CREDIT LOSS ACCOUNTING AND VALUE RELEVANCE

A COMPARATIVE STUDY OF ACCOUNTING STANDARDS IN EUROPEAN BANKS

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Abstract:

By comparing the value relevance of the incurred credit loss model under IAS 39 and the expected credit loss model under IFRS 9 we investigate whether the IASB has succeeded with its goal of improving accounting relevance and quality through the implementation of IFRS 9 and contributed to investors gaining better and more relevant information. Using a modified version of the Ohlson (1995) valuation framework on a sample of 163 European banks (3 756 unique observation) between 2010 and 2020, we find that credit loss accounting under IFRS 9 is more value relevant than under IAS 39, and that the IASB thus has succeeded in this regard. We contribute to current accounting literature by providing the first empirical testing of the value relevance of items related to the impairment models specifically where we can conclude that the improvement stems from the new impairment model while the new classification of financial assets in IFRS 9 has had limited, if any, effect on the overall value relevance of accounting.

Keywords:

IFRS 9, IAS 39, Credit loss accounting, Value Relevance, Expected credit loss model

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1 Introduction

In January 2018, almost exactly ten years after the outbreak of the financial crisis of 2008, the International Accounting Standards Board (IASB) implemented the new standard International Financial Reporting Standards (IFRS) 9 Financial Instruments (IASB, 2018). In response to the old standard, IAS 39, receiving heavy criticism during the financial crisis, the new standard was developed. The old standard, applying an incurred credit loss model (ILM), was considered a major weakness of the financial accounting standards (Novotny-Farkas, 2016; Gebhardt & Novotny-Farkas, 2010). Groups such as the G20, the Financial Crisis Advisory Group and the Financial Stability Forum argued that the ILM reinforced the pro-cyclical effects of bank regulation as it made banks recognize credit losses too late. As a result, these institutions demanded new standards which would allow for more forward-looking provisioning and earlier recognition of credit losses. They argued that earlier recognition of credit losses would mitigate pro-cyclicality and thus act to prevent future financial crises from happening (Novotny-Farkas, 2016). The old standard was also criticized for disclosing too little information as well as being complicated and hard to understand for the users of financial reports (Bengtsson, 2011).

The IASB took the criticism to heart and as stated by IAS board member Sue Lloyd, IFRS 9 represents the IASB's response to the global financial crisis and aims to solve the issue of recognition of impairment being 'too little, too late' (Lloyd, 2018). The most significant difference between IAS 39 and IFRS 9 is the new impairment model. IFRS 9 implements an expected credit loss model (ELM), a forward-looking model which requires firms to estimate and recognize future credit losses in the financial statements (Gerald & Edwards, 2016; Frykström & Li, 2018).

The change of impairment model has had a profound impact on the entire banking industry considering their significant loan activities, where credit losses have been the key determinant of profitability for a long time (Walter, 1991). The standards which govern how banks report their credit losses thus have a significant impact on banks' overall performance as well as the visibility of risk to customers and investors. The accuracy of IFRS 9, more specifically the new ELM, has become further evident during the current COVID-19 pandemic. For example, during the first quarter of 2020, the six major banks in Canada, applying IFRS 9, set aside 11 billion CAD in credit loss allowances to account for future expected credit losses during the pandemic, resulting in performance significantly below profit expectations (Bester & Wagner, 2020). Under IAS 39, this level of provisioning would not have been possible, and the potential credit losses related to the pandemic would not have been visible in the financial reports until after they had occurred. The importance of using the standard to provide transparency is emphasized in IASB's clarification about how to apply IFRS 9 during the pandemic. It states that: *in the current stressed environment, IFRS 9 and the associated disclosures can provide much needed transparency to users of financial statements* (IASB, 2020).

In 2015, prior to the implementation of IFRS 9, the chairman of the IASB, Hans Hoogervorst, stated in a speech that the new ELM *should help investors get a better picture of the risks banks face regarding potential losses on loans extended to customers* (Hoogervorst, 2015). Moreover, the purpose of the IFRS is to enable consistent, transparent and comparable financial statements around the world and thus increase accounting quality (IASB, 2021).

It has now been approximately three years since the implementation of IFRS 9, and the question whether the IASB has succeeded with its implementation of the standard or not remains. There are several possible ways to assess the quality of an accounting standard. We conduct a value relevance study, comparing the value relevance of the new ELM to the ILM, aiming to answer the following research question:

> *Has the IASB succeeded with its goal of improving accounting quality through the implementation of the new impairment model and contributed to investors gaining better and more relevant information?*

To answer this, we develop two overarching hypotheses. First, as a baseline hypothesis, we expect credit loss accounting information to be value relevant as credit losses are a key determinant of banks' performance and credit losses are highly affected by the employed impairment model. Second, as a main hypothesis, we expect the new ELM to be more value relevant compared to the ILM. This is mainly based on the IASB's aim to improve the transparency between the firm and the investor through IFRS 9 and previous research suggesting an ELM would lead to credit losses being recognized in a timelier manner. Furthermore, we develop three sub-hypotheses to our main hypothesis aimed to nuance our findings. We expect the new ELM to be more (less) value relevant in large (small) firms, in profitable (less profitable) firms and in firms with higher (lower) ratio of loan to total assets.

To test these hypotheses, we use an adjusted version of the Ohlson (1995) valuation framework on a sample of 163 European banks (3 756 unique observations) collected between 2010 and 2020. By testing the variables specifically related to the impairment model, credit losses and credit loss allowances, we can isolate the effect of the impairment model from that of the whole standard.

First, we find that credit loss accounting information is value relevant and can thus confirm our baseline hypothesis. Second, we find that the credit loss accounting under IFRS 9 is more value relevant than that under IAS 39. Hence, we can conclude, based on our sample of European banks, that the IASB has succeeded in improving the relevance and quality of accounting information regarding impairment of credit losses. Furthermore, we find the new ELM to be more (less) value relevant in large (small) firms and more (less) value relevant in firms with higher (lower) ratio of loan to total assets. However, we find no significant results regarding the effect of profitability.

Our second finding contrasts the existing, albeit scarce, research on the value relevance of the new ELM in IFRS 9. Mechelli & Cimini (2020) test the value relevance of earnings and book value of equity under IFRS 9 and IAS 39 and find that these are more value relevant under IFRS 9 than under IAS 39. They then stretch their conclusion to state that the ELM is more value relevant than the ILM. In contrast, we find no significant difference in value relevance between book value of equity before credit loss allowances and earnings before credit losses under either IFRS 9 or IAS 39. Our data thus indicate that the new scope and classification of financial assets in IFRS 9 has had limited, if any, effect on the overall value relevance of accounting. Instead, as we test the value relevance of the items related to the impairment models specifically, our results suggest that it is the ELM that generates the improvement in quality. This is likely due to its forward-looking nature, enabling better timeliness of credit losses and transparency into banks' underlying estimations.

The contribution of this study to the accounting literature consists of empirical evidence of the value relevance of the new ELM, implemented in IFRS 9. To the best of our knowledge, there is no previous research explicitly testing the incremental value relevance of the ELM over the ILM with empirical evidence. By providing empirical evidence, we contribute to the debate surrounding the quality of IFRS 9 as well as to opening up the discussion regarding what different factors affect the quality of accounting information provided by the new impairment model for practitioners.

The paper continues as follows. We present the two standards and describe similarities and differences between them in section 2. A summary of the existing prior literature, both ex-ante and ex-post implementation of IFRS 9, is presented in section 3. We present our hypotheses in section 4, our research method in section 5 and our sample selection in section 6. The results are presented in section 7. Finally, section 8 includes conclusions, limitations and future implications as well as potential developments of our study.

2 Regulatory Background and Review

In the following section, an overview of changes in accounting treatment between IFRS 9 and IAS 39 is presented. Thereafter, we describe the substantial changes in detail, notably the classification systems and impairment models under both standards, how they are similar and how they differ.

2.1 Overview of key changes

As outlined in the introduction, IFRS 9 was implemented to deal with the issue of credit losses being recognized 'too little, too late' (Lloyd, 2018) under IAS 39. Naturally, the transition from one accounting standard to another entails changes in more than one area. In this instance, whilst it is true that the change in impairment model has been described as the main change in IFRS 9 compared to IAS 39, it would be inaccurate to state that this is the only change. Hereafter follows a more detailed overview of the differences between the standards.

Table 1 summarizes the key differences between IAS 39 and IFRS 9 and is based on KPMG's review of the two standards prior to implementation (KPMG, 2014). In terms of *scope,* the two standards are almost identical in terms of what assets and liabilities fall within the scope of the respective standards, where all items within the scope of IAS 39 is within the scope of IFRS 9. In addition to these items, IFRS 9 however expands the scope somewhat, where certain loan commitments and contract assets are included in respect of the new impairment requirements (IASB, 2018; IASB, 2001).

In terms of *Recognition* and *Derecognition,* i.e., what fundamental logic is applied in how and when assets and liabilities are recognized, IAS 39 is carried forward in IFRS 9 more or less unaltered (KPMG, 2014).

Classification of financial assets presents us with the first major change in IFRS 9, where items are categorized as either measured at amortized cost (AC), fair value through other comprehensive income (FVOCI) or fair value through profit and loss (FVTPL) and thus replaces the previous definitions under IAS 39 (IASB, 2018; IASB, 2001). The classification method is also substantially altered. Because of these substantial changes, we detail this aspect in section 2.2. Notably, neither the *Classification of financial liabilities* nor their *subsequent remeasurements for financial liabilities* are substantially altered but instead carried forward from IAS 39 (KPMG, 2014).

Impairment presents us with the second major change. Whereas IAS 39 allowed different models depending on asset type and was based on incurred losses, IFRS 9 introduces a unison and forward-looking model based on expected losses (KPMG, 2014). Considering that also this aspect is substantially altered, we describe it in detail in section 2.3.

The final major consideration to note is that the *presentation and disclosure* requirements are substantially altered. However, this is a natural consequence of the alterations to the classification system for assets and to the impairment model (e.g. how classifications are made, how impairments based on expectations of credit losses are determined) (IASB, 2018; IASB, 2001; KPMG, 2014).

Table 1. An overview of key differences between IAS 39 and IFRS 9

Scope	IAS 39 carried forward with smaller additions such as e.g. certain loan commitments and contract assets
Recognition and derecognition	IAS 39 carried forward with minor amendments
Classification of financial assets	IFRS 9 contains three types of categories for financial assets (amortized cost, fair value through other comprehensive income, fair value through profit and loss) replacing the categories under IAS 39. Moreover, the classification method is substantially altered (see more under section 2.2)
Classification of financial liabilities	Requirements under IAS 39 carried forward substantially unaltered
Reclassification	Reclassification of assets required if business model is substantially altered (see more under section 2.2)
Initial measurement	Requirements under IAS 39 carried forward substantially unaltered
Subsequent measurement for financial assets	Following changes in classification subsequent measurement is also altered, see section 2.2 for more information
Subsequent measurement for financial liabilities	Requirements under IAS 39 carried forward substantially unaltered
Impairment	IFRS 9 replaces the incurred loss model under IAS 39 with the expected credit loss model (see more under section 2.3)
Presentation and disclosure	IFRS 9 introduces new requirements in terms of presentation and disclosure

Note: The table lists the major accounting changes from IAS 39 to IFRS 9 and is based on KPMG (2014) initial review of the new standard prior to implementation.

As highlighted in the table above, *Classification of financial assets* and *Impairment* represent the major changes in the new standard. Therefore, we provide further details regarding these changes in section 2.2 and 2.3, respectively.

2.2 Classification and measurement of financial assets in detail

Under IAS 39, financial assets were classified into four broad categories on a rule-based[1] system. Financial assets were either (1) financial assets at fair value through profit and loss (FVTPL), (2) financial assets held to maturity (HTM), (3) loans or receivables, or (4) financial assets available for sale (AFS). The table below summarizes what type of asset

[1] Rule-based accounting provides fixed rules/processes for financial reporting, e.g., specifies exactly how each type of economic activities should be reported. (IASB).

is classified into each category and how they were measured and recognized based on rule (IASB, 2001).

Table 2. Classification of financial assets under IAS 39

Category	Asset (Rule-based)	Measurement
FVTPL	Financial assets held for trading	Fair value with gains and losses recognized in profit and loss
HTM	Non-derivative financial assets which the entity intends to hold to maturity	Amortized cost using effective interest method with gains and losses recognized in profit and loss
Loans or receivables	Non-derivative financial assets which the entity intends to hold to maturity but is not quoted on an open market	Amortized cost using effective interest method with gains and losses recognized in profit and loss
AFS	Non-derivative financial assets which do not qualify in any of the above	Fair value with gains and losses recognized in other comprehensive income

Note: The table summarizes how assets were classified and measured under IAS 39. FVTPL: Fair value through profit and loss; HTM: Held to maturity; AFS: Available for sale.

Under IFRS 9, the classification is now instead principle-based[2] and done through a two-step approach which classifies all financial assets as either; at fair value through profit and loss (FVTPL), at fair value through other comprehensive income (FVOCI), or at amortized cost (AC) (IASB, 2018).

The first step in determining which classification in IFRS 9 is most appropriate is the so-called *Business Model Test* in which entities determine whether financial assets are held in order to collect contractual cash flows. The second step is the *Contractual Cash Flow Test* in which entities determine if cash flows represent solely payments of principal and interest. The table below summarizes what type of financial asset classifies into each category and how they are measured and recognized based on principle (IASB, 2018).

[2] In principle-based accounting, the standard provides broad guidelines for how to conduct the financial reporting and instead emphasize that the financial statements should be understandable, readable, comparable, and relevant to current financial transactions (IASB).

Table 3. Classification of financial assets under IFRS 9

Category	Asset (Principle-based)	Measurement
AC	Financial assets passing both the business model test and contractual cash flow test	Amortized cost using effective interest method with gains and losses recognized in profit and loss
FVOIC	Financial assets fail the business model test e.g. the purpose is both to hold the assets and also sell it if prices rise	Fair value with gains and losses recognized in other comprehensive income
FVTPL	Financial assets which do not qualify in any of the above	Fair value with gains and losses recognized in profit and loss

Note: The table summarizes how financial assets are classified and measured under IFRS 9. AC: Amortized cost; FVOIC: Fair value through other comprehensive income; FVTPL: Fair value through profit and loss.

Although IAS 39 was rule-based and IFRS 9 is principle-based, there are similarities in their classifications. The financial asset classification between the two standards is reconciled in the table below.

