THE RELEVANCE OF EXPECTED CREDIT LOSSES

THE EFFECT OF IFRS 9 ON ANALYST FORECAST ACCURACY

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The Relevance of Expected Credit Losses: The effect of IFRS 9 on analyst forecast accuracy

Abstract:

This study examines how the adoption of the expected loss model under IFRS 9 has affected the forecast accuracy of credit losses. Specifically, we investigate the effect on absolute forecast errors and forecast dispersion. To establish the effect, we employ a difference-in-differences analysis using a dataset that includes 39 European banks that adopted the standard on January 1, 2018. To control for the observed effect on the European data set, we employ a control group consisting of U.S. banks reporting under U.S. GAAP. The study covers 24 quarters between 2014 and 2019. Our results suggest that the absolute forecast errors and forecast dispersion increased more for the European banks than the U.S. banks after the IFRS 9 mandatory adoption date. Accordingly, we conclude that the forecast accuracy of credit losses has decreased. In relation to IASB's Conceptual Framework, our results imply that the relevance of credit losses has likewise deteriorated. However, we assert that the deterioration may only reflect a temporary effect as analysts adapt to the new information environment. Our study makes two primary contributions. First, we provide early evidence that the forecast accuracy of credit losses has deteriorated after the adoption of IFRS 9. Secondly, we add to the existing literature on forecast accuracy in relation to the adoption of new accounting standards by shedding light on analysts' adaption to a new information environment.

Keywords:

IFRS 9, Decision Usefulness, Accounting Relevance, Forecast Accuracy, Financial Analysts, Credit Losses, ELM, ECL, Difference-in-Differences

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1. Introduction

The systemic importance of the banking sector is typically regarded to warrant the deep regulation levied upon it. Through new accounting regulation, governing bodies ensure that the financial information disclosed by banks is accurately depicted and relevant to stakeholder's decision-making. For most banks, lending is the critical source of value creation and risk-taking, with economic profitability determined by the yield charged relative to credit losses realized. Therefore, credit losses are a direct function of loan quality, and as such, they represent an essential proxy for the banking sector's overall wellbeing. We believe that the ability of shareholders and analysts to establish the current and future quality of financial intermediaries using the information disclosed by them is an essential objective.

On January 1, 2018, IFRS 9 replaced IAS 39 as the general accounting standard for financial instruments (IFRS, 2021). This transition instituted significant changes to the accounting of credit losses, particularly affecting the banking sector. The information provided under IAS 39 was deemed insufficient for investors to assess the value and risk of financial assets (Barth & Landsman, 2010) and was generally thought to delay the recognition of credit losses (PwC, 2017). The term "too little, too late" has often been used to highlight the concerns regarding IAS 39's approach to recognizing credit losses. As such, the development of IFRS 9 reflects a response to criticisms aimed at the prior standard.

To promote pro-cyclicality, IFRS 9 introduces the "expected loss model" (ELM) as opposed to IAS 39's "incurred loss model" (ILM). The new model pivots the temporal focus of credit losses from a historical viewpoint to a forward-looking perspective. The ILM mandated that a "trigger event" had occurred before the reporting entity could record any provisions. Under the ELM, provisions are instead made at first recognition and continuously thereafter following asset deterioration. In making such assessments of the credit quality, IFRS 9 considers the assets' default probabilities. The new model increases the provision coverage ratios on the outset and subsequently improves the timeliness of loss recognition. However, IFRS 9 relies more heavily on preparer assumptions but supposedly provides a more accurate and timely measure of credit losses.

To support the development of new standards, IASB's Conceptual Framework (CF) states that the objective of financial reporting is to provide decision-useful information for investors in financial instruments. Decision usefulness is in turn underpinned by relevance, which is operationalized as the ability of financial information to influence decision-making through its predictive and confirmatory values. The predictive and confirmatory values of accounting information help users anticipate future outcomes and subsequently confirm prior predictions. (Runesson et al., 2018)

The earlier recognition of credit losses through increased preparer judgment under IFRS 9 reflects an effort to improve the relevance of the accounting information. Therefore, the implications of IFRS 9 on relevance and decision usefulness can be assessed through its effect on the predictive and confirmatory value of credit loss accounting. As the predictive and confirmatory values are closely related to projections, the effect can be examined in light of advanced users of financial statements who provide influential forecasts, e.g., financial analysts. Forecasts made by financial analysts play a well-recognized part in information intermediation in the capital markets (Schipper, 1991). Moreover, given the status of credit losses as indicators of credit quality and banking risk, there are also practical reasons to assess the forecasting implications of IFRS 9. Consequently, our research question is formulated according to the below.

How has the adoption of the expected credit loss model under IFRS 9 affected the forecast accuracy of credit losses?

1.1. Summary of Findings and Contribution

To establish the impact of IFRS 9 on analyst forecasting accuracy, we employ a difference-in-differences (DID) analysis focused on European banks and control for the effects using U.S. banks reporting under U.S. GAAP. These two groups are comparable as they both report credit losses using ILM methodologies in the pre-IFRS 9 periods. This period consists of 16 quarters between 2014 and 2017. After the IFRS 9 adoption for the European banks, the U.S. control group still reports under the US GAAP equivalent of ILM up until January 1, 2020. This creates a two-year window between 2018 and 2019 where the effects of IFRS 9 on the European group can be isolated. To assess forecast accuracy, we use two related measures, i.e., absolute forecast error and forecast dispersion. The first measure is used to understand how precise analysts are at forecasting credit losses. The second measure is used as a proxy for how well analysts agree with each other.

This study finds that the adoption of IFRS 9 had a negative effect on both absolute forecast errors and forecast dispersion. After the implementation of IFRS 9, absolute forecast errors for the European group increased by 6.22% more than the U.S. control group. Similarly, forecast dispersion increased 7.03% more for the European group. Both effects are significant below the 5%-level according to the results. Since forecast accuracy deteriorated after IFRS 9 introduction for European banks, the desired effect on relevance through predictiveness of credit losses was not achieved. An important caveat to our findings lies in the post-implementation period studied. In line with previous research on IFRS adoption, we assert that the observed deterioration may only be an initial effect. Accordingly, there may exist a learning period for the financial analysts following the introduction of a new standard.

While the adoption of IFRS 9 infers significant changes to the measurement of credit losses, the body of research on this specific topic is minimal. Naturally, this likely relates to the recent adoption of the framework. By answering our research question, we contribute with an early assessment of the predictive and confirmatory properties of IFRS 9. We also add to the current literature on analyst forecasting in relation to the adoption of new accounting standards and the subsequent adjustment to new information.

1.2. Disposition

This thesis is structured as follows. First, we develop the theoretical background and explain how decision usefulness and relevance relate to forecast accuracy. Next, we outline the relevant accounting standards and how the adoption of IFRS 9 is expected to affect the forecast accuracy of credit losses. We then expand on prior research focused on factors that affect forecast accuracy in relation to IFRS adoption. Thereafter, we formulate our hypotheses based on the theoretical background and the informational changes implied by IFRS 9. We also present our data and research methodology before analyzing and interpreting the results. Lastly, we discuss the findings and conclude our research.

2. Theoretical Background

2.1. IFRS and the IASB Conceptual Framework

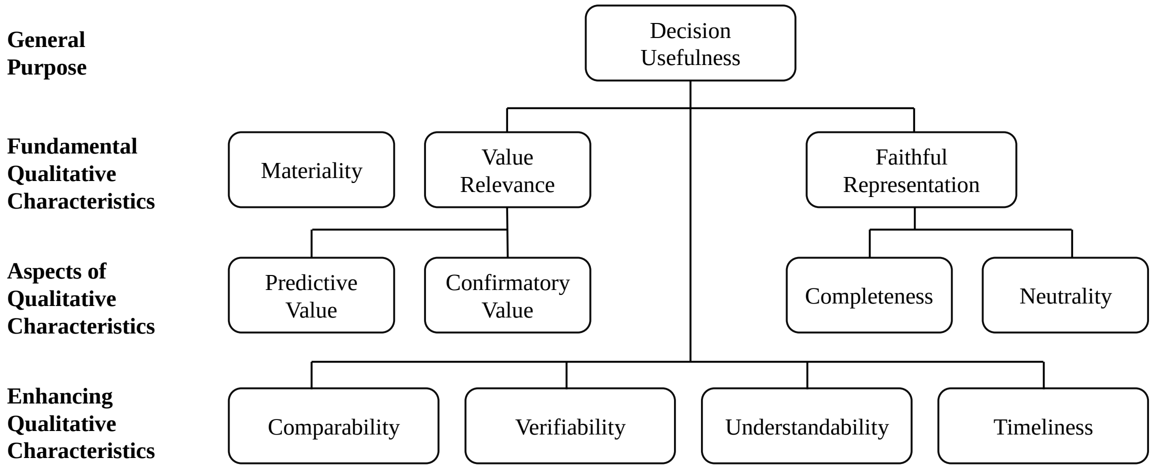
The International Accounting Standards Board (IASB) is the autonomous body of the IFRS Foundation, which is responsible for developing and publishing IFRS standards. The IFRS Foundation's purpose is formulated as "bringing transparency, accountability, and efficiency to financial markets" (IFRS, 2021b). This mission statement has an explicit focus on the usefulness of financial reports for market participants in making informed decisions. This purpose is also supported by academia on the back of a rich body of research that strengthens the notion that information contained in financial statements plays a vital role for investors in decision-making processes (Bushman & Smith, 2003).

