Gross Loans to Total Assets; SIZE = Natural logarithm of total assets converted in USD; ΔGDP = Year Change in Gross Domestic Product; ΔUNEMP = Year Change in Unemployment Rate; RATING_FE = Bank's country rating according to Moody's rating scale treated as a categorical variable at rating range level (Fixed Effects); BANK_FE = Bank categorical variable noted 1 for bank *i*, 0 otherwise (Fixed Effects). All variables are expressed in percentage except IFRS9, SIZE, RATING_FE and BANK_FE. *, ** and *** denote statistical significance at a level of 10%, 5%, and 1%, respectively.

5.3.2. *Dispersion of coverage ratio*

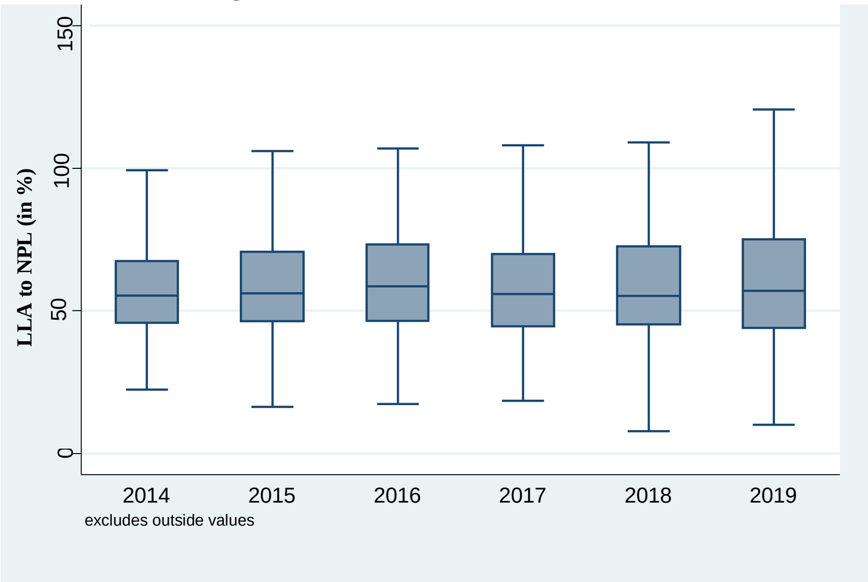
This result is confirmed by the evolution of the ratio of LLA to impaired (or Stage 3) loans over the period 2014 to 2019. While the mean and median ratio in the years 2018–2019 do not markedly differ from the mean in the years 2014 to 2017, we observe a pronounced increase in the standard deviation in 2018 compared to 2017 (Table 10). The coefficient of variation (Standard deviation to mean) clearly increases in 2018 compared to 2017 (0.538 vs. 0.410). The 3rd quartile takes higher values in 2019 and 2018 than in previous years (except 2016). This indicates that the coverage ratio is more dispersed around its mean after adopting IFRS 9 than before.

TABLE 10
Coverage ratio (LLA to NPL): Descriptive statistics, 2014–2019.

	Mean	SD	SD/Mean	1st Quartile	Median	3rd Quartile
2019	60.930	26.668	0.438	44.039	56.963	75.155
2018	61.785	33.226	0.538	45.037	55.131	72.688
2017	60.011	24.627	0.410	44.617	55.875	69.958
2016	61.601	25.334	0.411	46.387	58.628	73.334
2015	59.739	21.015	0.352	46.145	56.199	70.686
2014	58.299	20.515	0.352	45.575	55.404	67.416

The distribution of the coverage ratio for each of the six years retained in our study can be observed in Figure 3 (Box Plot), which shows extreme values and medians for the distribution. It indicates that the observations are more dispersed around their mean before in the 2014–2017 period than in the 2018–2019 period. In particular, in 2018, we observe many values diverging from the mean coverage ratio. The level of LLAs to be recognized for one unit of impaired loans fluctuates within a wider range since 2018. This translates the increased heterogeneity of provisioning practices since 2018.