Table 4. Reconciling of financial asset classifications

IAS 39	IFRS 9	Measurement
Loans or receivables	Amortized Cost	Amortized cost using effective interest method with gains and losses recognized in profit and loss
HTM	Amortized Cost	Amortized cost using effective interest method with gains and losses recognized in profit and loss
FVTPL	FTVPL	Fair value with gains and losses recognized in profit and loss
AFS	FVOCI	Fair value with gains and losses recognized in other comprehensive income

Note: The table shows a reconciliation between financial asset classified according to IAS 39 and IFRS 9. HTM: Held to maturity; FVTPL: Fair value through profit and loss; FVOCI: Fair value through other comprehensive income; AFS: Available for sale.

It should be noted that although *classification of financial assets* represents a major change in terms of definition and method, according to the European Banking Authority (EBA) the impact of these changes has been marginal for banks. In EBA's Impact Assessment of IFRS 9 (2018) they state that the impact of the change in classification does not seem significant for most banks and that the measurement basis for financial assets will likely remain largely the same. Thus, the reconciliation between IAS 39 and IFRS 9 presented in Table 4 has been widely applied in practice.

2.3 Impairment models in detail

The second major feature of IFRS 9, as outlined in section 2.1, is the new way of recognizing credit losses through impairment models; IAS 39 prescribed an ILM, whereas IFRS 9 prescribes an ELM. This is the main focus of this study and arguably the biggest change introduced through the new standard (Hoogervorst, 2016). The differences between the two standards are outlined below.

2.3.1 Overview of impairment models

Under the previous standard, credit losses were recorded through impairment of the respective assets if – and only if – there was objective evidence that the asset had been impaired as a result of one or more events that occurred after the initial recognition of the asset. This meant that provisions were not necessarily taken into consideration at initial measurement and that credit losses were only recognized in the financial statements when a loss event actually occurred. The assessment of whether a loss event had occurred would be done at each balance sheet date and, following any objective evidence that a loss-event had taken place, a credit loss allowance would be calculated and recorded. This would be done either through profit and loss or through other comprehensive income (OCI) depending on asset type, amounting to the difference between an asset's carrying amount and the present value of estimated cash flows discounted at the assets original effective interest rate. Note that although impairment under IAS 39 was based on the principle of incurred losses, as opposed to expected losses, different asset types could have different impairment models (IASB, 2001).

In stark contrast to IAS 39, IFRS 9 introduces a single model for impairment for *all* financial assets within the scope of impairment testing, which is instead based on expected credit losses measured and recognized in three stages (IASB, 2018).

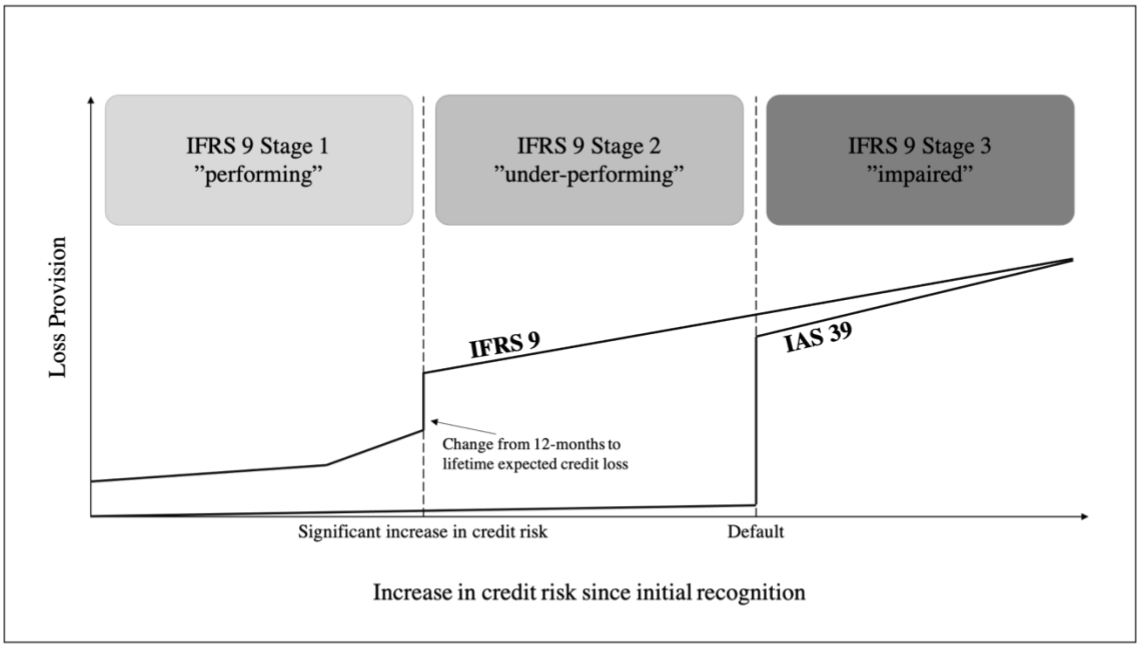
Most of banks' financial asset portfolios will be classified in stage one, consisting of financial instruments with no significant increased risk in the coming twelve months, calculated based on the probability of a default in the next twelve months. It is recognized either in profit and loss or OCI, depending on asset type, and serves as a proxy for the initial expected credit losses recognized at origination or following an asset purchase (IASB, 2018). The interest revenue is calculated on the gross carrying amount before the deduction of credit losses. This is to reflect that the financial instruments' interest yield works to cover the expected credit losses from the point in time when a financial instrument is first recognized. This addresses the concern that the interest revenue is overstated under IAS 39, where the full yield was recognized as interest revenue for the financial instrument without taking any expected credit losses into account when purchasing an asset (Novotny-Farkas, 2016).

Financial instruments with 'significant deterioration in credit quality', but with no hard evidence of impairment since initial recognition, are classified in stage two of credit losses. For these, expected credit losses for their full lifetime is recognized based on the cumulative probability of default in any period for the financial asset's lifetime. The rationale behind this classification is that an economic loss of a financial instrument should be recognized when the expected credit loss is significantly higher than the initial expectations. This makes the loss visible in the financial statements directly. However, interest revenue is still calculated as in stage one (IASB, 2018; Novotny-Farkas, 2016).

If the credit risk of financial instruments has increased to levels close to full impairment at the reporting date, it is classified in stage three. For these financial instruments, lifetime expected credit losses are recognized as in stage two, whereas interest revenue is calculated on the net carrying amount (gross carrying amount less loss allowance). The guidance for stage three recognition in IFRS 9 is similar to that in IAS 39, but lifetime expected credit losses are recognized already in stage two under IFRS 9 after a significant increase in credit risk has occurred (IASB, 2018).

Below is an illustration of how credit loss allowances (below denoted as 'Loss Provision') are recognized over time depending on which credit loss model is used. As is clear in the illustration, IFRS 9 recognizes greater amounts of loss provision earlier as it is based on expectations of default events whereas IAS 39 recognizes greater amounts later as it is based on actual default events.

Figure 1. Development of provisions under IFRS 9 and IAS 39 (Frykström & Li, 2018)

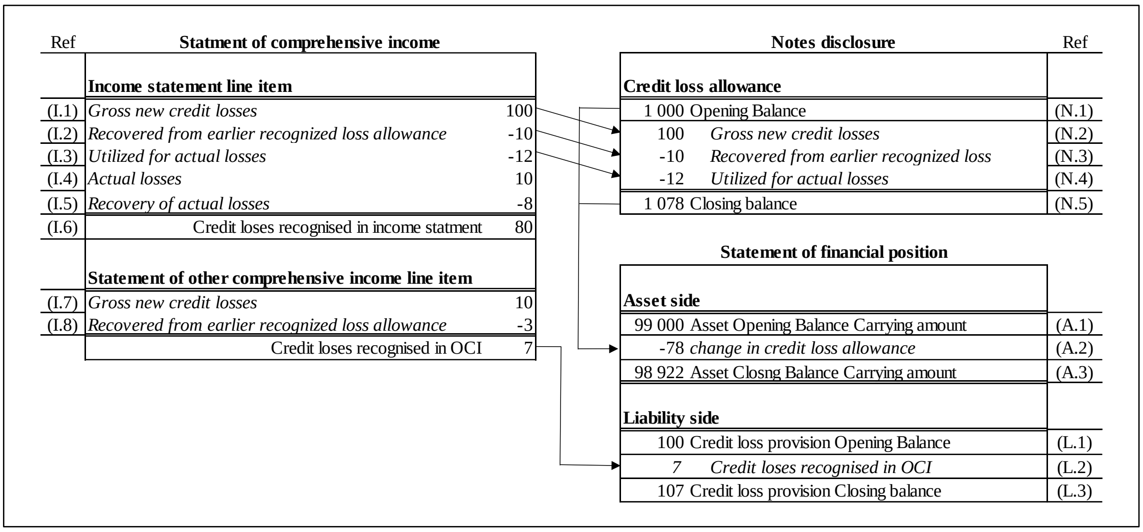


2.3.2 Accounting flows from the impairment models

As a final aspect of the two standards, we explain the accounting flows through the income statement and the statement of financial position for credit loss allowances which will be helpful in formulating our research design. For clarifications, we reference an illustrative figure describing the flows (Figure 2).

In our illustrative example we disregard all items irrelevant in terms of credit loss accounting information. All figures are purely illustrative and not reflective of any real example although the notation is drawn from an actual annual report (Ålandsbanken, 2018). Please also note that notation varies between banks. First, let us consider an asset measured at amortized cost where impairment allowances are recognized through the income statement.

Figure 2. Credit loss accounting flows



Starting with the income statement, new credit losses for the period (gross) are calculated using either ILM or ELM, i.e., credit losses stemming from for instance newly issued loans (naturally only relevant under ELM) or new estimations on already issued loans (I.1). We then subtract allowances for assets that we had previously established but no longer deem necessary (I.2). Similarly, the allowances which have been utilized for actual losses are subtracted (I.3). Actual losses for the period are then added back (I.4), i.e. the *de facto* loss, not the calculated loss according to either ILM or ELM. Note that if our ex-ante estimation of credit losses had been perfectly reflected by ex-post actual losses, (I.3) and (I.4) would have been equal. Lastly, any recovered losses that we had previously been written-off are subtracted (I.5). The net amount of these items is what is reported in the income statement (I.6). To determine the carrying value of our assets, we must first consider the changes to our credit loss allowance account. Starting with an opening balance (N.1), we add all new credit losses for the period (gross) as previously described (N.2). Similarly, we subtract any recoveries (N.3) and utilized loan losses (N.4). From this, we establish our outgoing credit loss allowance (N.5). Please note that actual losses, or eventual recoveries, naturally do not affect the credit allowance account. Also note that this account is not reflected in the statement of financial position but only disclosed in the notes section. Instead, an asset's carrying amount is adjusted for this established credit loss allowance (A.2) to give us an outgoing carrying amount (A.3) (Ålandsbanken, 2018).

The treatment for items measured through the OCI is largely the same. However instead of an asset being adjusted for credit loss allowances, we establish a provision as a liability (L.1) whose outgoing value (L.3) varies with the year's newly established provisions (I.7) and adjustments for provisions no longer considered necessary (I.8). Considering that an asset's carrying amount is not adjusted for this provision but reported gross, actual losses or recoveries do not affect this provisioning (KPMG, 2014; IASB, 2018).

The accounting flows are the same under both ELM and ILM *per se*, although the notation may vary. The main difference, as already highlighted (see section 2.3.1), is when in time our credit loss allowance is recognized with earlier recognition under ELM. Moreover, considering that credit loss allowances under ILM are estimated based on actual default events whereas credit loss allowances under ELM are estimated based on expectations of default events, it would be reasonable to expect a larger year-to-year variance in recognized credit losses under ELM than ILM. However, this is not the topic of this particular study.

3 Literature Review

In this section, we review previous studies across several key areas regarding the implications of the accounting differences between IFRS 9 and IAS 39. Since IFRS 9 was implemented recently, there are few published papers empirically testing the value relevance of credit loss accounting post-implementation. There are, however, several published ex-ante studies regarding the implementation of the new standard as well as previous research comparing the old standard to local accounting standards with similar characteristics to IFRS 9. These topics will be presented and discussed in the following section. Appendix A summarizes a selection of previous studies regarding the implementation of IFRS 9.

3.1 Ex-ante implementation literature review

As IAS 39 was heavily criticized after the financial crisis, the replacement of IAS 39 to IFRS 9 has been one of IASB's key issues during the past decade (Grant Thornton, 2013; IASB, 2019). This has resulted in several researchers investigating what effects the new standard would have on the market, prior to the standard being implemented in 2018. Novotny-Farkas (2016) concludes that the ELM incorporates larger and earlier recognition of credit losses than the ILM, potentially contributing to better financial stability and to solving part of the problems that arose during the financial crisis. However, he goes on to conclude that the ELM provides more room for managerial discretion and introduces more complexity, and that whether the new standard will have the desired benefits or not will be dependent on if the guidance will be applied in a proper and consistent manner.

Onali & Ginesti (2014) investigate the pre-adoption of IFRS 9 in the market and *whether national characteristics of the country where the firm is domiciled affects investors' reactions*. This study, in contrast to Novotny-Farkas' (2016), argues that IFRS 9 reduces complexity and simplifies the guidance in comparison to IAS 39 and thus increases cross-country comparability. Furthermore, they suggest that this in turn should result in less information asymmetry and increase the value relevance of the accounting information. The authors' findings suggest that investors would react positively to the reform, especially for firms in countries with little divergence between local accounting standards and IAS 39. Furthermore, the results suggest that investors are confident in IFRS 9 addressing the problems of IAS 39, but that cross-country differences are expected as IFRS 9 allows for more accounting discretion (Onali & Ginesti, 2014).

Another study made before the implementation of IFRS 9, with implications for the new standard's effects, is Marton & Runesson (2017). They investigate and compare the predictive ability of loan loss provisions with respect to actual losses under IFRS (at that time applying IAS 39) and local General Accepted Accounting Principles (GAAP) in banks in the EU and Switzerland. The authors' results indicate that loan loss provisions when using an ILM (IAS 39) have a lower predictive ability of gross charge-offs compared to the use of local GAAP (in many countries applying an ELM approach). However, the predictive ability of the different standards varies given different conditions. They conclude, like others before them, that the ILM is more objective than ELM but that this objectivity comes at the cost of the bank's management not reporting adequate information regarding credit losses in the period where they would be relevant. Moreover, there is a cost related to including discretion in accounting for credit losses too. The authors conclude that the ILM is superior to the ELM in small banks as well as in less profitable banks. Furthermore, they state that this indicates that when incentives to postpone or altogether avoid provisions are high, incentives to manage earnings offset any benefits of allowing discretionary loan loss provisioning (Marton & Runesson, 2017). Thus, in banks with low profitability, strict enforcement (as when applying an ILM) is important to accomplish timeliness of recognition of credit losses. Marton & Runesson (2017) end with the conclusion that since local GAAP in a majority of the investigated countries applied an ELM approach, their conclusion has implications for the implementation of IFRS 9.