In 1989, IASB released its first rendition of the "Framework", which presented a thorough depiction of the normative characteristics of accounting theory. To provide standard setters with a holistic accounting philosophy, this guide also stated the key objectives of financial reporting. Influenced by "A Statement of Basic Accounting Theory" (ASOBAT) by the American Accounting Association from 1966, the "Framework" recognizes that objectives of financial reporting are not by nature purely quantitative. The "Framework" clearly explains the objectives through terms such as relevance, understandability, verifiability, neutrality, timeliness, comparability, and completeness. With decision usefulness at the pinnacle of the financial reporting purpose hierarchy, the objectives support this general purpose as structural underpinnings. The fundamental qualitative characteristics of decision usefulness are materiality, relevance, and reliability. (Runesson et al. 2018)

Almost three decades later, in 2018, IASB released an updated version of this framework, now called the IASB Conceptual Framework (CF), in which the heritage from the ASOBAT is still pertinent. Decision usefulness remains the primary objective in developing new standards. The CF also defines a set of "qualitative characteristics" that enhances the usefulness of financial statements (see Fig. 1). These characteristics are recognized as the standard setters' definition of accounting quality (Runesson et al., 2018).

As accounting standards often incorporate a high degree of judgment and estimation rather than exact representations, the qualitative characteristics of accounting serve to support the IASB's development of new standards. These qualitative characteristics, herein ranked by significance, range from "fundamental" to "enhancing". The fundamental characteristics are relevance, faithful representation, and materiality. Relevance refers to the ability of financial information to impact decision-making. Faithful representation, on the other hand, requires that financial information faithfully represent the actual economic phenomena of an accounting event. Materiality reflects an aspect of relevance that implies that accounting information should be concise and thus omit topics that do not directly impact its decision usefulness. Given that the relevance criterion is more closely related to decision usefulness, it is of greater significance to our study. The next section outlines how decision usefulness and relevance relate to the predictive and confirmatory values of accounting, and by extension, forecast accuracy.

Figure 1. The Characteristics of Accounting (IASB Conceptual Framework, 2018)



2.2. Accounting Relevance

Accounting information is described as relevant when the information disclosed can be used for making predictions about the future and thereby support decision-making processes. Since decision usefulness aims to facilitate decisions related to the buying and selling securities, it is a highly market-oriented characteristic of accounting. Arguably, relevance establishes the bridge between accounting and the market. Specifically, investors benefit from relevance by having the ability to make better informed transactional decisions using accounting data. By this token, accounting data should influence the pricing (or value) of securities, depending on the performance of the underlying assets. Therefore, the relevance of accounting is interchangeable with the term “value relevance”. (Runesson, 2018)

Accounting information is value relevant when there exists a positive and causal correlation between the information disclosed and stock returns (Barth et al., 2001). Ball and Brown (1968) pioneered the relationship between stock returns and earnings news. According to this stream of theory, movements in stock prices can be explained by the underlying accounting data. Unambiguously, the critical argument is that information cannot be useful unless it has a bearing on the relevant subject, i.e., the pricing of securities.

Another prominent paper on this topic is Beaver (1968), who studied stock market reactions surrounding earnings events. According to this paper, there exists a relationship between earnings information and share price reactions. Particularly, Beaver finds that information asymmetries are lower around earnings announcement and that the stock market can effectively collect incremental information and incorporate it in firm valuation. Consider the efficient market hypothesis, which states that security prices at any time reflect all the available information that pertains to the individual securities in the market (Fama, 1970). When new information relevant to the pricing of securities is released, the market uses that information to execute transactions, thus normalizing the price of the security at hand. In effect, to examine if accounting information is relevant to the pricing of securities, it is possible to test the associations between the earnings releases and price reactions.

At one level deeper, relevance is operationalized through the accounting information's predictive and confirmatory values. Indeed, the Conceptual Framework states that relevant information must be material and possess characteristics of predictive and confirmatory nature. The predictive and confirmatory values of accounting hinge on one another. Information has predictive value if it is possible to use the information in past financial statements to facilitate predictions about future performance. The information's confirmatory value can be defined as the degree to which it is possible to use current financial statements to confirm past predictions. Naturally, the predictive and confirmatory values play a significant role in forecasting financial statements and forecast accuracy.

Using financial analysts' forecasts, Brown and Rozeff (1979) confirm the interdependencies between accounting information's predictive and confirmatory values. They show that historical interim reports have a significant impact on the forecasting of future annual earnings. More precisely, increasingly accurate predictions can be achieved by substituting previously forecasted quarters with their actual values and thereafter improving future forecasts based on learnings from such adjustments. The connection between relevance and its enhancing characteristics becomes clearer considering traditional asset pricing models. Under such models, estimates of future earnings are essential to the pricing of assets. If IFRS 9 is successful in improving the relevance of credit losses, it is likely to also create better-informed investors and potentially more accurately priced banks.

2.3. Forecast Accuracy

As referred to in this paper, financial analysts are recognized as sell-side analysts, in contrast to buy-side analysts. Buy-side analysts are typically employed by institutional investors to produce internal recommendations. Sell-side analysts, on the other hand, provide independent research reports using public and private information. Financial analysts have a well-recognized role in the capital markets as information intermediaries

(Lang & Lundholm, 1996). Listed firms have a wide range of stakeholders in investors, creditors, and the public. In common, these are all interested in the company's performance. Financial analysts, in turn, collect information and provide interpretations to the stakeholders.

Although analyst recommendations and forecasts have attracted considerable attention from researchers, many of the processes and mechanism by which analysts produce their work remains unknown. It has been called a "black box" (Ramnath et al., 2008). Asquith et al. (2005) provided the first catalog of content in a traditional analyst report. They explain that an analyst's report is the result of a process that includes the compilation, assessment, and distribution of information related to a firm's current and future performance. Furthermore, they find that most reports include three key summary measures, i.e., an earnings forecast, a stock recommendation, and a price target. Analysts also frequently present broad quantitative and qualitative evaluations to support the summary measures. The forecasting element is naturally of higher interest to this study. However, we extend beyond earnings forecasts and consider another specific line item on the income statement, i.e., credit losses.

Analyst forecast accuracy is a stream of research set to evaluate how precise analyst forecasts are in relation to reported figures. Common proxies for forecast accuracy include forecast error (FE) and forecast dispersion. FE can be applied to any forecasted accounting measure, although revenue and earnings are generally the most common ones. FE is calculated as the percentage difference between the actual amount and the forecast consensus (Bradshaw et al., 2012; Bonini et al., 2010; Bilinski et al., 2013; Mikhail et al., 1997; Capstaff et al., 2001). Accordingly, the lower the difference between the actual and forecasted amounts, the lower the forecast error. To adjust for both positive and negative forecast errors, absolute forecast errors (AFE) can be used. Meanwhile, forecast dispersion is calculated as the inter-analyst standard deviation for the forecasts, divided by the mean of all forecasts. It is applied in the context of this study as a proxy for analyst agreement. The lower the dispersion, the greater the agreement.

3. Accounting Standards Review

This section outlines IAS 39 and its successor, IFRS 9. It also includes a section on the U.S. GAAP equivalents of these standards, given their role in the design of our study. Considering the scope of our research, this section is primarily focused on the treatment of credit losses under the respective standards. Lastly, we provide an overview of the informational differences between the two standards and how analyst accuracy may be affected.

3.1. IAS 39

Under IAS 39, credit losses are recognized according to the “incurred loss model” (ILM), which is generally considered to recognize losses at a late stage but with a low degree of preparer judgment. Classification requirements under IAS 39 are considered rule-based, meaning that there is less room for individual interpretation of the standard. The ILM requires that a “trigger event” (see IAS 39 § 59) must have occurred before a provision is recognized. Such events could include covenant breaches or otherwise substantial financial strain for the borrower. Credit events that do not meet the criteria for being “triggering” may, therefore, not result in provisioning. The classification framework outlined in this section is also visualized in Appendix I.

The impairment process for loans and receivables under IAS 39 separates between specific provisions and collective provisions. The process further categorizes all outstanding loans as either impaired or non-impaired. Individual significant and non-significant assets that have experienced a triggering event (i.e., impaired) are specifically provisioned only if the scope of impairment continues to be recognized as a single transaction during the deterioration review. Such provisions are calculated by subtracting the present value of anticipated contractual and collateral cash flows from the loan’s current book value. Contractual and collateral cash flows should consider both net sizes and timing. All cash flows should be discounted by the contractual effective interest rate under fixed-rate loans and the current effective interest rate under variable-rate loans.

If there is no objective evidence of impairment for an individually assessed asset, irrespective of significance, it is included in the pool of assets that are to be collectively assessed. Provisions for such assets are referred to as “net collective provisions for individually assessed loans”. Moreover, individually assessed assets, irrespective of significance, that have been exposed to a triggering event and which deterioration scope has been graded portfolio level shall also be collectively provisioned. Provisions for such assets are referred to as “net collective provisions for portfolio assessed loans” (see Appendix II).