FIGURE 3
Evolution of Coverage Ratio



The Levene Test centered at the mean (W_{Mean}) and Levene Test with 10% trimmed mean [where the top and bottom 5% of mean values are trimmed ($W_{Trimmed}$)] were performed to test the null hypothesis where $\sigma(COVER_{PRE}) = \sigma(COVER_{POST})$. A statistical significance of W would lead to rejecting the null hypothesis. To ensure results from Levene Test, we also perform the Brown-Forsythe Test centered at the median (W_{Median}); an alternative in case of non-respect of the normal distribution of values.

The Levene and Brown-Forsythe Tests confirm that the increase in the dispersion of the coverage ratio observed in the Post-IFRS 9 period is statistically different. The values of both the W_{Mean} and $W_{Trimmed}$ statistics indicate that the null hypothesis of equality of variance for the two periods is rejected, with a confidence interval of 5%. Also, the Brown-Forsythe W_{Median} statistic rejects the null hypothesis at a level of 10%.

TABLE 11
Levene and Brown-Forsythe Tests of Equality of Variance.

Group	**Mean**		**Std. Dev.**		**Frequency**	
Pre	59.913		22.932		492	
Post	61.357		30.068		246	
Total	60.394		25.521		738	
Levene	W_{Mean}	=	5.365	Df (1, 736)	Pr > F =	0.021
Levene (Trimmed)	$W_{Trimmed}$	=	3.970	Df (1, 736)	Pr > F =	0.047
Brown-Forsythe	W_{Median}	=	3.531	Df (1, 736)	Pr > F =	0.061

These results do not allow us to conclude that the observed dispersion coverage ratio is due to the adoption of IFRS 9. However, in the absence of a notable economic event between these two periods that could have weighed on banks' individual provisioning practices, the largest dispersion of coverage ratio is consistent with the hypothesis that the adoption of IFRS 9 has allowed banks more flexibility in recognition of LLAs for a given level of loan impairment, which altered the homogeneity of banks' provisioning practices. In fact, our results demonstrate that comparability has not improved, or at the very least, that this improvement has not translated into increased homogeneity of the provisioning practices.

5.4. Effect on the ability of LLAs to predict charge-offs

The final step is to assess the effect of the IFRS 9 standard on the ability of LLAs to predict credit losses over the short term, defined as one-year-ahead net charge-offs.

TABLE 12
OLS Regression of Equation (4a)

		NCO_{it+1}		
	Expected Sign	Whole period 2014-2019	Post-IFRS 9 2018-2019	Pre-IFRS 9 2014-2017
Intercept	?	–6.047***	–10.033*	–4.384
		(–2.642)	(–1.863)	(–1.648)
LLA_{it}	+	0.362***	0.473**	0.307**
		(3.397)	(2.527)	(2.236)
$LOANS_{it}$	?	0.013	0.016	0.013
		(1.499)	(1.130)	(1.416)
$SIZE_{it}$	?	0.043	0.132	–0.012
		(0.616)	(1.321)	(–0.133)
ΔGDP_{it}	–	0.011	0.059	0.003
		(0.643)	(0.598)	(0.201)
$\Delta UNEMP_{it}$	+	0.006	0.046	0.005
		(0.245)	(1.350)	(0.166)
$RATING\_FE_{it}$		Yes	Yes	Yes
Observations		690	230	460
Adjusted R^2		0.3100	0.4547	0.2594

Note: Table 12 presents the OLS regression of Equation (4a). The numbers in parentheses are t-statistics. We control for time-series and cross-sectional dependence by robust standard errors clustered by bank and year. NCO_{t+1} = Net Charge-offs on t+1; LLA = Loan Loss Allowance to Gross Loans; LOANS = Gross Loans to Total Assets; SIZE = Natural logarithm of total assets converted in USD; ΔGDP = Year Change in Gross Domestic Product; ΔUNEMP = Year Change in Unemployment Rate; RATING_FE = Bank's country rating according to Moody's rating scale treated as a categorical variable at rating range level (Fixed Effects). All variables are expressed in percentage except SIZE and RATING_FE. *, ** and *** denote statistical significance at a level of 10%, 5%, and 1%, respectively.