Marton & Runesson (2017) are not the only ones discussing the timeliness of recognition in relation to changing the impairment model. O'Hanlon (2013) investigates whether *loan-loss provisioning in banks in the UK became less timely after implementation of IAS 39*. In contrast to Marton & Runesson (2017), O'Hanlon (2013) comes to the conclusion that stricter enforcements, which were implemented when changing from local GAAP to IAS 39, did not create less timely recognition of credit losses. However, as Marton & Runesson (2017) are comparing local GAAP in which most countries allow for an approach more in line with the ELM, and the UK had a local GAAP applying an ILM approach, the results are not directly comparable.

One study made in 2010 by Gebhardt & Novotny-Farkas, investigating the *mandatory IFRS adoption and accounting quality of European banks* reaches a similar conclusion as Marton & Runesson (2017), and concludes that the *application of the ILM approach results in less timely loan loss recognition implying delayed recognition of future expected loss*es (Gebhardt & Novotny-Farkas, 2010).

The level of accounting discretion allowed for in an accounting standard is heavily discussed in relation to the implementation of an ELM. A potential benefit discussed is the enablement of management to include exclusive information about underlying events and thus allow for the true value to be captured better (Fields et al., 2001). Prior research relating to the impairment model has shown that it is the allowance of judgement that enables more timely recognition of losses (Gebhardt & Novotny-Farkas, 2010; Marton & Runesson, 2017; Novotny-Farkas, 2016). However, having large complexity in an accounting standard comes at a cost. Giner & Mora (2019) state that the financial reporting view aims to provide information to investors, while the prudential view attempts to achieve financial stability. The authors state that investors benefit from forward looking information, but that accounting standard setters often avoid that sort of information as it risks putting forward unfaithful representation of the phenomena captured in the financial statements (Giner & Mora, 2019).

To conclude, there are both indicators of the ELM increasing as well as decreasing value relevance in comparison to the ILM. As brought up by Gebhardt & Novotny-Farkas (2010), Marton & Runesson (2017) and Novotny-Farkas (2016), it enables more timely recognition as well as provides more useful insights for investors by incorporating the forward-looking information. These features should contribute to an increased value relevance when changing to the new ELM. However, there are also features that could result in a decreased value relevance in the implementation of the new standard. The new standard has introduced more complexity in comparison to the old standard and allows for more accounting discretion (Giner & Mora, 2019; Novotny-Farkas, 2016), both features negatively affecting value relevance.

3.2 Studies comparing value relevance in changes from IAS 39 to IFRS 9

As mentioned above, the number of ex-post studies made on the implementation of IFRS 9 is small. One study testing the value relevance of IFRS 9 in comparison to IAS 39 is Mechelli & Cimini (2020). The authors investigate the change in value relevance in accounting information when going from IAS 39 to IFRS 9 as well as whether corporate governance quality can explain the difference in value relevance between the two standards. They ponder whether IFRS 9 is more value relevant than IAS 39 in firms that rely on high-quality firm-level corporate governance or are listed in countries with a high-quality country-level investor protection environment and vice-versa. Their results show higher value relevance for book value of equity under IFRS 9 than IAS 39 under the setting of high-quality corporate governance and that IAS 39 is more value relevant in firms with lower quality corporate governance. The authors argue that this result has a twofold explanation. First, higher quality corporate governance *mitigates the agency problem and reduces agency costs and thus creates value for shareholders that want to maximize their return on investment* (Mechelli & Cimini, 2020). Second, higher quality corporate governance, implying more monitoring from the boards, contributes to the control of incentives for opportunism which could otherwise influence the financial reporting process and thus decrease the value relevance. These results are in line with both Marton & Runesson (2017) and Gebhardt & Novotny-Farkas (2010). It should be noted that the study also includes a minor section specifically studying the value relevance from the transitioning effect on book value of equity and whether this can be explained by the quality of corporate governance. They find evidence that the transitioning effect of equity is value relevant and as they assume all transitioning effects are from the impairment model, they conjecture the new impairment model itself to be more value relevant than the previous model.

To the best of our knowledge there is only one other study testing the value relevance of IFRS 9 in comparison to IAS 39. Schaap (2020)[3] studied the incremental change in value relevance in accounting information when switching from IAS 39 to IFRS 9 by using annual report data for the period of 2011-2019 for European banks. Schaap reaches the conclusion that earnings are more value relevant under IFRS 9 than under IAS 39 whereas book value of equity is less value relevant (Schaap, 2020).

3.3 Research gap

Although there has been a number of studies written regarding IFRS 9 in comparison to IAS 39 ex-ante implementation, the empirical evidence of the comparative value relevance ex-post implementation is noticeably limited. In fact, one of the two previous value relevance studies mentioned, Mechelli & Cimini (2020), explicitly states that their results provide the first empirical evidence on the value relevance of the new accounting standard on financial instruments, highlighting the fact that this is more or less unexplored territory. Furthermore, there are no studies to date which explicitly test the incremental value relevance in the ELM over the ILM using a value relevance model or by any other methods using empirical evidence. Although Mechelli & Cimini (2020) do mention the impairment model and its theorized implications, they only study value relevance in transitioning effects on net income and book value of equity when switching accounting standards, which does not isolate the credit loss model by itself, as noted by the authors themselves. Furthermore, they use a cross-sectional approach which, although beneficial in terms of controlling for time-varying factors, has drawbacks such as fewer degrees of freedom and less sample variability which ultimately decreases the efficiency of econometric estimates (Hsaio, 2007).

Besides adding to the lacking empirical evidence regarding value relevance of the new impairment model, this study further contributes to the debate regarding the quality of the new standard and what different factors affect the quality of financial reporting. The background to why the standard was developed, contributing to the outburst of the financial crisis in 2008, crystalizes the importance of both the change in standard as well as having high quality financial reporting. The trade-off between the increased level of transparency and incorporation of forward-looking information *and* the increased level of accounting discretion seen in the new impairment model is a key issue (Novotny-Farkas, 2016). The question is whether the information presented under the new standard is trusted by practitioners or not. This will likely vary depending on factors such as size and type of financial entity and profitability (Marton & Runesson, 2017; Mechelli & Cimini, 2020). By breaking down which factors affect the value relevance of the impairment models, we contribute with practical insights for several actors.

[3] Note that this is a master thesis from a student at the Erasmus School of Economics in Rotterdam, NL.

4 Hypothesis Development

This section is devoted to detail testable hypotheses that can answer our research question. Drawing from previous literature, we generate five hypotheses: one baseline hypothesis, one main hypothesis and three sub-hypotheses aiming to nuance and deepen the results from our main hypothesis.

4.1 Credit loss accounting and value relevance

As described in section 1, credit losses represent perhaps the most influential driver of profitability and expected profitability in banks (Walter, 1991). Hence, from an investor perspective, the way in which credit losses are accounted for in financial reporting presumably holds value relevant information to varying degrees depending on the characteristics of the model employed. Combining this with the harsh critique of the impairment model after the financial crises in 2008 generates the foundation for our first hypothesis. We expect that credit loss accounting holds value relevant information to some degree. Moreover, this baseline hypothesis is crucial to examine before answering our following hypotheses. Our baseline hypothesis (H1) can be expressed as:

H1: Credit loss accounting information is value relevant

4.2 Comparative value relevance

Following the harsh criticism levied at the IASB for the ILM recognizing credit losses too late (Lloyd, 2018), IASB implemented IFRS 9 in 2018 (IASB, 2018) which brought a forward-looking credit loss model which, in theory, would more fairly and timely recognize credit losses (Novotny-Farkas, 2016; Gebhardt & Novotny-Farkas, 2010; Marton & Runesson, 2017). As seen in section 3, the ex-ante implementation literature highlights arguments in favor of the ELM as well as arguments against it in terms of increasing value relevance from an investor perspective. Arguments in favor of the ELM highlight its forward-looking nature and the presumed increased timeliness of credit loss recognition (e.g. Novotny-Farkas, 2016; Marton & Runesson, 2017) whereas arguments against it highlight the increased complexity and managerial discretion inherent in the new model (e.g. Giner & Mora, 2019; Novotny-Farkas, 2016) which could mean less comparability and therefore less value relevance. Still, considering that the IASB's stated purpose when developing accounting standards is to enable consistent, transparent and comparable financial statements around the world as to increase accounting quality (IASB, 2021), and that Hans Hoogervorst, chairman of the IASB, stated that the new ELM *should help investors get a better picture of the risks banks face regarding potential losses on loans extended to customers* (Hoogervorst, 2015), we expect that the new ELM holds greater value relevance than the previous standard. Therefore, we express our main hypothesis (H2) as:

> **H2:** The expected credit loss model is more value relevant than the incurred credit loss model

However, compared to an ILM, an ELM increases complexity and allows for more accounting discretion (Giner & Mora, 2019; Novotny-Farkas, 2016), implying that the ELM could be *less* value relevant. This has been proved to be prominent in financial entities where the incentives to postpone or altogether avoid loan loss provisions are high, as earnings management incentives offset the benefits of discretionary loan loss provisioning (Marton & Runesson, 2017). Furthermore, H2 could be affected by the size of the financial entity. As larger entities often practice stronger corporate governance, the problem with increased complexity and accounting discretion is suggested to be mitigated. Stronger board monitoring often acts to control incentives for opportunism which could otherwise influence the financial reporting process (Mechelli & Cimini, 2020). Large financial entities are also expected to have more advanced systems for estimating credit losses and to be exposed to greater political costs stemming from questionable numbers (Marton & Runesson, 2017). We thus express our part hypotheses as follows:

> **H2a:** The incremental increase in value relevance from the expected credit loss model over the incurred credit loss model is less pronounced for less profitable firms
>
> **H2b:** The incremental increase in value relevance from the expected credit loss model over the incurred credit loss model is less pronounced for smaller firms

Building on the argument presented above, we hypothesize that this relationship, found by Mechelli & Cimini (2020), can be further explained through the nature of larger financial entities' core business. Many large financial entities have lending as their core activity, meaning a lot of effort and resources are likely put into estimating the inherent risk of these. Similar to the reasoning regarding why smaller firms would have a less pronounced difference between ILM and ELM, we hypothesize the following:

> **H2c:** The incremental increase in value relevance from the expected credit loss model over the incurred credit loss model is more pronounced for firms with greater share of loans to total assets

5 Research Method

In this section, we present the research method used for the thesis. First, the concept of value relevance is presented and discussed (section 5.1). The value relevance of accounting information is a matter of great debate in the academic community both in terms of definition, measurement, and interpretation. This is followed by a review of three different methods for measuring value relevance, in which a price regression model is chosen. The model for each hypothesis is then derived and presented (section 5.2).

5.1 Value Relevance Framework

5.1.1 Defining Value Relevance

Value Relevance is commonly defined as the measure of ability for financial statement information to capture information that affects share value (Francis & Schipper, 1999). To simplify, one can view the value relevance of accounting information as the explanatory power such information has in explaining prices observed in the market, and the mechanics behind them.

It is important to note that the concept of *relevance* is also emphasized in the accounting standard-setting context. The IASB defines accounting information as being useful only if it is *relevant* and *faithfully represented.* Within their *Conceptual Framework*[4] (IASB, 2021) they define *relevant information* as information impacting the decision-making process, hinged upon whether the information carries predictive value, confirmatory value, or both. Hence, the definition of *relevance* in the context of standard-setting is very similar to that in the market pricing definition, but with the focus on ex-ante relevance in the decision-making process rather than ex-post relevance in terms of explanatory value. That being said, one should not construe these two definitions as interchangeable. Nevertheless, with the two definitions in mind one can view studies measuring value relevance in accordance with the ex-post definition as being an approach to operationalizing and/or test the ex-ante definition as information deemed relevant from an ex-ante definition should be relevant from an ex-post definition (Barth et al., 2001).

5.1.2 Approaches to measuring value relevance

The first definition of *value relevance* stated above is most commonly measured as the statistical association between *accounting metrics* and *market prices* or *market returns*

[4] The *Conceptual Framework* lays down fundamental concepts for reporting with the purpose of guiding the board when developing IFRS Standards.

(Hellström, 2007); (Barth et al., 2001).[5] Mechanically speaking, this is performed by using accounting information as input in a valuation model, regressed against either market prices or returns. The choice between using price or return as the dependent variable depends on what association is being tested. For example, when studying what is reflected in firm value or how the association changes over time, market prices should be used as dependent variables. If the aim is, however, to study the association between changes in accounting values and price changes, market returns should be used as the dependent variable (Barth et al., 2001).

Studies measuring the value relevance in terms of market prices usually build on what is commonly referred to as the Ohlson (1995) model, modelling market prices as a linear function of book value of equity and abnormal earnings (Barth et al., 2001). In contrast, studies measuring the value relevance in terms of market returns usually build on the work by Easton & Harris (1991), modelling market returns as a linear function of earnings and changes in earnings (Hellström, 2007). However, please note that the market return model is in fact itself based on the fundamental valuation framework as outlined by Ohlsson (1995) meaning that the underlying assumption are similar, if not identical.

For the purpose of this study, we opt for a model measuring value relevance in terms of market prices. The choice is motivated by the fact that credit loss information is recognized in both the statement of income and statement of financial position, albeit as a contra asset account[6] as described in section 2.3.2. Therefore, we cannot opt for a return-based model as we conjecture that value relevance and, more importantly, changes in value relevance in switching from ILM to ELM will be captured both in the income statement and the statement of financial position.

5.1.3 Detailed review of the Market Price Model

Underlying model mechanics and derivation

As mentioned above, we adopt a model based on the Ohlson (1995) valuation framework which models a firm's market value as function of the book value of equity and abnormal earnings. It is based on three main underlying assumptions.

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[5] Note that Hellström (2007) suggests a third alternative which entails modelling the logarithm of share prices as a function of the logarithm of equity and earnings such that $\ln(\text{market price}) = \alpha_0 + \alpha_1 \ln(\text{equity}) + \alpha_2 \ln(\text{earnings})$. However, as noted by the author, this relationship implies an underlying non-logarithmic relationship such that $\text{Market price} = e^{\alpha_0} * \text{equity}^{\alpha_1} * \text{earnings}^{\alpha_2}$ which is a relationship not proven from a theoretical standpoint. We therefore refrain from considering this alternative henceforth.