The pool of assets for collective provisioning is further grouped according to their credit risk parameters that are indicative of the probability of recovery. For example, such parameters can include collateral types and past-due conditions. Future cash flows for each group of assets that are to be collectively provisioned are assessed based on historical default outcomes for similar groups. Such historical information shall be adjusted to reflect current observable macroeconomic factors and conditions. Adjustments will only serve to correct intertemporal differences between historical and current cohorts. Collective provisions are calculated similarly to specific provisions, with the provisioned size determined by the current book value of loans less the present value of recoverable cash flows. Cash flows should be discounted by the contractual effective interest rate.

If at any stage the objectives for specific provision are reversed, the affected assets are to be collectively evaluated. Likewise, assets that have been assigned to the pool of collective provisions and where objectives for individual impairment exists will be specifically provisioned. It is important to note that provisions for non-impaired loans are minimal, while provisions for impaired loans shall approximate the lifetime incurred and expected loss. If in future periods the impairment loss has decreased due to objective and unforeseen factors, previously recognized provisions shall be reversed by the respective amounts. Write-offs under IAS 39 constitute a de-recognition event and are only to be established when there are no realistic expectations of recovery. The net amount of provisions and write-offs is recognized as a net credit loss line item in the income statement for the period. IAS 39 makes clear that future losses, no matter how probable, are not to be recognized unless verifiable and objective triggering event criteria can be evidenced. (KPMG, 2007)

3.2. IFRS 9

IFRS 9 introduces the “expected loss model” (ELM) for recognizing credit losses. Under the new standard, entities must account for excepted credit losses from the point of first recognition and continuously thereafter (see IFRS 9 § IN9). By using forward-looking variables, credit losses under ELM are recognized at an earlier stage compared to the ILM. However, as forward-looking information used in the ELM is based on assessments and assumptions, the model is naturally more dependent on preparer judgment. This also relates to the idea that classifications under IFRS 9 follow a more principle-based system, implying greater flexibility for interpretation.

In essence, credit impairments under IFRS 9 are calculated by three components, “probability of default” (PD), “loss given default” (LGD), and “exposure at default” (EAD). PD is forward-looking and may incorporate both universal variables such as macroeconomic forecasts and bank-specific variables such as credit ratings or internal risk scores. LGD is calculated as the percentage of all expected cash flows (including collateral cash flows) in relation to the total exposed amount. EAD is simply the remaining loan balance. As a key feature of the ELM, IFRS 9 also introduces three stages that segment loans by their quality. Stage 1 is reserved for “performing assets”, stage 2 holds all “underperforming assets”, and stage 3 books all “non-performing assets”. In many ways, IAS 39’s credit impairment process closely resembles stage 3 impairments under IFRS 9.

Stage 1 assets include loans and receivables that have not significantly deteriorated in credit risk or remain at low credit risk levels. For this stage, which typically comprises the majority of a bank’s assets, the expected credit losses (ECL) are calculated using default events that are foreseeable within 12 months. Moreover, all new internal credit originations are classified at stage 1 during the initial recognition. Stage 2 includes financial instruments whose credit quality has significantly deteriorated since initial recognition. For stage 2, ECL is calculated using lifetime default probabilities.

In determining whether the credit has significantly deteriorated, collateral is not considered as it does not affect the risk of default. IFRS 9 provides a non-exhaustive list of information that could serve as the basis for such an assessment. These include external market indicators and borrower-specific information. Last, stage 3 includes financial assets for which there is evidence that an impairment has occurred at the reporting date. The difference between stages 2 and 3 is the basis on which interest revenue is calculated. In stage 2, it is calculated on gross carrying amount and in stage 3 on amortized cost net of loss allowance (see Appendix III).

Staging is one of the most critical determinants for changes in credit losses. When an asset has deteriorated significantly, IFRS 9 warrants an increase in ECL. A shift in stage level actualizes this increase. Several underlying factors are taken into consideration when staging an asset. For example, assets with significant payments close to the maturity date will typically experience a slighter decrease in PD over time. PD also increases with maturity, and variations in PD may be more significant for assets with higher quality at initial recognition.

To establish asset deterioration, banks may use three sets of factors. The first set is quantitative, which mainly relates to changes in PD, is called a “primary driver”. For example, an increase in PD by some multiple can be declared a staging event. Ultimately, PD is governed by changes in the forward-looking macroeconomic variables. The second set is “qualitative”, which may include changing business environments and expectations of forbearance, among many other things. The third set is called “backstops”, which includes covenant breaches, significant past due payments, and bankruptcy. Taken as a whole, if any of these three indicators have materialized, an asset shall be staged. (PwC, 2017)

3.3. U.S. GAAP

The Financial Accounting Standards Board (FASB) is the governing body responsible for developing Generally Accepted Accounting Principles (GAAP or U.S. GAAP). U.S. GAAP is a set of shared accounting principles for financial accounting and reporting. The standards under U.S. GAAP aim to guarantee transparency and consistency of financial reporting across national organizations. Over recent years, users of accounting information have witnessed a convergence between the standards issued by FASB and IASB. It is probable that the harmonization between international standards will continue to increase in the future. (CFA, 2021)

In June 2016, FASB announced a new forthcoming accounting standard called ASU 2016-13 that closely matches IFRS 9. The standard update was effective starting January 1, 2020. ASU 2016-13 is designated for U.S.-based banks, savings companies, and credit institutions. The credit losses under FASB's new standard are referred to as "current expected credit losses" (CECL). Like IFRS 9, the main purpose of ASU 2016-13 is to measure financial assets at a value that reflects the anticipated net collection amounts. Another purpose is to widen the data range of supportive metrics in the calculation of credit losses, including forward-looking information (Federal Reserve, 2020). The most important difference between ASU 2016-13 and IFRS 9 is that the former measures losses over the lifetime of all assets (no staging), while IFRS 9 also measure 12-month losses for stage 1 assets (see Appendix IV). (KPMG, 2021)

Prior to ASU 2016-13, a range of principles that collectively resembled IAS 39 was applied for the accounting for credit losses for U.S.-based entities. The prior methodology for credit losses incorporates estimations models from principles such as ACS 450-20 (general reserve), ASC 310-10 (specific reserves), and ASC 310-30 (purchased credit impaired) (Deloitte, 2015). From here on, these U.S. GAAP standards are collectively referred to as U.S. GAAP ILM. These sets of principles used the same incurred loss methodology as IAS 39 and deferred the recognition of losses until they were probable. In practice, there is high consistency between the IASB and FASB standards regarding incurred credit loss accounting (SEC, 2011).

3.4. Summary of Accounting Standards

IAS 39 and U.S. GAAP ILM are highly comparable with regard to the recognition of credit loss provisions. Accordingly, both standards received similar criticism for delayed recognition of credit losses during the financial crisis of 2008. Given that ASU 2016-13 is not adopted until January 1, 2020, the similarity between IAS 39 and U.S. GAAP ILM provides the regulatory conditions to enable a difference-in-differences study. Furthermore, the adoption of IFRS 9 and ASU 2016-13 implies a significant change to the accounting of credit losses. Under the ELM, banks are likely to anticipate more losses from the outset to better depict the underlying economic reality of the loan portfolio. In contrast, IAS 39's late recognition of credit loss provisions could create hidden hazards since the quality of the loan portfolio may have had deteriorated for some time without it being recorded. However, it should be noted that while IFRS 9 impacts the structure of the credit cycle, it does not change the banks' actual credit risk.

Concerning IASB's Conceptual Framework, the adoption of IFRS 9 reflects an effort to improve the relevance aspects of credit loss accounting to facilitate decision usefulness. It does so through the implementation of the ELM, which enables more timely recognition of credit losses but is also more dependent on preparer judgment. As such, the heightened reliance on assumptions may also indicate a decreased emphasis on faithful representation as increased judgment increases the possibility of biased accounting information. Naturally, it follows that IFRS 9 is more of a principle-based framework, in contrast to IAS 39's rule-based approach. This shift in emphasis is not surprising, given that the conflict between relevance and faithful representation is an inherent and definitive issue in accounting theory (Whittington, 1989).

3.5. Forecasting Implications of IFRS 9

We assert that IFRS 9 aims to improve the information environment for credit losses in two primary ways. First, information under IFRS 9 is more disaggregated. With staging, loans are split into three categories, depending on their deterioration degree. This possibly helps analysts form a better sense of how the risk of the assets is distributed. Over time, movements across asset stages and the relationship between such movements and various macroeconomic factors could also become easier to predict. Although actual disclosure differs greatly between banks, we anticipate that this separation, together with the added information on the default probabilities of various assets, improves credit losses' predictive and confirmatory values. Collectively, these aspects are thought to increase the quality of information.

Secondly, we believe that IFRS 9 also improves the quantity of information provided. The added information under IFRS 9 includes, for example, loan values for each asset stage and internal risk grade, as well as the respective default probabilities for each risk grade (see Appendix V). There is often also information about loan values across industries and geographies. Moreover, banks disclose information about the macroeconomic variables that enter the probability of default calculations. For example, such variables include GDP growth, inflation, unemployment, and interest rates. It is uncommon for banks to disclose the forecasts explicitly, but the variables themselves are included in the financial reports to highlight the parameters that are key to the ECL calculation.