The coefficient associated with LLAs has increased in the 2018–2019 period compared to 2014–2017 (Table 12). It remains significant at the 5% level, which provides evidence of a moderate improvement in the short-term predictability of LLAs. The R^2 has increased in the 2018–19 period, but the Chow Test conducted on the model (Table 12) indicates that the null hypothesis of equality of the coefficients of the model cannot be rejected; hence, the hypothesis of a structural change in the ability of LLAs to predict one-year-ahead charge-offs following the adoption of IFRS 9 cannot be accepted.

In 2018–2019, nearly half (0.473) of NCO in a given year are explained by LLAs recognized in the year before (versus 0.307 before 2018) (Table 11); this means that the adoption of IFRS 9 has reinforced the short-term time horizon of credit losses, which provisions aim to cover. The hypothesis that the ability of LLAs under IFRS 9 to predict long-term losses is not rejected – in fact, it cannot be tested in the absence of observation of longer time span starting in 2018 – but accepting this hypothesis would imply that the amount of one-year-ahead charge-offs is equal or close to the amount of charge-offs recognized several years later, which does not seem realistic.

TABLE 13
Chow's Test on Equation (4b) (N = 690)

IFRS 9 related Variables (H_0: $\beta_{IFRS9} = 0$):	β_i (Post) – β_i (Pre)	*F*	*p-value*
$IFRS9_t$	–0.925	0.025	0.875
$IFRS9_t \times LLA_{it}$	0.166	0.517	0.472
$IFRS9_t \times LOANS_{it}$	0.003	0.036	0.849
$IFRS9_t \times SIZE_{it}$	0.145	1.128	0.289
$IFRS9_t \times \Delta GDP_{it}$	0.056	0.317	0.573
$IFRS9_t \times \Delta UNEMP_{it}$	0.041	0.027	0.869
All IFRS 9 variables clustered (ex. RATING_FE):		1.316	0.255
$IFRS9_t \times RATING\_FE_{it}$ (clustered)		1.144	0.318
All IFRS 9 variables clustered (H_0: $RSS_{IFRS9} = 0$):		1.092	0.356

Note: Table 13 presents coefficients of IFRS 9-related variables from the OLS regression of Equation (4b). We control for time-series and cross-sectional dependence by robust standard errors clustered by bank and year. F is Fisher's statistic. IFRS9 is a dummy variable noted 1 for the years 2018 and 2019, 0 otherwise; NCOt+1 = Net Charge-offs on t+1; LLA = Loan Loss Allowance to Gross Loans; LOANS = Gross Loans to Total Assets; SIZE = Natural logarithm of total assets converted in USD; ΔGDP = Year Change in Gross Domestic Product; ΔUNEMP = Year Change in Unemployment Rate; RATING_FE = Bank's country rating according to Moody's rating scale treated as a categorical variable at rating range level (Fixed Effects). All variables are expressed in percentage except IFRS9, SIZE and RATING_FE. *, ** and *** denote statistical significance at a level of 10%, 5%, and 1% percent, respectively.

The association between LLAs and one-year-ahead NCOs suggests that the ability of IFRS 9 to provide forward-looking predictions can be contested. Indeed, despite the introduction of provisions rules that anticipate, in principle, long term losses, LLAs remain strongly associated with short-term credit losses. This does not constitute evidence that their ability to predict long term losses has not been improved; but accepting this hypothesis would imply that long term losses are strongly correlated to short-term losses.

6. Conclusion

This research raises questions on the gains provided by the IFRS 9 standard in terms of quality of financial reporting. At first view, information on provisions disclosed under the new standard is more useful than under IAS 39 for investors and creditors. Provisions are measured based on forward-looking expected losses, which should enable users of financial reports to draw more accurate projections than with the previous IAS 39 rules, based on past events. Besides, the new standard appears more conservative than IAS 39: its adoption translated into higher LLAs on the day of its adoption, and generated, on average, a moderate loss for banks. This can be explained by the extended range of financial assets subject to provisions under the new standard.