[6] A contra asset is an asset which is recognized as a credit to some asset i.e., not recognized as a line item in the statement of financial position. The item, in our case, is however reflected in the note's disclosure.

First, it relies on a clean surplus relationship of accounting such that:

$$\mathrm{BV_t = BV_{t-1} + NI_t - D_t} \quad [1]$$

Where:

$\mathrm{BV_t}$: Book value of equity at time t

$\mathrm{NI_t}$: Net income at time t

$\mathrm{D_t}$: Dividend at time t

Second, the market value of firm equity at any point in time is given by the present value of all future expected dividends such that:

$$\mathrm{MV_t} = \sum_{\tau=1}^{\infty} (1+\mathrm{r})^{-\tau} \mathrm{E_t[D_{t+\tau}]} \quad [2]$$

Where:

$\mathrm{MV_t}$: Market value at time t

r: discount rate (assumed constant for all values of t)

Abnormal earnings ($\mathrm{x_t^a}$) is defined as ($\mathrm{x_t^a = NI_t - r * BV_{t-1}}$). The third and final assumption of the Ohlson model is the stochastic process of abnormal earnings and other value relevant information ($\mathrm{v_t}$) where:

$$\mathrm{x_{t+1}^a = \omega x_t^a + v_t + \varepsilon_{1t+1}} \quad [3]$$

$$\mathrm{v_{t+1} = \gamma v_t + \varepsilon_{2t+1}} \quad [4]$$

Where:

ε_{1t}: error term with mean greater than 0

ε_{2t}: error term with mean greater than 0

ω: parameter for persistence of abnormal earnings which must be greater than 1

y: parameter for persistence of other information which must be greater than 1

From these three assumptions the underlying model of firm value as a function of the present value of all future expected dividends given in equation [2] can be restated such that:

$$\mathrm{MV_t = BV_t + \alpha_1 x_t^a + \alpha_2 v_t} \quad [5]$$

Where:

$\alpha_1 = \frac{\omega}{(1+r-\omega)} > 0$

$\alpha_2 = \frac{1+r}{(1+r-\omega)(1+r-\gamma)} > 0$

One inherent issue in equation [5] is that estimating market value by this equality requires an ex-ante estimation of the required rate of return. Considering data constraints, no generally accepted method for doing this applies in this case (Hassel et al., 2005). We therefore make use of the further derivation suggested by Ohlson (1995) which has been employed in various similar research papers (e.g Agostino et al., 2010) in which we instead model share price (MV_t) as a function of book value of equity (BV_t), earnings (NI_t) and other value-relevant information (V_t) such that:

$$MV_t = \beta_1 BV_t + \beta_2 NI_t + \beta_3 v_t \qquad [6]$$

For the full derivation reconciling equation [5] and [6] please see Appendix B. In regard to equation [6], the value relevance of book value of equity and earnings is given by the statistical significance of (β_1) and (β_2) respectively. The testing of the value relevance of other theorized explanatory variables would be done by replacing (v_t) with the variable of interest and studying the statistical significance of (β_3).

Please note that although Ohlson (1995) uses book value of equity and earnings as main explanatory variables, these can be partitioned into separate line items. For example, Gong & Wang (2016) studied the value relevance of various accounting treatments related to research-and-development spending (R&D). The authors partitioned earnings into *R&D* and *earnings before R&D* while book value of equity was portioned into *book value of equity before capitalized R&D* and *capitalized R&D*, respectively. Burke & Weiland (2017) performed a similar partitioning when examining the value relevance of banks' cash flows from operations, separating out the goodwill item.

Econometric issues and considerations

One inherent issue of the valuation framework of Ohlson (1995), in addition to the three assumptions already stated, is that the model assumes full market efficiency. This means that at any given time, the price of a particular stock fully reflects the value given all publicly available information (Fama, 1970). This assumption has been questioned in practice (Shostak, 1997). However, by limiting conclusions made as referencing only to what extent accounting information reflects and explains share prices, with no reference to 'true value', the assumption of market efficiency is not necessitated (Barth et al., 2001). Instead, we only need to assume that share prices reflect the investors' consensus 'belief about value', which is a far less controversial assumption that we can make without further review.

Another issue raised in the valuation framework of Ohlson (1995) is the assumed linear dynamics in that market value is modelled as a linear function of book value of equity and abnormal earnings (see equation [5]). However, although it is true that market value follows a linear function, the persistence of abnormal earnings (ω) does not assume a linear function in that for given values of book value of equity and abnormal earnings the marginal difference in persistence is not associated with constant marginal difference in market value (Barth et al., 2001).

The clean surplus assumption mentioned above is another drawback of the Ohlson (1995) model, but given the empirical findings suggesting negligible effect on estimates and inferences when studying the incremental effect from having a *dirty surplus* variant of the model (Barth et al., 2001) we disregard this aspect hereafter.

5.2 Final model specifications

5.2.1 Capturing credit losses information

Following previous research on the value relevance of various accounting treatments we base our regression model on the Ohlson (1995) valuation framework described in section 5.1.3. In order to capture the value relevance of credit loss accounting information specifically we split up both the metrics book value of equity and earnings as has been done in previous research (e.g. Gong & Wang, 2016; Burke & Wieland, 2017). Following the accounting flows from credit loss accounting as described in section 2.3.2 book value of equity ($\mathrm{BV_t}$) is partitioned into book value of equity before credit loss allowance considerations ($\mathrm{BVEBLL_t}$) and credit loss allowance ($\mathrm{LL_t}$) such that:

$$\mathrm{BV_t} = \mathrm{BVEBLL_t} - \mathrm{LL_t} \qquad [7]$$

Earnings ($\mathrm{NI_t}$) is partitioned into earnings before credit loss considerations ($\mathrm{EBCL_t}$) and credit losses ($\mathrm{CL_t}$) such that:

$$\mathrm{NI_t} = \mathrm{EBCL_t} - \mathrm{CL_t} \qquad [8]$$

With this partition we disregard credit losses recognized through OCI and provisions recognized in the statement of financial position as a liability. This is done as credit losses recognized through the OCI and provisions are usually aggregated with other items which complicates the process of retrieving the isolated effect. Although we expect these items to be only a small part of banks total recognized credit losses, we do regard this as a noteworthy limitation of our model specification, albeit marginal.

By reconciling equation [6] with our aforementioned partitioning, we arrive at the underlying function below with all variables already defined:

$$\mathrm{MV_t} = \beta_1 \mathrm{BVEBLL_t} + \beta_2 \mathrm{EBCL_t} + \beta_3 \mathrm{CL_t} + \beta_4 \mathrm{LL_t} + \beta_3 \mathrm{v_t} \qquad [9]$$

Within the context of equation [9] the value relevance of credit loss accounting information is given by statistical significance of coefficients (β_3) and (β_4) respectively.

5.2.2 Dealing with inherent issues in value relevance models

Assuming a regression model solely based on equation [9] would result in erroneous results owing to both research-related and statistical issues. These issues and how they are managed are outlined below.

Research-related issues

One issue with using a model based on equation [9] is that firms can vary in absolute size in terms of equity or earnings but be similar in relative size (such as earnings related to shares outstanding or total asset base). This potential scale effect can cause the error term to violate the assumptions on which equation [9] is based. We manage this by deflating all variables by each respective firm's number of shares outstanding at each respective reporting date. This has been suggested as a superior deflating metric when dealing with this particular scale effect (Barth & Clinch, 2009).

Another similar issue is the impact from variations in size owing exclusively to differences in what currency the accounting information is stated in. We therefore translate all relevant accounting items to euro, where applicable, at the fiscal periods average rate for income statement items and at the closing rate for balance sheet items as has been done in previous studies (e.g. Gong & Wang, 2016).

As value relevance studies aim to test the statistical association of accounting information and market prices, an assumption regarding when markets receive fiscal information must be made, i.e. the time between the end of the fiscal period and the time when figures are reported to the public and thus fully priced-in in the market value. Considering extant studies (e.g. Aboody & Lev, 1999; Lorenzo Valdés & Durán Vázquez, 2010; Agostino et al., 2010) we set this time lag to three months following fiscal period end.

Previous research (e.g. Hayn, 1995; Collins et al., 1999) has also shown that including observations with negative earnings significantly depresses the earnings coefficient, thereby complicating the interpretation in terms of value relevance. To avoid this complication, we drop all observations with negative earnings (see section 6.1 for the overall effect on our sample size).

Statistical issues

The variable (v_t) in equation [9] represents value relevant information not captured by the chosen independent variables of choice. Since we do not model these parameters, the variable (v_t) will not be 'included' in the final model. However, this presents us with the potential issue of omitted-variable bias[7] meaning that effects relating to other variables not modelled will potentially instead be erroneously attributed to our independent

[7] An omitted-variable bias occurs when a model relevant variable is not included in the function.

variables (Kleiber & Zeileis, 2008). To control for this, we estimate our model with a firm fixed-effect estimator[8].

Although variables are deflated by shares outstanding, we still observe a disproportionate effect from extreme values in our sample. To reduce the potential disproportionate impact from these extreme values all variables are winsorized at the 5% level at both ends[9] in line with other studies on similar sample data (e.g. Agostino et al., 2010).

Although we pool our observations, they are pulled from various time periods. We must therefore consider and control for the potential exogenous growth of variables over time. To do so, we introduce a firm-specific time trend variable (δT_i) which serves as a proxy to capture this effect (Perron, 2019).

Finally, in order to deal with potential underestimation of standard errors owing to the presence of heteroskedastic data we cluster standard errors on the firm-specific level (robust standard errors), a method applied in previous studies (e.g. Gong & Wang, 2016). Note that when testing both H1 and H2 we report the results both with and without robust standard errors.

5.2.3 Final model for testing H1

Building on the well-known Ohlson (1995) valuation framework and adjusted for considerations described above we estimate the following model for testing H1:

$$SP_{i\tau} = \beta_0 + \beta_1 BVEBLLPS_{it} + \beta_2 EBCLPS_{it} + \beta_3 CLPS_{it} + \beta_4 LLPS_{it} + \delta T_i + \varepsilon_{it} \qquad [10]$$

Where:

$SP_{i\tau}$: Share price for firm *i* at time *τ* (*τ* = *t* + 3 months) stated in euro.

$BVEBLLPS_{it}$: Fiscal period closing book value of equity before adjustment for credit loss allowances deflated by shares outstanding for firm *i* at time *t* stated in euro.

$EBCLPS_{it}$ Fiscal period earnings before credit loss expense deflated by shares outstanding for firm *i* at time *t* stated in euro.

$CLPS_{it}$ Fiscal period credit loss expense deflated by shares outstanding for firm *i* at time *t* stated in euro.

[8] A fixed-effect estimator is used when an omitted-variables bias is either assumed to be or concluded to be present. We test this by (1) through the Breusch & Pagan Lagrangian multiplier test in which we can reject the null-hypothesis that the variance in our error term is equal to zero implying that an omitted-variable bias has an effect in our sample and secondly (2) through the Hausman test we reject the null hypothesis of no correlation between fixed effects and explanatory variables. In this setting opting for a fixed-effects estimator in our model is most prudent (Onali et al., 2017) See Appendix C & D for the results.

[9] In short this is done by assigning values above (below) the 95th (5th) percentile to the closest value not considered an outlier.

$LLPS_{it}$: Fiscal period closing credit loss allowance deflated by shares outstanding for firm *i* at time *t* stated in euro.

δT_i: Firm specific (*i*) time-trend variable.

ε_{it}: Error term.

Following equation [10] our coefficients of interest are (β_3) and (β_4). In order to conclude whether or not credit loss accounting information is value relevant, these variables need to be statistically significant. As previous research and statements suggest that credit losses represent a major drawback to bank profitability (see section 1 and 4) we expect both (β_3) and (β_4) to have a negative association with share prices, i.e., be estimated with a negative sign. Although the focus of this study is not earnings or book value of equity, we expect both coefficients (β_1) and (β_2) to be significant and positive (Mechelli & Cimini, 2020; Marton & Runesson, 2017; Novotny-Farkas, 2016; Schaap, 2020).

5.2.4 Measuring changes in value relevance

Building on equation [10] we also aim to test the increase (decrease) in value relevance in credit loss accounting information captured in coefficient (β_3) and (β_4) from switching from an ILM to an ELM. The mechanical differences are explained in section 2 and its theorized implications in terms of value relevance are explained in section 3. Extant literature suggests two common methodologies to do so: (1) interaction with the use of dummy variables[10] or (2) comparing goodness-of-fit[11] from two different regressions.

Interaction approach

One approach when comparing the value relevance in accounting information from two different accounting treatments is to introduce what is often referred to as an interaction variable or dummy variable. In order to understand the approach, consider the following model where (y) is given as function of (x) such that:

$$y = \alpha_0 + \alpha_1 x \qquad [11]$$

Assume we want to test whether the association between (y) and (x) is dependent on the known variable (z). To test this using an interaction approach we expand the model by introducing (z) as a variable and an interaction term such that:

$$y = \alpha_0 + \alpha_1 x + \alpha_2 xz + \alpha_3 z \qquad [12]$$

[10] A dummy variable is a variable which can only take the value 0 or 1.

[11] In statistical analysis, goodness-of-fit is usually measured by what is commonly referred to as the estimated R^2-value defined as the coefficient of determination which explains the portion of variance in the dependent variable which can be predicted using the independent variables.

Where: $z = \{1,0\}$

Consider an output based on equation [11] and [12] given as:

equation [11]: $y_1 = \alpha_0 + \alpha_1 x = 0 + 1x$

equation [12]: $y_2 = \alpha_0 + \alpha_1 x + \alpha_2 xz + \alpha_3 z = 0 + 0.5x + 1.5xz + 0.5z$

In (y_1) we conclude that (x) has a positive association with (y) with an association of 1. However, in (y_2) our interpretation is more complex. First consider that (α_1) is now 0.5 and that (α_2) is 1.5. This implies that the total association between (x) and (y) when (z = 0) is 0.5 but that the marginal increase in association between (x) and (y) when (z = 1) is 1.5[12]. From this we can conclude the following:

(1) (x) is positively associated with (y) but

(2) (x) is more positively associated with (y) if (z =1) than if (z = 0)

From a value-relevance perspective, assuming (y) is analogous to market prices, (x) is analogous to accounting information and (z) is analogous to which accounting standard is applied (1 for some standard, 0 for some other), then we would infer that the accounting information of (x) is more value relevant when accounted for according to the standard which entails (Z = 1) compared to the standard when (Z = 0). This approach has been used in studies in order to compare different accounting treatments and their impact on value relevance (e.g. Agostino et al., 2010; Gong & Wang, 2016) and has the benefit of not needing to subdivide a sample into smaller parts.