As a result of the aspects discussed above, IFRS 9 improves both information quality and quantity. This may ultimately affect relevance positively. However, the application of forward-looking estimates also risks compromising the stability of the credit losses.

As forward-looking information is naturally more prone to change, so too are the credit losses. An asset may deteriorate and subsequently improve several times during its life cycle. Such movements will then be reflected in the credit loss provisions under IFRS 9. The increased volatility that follows this may create additional noise and therefore impact the predictive and confirmatory values negatively.

Furthermore, Ball (2006) asserts that IFRS adoption and new standards, in general, may initially increase forecast errors since the information that analysts previously could rely on is now obsolete. That is, the confirmatory value of the data is reset. Specifically, with IFRS 9, we believe that analysts may initially struggle with the new framework before understanding which factors have the most significant bearing on the calculation of expected credit losses. Arguably, the key to predicting ECLs is to understand the movement across stages.

In sum, there are many informational aspects of ELM that influence the relevance of credit losses. With the added benefit of more information about the critical parameters included in the calculation of ECL under IFRS 9, analysts have a stronger foundation for making estimates and subsequently confirm the quality of those forecasts. Through staging loans based on their performance, there exists increasingly disaggregated information about credit losses. Loan values are also often coupled with internal risk grades and default probabilities across stages. This, together with details on macroeconomic variables that impact the default probabilities, is likely to assist analysts in making accurate forecasts over the long term. In the short term, however, forecast accuracy may be hampered by opaque preparer assumptions and sluggish analyst learning.

4. Previous Research

4.1. Analyst Forecasting

Factors that affect forecast accuracy have attracted notable attention from researchers in recent years. This body of research can be divided into two streams. One stream is focused on the drivers of forecast accuracy related to aspects concerning the company, the analyst, or the economic context. Another stream is focused on financial reporting. As the primary purpose of this paper is to evaluate the effect of IFRS 9 on forecast accuracy, the stream of research related to IFRS reporting is of higher relevance and can be found in the next section. Below is a brief compilation of the research focused on aspects concerning the company, the analyst, or the economic context.

Studies that cover company-specific factors that affect forecast accuracy have been conducted in a wide range of contexts. For example, marketing researchers Luo et al. (2010) have found that positive changes in customer satisfaction not only improve analyst recommendations but also lower dispersion in those recommendations for the firm. Furthermore, Barron et al. (2002) have shown that analyst forecast accuracy is negatively associated with a firm's level of intangible assets and more so for R&D-driven high-technology manufacturers. However, the combined research effort remains anecdotal. Moreover, as our study is solely focused on banks, the operational differences are relatively small and not likely to have a significant effect on forecast accuracy.

Findings regarding analyst-specific factors are often strikingly intuitive. Accordingly, Jacob et al. (1999) have shown that industry specialization is positively correlated with increased forecast accuracy, and Clement (1999) has found that forecast accuracy is positively associated with analysts' experience and negatively associated with the number of firms and industries followed by the analyst. Similarly, Mikhail et al. (1997) have also found that an analyst's firm-specific experience helps them to forecast more accurately. These studies suggest that sector specialization and longer experience from covering a firm helps to produce forecasts that are more accurate. As the banking industry is in many ways unique, we expect sector specialization among analysts to be high but not change meaningfully during the period of our study.

Last, the economic context in which the firm operates has an apparent impact on forecast accuracy. Hope & Kang (2005) have found that inflation and foreign exchange volatility as measures of macroeconomic uncertainty are negatively correlated with forecast accuracy. This effect also appears more pronounced in emerging economies. Furthermore, Chopra (1998) has shown that forecasts are more accurate in times of economic growth. Black & Carnes (2006) have also shown through a study of 13 economies in the Asia Pacific region that countries more open to foreign trade and investments have more accurate analyst forecasts. Altogether, prior research on factors affecting forecast accuracy has a limited impact on the prerequisites for our study, given the geographical focus and time. However, they provide an additional lens through which our results can be interpreted.

4.2. Forecast Accuracy and IFRS

There are no published studies that directly cover IFRS 9 or the ELM, given its recent implementation. Instead, we draw insights from a broader body of research covering either the general mandatory adoption of IFRS in 2005 or later individual IFRS standards.

Tan et al. (2011) provided an early study of the effect of mandated IFRS adoption on forecast accuracy and analyst following. The study is primarily concerned with the harmonization effect of adopting a single accounting standard across a wide range of countries. Therefore, Tan et al. (2011) hypothesizes that IFRS adoption is closely connected to an increase in foreign analyst following and forecast accuracy. However, more relevant to this study is that the authors assert that IFRS has more comprehensive disclosure requirements with a higher emphasis on timeliness than most local GAAPs. Essentially IFRS is steered towards relevance. As such, the authors predict that analyst forecast accuracy may improve. On the other hand, they also acknowledge that opponents argue that new standards that increase judgment and timeliness increase volatility and may ultimately affect forecast accuracy negatively.

Using a sample that includes 12,010 firm-year observations from 3,280 individual firms in 25 countries between 1988 and 2007, the results in Tan et al. (2011) indicate that adoption of IFRS has bearing on the number of foreign analysts covering local firms. There is also evidence of improved forecast accuracy of earnings for foreign analysts. These improvements are more significant for firms domiciled in countries with more considerable differences between local GAAP standards and IFRS. As such, the harmonization effect has a positive impact on foreign analyst following and forecast accuracy. The data also indicates that IFRS adoption has a positive association with local analyst following. However, the local analysts' forecasting ability is not affected by IFRS adoption. Consequently, the adoption of new accounting standards that emphasize relevance has no significant effect on forecast accuracy for analysts that also covered the company in the pre-IFRS period.

Byard et al. (2011) also studied the mandatory adoption of IFRS across Europe. They argue that the adoption of IFRS may improve the information environment by increasing mandatory disclosures and transparency. On the other hand, the study contends that IFRS's "one-size-fits-all" approach may negatively impact analysts' forecast ability if it undermines local GAAP standards that have been developed over a long time to portray local firms' performance accurately. The study uses a difference-in-differences approach to test a sample of 1,168 European firms that mandatorily adopted

IFRS in 2005. The study establishes a control group of 250 firms that had voluntarily adopted IFRS at least two years before the mandatory adoption date. Relative to this control group, the study finds that for firms in countries with strong enforcement regimes and local accounting standards that significantly differed from IFRS, the adoption reduced analysts' absolute forecasting error and forecast dispersion. The results likewise indicate that forecast accuracy increases for companies in domiciles with weaker enforcement regimes but with substantial reporting incentives.

Horton et al. (2013) looks at the impact of IFRS on analysts' information environment. They specifically study the attributes of IFRS that would cause an improvement in the information environment. The study acknowledges a rich body of prior literature inquiring about the effect of IFRS on forecast accuracy but finds few explanations for why changes occur. Data between 2001 and 2007 on 2,235 global firms that mandatorily adopted IFRS is used. The paper considers that IFRS improves earnings forecast accuracy and other qualitative aspects of accounting. The improved information environment is attributed to higher accounting quality and increased comparability. Comparability effects relate to analysts' ability to use historical information from a more comprehensive array of firms reporting under the same principles. These results imply that the more relevance-focused IFRS improves the information environment compared to local GAAPs.

Jiao et al. (2012) examined the impact of mandatory IFRS adoption on analyst earnings forecast accuracy and dispersion. The study compares forecast error and forecast dispersion data for firms in 19 European countries for 2004 and 2006, intentionally ignoring the transition year 2005. The forecast error sample contains 1,612 observations, whereas the forecast dispersion sample contains 1,328 observations. When comparing the data in the years preceding and succeeding mandatory IFRS adoption, the researchers found that analysts' forecasts and dispersions improved. Such effects are persistent after adjusting for variables like analyst following, firm sizes, stock volatility, and earnings volatility. The study concludes that the improved accounting quality associated with IFRS adoption has a positive effect on the predictive value of accounting data and analyst forecasting accuracy.

Beuselinck et al. (2017) studied relative earnings forecast accuracy for analysts covering firms that adopted IFRS. The data comprises 68,665 firm-year observations for 1,980 firms in 19 European countries between 2000 and 2009. Specifically, the paper studies the impact on two types of analysts, sector-specialists and country-generalists. The study employs a relative measure of earnings forecast accuracy, which is defined as the accuracy of individual analysts compared to the average of their peer group. The findings imply that mandatory IFRS adoption across European firms resulted in greater improvements for sector analysts than for country analysts. The difference is more pronounced for firms in countries with large differences between local GAAP standards and IFRS. The research is consistent with the harmonization of accounting across domiciles, which implies that sector analysts can better cover firms from different countries.