Our study provides evidence that the IFRS 9 standard has adverse effects on the quality of financial information. These adverse effects are rooted in the use of ECL models to measure provisions for credit losses, an approach that presents several undesirable effects. First, under the IFRS 9 standard, the relative influence of credit ratings on provisions have increased, while the influence of impaired loans has been reduced. Indeed, by construction, ECL is closely related to credit ratings and, as a result of the sovereign ceiling principle, to the rating of the countries where banks are based. The increased association, since 2018, between sovereign ratings and LLAs has been proven by our tests. Our results show that banks based in economically weaker countries suffered higher transition losses than those based in highly-rated countries, and that the association between provisions and sovereign ratings has become closer after 2018. We consider this result to be a key contribution of our research: it means that, under the new standard, provisions have become more influenced by external factors on which the banks have no control, which is of limited use in terms of information on asset quality.

Second, we demonstrate that because of the insufficient standardization of ECL computation methods, the recourse to ECL offers bank managers a higher degree of discretion in measuring provisions. We provide evidence that this has led to an increase in the heterogeneity of provisioning practices since 2018: the significant increase in the dispersion of the coverage ratio after 2018 suggests that banks now enjoy more discretion in determining the level of provisions necessary to cover impaired loans. For users of financial reports, the adoption of IFSR 9 implies a loss of comparability of information on the level of loan loss coverage by LLAs.

Our results also suggest that the adoption of IFRS 9 might not translate into an improvement of LLAs' ability to predict loan losses over the long term. Indeed, our tests demonstrate that the association between LLAs and one-year-ahead charge-offs has remained close, and even improved, following the adoption of IFRS 9. One would expect this relationship to be altered due to the long-term time horizon of ECL under the new standard, unless it assumes equality between that long-term and short-term ECL, which would deny the effect of the economic cycle on credit losses. This point will need to be verified by future research investigating the relationship between provisions and charge-offs recognized with a longer time lag.

Future research will need to further study the association between credit ratings and LLAs. This analysis would be enhanced if the ratings of banks' loan portfolios were used instead of the sovereign ratings, which we retained as a proxy in this study. Our conclusions on the comparability of LLAs also needs further investigation: finding measures of heterogeneity of provisioning practices across banks other than the dispersion of the coverage ratio would certainly be helpful to the discussion.

Although we are conscious of these limits, we believe that our contribution is important. It challenges the widely accepted view that the IFRS 9 standard improves the quality of financial information disclosed to investors and other creditors.

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APPENDIX

ANNEX 1
Definition of Variables

Variables	*Definitions*	*Sources*
BANK_FE	Dummy variable noted 1 for the bank *i* at its own level, 0 otherwise.	-
COVER	Coverage ratio computed as LLA to Gross Non-performing Loans (expressed in percentage).	Bureau Van Dijk's BankFocus
D1_ECL	Change in LLA in bank *i* due to the adoption of IFRS 9 on 1st January 2018, scaled by gross loans (expressed in percentage).	Annual financial reports
IFRS9	Dummy variable noted 1 for the years 2018 and 2019, 0 otherwise.	-
LLA	Loan Loss Allowances scaled by gross loans (expressed in percentage).	Bureau Van Dijk's BankFocus
LOANS	Gross loans scaled by total assets (expressed in percentage).	Bureau Van Dijk's BankFocus
NCO	Net Charge-Offs to gross loans (expressed in percentage).	Bureau Van Dijk's BankFocus
NPL	Gross Non-performing Loans to gross loans (expressed in percentage).	Bureau Van Dijk's BankFocus
RATING	Bank's country rating according Moody's scale for which assigned values range to 21 (Aaa) from 1 (C), treated as a continuous variable.	Moody's
RATING_FE	Dummy variable noted 1 for the bank *i* at its country rating level, 0 otherwise.	Moody's
SIZE	Natural logarithm of total assets.	Bureau Van Dijk's BankFocus
ΔGDP	Change in country *j* of Gross Domestic Product (expressed in percentage).	World Bank
ΔNPL	Slope of Gross NPL to gross loans computed to *t* from *t*-5	Bureau Van Dijk's BankFocus
ΔUNEMP	Change in country *j* of Unemployment rate (expressed in percentage).	World Bank