Comparing goodness-of-fit

Another proposed method is to compare measurements of goodness-of-fit for various samples as used by e.g. Barth et al. (2008). In reference to our previous example, we would split the sample of observations into two groups based on whether (Z = 1) or (Z = 0), instead of introducing variable (Z) to indicate e.g. accounting standard. We would then regress using equation [11] separately for both subsamples and compare measures for goodness-of-fit. This approach, although practical from an interpretation perspective, has been proven troublesome for various reasons. One inherent issue when comparing goodness-of-fit between subsamples is that it is impossible to know whether the differences are explained by differences in structural coefficients, variances of the exogenous variables or indeed from the variances in the error term (Agostino et al., 2010). Moreover, Brown et al. (1999) concluded that, if not properly controlled for, between-sample comparisons are in fact impossible to make and therefore erroneous if pursued.

[12] The full effect of (x) on (y) when (z = 1) would be calculated as $\alpha_1 + \alpha_2$ (0.5 + 1.5 = 2) whereas the full effect of (x) on (y) when (z = 0) would be simply α_1 (0.5).

Thus, we refrain from this method of comparison and instead opt for a dummy variable approach which we apply in testing H2a-c.

5.2.3 Final model for testing H2

In line with our reasoning in section 5.2.2 we introduce a dummy variable to test whether credit loss accounting is more value relevant under IFRS 9, which entails an ELM, than under IAS 39 which entails an ILM. To do this mechanically we introduce a dummy variable which takes the value of 1 for observations accounted for according to IFRS 9 and takes the value 0 for observations accounted for according to IAS 39. We then estimate the following model to test H2:

$$\mathrm{SP}_{i\tau} = \beta_0 + \beta_1 \mathrm{BVEBLLPS}_{it} + \beta_2 \mathrm{EBCLPS}_{it} + \beta_3 \mathrm{CLPS}_{it} + \beta_4 \mathrm{LLPS}_{it} + \delta \mathrm{T}_i + \beta_5 \mathrm{ECL}_{it}$$
$$+ \beta_6 (\mathrm{BVEBLLPS}_{it} * \mathrm{ECL}_{it}) + \beta_7 (\mathrm{EBCLPS}_{it} * \mathrm{ECL}_{it}) + \beta_8 (\mathrm{CLPS}_{it} * \mathrm{ECL}_{it})$$
$$+ \beta_9 (\mathrm{LLPS}_{it} * \mathrm{ECL}_{it}) + \varepsilon_{it} \qquad [13]$$

Where:

ECL_{it}: Dummy variable equal to 1 for observations accounted for according to IFRS 9 and equal to 0 for observation accounted for according to IAS 39[13].

All other variables are as defined earlier. Provided our expectation of credit loss accounting information to have a negative association with share prices we similarly expect the coefficients of (β_3) and (β_4) to be negative and statistically significant. Following our hypothesis regarding the increased incremental value relevance in the ELM we also expect both (β_8) and (β_9) to be negative and statistically significant (Hoogervorst, IFRS, 2016) which would be evidence of an increased value relevance, analogous to the interpretation from the simplified model as described in equation [12]. As the purpose of this study is not to investigate the incremental value relevance of accounting items not related to credit loss accounting, we make no prediction regarding (β_6) and (β_7). Finally, in order to test our sub-hypothesis H2a-c, we again refrain from subdividing our initial sample, for reasons explained in section 5.2.2, and instead introduce another dummy variable to indicate which category a firm falls under based on the following definitions.

Final model for testing H2a

In H2a we aim to test whether the hypothesized incremental increase in value relevance from the ELM is less pronounced for less profitable firms. To do this we introduce a dummy variable (LPROF_{it}) which takes the value 1 (0) if the return on equity for the

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[13] Please note that, owing to the adoption schedule set out for IFRS 9, in our sample data ECL = 1 coincides with the fiscal period beginning in 2018 or later with ECL = 0 for periods before with no observed overlap.

particular firm observation in the sample is lower (higher) than the median return on equity in the sample of observations. We then estimate the following models to test H2a:

$$SP_{i\tau} = \beta_0 + \beta_1 BVEBLLPS_{it} + \beta_2 EBCLPS_{it} + \beta_3 CLPS_{it} + \beta_4 LLPS_{it} + \delta T_i + \beta_5 ECL_{it}$$

$$+\beta_6(BVEBLLPS_{it} * ECL_{it}) + \beta_7(EBCLPS_{it} * ECL_{it}) + \beta_8(CLPS_{it} * ECL_{it})$$

$$+ \beta_9(LLPS_{it} * ECL_{it}) + \beta_{10} LPROF_{it} + \beta_{11}(LPROF_{it} * CLPS_{it} * ECL_{it})$$

$$+\beta_{12}(LPROF_{it} * LLPS_{it} * ECL_{it}) + \beta_{13}(LPROF_{it} * CLPS_{it}) + \beta_{14}(LPROF_{it} * LLPS_{it})$$

$$+\beta_{15}(LPROF_{it} * ECL_{it}) + \varepsilon_{it}$$

From a statistical perspective it is necessary to include all lower-order products[14] when introducing interaction terms which have been done accordingly. However, for the purposes of this report we are only interest in studying the sign and significance of coefficients (β_{11}) and (β_{12}). These indicate the marginal impact from ($LPROF_{it}$), on the association between share prices and credit loss information when accounted for according to ELM. Furthermore, we expect these to have positive signs as we expect less profitable firms to enjoy less incremental value relevance from the ELM. Thus, a positive sign would have a moderating effect on overall value relevance of ELM as, assuming credit loss information has a negative association with share prices, this theorized moderating effect would bring the full effect closer to zero if positive which is analogous to reducing the association with share prices.

Final model for testing H2b

In H2b we aim to test whether the hypothesized incremental increase in value relevance from the expected credit loss model is less pronounced for smaller firms. To do this we introduce a dummy variable ($SMALL_{it}$) which takes the value 1 (0) if the size, measured as the natural logarithm of firm total asset at t, is smaller (larger) than the median size in the sample period of observations.

Thus, we estimate the following model to test H2b:

$$SP_{i\tau} = \beta_0 + \beta_1 BVEBLLPS_{it} + \beta_2 EBCLPS_{it} + \beta_3 CLPS_{it} + \beta_4 LLPS_{it} + \delta T_i + \beta_5 ECL_{it}$$

$$+\beta_6(BVEBLLPS_{it} * ECL_{it}) + \beta_7(EBCLPS_{it} * ECL_{it}) + \beta_8(CLPS_{it} * ECL_{it})$$

$$+ \beta_9(LLPS_{it} * ECL_{it}) + \beta_{10} SMALL_{it} + \beta_{11}(SMALL_{it} * CLPS_{it} * ECL_{it})$$

$$+\beta_{12}(SMALL_{it} * LLPS_{it} * ECL_{it}) + \beta_{13}(SMALL_{it} * CLPS_{it}) + \beta_{14}(SMALL_{it} * LLPS_{it})$$

$$+\beta_{15}(SMALL_{it} * ECL_{it}) + \varepsilon_{it}$$

[14] E.g. if we introduce a three-way interaction ABC we must similarly include A, B, C, AB, AC and BC in our model for it to be properly modelled.

[15]

Analogous to our description of coefficients of interest for the estimated model regarding H2a we are only interested in studying the sign and significance of coefficients (β_{11}) and (β_{12}) which indicate the marginal impact from ($\mathrm{SMALL_{it}}$) on the association between share prices and credit loss information when accounted for according to ELM. We furthermore expect these to have positive signs as we expect smaller firms to enjoy *less* incremental value relevance from the ELM and so a positive sign would have a moderating effect on overall value relevance of ELM.

Final model for testing H2c

In H2c we aim to test whether the hypothesized incremental increase in value relevance from the expected credit loss model is more pronounced for loan-intensive firms i.e. firms with a greater part of assets from loan-activities. To do this we introduce a dummy variable ($\mathrm{HLTA_{it}}$) which takes the value 1 (0) if the loan-to-asset ratio of a particular firm observation in the sample period is larger (smaller) than the median loan-to-asset ratio in the sample of observations. Following this we estimate the following model to test H2c:

$$\begin{aligned}
\mathrm{SP_{i\tau}} = {} & \beta_0 + \beta_1\mathrm{BVEBLLPS_{it}} + \beta_2\mathrm{EBCLPS_{it}} + \beta_3\mathrm{CLPS_{it}} + \beta_4\mathrm{LLPS_{it}} + \delta\mathrm{T_i} + \beta_5\mathrm{ECL_{it}} \\
& + \beta_6(\mathrm{BVEBLLPS_{it}} * \mathrm{ECL_{it}}) + \beta_7(\mathrm{EBCLPS_{it}} * \mathrm{ECL_{it}}) + \beta_8(\mathrm{CLPS_{it}} * \mathrm{ECL_{it}}) \\
& + \beta_9(\mathrm{LLPS_{it}} * \mathrm{ECL_{it}}) + \beta_{10}\mathrm{HLTA_{it}} + \beta_{11}(\mathrm{HLTA_{it}} * \mathrm{CLPS_{it}} * \mathrm{ECL_{it}}) \\
& + \beta_{12}(\mathrm{HLTA_{it}} * \mathrm{LLPS_{it}} * \mathrm{ECL_{it}}) + \beta_{13}(\mathrm{HLTA_{it}} * \mathrm{CLPS_{it}}) + \beta_{14}(\mathrm{HLTA_{it}} * \mathrm{LLPS_{it}}) \\
& + \beta_{15}(\mathrm{HLTA_{it}} * \mathrm{ECL_{it}}) + \varepsilon_{it} \qquad [16]
\end{aligned}$$

Analogous to our description of coefficients of interest for the estimated model regarding H2a and H2b we are only interested in studying the sign and significance of coefficients (β_{11}) and (β_{12}) which indicate the marginal impact from ($\mathrm{HLTA_{it}}$), as defined above, on the association between share prices and credit loss information when accounted for according to ELM. We furthermore expect these to have negative signs as we expect loan-intensive firms to enjoy *more* incremental value relevance from the ELM and so a negative sign would have an increasing effect on overall value relevance of ELM.

It should be noted that, given the variable definitions above the same firm could potentially be classified within e.g. the low profitability sample ($\mathrm{LPROF_{it}} = 1$) for some values of (t) whilst also be classified within the non-low profitability sample ($\mathrm{LPROF_{it}} = 0$) for other values of (t). An alternative method would be to determine one single time-invariant classification for each firm (i.e. the classification of low-profitability or non-low profitability for a given firm is fixed for the entire period) based on that firm's average value compared to the average of the sample of observations. This would however cause issues in our model since we employ a firm fixed effect estimator (see section 5.4.2), and these added variables would be completely collinear with this estimator as these variables would always take on the same value for all observations in any given panel/firm. This perfect collinearity causes most statistical software to omit the variable from the regression[15]. We therefore refrain from this alternative as having omitted variables would cause some concern in terms of model interpretation. We do however use this definition as a robustness check where we respecify the model somewhat in order to deal with this particular issue (section 7.4).

[15] This holds true when we try this approach when using a fixed-effect regression in the statistical software Stata.

6 Sample Selection and Descriptive Statistics

The section below consists of three parts. The data collection process is detailed out in section 6.1, followed by descriptive statistics and sample composition in section 6.2 and lasty, we discuss potential data biases in section 6.3.

6.1 Data collection process and data quality

To test our hypotheses, we investigate listed financial institutions in Europe. We collect data on the financial entities from Thomson Reuters EIKON (EIKON), a global database containing firm and market specific information. We start with a sample including all firms included in the Global Industry Classification Standard (GICS)[16] 'Banks' in Europe. From this, institutions that did not apply either IAS 39 or IFRS 9 in the years 2010-2020 are removed, leaving a sample of 5 189 observations. Lastly, financial institutions which did not disclose all necessary variables are removed, reducing the sample to 4 254 observations. Only observations presenting positive earnings can be used (as detailed out in section 5.1.3), and after removing all observations with negative earnings we are left with 3 756 observations. Sample collection and elimination is summarized in table 5.

Table 5. Sample selection and elimination

	Observations
Total observations where GICS industry is Banks, accounting treatment is IFRS9/IAS and entity is listed	5 189
less observations with missing data*	-935
Unbalanced panel data (all observations)	4 254
less non-positive earnings observations	-498
Unbalanced panel data (positive earnings observations)	3 756

* Entities without disclosed loan-loss provisions according to Thomson Reuters EIKON

For the regressions, we compute both a balanced and an unbalanced panel dataset (see table 6). The balanced panel data includes 53 different financial entities in the period 2015-2020. We choose not to include 2010-2014 in the balanced panel data as the number of financial entities with all data available decreased significantly with more periods included. The fourth quarter in 2020 is not included for the same reason. The unbalanced dataset includes observations from 2010 to 2020, in order to include as many observations as possible without including the immediate effect of the financial crisis in 2008-09, as to not risk skewing the data. Moreover, as referenced to in the introduction, the crisis itself induced that change in standard and so seems like a natural cut-off point for this study.

[16] GICS is a classification method for categorizing companies to a specific industry group which defines its business operations. It is developed by Morgan Stanley Capital International and Standard & Poor's (MSCI, 2021).

Table 6. Frequency table of observations

	FQ	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Total
		FY											
Unbalanced panel data	1	77	78	78	82	84	88	98	111	119	127	109	1 051
	2	76	76	65	65	70	68	82	92	97	105	104	900
	3	75	66	72	74	79	95	102	116	125	121	122	1 047
	4	65	66	58	66	58	69	86	102	107	103	69	849
Balanced panel data	1	-	-	-	-	-	53	53	53	53	53	53	318
	2	-	-	-	-	-	53	53	53	53	53	53	318
	3	-	-	-	-	-	53	53	53	53	53	53	318
	4	-	-	-	-	-	53	53	53	53	53	-	265

Note: The table shows the number of observations per fiscal quarter in our unbalanced and balanced panel data sets.

6.2 Descriptive statistics

Full descriptive statistics are provided in Table 7 for all variables for both datasets, under IAS 39 (Fiscal year 2010-2017) and IFRS 9 (Fiscal year 2018-2020). For both datasets, the average share price is lower during 2018-2020 than 2010-2017, partly explained by the general downturn of share prices of banks during the past years (MSCI, 2021) as a result of increased regulations and a low-interest rate environment (Demirguc-Kunt et al., 2004). Credit losses are also lower under IFRS 9 than under IAS 39, which can partly also be explained by the low-interest rate environment in Europe; when interest rates are low fewer loans default (Berger et al., 2009). Please note, however, that the observed changes in means in accounting metrics before and after the implementation of IFRS 9 does not, by themselves, impact the value relevance estimates before and after the implementation of IFRS 9.