Aboud et al. (2018) is one of the few papers published in an international journal that studies the impact of a specific IFRS standard, namely, segment reporting under IFRS 8. The study uses data for 843 firm-year observations from 255 of the largest firms across 18 European countries. The researchers in this study hypothesize that IFRS has higher quality than its predecessor, IAS14R and that the effect of more detailed geographical information will lead to more exceptional earnings forecast accuracy. Like many other studies, Aboud et al. (2018) acknowledge that enforcement regimes shape the impact of new accounting standards on forecast accuracy. Under IFRS 8, firms disclose more detailed information about country-specific aspects such as GDP levels, interest, inflation, and currency exchange rates. Such aspects imply greater information quality and thereby assist analysts in forecasting development across the different countries in which a firm operates. Accordingly, the study concludes that the increased disaggregation of the information under IFRS positively impacts forecast accuracy and the predictive value of accounting data.

There are several aspects from the general IFRS adoption that may be extrapolated to guide analysts' ability to forecast credit losses under IFRS 9. Tan et al. (2011) acknowledge that adopting IFRS generally suggests adopting accounting standards that shift the balance towards relevance and timeliness. Similarly, the adoption of IFRS 9 compared to IAS 39 implies the same type of shift. However, the results from the studies provide different kinds of conclusions. Tan et al. (2011) found that forecast accuracy did not improve for the analysts that did not benefit from the harmonization effects. In contrast, Jiao et al. (2012), Horton et al. (2013), and Aboud et al. (2018) find that forecast accuracy improved given an enhanced information environment due to IFRS's focus on relevance. However, these studies have not controlled for the harmonization effects.

Table 1. Literature Overview

Authors	Title	Journal	Focus	Data	Results
Tan, Wang & Walker, 2011	"Analyst Following and Forecast Accuracy After Mandated IFRS Adoptions"	Journal of Accounting Research	IFRS adoption	12,010 firm-year observations in 25 countries between 1988 and 2007	Increased analyst following, improved predictive value
Byard, Li & Yu, 2011	"The Effect of Mandatory IFRS Adoption on Financial Analysts' Information Environment"	Journal of Accounting Research	IFRS adoption	2,836 firm-year observations in 20 countries between 2003 and 2006	Reduced forecasting errors and dispersion for countries with local GAAP differing significantly from IFRS
Horton, Serafeim & Serafeim, 2012	"Does Mandatory IFRS Adoption Improve the Information Environment?"	Contemporary Accounting Research	IFRS adoption	5,484 firm-year observations in 46 countries between 2001 and 2007	Improved forecast accuracy, accounting quality and comparability
Jiao, Koning, Mertens & Roosenboom, 2012	"Mandatory IFRS adoption and its impact on analysts' forecasts"	International Review of Financial Analysis	IFRS adoption	2,940 firm-year observations in 19 countries for 2004 and 2006	Positive effect on the predictive value of accounting data and analyst forecasting quality
Beuselinck, Joos, Khurana & Meulen, 2017	"Which Analysts Benefited Most from Mandatory IFRS Adoption in Europe?"	Journal of International Accounting Research	IFRS adoption	68,665 firm-year observations in 19 countries between 2000 and 2009	Improved forecast accuracy, specifically for sector-specialists
Aboud, Roberts & Zalata, 2018	"The impact of IFRS 8 on financial analysts' earnings forecast errors: EU evidence"	Journal of International Accounting, Auditing and Taxation	IFRS 8 adoption	843 firm-year observations in 18 countries between 2001 and 2009	Increased disaggregation of information under IFRS, positive impact on analyst forecasting ability

5. Hypotheses Development

Previous research on the topic of forecast accuracy and IFRS provides mixed results. Tan et al. (2011) showed that the adoption of IFRS in 2005 only benefitted foreign analysts because of its harmonization effects. Local analysts' forecast accuracy had not improved even though their access to information had. However, harmonization effects are not relevant to this study, given that IAS 39 had already harmonized the accounting of credit losses in Europe. In contrast to these results, Aboud et al. (2018), Byard et al. (2011), Horton et al. (2012), and Jiao et al. (2012) all found that the improved forecast accuracy following IFRS adoption could be explained by a greater information environment. An interpretation of these findings brought forward by Tan et al. (2011) relates to IFRS's tendency to emphasize relevance.

IFRS 9 introduces several new features through the ELM. Most centrally, the ELM applies forward-looking information to make provisions for expected credit losses. This information includes various macroeconomic factors used to establish the default probabilities for respective outstanding loan portfolios. The credit loss information under IFRS 9 is also more disaggregated, which could simplify the process of understanding movements in risk over time. Under IFRS 9, banks also disclose more information about default probabilities and asset staging across industries, which could potentially aid analysts in predicting credit losses.

An important caution to the findings from the previous literature is Ball (2006), who asserts that confirmatory values of past forecasts are rendered obsolete when a new accounting standard is adopted. Therefore, deteriorating forecast accuracy could be expected in the periods immediately following the implementation while analysts adapt to the new information being provided. As our study is limited to the first eight quarters after the implementation of IFRS 9, such an effect may manifest. Moreover, since the ELM warrants higher preparer discretion and professional judgment, there potentially exists a risk of more volatile credit losses. Ultimately, this is something that could negatively impact forecast accuracy.

We base our hypotheses on the shift in the information environment and the overall tendency for IFRS standards to emphasize relevance. However, we acknowledge some potentially offsetting factors relating to analyst learning curves and preparer judgment. Considering these effects that could affect forecast accuracy either positively or negatively, our hypotheses are formulated as "null" according to the below.

5.1. Null Hypotheses

H_1: Analysts' absolute credit loss forecast errors are unaffected by the IFRS 9 adoption.

H_2: Analysts' credit loss forecast dispersion is unaffected by the IFRS 9 adoption.

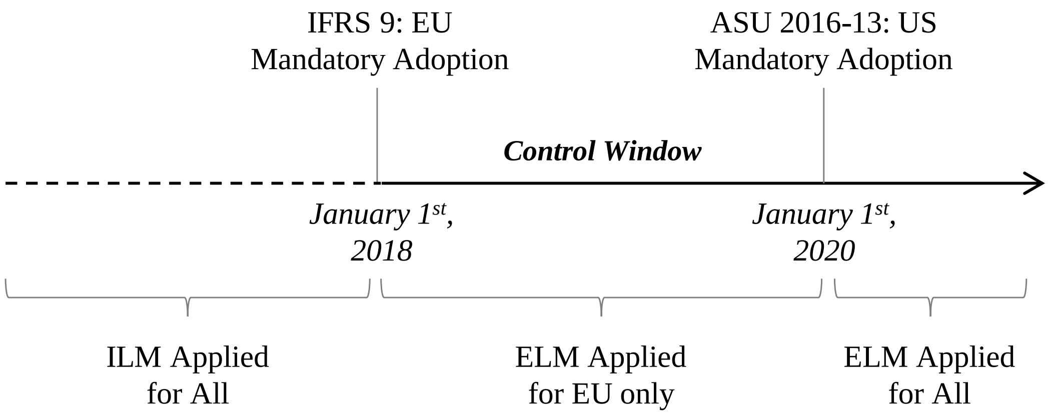
6. Data and Matching

6.1. Data

Our primary sample is made up of all listed banks based in Europe that reports on a quarterly basis and have analyst coverage. This sample amounts to 39 separate banks. The study is limited to the banking sector given the scope of IFRS 9 and the delayed implementation for insurance companies. Europe was chosen because IFRS has been mandatory for listed firms since 2005, longer than any other region, and because banks in this region have an adequate analyst following. The pre-matching control group consists of 48 banks based in the U.S. that similarly reports on a quarterly basis and have analyst coverage. Barth et al. (2012) concluded that IFRS-based and U.S. GAAP-based accounting amounts are largely comparable. We argue that this validates the notion of comparing European and U.S. banks in the context of this research.

All European banks in our sample adopted IFRS 9 on January 1, 2018. This is somewhat surprising as early adoption was allowed and has been found to be associated with positive signaling effects (Katselas & Rosov, 2018). Furthermore, ASU-2016-13, the U.S. GAAP equivalent of IFRS 9 was not mandatory before January 1, 2020 and none of the control banks adopted the new standard early. Hence, there is an opportunity to use U.S. banks as a control group in this study, given the two-year gap between the European and U.S. implementation. The study is based on quarterly data starting in the first quarter of 2014 until the final quarter of 2019. The selected horizon consists of 16 quarters in the pre-intervention period and 8 quarters in the post-intervention period. Any data after the final quarter of 2019 has been omitted, most importantly because the U.S. control group switches to ASU 2016-13 after that period, making it impossible to continue to ascribe the "control" designation to the group.

Figure 2. Adoption Timeline



Accounting measures, market data, as well as analyst forecasts have been obtained from Refinitiv Eikon. The accounting data collected in this study comprises Book Value of Equity (Equity), Assets, and Net Income (NI). Our market data refers to the Market Value of Equity (MCAP) for each quarter. Using these measures, we calculate Price-to-Book (PB) and Return on Equity (ROE) ratios. We also employ the number of analysts following each bank (Following). With regards to analyst accuracy data, we rely on Absolute Forecast Error (AFE) and Forecast Dispersion (DISP) as our dependent variables.