ANNEX 2
Rating Scales and Assigned Values

	Moody's	Fitch Rating	Standard & Poor's	Assigned Values
Investment grade	Aaa	AAA	AAA	21
	Aa1	AA+	AA+	20
	Aa2	AA	AA	19
	Aa3	AA–	AA–	18
	A1	A+	A+	17
	A2	A	A	16
	A3	A–	A–	15
	Baa1	BBB+	BBB+	14
	Baa2	BBB	BBB	13
	Baa3	BBB–	BBB–	12
Speculative grade	Ba1	BB+	BB+	11
	Ba2	BB	BB	10
	Ba3	BB–	BB–	9
	B1	B+	B+	8
	B2	B	B	7
	B3	B–	B–	6
	Caa1	CCC+	CCC+	5
	Caa2	CCC	CCC	4
	Caa3	CCC–	CCC–	3
	Ca	CC	CC	2
	C	C, RD, D	C, D	1

ANNEX 3
Day One Impact by Country

	N	Mean ECL at 01.01.2018	Country Rating at 31.12.2017 (Moody's)	Change in LLA to Gross Loans 2018	LLP to Gross Loans 2018	NPL to Gross loans 2018
Slovenia	3	–0.563	Baa1	–5.406	–0.575	7.111
Malta	1	–0.371	A3	–1.393	–0.221	5.289
Hungary	1	0.001	Baa3	–1.731	0.447	8.976
Norway	1	0.020	Aaa	–0.179	–0.009	1.732
Finland	4	0.032	Aa1	–0.052	0.039	1.076
Switzerland	2	0.035	Aaa	0.018	0.022	0.460
Netherlands	5	0.070	Aaa	–0.111	0.048	2.583
Belgium	5	0.076	Aa3	–0.296	–0.004	2.000
Estonia	1	0.094	A1	0.008	0.525	1.433
Czech Republic	2	0.099	A1	–0.095	0.000	2.565
Iceland	3	0.101	A3	–0.502	0.074	2.484
Germany	10	0.138	Aaa	–0.822	0.365	2.105
Sweden	5	0.141	Aaa	0.107	0.283	0.982
Slovakia	3	0.163	A2	–0.126	0.296	3.000
Luxembourg	2	0.166	Aaa	0.020	0.005	2.782
Denmark	5	0.208	Aaa	0.094	0.071	4.533
Austria	3	0.233	Aa1	–0.457	0.086	3.134
France	7	0.240	Aa2	–0.002	0.204	3.383
Ireland	3	0.317	A2	–2.459	–0.090	8.314
Spain	10	0.359	Baa2	–0.492	0.380	4.881
Romania	1	0.385	Baa3	0.775	0.736	7.618
United Kingdom	8	0.445	Aa2	0.250	0.358	2.704
Serbia	1	0.447	Ba3	–2.501	0.093	10.002
Portugal	4	0.464	Ba1	–0.580	0.418	16.489
Croatia	1	0.590	Ba2	–0.892	0.589	11.250
Lithuania	1	0.664	A3	0.343	0.239	5.409
Italy	11	0.742	Baa2	–3.461	0.567	9.824
Poland	6	0.824	A2	0.911	0.825	8.149
Cyprus	3	0.948	Ba3	–6.041	1.216	23.011
Russia	6	2.125	Ba1	–1.412	0.974	9.824
Greece	4	2.477	Caa2	–0.098	1.647	45.111
Bulgaria	1	4.481	Baa2	1.149	1.554	21.891
Weighted Average :	**123**	**0.495**		**–0.859**	**0.376**	**6.981**