Table 7. Sample summary statistics

Unbalanced panel data										
Variable	Observations		Mean		Std. Dev.		Min		Max	
	IAS 39	IFRS 9	IAS 39	IFRS 9	IAS 39	IFRS 9	IAS 39	IFRS 9	IAS 39	IFRS 9
SP	2 539	1 308	15.97	13.28	17.59	15.43	0.41	0.41	65.74	65.74
BVEBLLPS	2 539	1 308	28.23	26.78	28.17	28.16	0.69	0.69	102.64	102.64
EBCLPS	2 539	1 308	0.78	0.63	0.79	0.68	0.02	0.02	2.80	2.80
CLPS	2 539	1 308	0.23	0.13	0.30	0.21	-0.03	-0.03	1.02	1.02
LLPS	2 539	1 308	4.73	3.41	5.70	4.62	0.08	0.08	20.15	20.15
SMALL	2 539	1 308	0.48	0.53	0.49	0.50	0.00	0.00	1.00	1.00
HLTA	2 539	1 308	0.50	0.50	0.50	0.50	0.00	0.00	1.00	1.00
LPROF	2 539	1 308	0.48	0.53	0.49	0.50	0.00	0.00	1.00	1.00
Balanced panel data										
Variable	Observations		Mean		Std. Dev.		Min		Max	
	IAS 39	IFRS 9	IAS 39	IFRS 9	IAS 39	IFRS 9	IAS 39	IFRS 9	IAS 39	IFRS 9
SP	636	583	18.69	17.88	17.05	16.71	0.41	0.41	65.74	65.74
BVEBLLPS	636	583	28.20	30.94	23.82	26.86	0.69	0.69	102.64	102.64
EBCLPS	636	583	0.75	0.77	0.65	0.66	0.02	0.02	2.80	2.80
CLPS	636	583	0.14	0.15	0.20	0.24	-0.03	-0.03	1.02	1.02
LLPS	636	583	4.00	3.28	4.66	3.76	0.08	0.08	20.15	19.49
SMALL	636	583	0.51	0.49	0.50	0.50	0.00	0.00	1.00	1.00
HLTA	636	583	0.50	0.50	0.50	0.50	0.00	0.00	1.00	1.00
LPROF	636	583	0.47	0.53	0.50	0.50	0.00	0.00	1.00	1.00

Note: The table present summary statistics for both the unbalanced and balanced panel data sets and is split between IAS 39 and IFRS 9 respectively for the purpose of comparison. All variables are defined in section 5. As a result of winsorizing the variables based on the full sample, minimum and maximum values are the same in both IFRS 9 and IAS 39.

Table 8 below presents the spearman-correlation matrix for our main variables of interest i.e. share price (SP), book value of equity before credit loss allowance per share (BVEBLLPS), earnings before credit losses per share (EBCLPS), credit losses per share (CLPS) and credit loss allowance per share (LLPS). Unsurprisingly, we observe high correlation between all variables as is common in value relevance studies. Still, we include a multicollinearity check in section 7.4 as a robustness check.

Table 8. Spearman correlation

	Unbalanced panel data					Balanced panel data				
Variable	SP	BVE BLLPS	EBCLPS	CLPS	LLPS	SP	BVE BLLPS	EBCLPS	CLPS	LLPS
SP	1.00					1.00				
BVEBLLPS	0.71	1.00				0.64	1.00			
EBCLPS	0.72	0.89	1.00			0.65	0.87	1.00		
CLPS	0.52	0.63	0.71	1.00		0.34	0.48	0.55	1.00	
LLPS	0.63	0.73	0.68	0.72	1.00	0.66	0.64	0.60	0.59	1.00

Note: The table above reports the spearman-correlations between our main variables from our sample, both for the unbalanced and balanced datasets. All correlations are significant at the 1%-level.

6.3 Data bias

The reason for not including all countries applying IFRS in the sample is to limit the country specific effects. By solely looking at European banks, the effect of first-time adoption is also somewhat limited, as all financial institutions in the EU were obliged to adopt IFRS in 2005 (Guggiola, 2010). This implies that most of the financial institutions in our sample have had an equal amount of time to set up processes and systems to properly adapt to the new standard. By solely using listed firms we also mitigate the differences in accounting treatment as they were all covered by the compulsory adoption of IFRS in 2005. The aspect of time needed to collect data if we were to include non-listed firms was also considered but by using listed firms the data could be collected directly from EIKON. The removal of the observations with negative earnings could possibly impact the results, as when incentives to postpone or altogether avoid provisions are high, the manipulation of accounting information aspect increases (Marton & Runesson, 2017). However, as mentioned in section 5.2.2 this is necessary as including negative earnings significantly complicates the interpretation of the value relevance (Hayn, 1995; Collins et al., 1999).

Despite the aforementioned measures taken to mitigate biases in the data sample, some might remain. As an example, Mechelli & Cimini (2020) highlight country bias as they conclude that strong corporate governance results in an ELM being more value relevant than an ILM and vice versa. We mitigate this bias in our sub-hypotheses, where we split the sample according to size, profitability, and nature of business. By doing this, we can provide a more elaborate answer to our main hypothesis. Furthermore, we touch on this consideration as a robustness check, where we cluster standard errors on both the firm and country level (see section 7.4). This sample split also addresses the critical characteristics for determining in what particular setting each respective impairment model is more value relevant. We do this as scholars such as Novotny-Farkas (2016) and Marton & Runesson (2017) have suggested that this may vary.

7 Results

In this section we estimate the model in its various configurations according to which hypothesis we aim to test (section 5). First, we present the results related to H1 (section 7.1), thereafter we present the results related to H2 (section 7.2) and the results related to H2a-c (section 7.3). Note that we include both regressions on an unbalanced and a balanced panel data set for each test, both of which are presented in the same table for each model specification. Finally, we present some robustness checks (section 7.4).

7.1 Value relevance of credit loss accounting information

Table 9. Estimation of coefficients for model testing H1

Model: $SP_{it} = \beta_0 + \beta_1 BVEBLLPS_{it} + \beta_2 EBCLPS_{it} + \beta_3 CLPS_{it} + \beta_4 LLPS_{it} + \delta T_i + \varepsilon_{it}$

	Unbalanced panel data		Balanced panel data	
	FEM[1]	FEM with robust standard errors	FEM	FEM with robust standard errors
	(1)	(2)	(3)	(4)
BVEBLLPS	0.360*** (0.014)	0.360*** (0.080)	0.083*** (0.030)	0.083 (0.061)
EBCLPS	4.093*** (0.350)	4.093*** (0.960)	2.204*** (0.439)	2.204** (0.905)
CLPS	-5.617*** (0.630)	-5.617*** (1.945)	-7.302*** (0.845)	-7.302*** (1.997)
LLPS	-0.462*** (0.065)	-0.462* (0.269)	-0.609*** (0.094)	-0.609*** (0.202)
Trend	-0.021** (0.0098)	-0.021 (0.037)	-0.105*** (0.019)	-0.105** (0.049)
Constant	5.552*** (0.306)	5.552*** (1.569)	18.760*** (0.795)	18.760*** (1.408)
Observations	3 847	3 847	1 219	1 219
No of Banks	163	163	53	53
R-squared	0.366	0.366	0.141	0.141

Note: [1]Fixed effects model. The table shows the estimation of coefficients for our model testing H1 where the coefficients show the association between the independent variables and our dependent variable (Share price). Standard errors are reported in parenthesis below the coefficient estimates. (*), (**), (***) denotes statistical significance at the 10, 5 and 1% level. Robust standard errors mean that standard errors are clustered at the firm level. Independent variables are winsorized at the 5% level. Unbalanced panel data includes observations from Q1 2010 up to Q4 2020 whereas the balanced data only includes observations between Q1 2015 up to Q3 2020 to retain a large enough sample data. R^2-values are reported as within-estimates.

Table 9 reports the results from the regression model testing H1 as specified in section 5.2.3. Regressions have been made on both datasets (balanced and unbalanced) and with and without robust standard errors. In column (1) both coefficients on (β_1) and (β_2) are positive and significant, indicating that these variables are value relevant and carry positive associations with share prices. Moreover, the results hold when applying robust standard errors in column (2). Similar results are ascertained in both columns (3) and (4) with positive signs on coefficients (β_1) and (β_2) and these are statistically significant in all but one iteration, where (β_1) is not statically significant in the balanced panel data with robust standard errors. These results indicate a principally significant and positive association between earnings and share prices and book value of equity and share prices.

The included trend variable (δT_i) is also statistically significant at either the 5% or 1%-level in all iterations with the exception for the unbalanced panel data regression with robust standard errors in column (2). These results indicate that the firm-specific exogenous growth in variables over time has an underlying effect on share prices and the prudent method is to include it in regressions going forward.

Turning to our main variables of interest we note that both coefficients (β_3) and (β_4) have a statistically significant negative association with share prices in all iterations of the model. These results, highlighted in grey for ease of reference, indicate that credit loss accounting information captured through credit losses recognized in the income statement and statement of financial position is value relevant and has a negative association with share prices.

7.2 Comparing value relevance of credit loss accounting methods

Table 10. Estimation of coefficients for model testing H2

Model: $SP_{i\tau} = \beta_0 + \beta_1 BVEBLLPS_{it} + \beta_2 EBCLPS_{it} + \beta_3 CLPS_{it} + \beta_4 LLPS_{it} + \delta T_i + \beta_5 ECL_{it} + \beta_6(ECL_{it} * BVEBLLPS_{it}) + \beta_7(ECL_{it} * EBCLPS_{it}) + \beta_8(ECL_{it} * CLPS_{it}) + \beta_9(ECL_{it} * LLPS_{it}) + \varepsilon_{it}$

	Unbalanced panel data			Balanced panel data		
	FEM	Fully interactive FEM	Fully interactive FEM with RSE[1]	FEM	Fully interactive FEM	Fully interactive FEM with RSE
	(1)	(2)	(3)	(4)	(5)	(6)
BVEBLLPS	0.360***	0.388***	0.388***	0.083***	0.154***	0.154**
	(0.014)	(0.016)	(0.083)	(0.030)	(0.037)	(0.069)
EBCLPS	4.093***	2.771***	2.771***	2.204***	0.951*	0.951*
	(0.350)	(0.392)	(0.929)	(0.439)	(0.550)	(0.567)
CLPS	-5.617***	-4.081***	-4.081**	-7.302***	-3.587***	-3.587*
	(0.630)	(0.746)	(2.029)	(0.845)	(1.192)	(2.076)
LLPS	-0.462***	-0.531***	-0.531**	-0.609***	-0.698***	-0.698***
	(0.065)	(0.071)	(0.255)	(0.094)	(0.104)	(0.222)
Trend	-0.021**	0.080***	0.080*	-0.105***	-0.032	-0.032
	(0.010)	(0.013)	(0.044)	(0.019)	(0.035)	(0.061)
ECL		-0.931***	-0.931		-0.235	-0.235
		(0.357)	(0.829)		(0.539)	(0.582)
ECLx BVEBLLPS		-0.037**	-0.037		-0.021	-0.021
		(0.018)	(0.042)		(0.020)	(0.035)
ECLx EBCLPS		1.732***	1.732		1.847**	1.847
		(0.659)	(1.258)		(0.743)	(1.421)
ECLx CLPS		-6.617***	-6.617***		-5.530***	-5.530**
		(1.199)	(2.481)		(1.430)	(2.714)
ECLx LLPS		-0.435***	-0.435***		-0.326***	-0.326*
		(0.065)	(0.164)		(0.083)	(0.182)
Constant	5.552***	5.064***	5.064***	18.760***	17.140***	17.140***
	(0.306)	(0.303)	(1.491)	(0.795)	(0.861)	(1.471)
Observations	3 847	3 847	3 847	1 219	1 219	1 219
No of Banks	163	163	163	53	53	53
R-squared	0.366	0.421	0.421	0.141	0.189	0.189

Note: [1]Robust Standard Errors. The table shows the estimation of coefficients for our model testing H2 where the coefficients show the association between the independent variables and our dependent variable (Share price). Interaction terms are shown with "x" joining the independent variables. Standard errors are reported in parenthesis below the coefficient estimates. (*), (**), (***) denotes statistical significance at the 10, 5 and 1% level. Robust standard errors mean that standard errors are clustered at the firm level. Independent variables are winsorized at the 5% level. Unbalanced panel data includes observations from Q1 2010 up to Q4 2020 whereas the balanced data only includes observations between Q1 2015 up to Q3 2020 to retain a large enough sample data. R^2-values are reported as within-estimates.

Table 10 reports the results from the regression model testing H2 as specified in section 5.2.3. Regressions have been made on both datasets (balanced and unbalanced) and with or without robust standard errors. Columns (1) and (4) are regressions without interaction and therefore identical to Table 9 in section 7.1. Columns (2) and (5) are estimates of the fully interactive model as stated in section 5.2.3 whereas columns (3) and (6) are estimated for the fully interactive model but with the addition of robust standard errors. As described in section 5.2.4, the interpretation of coefficients changes when interaction terms are introduced. Whereas (β_1) in table 9 reported the association between (BVEBLLPS) and share prices, (β_1) in this table reports the association between (BVEBLLPS) and share prices when accounted for under IAS 39 (i.e., ECL = 0). (β_6) instead reports the incremental increase/decrease in association between (BVEBLLPS) and share prices when accounted for according to IFRS 9. The full association between (BVEBLLPS) and share prices can thus be calculated as ($\beta_1 + \beta_6$)[17]. Following this, with reference to the example described in section 5.2.4 we are mainly interested in studying the coefficients on the interaction terms ($\beta_6, \beta_7, \beta_8, \beta_8$).

Notably, when including robust standard errors neither interactions for BVEBLLPS (β_6) nor EBCLPS (β_7) are statically significant. This indicates that the introduction of IFRS 9 does not seem to have influenced the value relevance of either earnings before credit losses or book value of equity before credit loss allowance.

We do, however, note that both coefficients (β_8) and (β_9) are statistically significant and have a negative sign. Moreover, these results tend to hold regardless of iteration although the significance does drop from the 1%-level to the 5% and 10%-level respectively for CLPS (β_8) and LLPS (β_9) in the balanced panel data iteration with robust standard errors, reported in column (6). These results favor our hypothesis that expects credit loss accounting information to be more value relevant under IFRS 9 than under IAS 39. This is as the interaction terms are highly significant and have an added negative association with share prices, implying that share prices are more affected by credit loss accounting information under IFRS 9 than under IAS 39 pointing toward the ELM being more value relevant than the ILM.