We employ a similar method as Bradshaw et al. (2012), Bonini et al. (2010), and Bilinski et al. (2013) do for target price error, and Mikhail et al. (1997) and Capstaff et al. (2001) do for earnings forecast error. For our consensus estimate, we use the mean of all available forecasts. Our absolute forecast error measure is as below, where the absolute difference between actual credit losses and the consensus estimate is deflated by the consensus estimate.

$$\mathrm{AFE}_{\mathrm{ti}} = \frac{|\mathrm{A}_{\mathrm{ti}} - \mathrm{F}_{\mathrm{ti}}|}{\mathrm{F}_{\mathrm{ti}}}$$

To measure forecast dispersion, we employ a model that is comparable to that of Lang and Lundholm (1996). The consensus credit losses according to the below deflate the inter-analyst standard deviation.

$$\mathrm{DISP}_{\mathrm{ti}} = \frac{\sigma_{\mathrm{ti}}^{\mathrm{F}}}{\mathrm{F}_{\mathrm{ti}}}$$

As forecast errors are estimated using ratios, they are prone to statistical outliers (Ayres et al., 2017). Consequently, the dataset has been trimmed to prevent results biased by outliers in accordance with prior studies (Brown & Rozeff, 1978, 1979; Brown et al., 1987; Capstaff et al., 2001). Given that there is no single definition of what constitutes an outlier, we adopt the same procedure as Easterwood & Nutt (1999), Ali et al. (1992), and Capstaff et al. (2001) and eliminate values over 100%. With regards to dispersion, however, it is difficult to establish a threshold for data trimming based on previous research. Therefore, we have decided to exclude forecast dispersions exceeding 50%. Not all banks have forecast figures for all quarters, which creates missingness in the data set. Furthermore, there are some quarters where there is only one analyst forecast for a bank, which makes the standard deviation for that quarter misleading. Such data as just described is omitted.

6.2. Matching

To maximize homogeneity across the data for the European and U.S. groups, we employ a “propensity score matching” (PSM) technique. In observational studies, groups should ideally be randomly constructed so that each subject is equally likely to have received intervention, as those who did not receive intervention. Randomization implies that there may not exist any pattern between the characteristics of the banks and their group assignment. In this study, group randomization is not a realistic assumption as it is not reasonable to accept that European and U.S. firms are equally likely to receive the same regulatory intervention. Naturally, IFRS regulations do not affect U.S. firms as they follow U.S. GAAP practices. Nonetheless, with matching, difference-in-differences is still regarded as a suitable research methodology when randomization at firm level is not possible (Austin, 2007).

Matching is a technique whereby treated firms are paired with non-treated firms based on ex-ante characteristics (Shipman et al., 2017). This reduces patterns stemming from the differences between the two groups. Moreover, this technique discards unmatched control units and thereby creates an equally weighted sample. The PSM method applied pairs treated firms with control firms based on their conditional probability of receiving treatment (Rosenbaum and Rubin, 1983). There are two primary algorithmic approaches to PSM, i.e., optimal matching and nearest neighbor matching. The objective of both methods is to create a set of matched firms that creates improved balance to the distribution of the selected independent variables between treatment and control firms. However, nearest neighbor matching only considers one treated unit at a time. Therefore, this approach favors simplicity over global distance minimization.

To create a homogenous data set, we use nearest neighbor matching without replacement. Once a match between a control bank and a treated bank has been found, that same treated bank will not be subjected to further matching. To perform the matching, we use average values between the first quarter of 2015 and the last quarter of 2017 for all independent variables. This dramatically simplifies the data’s structure and makes it possible to compare and evaluate the banks on a single data point per variable. Naturally, it is important that no data from any of the quarters after the intervention date is included in the averages, as this would result in a form of look-ahead bias.

Based on the data described above, we employ matching regressions to measure and analyze the matching effect on the homogeneity of our final data set. To test the initial balance, we construct a pre-matching object that assesses the as-is balance based on Equity, PB, ROE, and NI. The balance is assessed by looking at how large the differences between the control and treatment groups are based on these measures. The function used to establish pre-test balance is expressed in Appendix VI. When called, the function summarizes as below.

Table 2. Pre-Matching Balance Summary

	Std. Mean Diff.	Var. Ratio	eCDF Mean
distance	0.9846	1.5983	0.2815
Equity	0.1216	0.2269	0.1902
P/B	-0.9189	1.3705	0.2671
ROE	-0.2003	16.4005	0.1536
Net Income	0.0017	0.4910	0.1308

Table 2 describes the relatively high imbalance of the unmatched set (see "distance"). When the variance ratio and standardized mean differences approximate one and the eCDF (empirical cumulative distribution function) mean is close to zero for the distance variable, there is a strong balance across the control and treatment sets. In the initial assessment, each of these measures are relatively askew. In hopes of improving the balance, we call the matching function, also expressed in Appendix VI. When called, the function expressed above summarizes as below.

Table 3a. Post-Matching Balance Summary

	Std. Mean Diff.	Var. Ratio	eCDF Mean
distance	0.7569	2.1100	0.2160
Equity	0.1035	0.2213	0.1745
P/B	-0.6552	2.4073	0.2066
ROE	-0.1381	33.7926	0.2028
Net Income	0.0478	0.5280	0.1288

Table 3b. Post-Matching Bank Count

	Control	Treated
All	48	39
Matched	39	39
Unmatched	9	0

As is seen in Table 3a, the matching has improved the standardized mean differences and the eCDF, which are now closer to their ideal values when compared to the pre-matching balance. On the other hand, the variance ratio has deteriorated. A visual representation of the overall distance improvement can be found in Appendix VII. The matched pairs and the complete set of banks employed in the sample are expressed in Appendix VIII.

In many observational studies, the number of observations in the control group exceeds the number of observations in the treatment group (D'Agostino, 1998). This is ideal as the likelihood of finding close pairs increases with the matching ratio. In this study, the treatment sample consists of 39 banks whereas the control sample consists of 48 banks. As such, the matching ratio is close to one. The matching regression performed in this case increases the balance, but probably not as significantly as it would have with a larger control sample.

6.3. Summary of Data

For both absolute forecast error and forecast dispersion, the initial number of banks included in the sample amounted to 87, where 48 of these were U.S. banks. A total of 78 banks remains after the matching. These remaining banks are equally divided between European and U.S. groups. Given the study period between 2014 to 2019, this gives rise to 1,872 theoretical firm-quarter observations. Several firm-quarter observations are missing from the original data and some observations were also removed due to our trimming criteria previously described. Ultimately, there are 1,541 and 1,481 observations included in the data sample for absolute forecast error and forecast dispersion, respectively.

Table 4. Summary of Data

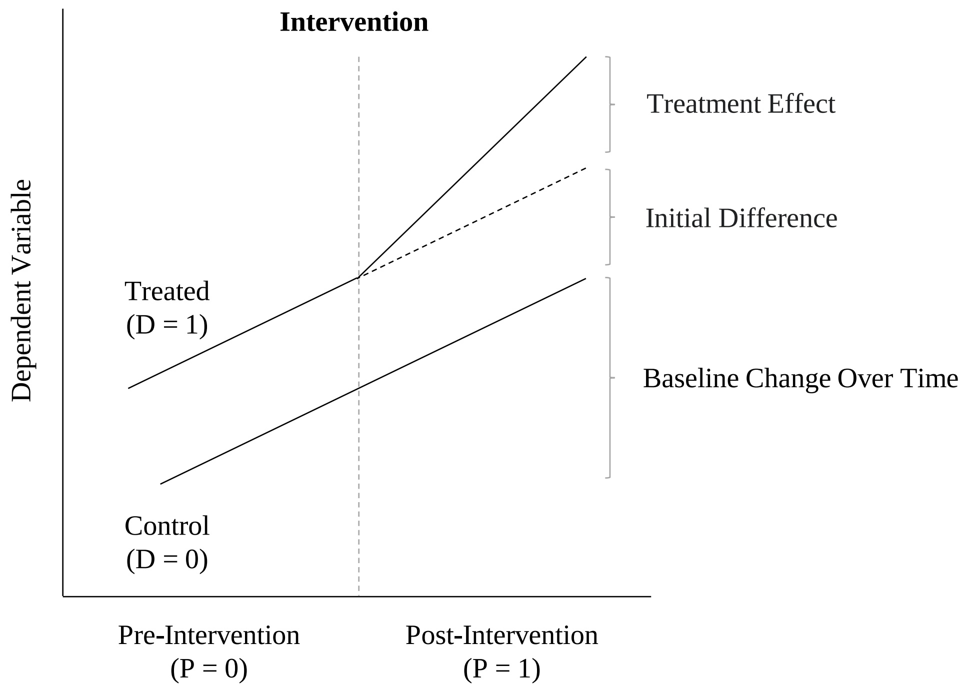
	Abs. Forecast Error	**Forecast Dispersion**
Number of Banks in Initial Sample	87	87
Number of US Banks Removed due to Matching	9	9
Number of Banks in Final Sample	78	78
Number of Quarters Included (2014-209)	24	24
Theoretical Number of Quarter Observations	1,872	1,872
Outliers Removed and Missingness	331	391
% EU firms	*69%*	*82%*
% US firms	*31%*	*18%*
Final Number of Observations Included	**1,541**	**1,481**

7. Methodology

This section explains the research methodology developed to measure the impact of IFRS 9 on forecast accuracy. Difference-in-differences rely on the assumption of parallel trends, i.e., that the slopes of the trends are approximated by each other in the pre-intervention period. This is highlighted by the illustrative example in Fig. 3. Violation of this assumption would result in unconvincing conclusions and a biased assessment of the causal effect (Abadie, 2005; Godard-Sebillotte & Karunananthan, 2019). Therefore, the differences in slopes will be tested statistically. However, we rely on the assumption that in the absence of any intervention, the trends would continue to be parallel in the post-intervention period as well. Under this final assumption, we can separate the initial difference from the treatment effect.

The methodology is separated into two parts, we first present how we will test the parallel trends assumption for both measures of forecast accuracy. Note that the parallel trends assumption only needs to be validated in the pre-intervention period. Secondly, we develop our regression models for the difference-in-differences analysis.

Figure 3. Illustrative Representation of Difference-in-Differences



7.1. Parallel Trends Models

To test for parallel trends in absolute forecast error and forecast dispersion we employ two separate regressions for each of the two dependent variables. Irrespective of measure, the null hypotheses are formulated such as that the slope of the lines for the groups are equal (i.e., that the difference in slopes is equal to zero). There must be substantial evidence to support the null hypothesis for the difference-in-difference to be a credible research methodology in this context.

$$\mathrm{AFE}_{\mathrm{ti}}^{\mathrm{NULL}} = \beta_0 + \beta_1 \mathrm{QUARTER}_{\mathrm{t}} + \beta_2 \mathrm{GROUP}_{\mathrm{i}}$$

$$\mathrm{AFE}_{\mathrm{ti}} = \beta_0 + \beta_1 \mathrm{QUARTER}_{\mathrm{t}} + \beta_2 \mathrm{GROUP}_{\mathrm{i}} + \beta_3 (\mathrm{QUARTER}_{\mathrm{t}} \times \mathrm{GROUP}_{\mathrm{i}})$$

$$\mathrm{DISP}_{\mathrm{ti}}^{\mathrm{NULL}} = \beta_0 + \beta_1 \mathrm{QUARTER}_{\mathrm{t}} + \beta_2 \mathrm{GROUP}_{\mathrm{i}}$$

$$\mathrm{DISP}_{\mathrm{ti}} = \beta_0 + \beta_1 \mathrm{QUARTER}_{\mathrm{t}} + \beta_2 \mathrm{GROUP}_{\mathrm{i}} + \beta_3 (\mathrm{QUARTER}_{\mathrm{t}} \times \mathrm{GROUP}_{\mathrm{i}})$$

In all the equations above, β_{i} are model coefficients and GROUP_i denotes the grouping factor. The simpler regression model simply assumes that the slopes of the two lines of the data are equal through β_1 but that they are counterbalanced from one another by an amount equal to β_2. The more complex regression model includes an interaction term between the slope and the grouping factor.

Using the regressions outlined above, the parallel trends assumption can be validated in either of two ways. First, it is possible to test if the complex model better fits the data. If so, the null hypothesis (or null regression) must be rejected. An analysis of variance (ANOVA) table is used to test if the complex model is a better fit. The F-statistic in the ANOVA table will be examined to see if the second model has statistical significance. A statistically significant p-value of the F-statistic would signify that the complex model is a better fit for the data. Ultimately, that would provide evidence against the null hypothesis, leading to a conclusion that the slopes are not equal.

A second way to test for parallel trends is to see if the coefficient for the interaction term differs significantly from zero. If so, the null hypothesis of equal slopes must also be rejected. The interaction coefficient gauges the difference between the slopes. A t-test on the interaction coefficient will assist in assuring that the conclusions drawn are correct. If the p-value of the interaction coefficient in the t-test is statistically significant, there is sufficient power to reject the null hypothesis.

7.2. Difference-in-Differences Models

$$\begin{aligned}\mathrm{AFE}_{\mathrm{ti}} = \beta_0 + \beta_1 \mathrm{IFRS}_{\mathrm{t}} + \beta_2 \mathrm{GROUP}_{\mathrm{i}} + \beta_3 (\mathrm{IFRS}_{\mathrm{t}} \times \mathrm{GROUP}_{\mathrm{i}}) + \beta_4 \mathrm{MCAP}_{\mathrm{ti}} + \beta_5 \mathrm{PB}_{\mathrm{ti}} \\ + \beta_6 \mathrm{ASSETS}_{\mathrm{ti}} + \beta_7 \mathrm{ROE}_{\mathrm{ti}} + \beta_8 \mathrm{FOLLOWING}_{\mathrm{ti}}\end{aligned}$$

$$\begin{aligned}\mathrm{DISP}_{\mathrm{ti}} = \beta_0 + \beta_1 \mathrm{IFRS}_{\mathrm{t}} + \beta_2 \mathrm{GROUP}_{\mathrm{i}} + \beta_3 (\mathrm{IFRS}_{\mathrm{t}} \times \mathrm{GROUP}_{\mathrm{i}}) + \beta_4 \mathrm{MCAP}_{\mathrm{ti}} + \beta_5 \mathrm{PB}_{\mathrm{ti}} \\ + \beta_6 \mathrm{ASSETS}_{\mathrm{ti}} + \beta_7 \mathrm{ROE}_{\mathrm{ti}} + \beta_8 \mathrm{FOLLOWING}_{\mathrm{ti}}\end{aligned}$$

In each of the DID regressions above, IFRS_t is a dummy variable that assumes values of one in periods after January 1, 2018. Likewise, GROUP_i is also a dummy variable that assumes values of ones for European firms, and zero for U.S. firms. $\mathrm{IFRS} \times \mathrm{GROUP}$ is an interaction term, also referred to as the DID term. The coefficient for the interaction term will estimate the treatment effect of IFRS 9 on each of the dependent variables (see Table 5a and 5b). The fundamental objective of this study is to establish the treatment effect as measured by the interaction coefficient. The effect describes the level change between the initial difference and the treatment difference. If there is a significant change, there is evidence to establish a causal relationship between the intervention and the outcome. We reject the null hypothesis if the interaction coefficient is significant.

We control for a set of factors that have been shown to affect forecast accuracy. First, we control for size through MCAP and Assets. The underlying logic is that large firms supply more information which improves forecast accuracy (Brown, 1987; Hussain, 1997). We use both market cap and total assets to account for varying degrees of financial leverage. Secondly, we control for valuation through PB (Tan et al., 2011). Our third control variable is profitability through ROE in accordance with Lang and Lundholm (1996). Last, we also control for the number of analysts providing forecasts as it has been proven to affect forecast accuracy (Clement, 1999).

Table 5a. Difference-in-Differences Calculation Summary

y_{it}	GROUP = 1	GROUP = 0	**Difference**
IFRS = 1	y_{11}	y_{01}	$y_{01} - y_{11}$
IFRS = 0	y_{10}	y_{00}	$y_{00} - y_{10}$
Change	$y_{10} - y_{11}$	$y_{00} - y_{01}$	$(y_{01} - y_{11}) - (y_{00} - y_{10})$

Table 5b. Difference-in-Differences Coefficient Summary

β_i	GROUP = 1	GROUP = 0	**Difference**
IFRS = 1	$\beta_0 + \beta_1 + \beta_2 + \beta_3$	$\beta_0 + \beta_1$	$\beta_2 + \beta_3$
IFRS = 0	$\beta_0 + \beta_2$	β_0	β_2
Change	$\beta_1 + \beta_3$	β_1	β_3

8. Results

8.1. Parallel Trends Results

We first establish whether the trends for the treatment and control group remain parallel throughout the pre-intervention period. For visual comparison, we plot the average absolute forecast error for all banks by their respective group for the first 16 quarters (2014-2017). As is seen in Fig. 4, changes in the averages tend to be similar between the U.S. control group and the European treatment group. The statistical tests below aim to determine whether the difference in the slopes is zero.