7.3 Nuancing changes in value relevance

Table 11 reports the results from the regression model testing H2a-c as specified in section 5.2.4. Regressions have been performed on both balanced and unbalanced data sets as well as with and without robust standard errors. However, the following table only

[17] The coefficient for the 'full association or effect' from e.g. book value of equity before credit loss allowance when (ECL = 1) would be calculated as ($\beta_1 + \beta_6$) and significance of the full effect would be tested by the relative standard errors such that ($\sigma_{\mathrm{BVEBLLPS}} = \sqrt{\mathrm{var}(\beta_1) + \mathrm{var}(\beta_6) + 2\mathrm{cov}(\beta_1, \beta_6)}$). These 'full associations/effects' are highly significant for all variables but not reported as they are not important for our interpretation.

reports iterations with robust standard errors. Please note that the variable (VAR) denotes either the variable relating to profitability ($\mathrm{LPROF_i}$), size ($\mathrm{SMALL_i}$) or loan-intensity ($\mathrm{HLTA_i}$), as previously defined, depending on iteration. As noted in section 5.4.4 we are, with the addition of a third interaction term, only interested in examining the coefficients for our three-way interactions (β_{11}) and (β_{12}).

In reference to our model testing the impact of lower profitability (H2a) on the increased value relevance from the expected credit loss model, we do not note any statistically significant results on either (β_{11}) and (β_{12}). This implies that profitability, based on our definition, does not seem to have an effect on the incremental increase in value relevance stemming from the ELM. Put differently, the association between credit loss accounting information and share prices under the ELM *does not* seem be significantly affected by profitability.

In reference to our model testing the impact of smaller size (H2b) on the increased value relevance from the expected credit loss model, we note statistically significant results on at least the balance sheet item credit loss allowance (β_{12}). This implies that size, based on our definition, may influence the incremental increase in value relevance stemming from the ELM. Put differently, the association between credit loss accounting information and share prices under the ELM *does* seem be significantly affected by size. In fact, in both reported iterations (balanced and unbalanced) we note that the three-way interaction on credit loss allowance is statically significant and has a positive sign. Although interpretating models with three-way interactions are notoriously difficult, we regard this as an indication that the ELM is *less* value relevant for smaller firms as these positive coefficients on the three-way interaction term bring the full effect (not reported) of credit loss allowance on share prices closer to zero, i.e., effectively reducing the association between share prices and credit loss allowances.

In reference to our model testing the impact of loan-intensity (H2c) on the increased value relevance from the expected credit loss model, we similarly note statistically significant results on at least the balance sheet item credit loss allowance (β_{12}). This implies that loan-intensity, based on our definition, may influence the incremental increase in value relevance stemming from the ELM. Put differently, the association between credit loss accounting information and share prices under the ELM *does* seem be significantly affected by loan-intensity. However, for this model we only note a significance at the 5%-level. Moreover, only on the balanced panel iteration. We regard this as an indication that the ELM is *more* value relevant for loan-intensive firms, as the three-way interaction term has a negative coefficient, bringing the full effect (not reported) of credit loss allowance on share prices further away from zero. That is, effectively increasing the negative association between share prices and credit loss allowances.

Table 11: Estimation of coefficients for model testing H2a-c

Model: $P_{it} = \beta_0 + \beta_1 BVEBLLPS_{it} + \beta_2 EBCLPS_{it} + \beta_3 CLPS_{it} + \beta_4 LLPS_{it} + \delta T_i + \beta_5 ECL_{it} + \beta_6(ECL_{it} * BVEBLLPS_{it}) + \beta_7(ECL_{it} * EBCLPS_{it}) + \beta_8(ECL_{it} * CLPS_{it}) + \beta_9(ECL_{it} * LLPS_{it}) + \beta_{10} VAR_{it} + \beta_{11}(VAR_{it} * ECL_{it} * CLPS_{it}) + \beta_{12}(VAR_{it} * ECL_{it} * LLPS_{it}) + \beta_{13}(VAR_{it} * CLPS_{it}) + \beta_{14}(VAR_{it} * LLPS_{it}) + \beta_{15}(VAR_{it} * ECL_{it}) + \varepsilon_{it}$

	VAR=LPROF		*VAR*=SMALL		*VAR*=HLTA	
	Unbalanced panel data	Balanced panel data	Unbalanced panel data	Balanced panel data	Unbalanced panel data	Balanced panel data
BVEBLLPS	0.398***	0.202***	0.406***	0.132*	0.403***	0.143**
	(0.076)	(0.073)	(0.077)	(0.074)	(0.084)	(0.070)
EBCLPS	0.826	-0.396	2.423***	0.614	2.653***	0.888*
	(0.969)	(0.536)	(0.828)	(0.458)	(0.915)	(0.497)
CLPS	-3.109	-3.113	-5.897	-8.368***	-6.596**	-5.258**
	(3.553)	(4.042)	(3.578)	(2.263)	(2.985)	(2.252)
LLPS	-0.241	-0.536**	-0.360	-0.759***	-0.455	-0.774***
	(0.246)	(0.249)	(0.315)	(0.264)	(0.285)	(0.233)
Trend	0.089**	-0.007	0.074*	-0.035	0.071	-0.036
	(0.042)	(0.061)	(0.043)	(0.064)	(0.043)	(0.061)
ECL	-1.203	-0.889	-0.599	-1.122	-1.606*	-1.907**
	(0.824)	(0.560)	(0.804)	(0.745)	(0.843)	(0.808)
ECLxBVEBLLPS	-0.021	0.008	-0.080*	-0.063	-0.052	-0.031
	(0.044)	(0.039)	(0.041)	(0.038)	(0.041)	(0.034)
ECLxEBCLPS	1.099	0.650	2.158	2.653*	1.808	1.922
	(1.417)	(1.489)	(1.363)	(1.422)	(1.247)	(1.325)
ECLxCLPS	-4.064	-2.337	-5.417	-5.071	-6.265*	-6.035**
	(3.518)	(3.724)	(3.426)	(3.835)	(3.190)	(2.850)
ECLxLLPS	-0.363**	-0.109	-0.628***	-0.226	-0.312**	-0.065
	(0.167)	(0.203)	(0.182)	(0.233)	(0.148)	(0.197)
VAR	-0.090	-0.942***	2.002	-7.583***	0.286	-1.699
	(0.509)	(0.330)	(1.460)	(2.482)	(1.012)	(1.571)
VARxECLxCLPS	-3.379	-3.517	1.014	-1.153	-0.809	-0.666
	(3.724)	(5.321)	(4.543)	(4.580)	(4.558)	(3.836)
VARxECLxLLPS	-0.065	-0.352	0.876***	0.452*	-0.222	-0.515**
	(0.195)	(0.272)	(0.205)	(0.245)	(0.255)	(0.232)
VARxCLPS	3.010	2.421	2.444	11.930***	5.695	5.847**
	(3.644)	(3.845)	(4.277)	(3.339)	(4.021)	(2.690)
VARxLLPS	-0.511**	-0.202	-0.763***	-0.104	-0.298	0.234
	(0.198)	(0.124)	(0.266)	(0.409)	(0.202)	(0.191)
VARxECL	0.166	0.549	-0.316	1.465	1.990***	3.610***
	(0.590)	(0.693)	(0.776)	(1.077)	(0.719)	(0.954)
Constant	5.480***	16.580***	4.583***	22.220***	4.916***	18.270***
	(1.395)	(1.514)	(1.645)	(2.649)	(1.623)	(2.008)
Observations	3 847	1 219	3 847	1 219	3 847	1 219
No of Banks	163	53	163	53	163	53
R-squared	0.449	0.231	0.451	0.257	0.429	0.227

Notes: The table shows the estimation of coefficients for our model testing H2a-c where the coefficients show the association between the independent variables and our dependent variable (Share price). Interaction terms are shown with "x" joining the independent variables and *VAR* denotes the specific variable being tested. All estimation shown are with robust standard errors and fixed effect estimator. Standard errors are reported in parenthesis below the coefficient estimates. (*), (**), (***) denotes statistical significance at the 10, 5 and 1% level. Robust standard errors mean that standard errors are clustered at the firm level. Independent variables are winsorized at the 5% level. Unbalanced panel data includes observations from Q1 2010 up to Q4 2020 whereas the balanced data only includes observations between Q1 2015 up to Q3 2020 to retain a large enough sample data. R^2-values are reported as within-estimates.

7.4 Additional robustness considerations

7.4.1 Considerations regarding fiscal year 2020

We believe that the year 2020, in hindsight, will probably be considered as an outlier year in many respects owing to the pandemic[18]. Notably, banks faced arguably greater difficulties in estimating expected credit losses for the respective quarters. Investors similarly likely faced even greater difficulties in using the reported figures in equity valuation models. In order to control for the potential outlier-effect from the pandemic in terms of value relevance of credit loss accounting information, we re-estimate our model by excluding all observations from fiscal year 2020. However, the results from these regressions are identical to our original estimates in terms of coefficient signs and significance and we therefore regard our findings as robust in this regard.

7.4.2 Considerations regarding multicollinearity

As mentioned in section 6, we observe high levels of correlation between variables, raising the potential issue of multicollinearity. To determine whether such an issue exists in our estimations, we perform collinearity diagnostics (see Appendix E). However, all variables show variance inflation factors below 10, why we do not consider the correlations observed in section 6 an issue (Mitra, 2011).

7.4.3 Considerations regarding country-fixed effects

In prior research regarding value relevance clustering is usually conducted either at the firm level or at the country level. For example, Agostino et al. (2010) mentions that clustering standard errors on country-level is a good way of controlling for e.g., country-specific listing requirements, market microstructure, and enforcement. To control for any country-specific effects, we therefore re-estimate our model regarding our main hypothesis (H2) but cluster standard errors on both the country and firm level. In this iteration, the interaction terms of interest, namely that on CLPS and LLPS, are again highly statically significant and negative whereby we regard our main findings as robust in this regard, too.

7.4.2 Considerations regarding alternative subsampling method

As expressed in section 5.2.3, when specifying the model for testing hypothesis H2a-c, this model is inherently flawed in the sense that one firm can classify into both subsamples where they fall within one category for some years and another category for others. To control for this, we re-specify our definition with regard to which category a firm is placed

[18] At the time of writing this thesis the COVID-19 pandemic was currently ongoing. For more information regarding the pandemic a simple google query for e.g. “COVID-19”, “Corona virus” should suffice.

in based on that firm's average value over the entire timeframe compared to the average for the sample of banks. In this specification, a firm will have one time-invariant classification within the panel. As noted in section 5.2.3, this causes issues to our original model as this variable would be completely collinear with our firm fixed effects estimator as these variables would always take on the same value for all observations in any given panel or firm. This perfect collinearity causes most statistical software to omit the variable from the regression.

In this robustness check, we respecify our model for testing H2a-c using the redefined variable according to the description above and instead employ a random effects estimator[19]. Please note that this model is not free from flaws, as we previously provided evidence that a fixed effects estimator was the most prudent choice given our sample. Hence, employing a random effects estimator is incorrect in this regard. However, these tests do indicate similar results where the incremental increase in association between share price and credit loss allowance (LLPS) under ELM is *less* pronounced for smaller firms and where the incremental increase in association between share price and credit loss expense (CLPS) is *more* pronounced for more loan-intensive firms, albeit these results only hold in the unbalanced panel data iteration.

[19] Using a random effects estimator is suggested as a good approach if: (1) one cannot reject the null hypothesis of the Hausman test, i.e. that we have no correlation between fixed effects and explanatory variables, and (2) through the Breusch & Pagan Lagrangian multiplier test we can reject the null hypothesis that the variance in our error term is equal to zero. If we cannot reject the null hypothesis of the Breusch & Pagan Lagrangian multiplier test we should opt for an ordinary least square model (OLS) specification (Onali et al., 2017).

8 Concluding Discussion and Implications

8.1 Concluding discussion

By comparing the value relevance of the new ELM with the prior ILM in 163 European banks, we set out to answer whether the IASB, through the implementation of the new impairment model, has succeeded with its goal – to improve accounting quality and contribute to investors gaining better and more relevant information on credit losses in banks (Hoogervorst, 2015).

First, by testing our baseline hypothesis, we find that items relating to credit losses are significantly value relevant, in line with previous research (e.g. Novotny-Farkas, 2016; Marton & Runesson, 2017; Mechelli & Cimini, 2020).

Second, we find that the credit loss accounting under IFRS 9 is more value relevant than under IAS 39, in line with the conclusions drawn by Mechelli & Cimini (2020). However, in contrast to Mechelli & Cimini (2020) we find no significant difference in value relevance between book value of equity before credit loss allowance and earnings before credit losses under either IFRS 9 or IAS 39. Our data thus indicate that the new scope and classification of financial assets in IFRS 9 has had limited, if any, effect on the overall value relevance of accounting. Instead, the results of our test specified for the value relevance of the items related to the impairment models, suggest that it is the ELM that generates the improvement in quality. This is likely due to its forward-looking nature, enabling better timeliness of credit losses and transparency regarding banks' underlying estimations. Thus, we find that, based on our sample of European banks, the IASB has succeeded in improving the relevance of accounting for impairment of credit losses.

Third, our sub-hypotheses give rise to further nuancing of these findings as we find, based on prior research, that the ELM might not be equally optimal across all organizational settings. The increase in value relevance from the ELM is less pronounced in smaller firms than in larger ones. It is also more pronounced for firms with greater share of loans to total assets than in firms with smaller share of loans to total assets. The results from sub-hypotheses H2b and H2c thus suggest that the optimal trade-off, between the level of transparency and incorporation of forward-looking information *and* the increased level of accounting discretion stemming from the ELM, differ depending on the bank's size and loan-intensity. The results should be interpreted with caution though. They do not necessarily state that the ILM is superior (inferior) to the ELM in smaller firms (firms with greater share of loans to total assets), it simply states that ELM seemingly provides less (more) incremental value relevance in smaller firms (firms with greater share of loans to total assets) than in larger firms (firms with smaller share of loans to total assets) for this particular sample data and considering our definitions of small firm and more loan-intensive firm. The three-way interaction model used to test this does include several difficulties and limitations (see section 5.2.3 and 7.3), and these findings should, therefore, despite two of them being statistically significant, be regarded with caution. However, our findings are in line with the reasoning of several scholars before us (e.g Novotny-Farkas, 2016; Gebhardt & Novotny-Farkas, 2010; Marton & Runesson, 2017).

Based on previous discussion (section 4.3), this difference in value relevance may depend on two things. First, accounting information produced by smaller firms is not trusted to the same extent as that produced by larger entities, as the complexity in the new impairment model complicates the process of producing the accounting information, and smaller banks might not have the same advanced processes in place (Marton & Runesson, 2017). Second, investors might fear that smaller firms misuse the larger allowance for accounting discretion under IFRS 9, thus providing less accurate numbers in their financial statements (Novotny-Farkas, 2016; Mechelli & Cimini, 2020). Given this, the cost of subjectivity under the ELM is that it could lead to less trust in accounting information produced by smaller banks and by banks with smaller proportion of loans to total assets. However, our non-significant result regarding the effect profitability has on the value relevance of the ELM (H2a) can be seen as an indicator that the lower incremental value relevance in smaller banks is due to the lack of trust stemming from their size or the inability to produce accurate information, rather than a question of manipulation as a result of allowance for more accounting discretion. This finding stands in contrast to that of Marton & Runesson (2017), potentially explained by the exclusion of unprofitable banks in our sample. Including banks with negative results could have an impact on our findings. The aspect of increased accounting discretion under ELM, and thus manipulation, might be more accurate in the new impairment model if banks with negative results were included in the sample.

8.2 Limitations

There are several limitations to this paper. One is related to the size of our sample, which is rather limited with 163 unique firms in the unbalanced sample and 53 in the balanced sample, constrained by the limited amount of listed financial entities in Europe disclosing all necessary accounting information. Furthermore, all items affected by the impairment models are not included in our model. When partitioning the earnings and book value of equity variables, we disregard credit losses recognized through OCI and provisions recognized in the statement of financial position as a liability. This, however, represents a marginal part of credit losses.

As noted in section 2.1, the scope of the two standards is *substantially* unaltered. However, some items, such as loan commitments, that were previously outside the scope of impairment requirements under IAS 39 are now included under IFRS 9 (IASB, 2018; IASB, 2001). Therefore, it is not unreasonable to suggest that some incremental gain in value relevance in credit loss accounting information, as defined in this study, could be explained by this marginal increase in scope. We would, however, argue that this marginal increase in scope cannot explain the increase in value relevance observed.

As previously mentioned, three-way interactions are notoriously tricky to interpret and so conclusions drawn for hypothesis H2a-c are stated with caution. Moreover, our approach for classifying firm observations in which we compare the observation value against the sample data median is also not necessarily the most appropriate approach, and alternative approaches could generate alternative results.

Using a panel data set brings further limitations. As all observations accounted for according to IFRS 9 are from fiscal year 2018 or later whereas all observations accounted for according to IAS 39 are prior to fiscal year 2018, we cannot rule out the possibility of some other event, unrelated to the changes in standard, causing the observed change in value relevance. We do however consider this somewhat unlikely to be the case since we have partitioned accounting items and isolated items related to credit losses (see section 5.2.1) and, to the best of our knowledge, there are no other events that would have a similar effect on the value relevance of these particular accounting items. Other limitations and assumptions are stated throughout the paper.

8.3 Contribution and future research

This study contributes to accounting literature by providing empirical evidence of the value relevance of the new ELM, implemented in IFRS 9. Although there has been one previous published article (Mechelli & Cimini, 2020) investigating the value relevance of IFRS 9, we are, to the best of our knowledge, the first ones to explicitly test the incremental value relevance in the ELM over the ILM using empirical evidence. By providing empirical evidence, we also contribute to the debate surrounding the quality of IFRS 9 as well as to opening up the discussion regarding what different factors are affecting the quality of the accounting information provided by the new impairment model for practitioners.

Our sub-hypotheses H2a-c represents attempts at explaining the results from H1 and H2. However, we are only scratching the surface in trying to explain in what settings the ELM is more value relevant than the ILM. Hence, we suggest that these hypotheses are further investigated. In addition, the implementation of the new impairment model was fairly recent which is why we would encourage investigations into whether the observed increase in value relevance from the standard endures over time. Moreover, in this study the country differences are not investigated. Therefore, another suggestion for future research is to study if the value relevance differs significantly across countries.

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10 Appendices

Appendix A. Summary of selected studies revolving around implementation of IFRS 9

Author & Year	Title	Emprirics	Purpose/Question	Findings
Gebhardt, G. & Novotny-Farkas, Z. (2010)	*Mandatory IFRS Adoption and Accounting Quality of European Banks*	70 listed banks in EU excl. Austria & Germany, 2000-2007	Examining the implications of mandatory IFRS adoption on the accounting quality of banks in EU countries.	Recognition of only incurred losses (IAS 39) reduces income smoothing, less pronounced in countries with stricter bank supervision, dispersed bank ownership and for EU-US cross-listed banks. Incurred loss approach results in less timely loan loss recognition and delayed future expected loss recognition.
Giner, B.; Mora, A. (2019)	*Bank Loan Loss Accounting and its Contracting Effects: The New Expected Loss Models*	IFRS 9 and FCAG (2009) standard	To investigate the differences between the IASB and the FASB models and identify potential consequences of implementation.	The objective to reduce information asymmetry after the financial crisis explains the change to the ELM. In contrast to the ILM, the ELM is unconditionally conservative. The lack of convergence between IASB's and FASB's approach can be explained by the difference in bank business models, originate to-hold vs originate-to-distribute.
Marton, J; Runesson, E (2017)	*The predictive ability of loan loss provisions in banks – Effects of accounting standards, enforcement and incentives*	628 European banks, 2000–2010	Comparing the ability of loan loss provisions to predict actual losses under IFRS and local GAAP.	Loan loss provisions under IAS 39 predict future credit losses less than under local GAAP standards. Predictive ability varies on bank size and profitability, IAS 39 is superior in small banks and in less profitable banks. In banks with low profitability strict enforcement, e.g. an ILM, increases the timeliness of loss recognition.
Mechelli, A.; Cimini, R. (2020)	*The effect of corporate governance and investor protection environments on the value relevance of new accounting standards: the case of IFRS 9 and IAS 39*	Sample of 316 listed financial entities of 43 countries worldwide, in 2018.	Does the quality of corporate governance and the investor protection environment affect the value relevance of IFRS 9 and IAS 39?	IFRS 9 has increased the value relevance of accounting information in comparison to IAS 39. This varies depending on corporate governance and In the presence of high-quality corporate governance or a high-quality investor protection environment, IFRS 9 is more value relevant than IAS 39 and vice versa.
Novotny-Farkas, Z. (2016)	*The Interaction of the IFRS 9 Expected Loss Approach with Supervisory Rules and Implications for Financial Stability*	Examining the interaction of the new ELM approach with supervisory rules and evaluate potential implications for financial stability.	Examining the interaction of the new expected credit loss approach of IFRS 9 with supervisory rules and evaluate potential implications for financial stability.	The expected credit loss approach under IFRS 9 incorporates more information relevant for identifying future credit losses and result in earlier recognition of credit losses than IAS 39. IFRS 9 require larger loan loss allowances. Earlier and larger loan loss allowances under IFRS 9 limit the possibility of distributing overstated profits, thus IFRS 9 has the potential to reduce capital inadequacy concerns during a crisis.
O'Hanlon, J. (2013)	*Did loan-loss provisioning by UK banks become less timely after implementation of IAS 39?*	Did loan-loss provisioning by UK banks become less timely after implementation of IAS 39?	Did loan-loss provisioning by UK banks become less timely after implementation of IAS 39?	Loan-loss provisioning by UK banks was less timely under the stricter evidence requirements of the IAS 39 incurred-loss regime implemented in 2005 than under the less strict evidence requirements of the previous UK incurred-loss regime.
Onali, E.; Ginesti, G (2014)	*Pre-adoption market reaction to IFRS 9: A cross-country event-study*	What does the market think about the new potential accounting regime for financial instruments?	What does the market think about the new potential accounting regime for financial instruments?	Investors in the EU are positive to the implementation of IFRS 9, and perceive the new regulation as having a positive impact on shareholder wealth. In countries with a weaker rule of law and smaller difference between local GAAP and IAS 39 the investors are more positive to the new standard, this contrasts other studies.
Schaap, C.M. (2020)	*The impact of IFRS 9 on the Value Relevance of Accounting Information: Evidence from European Union Banks*	Has the value relevance of accounting information increased post IFRS 9 implementation?	Has the value relevance of accounting information increased post IFRS 9 implementation?	The value relevance of accounting information for EU banks has declined after the introduction of IFRS 9 in general. However, earnings are more value relevant under IFRS 9 than under IAS 39 whereas the book value of equity is less value relevant.

Appendix B. Derivation of the Ohlson model

The model is conditioned on three main assumptions. First and foremost, the model relies on a clear surplus relationship of accounting such that:

$$\mathrm{BV_t = BV_{t-1} + NI_t - D_t} \qquad [A1]$$

Where:

$\mathrm{BV_t}$ = Book value of equity at time t

$\mathrm{NI_t}$ = Net income at time t

$\mathrm{D_t}$ = Dividend at time t

Secondly the value of firm equity at any point in time is given by the present value of all future expected dividends such that:

$$\mathrm{MV_t} = \sum_{\tau=1}^{\infty} (1 + r)^{-\tau} \mathrm{E_t[D_{t+\tau}]} \qquad [A2]$$

Where:

$\mathrm{MV_t}$ = Market value at time t

r = discount rate assumed constant

Abnormal earnings (x_t^a) are defined as ($x_t^a = \mathrm{NI_t} - r * \mathrm{BV_{t-1}}$) and the final assumption of the Ohlson model is the stochastic process of abnormal earnings and other value relevant information (v_t) such that:

$$x_{t+1}^a = \omega x_t^a + v_t + \varepsilon_{1t+1} \qquad [A3]$$

$$v_{t+1} = \gamma v_t + \varepsilon_{2t+1} \qquad [A4]$$

Where:

ε_{1t}: error term with mean greater than 0

ε_{2t}: error term with mean greater than 0

ω: parameter for persistence of abnormal earnings which must be greater than 1

y: parameter for persistence of other information which must be greater than 1

From these three assumptions the underlying model of firm value as a function of the present value of all future expected dividends given in equation [A2] can be restated such that:

$$\mathrm{MV_t = BV_t} + \alpha_1 x_t^a + \alpha_2 v_t$$

[A5]

Where:

$$\alpha_1 = \frac{\omega}{(1 + r - \omega)} > 0$$

$$\alpha_2 = \frac{1 + r}{(1 + r - \omega)(1 + r - \gamma)} > 0$$

Following the definition of abnormal earnings (x_t^a) we can further restate the model as such:

$$MV_t = BV_t + \alpha_1 NI_t - \alpha_1 r BV_{t-1} + \alpha_2 v_t \quad [A6]$$

Further following our assumption of clear surplus relationship, we can further restate the model as such:

$$MV_t = BV_t + \alpha_1 NI_t - \alpha_1 r(BV_t - NI_t + D_t) + \alpha_2 v_t \quad [A7]$$

Simplifying and reconfiguring the model above gives us:

$$MV_t = (1 - \alpha_1 r)BV_t + \alpha_1(1 + r)NI_t - \alpha_1 D_t + (\alpha_2)v_t \quad [A8]$$

As is common in value relevance studies the net dividend term is not included in the final model and likewise dropped here (Hand & Landsman, 1998). Following this and reconciling the model above to a model suitable for empirical regression testing we get the model stated below which implies that firm value at t is given by current book value of equity, current earnings, and other value relevant information.

$$MV_t = \beta_1 BV_t + \beta_2 NI_t + \beta_3 v_t \quad [A9]$$

Appendix C. Breusch and Pagan Lagrangian multiplier test for random effects

	Unbalanced panel data		Balanced panel data	
Variable	Variance	Std. Dev.	Variance	Std. Dev.
SP	286.808	16.935	285.154	16.886
e	31.121	5.578	15.198	3.898
u	79.577	8.920	86.321	9.290
	Test: H_0 that Variance of u = 0		Test: H_0 that Variance of u = 0	
	$\chi^2 = 32982.97$		$\chi^2 = 7485.95$	
	Prob $> \boldsymbol{\chi^2} = \mathbf{0.0000}$		**Prob** $> \boldsymbol{\chi^2} = \mathbf{0.0000}$	

Note: The table above presents the results from the Breusch & Pagan Lagrangian multiplier test for random effects in which we test whether or not we can reject the null hypothesis that the variance in our error term is equal to zero. The results (stated in bold) indicate that we can in fact reject the null hypothesis.

Appendix D. Hausman specification test

	Unbalanced panel data				Balanced panel data			
Variable	FE	RE	Diff	S.E	FE	RE	Diff	S.E
BVEBLLPS	0.359	0.351	0.008	0.003	0.082	0.159	-0.767	0.013
EBCLPS	4.092	4.284	-0.191	0.035	2.203	2.232	-0.028	0.027
CLPS	-5.616	-5.778	0.161	0.063	-7.302	-7.804	0.502	0.078
LLPS	-0.462	-0.332	-0.129	0.019	-0.609	-0.442	-0.166	0.020
trend	-0.021	-0.014	-0.006	0.001	-0.105	-0.112	0.007	0.003
	Test: H_0 that difference in coefficients is not systematic				Test: H_0 that difference in coefficients is not systematic			
	$x^2(5) = 79.95$				$x^2(4) = 96.82$			
	$\mathbf{Prob} > \boldsymbol{x^2(5) = 0.0000}$				$\mathbf{Prob} > \boldsymbol{x^2(5) = 0.0000}$			

Note: The table above presents the results from the Hausman specification test in which we test whether or not we can reject the null hypothesis of no correlation between fixed effects and explanatory variable or, as stated above, that the difference in coefficients is not systematic. The results (stated in bold) indicate that we can in fact reject the null hypothesis.

Appendix E. Collinearity diagnostics

	Unbalanced panel data				Balanced panel data			
Variable	VIF	$\sqrt{\text{VIF}}$	Tol.	R^2	VIF	$\sqrt{\text{VIF}}$	Tol.	R^2
BVEBLLPS	6.45	2.54	0.155	0.844	4.86	2.21	0.205	0.794
EBCLPS	6.32	2.51	0.158	0.841	4.70	2.17	0.212	0.787
CLPS	2.80	1.67	0.356	0.643	1.75	1.32	0.572	0.427
LLPS	3.00	1.73	0.333	0.666	2.16	1.47	0.463	0.537
trend	1.07	1.03	0.935	0.064	1.06	1.03	0.946	0.053

Note: The table above presents the collinearity diagnostics for both the unbalanced and balanced panel data samples. Note that we only perform collinearity diagnostics on our main variables of interest without their respective interaction terms as including interactions naturally increases collinearity.