Figure 4. Parallel Trends: Visual Representation of Average Absolute Forecast Error

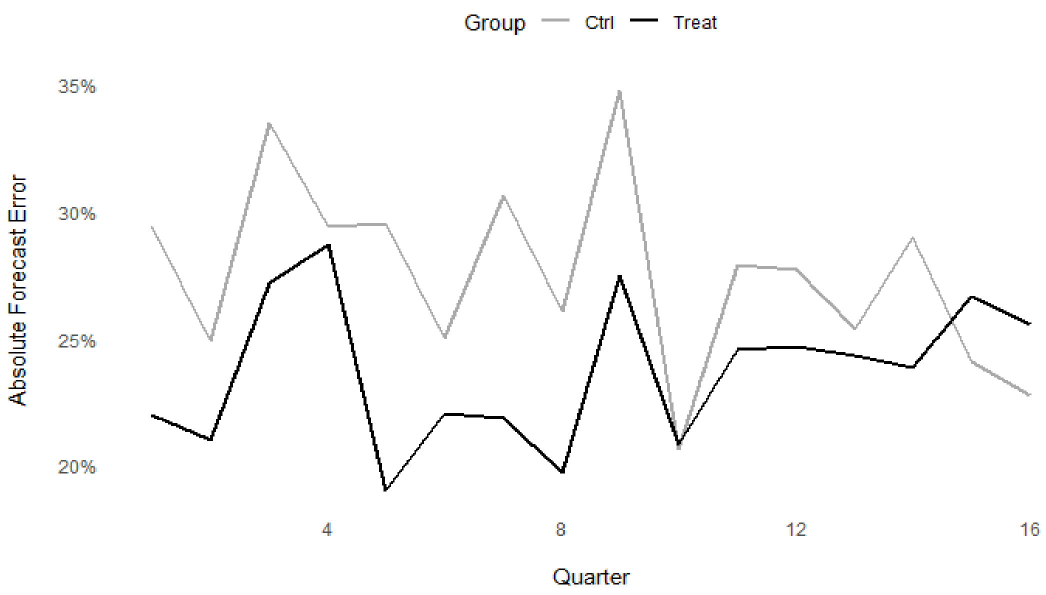


Table 6. Parallel Trends: Absolute Forecast Error ANOVA

Model 1: AFE ~ Quarter + Group
Model 2: AFE ~ Quarter × Group

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
998	52.018				
997	51.909	1	0.10922	2.0977	0.1478

We run an ANOVA on the trend lines for absolute forecast error. The result from this analysis is seen in Table 6. The high p-value for the F-statistic indicates that we initially fail to reject the null hypothesis that the slopes are equal. We do this since the p-value is significantly greater than zero, which is the actual value of the null hypothesis' F-statistic. This also implies that the more complex model (Model 2) does not fit the data better than the simple model (Model 1).

Table 7. Parallel Trends**:** Absolute Forecast Error Coefficients

(Intercept)	Quarter	GroupTreat	Quarter:GroupTreat
0.3039	-0.0033	-0.0797	0.0047

After the ANOVA, we analyze the difference between the slopes of the trends. As is seen in Table 7, the difference in slopes is small (0.0047). The slope for the U.S. control group is -0.0033 while the slope European treatment group is 0.0014 (-0.0033 + 0.0047). A t-test on the interaction coefficient will determine if the difference in the slopes is statically different from zero.

Table 8. Parallel Trends: Absolute Forecast Error Regression Summary

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.3039	0.0213	14.2570	< 2e-16	***
Quarter	-0.0033	0.0022	-1.4970	0.1348	
GroupTreat	-0.0797	0.0305	-2.6160	0.0090	**
Quarter:GroupTreat	0.0047	0.0032	1.4480	0.1478	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The inability to reject the null hypothesis that the difference in slopes is zero persists after the t-test. This can be concluded by the of high p-value of the t-statistic. We therefore have sufficient evidence to prove that the parallel trends assumption holds for this data set.

By visual examination of Fig. 5, there exists a high degree of similarity between the trends for the European group and the U.S. group. There is also a shared downward trend in the pre-intervention period examined here, indicating that financial analysts covering the banking sector became more coordinated during the 2014-2017 period.

Figure 5. Parallel Trends: Visual Representation of Average Forecast Dispersion

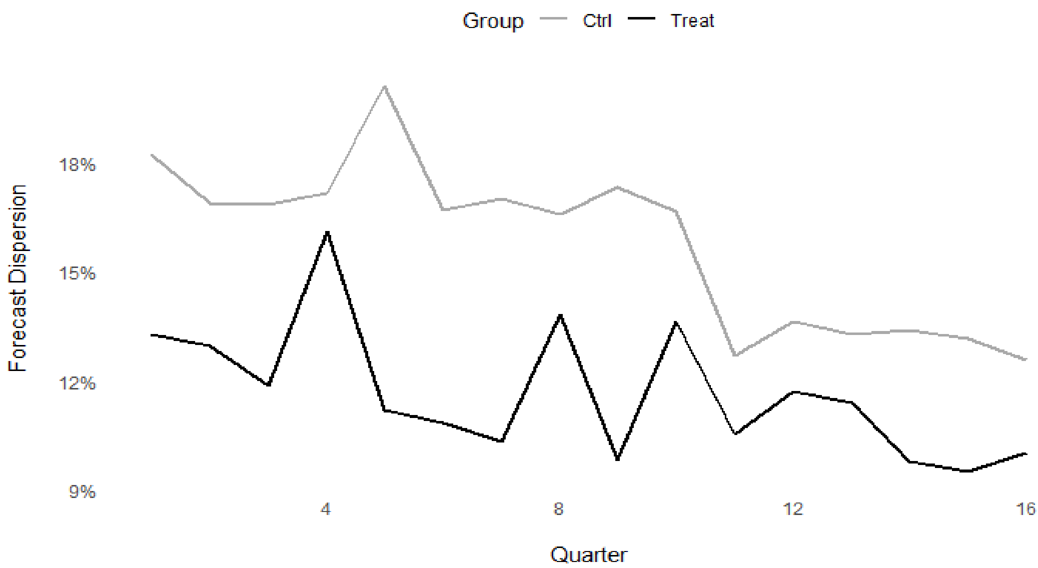


Table 9. Parallel Trends: Forecast Dispersion ANOVA

Model 1: DISP ~ Quarter + Group
Model 2: DISP ~ Quarter × Group

Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
960	7.976				
959	7.5798	1	0.0182	2.1978	0.1385

The ANOVA on the trend lines for forecast dispersion is displayed in Table 9. Following the same reasoning as for absolute forecast error, the high p-value for the F-statistic indicates that we initially fail to reject the null hypothesis.

Table 10. Parallel Trends: Forecast Dispersion Coefficients

(Intercept)	Quarter	GroupTreat	Quarter:GroupTreat
0.1932	-0.0041	-0.0575	0.0020

After the ANOVA, we again analyze the difference between the slopes of the trends. As is seen in Table 10, the difference in slopes is small (0.0020). The slope for the U.S. control group is -0.0041, while the slope European treatment group is -0.0021 (-0.0041 + 0.0020). A t-test on the interaction coefficient will determine if the difference in the slopes is statically different from zero.

Table 11. Parallel Trends: Forecast Dispersion Regression Summary

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.1932	0.0084	22.8960	< 2e-16	***
Quarter	-0.0041	0.0009	-4.7990	1.85e-06	***
GroupTreat	-0.0575	0.0126	-4.5720	5.45e-06	***
Quarter:GroupTreat	0.0020	0.0014	1.4830	0.1390	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The p-value for the interaction coefficient shows that we again cannot reject the null hypothesis. Thus, we have validated the parallel trends assumption across both data sets.

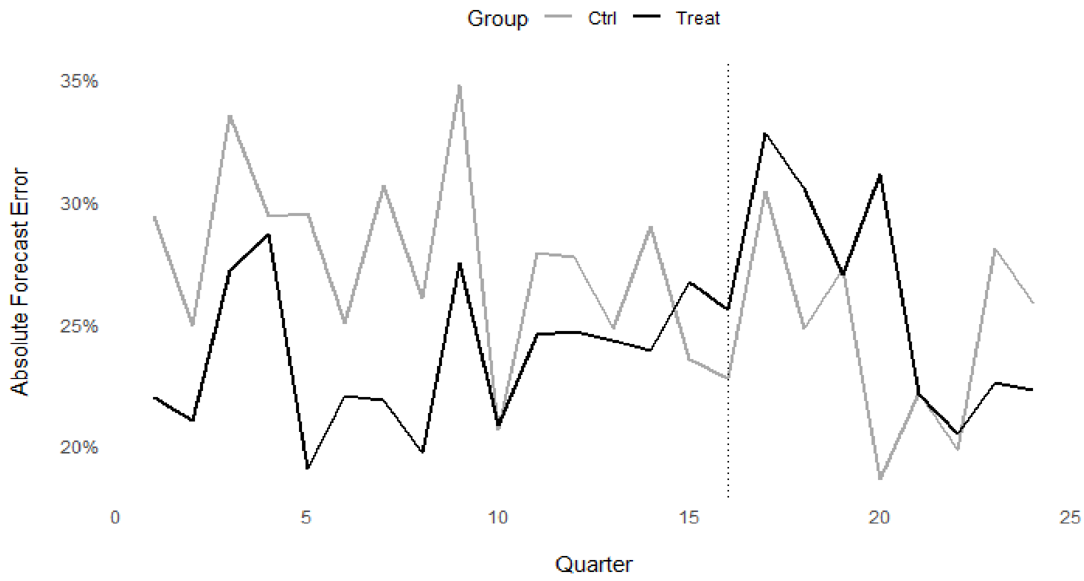
Although the trends in the pre-intervention periods for both data sets are parallel, there is an initial level difference that is interesting to examine further. For absolute forecast error, the initial level difference is quite large, with average absolute forecast error being larger for the control group. Towards the end of the pre-intervention period, this level difference has shifted. For forecast dispersion, the initial level difference instead seems to persist throughout the whole pre-intervention period.

In the following section, we will show data on how absolute forecast error and dispersion change after the intervention date. We will also summarize the results from the difference-in-differences regressions.

8.2. Difference-in-Difference Results

Fig. 6 illustrates a level shift between the control group and the treatment group just prior to the intervention date (represented through the vertical dashed line). This shift becomes more pronounced and persists in the periods directly after the intervention date. Towards the final quarter of 2019, the treatment group again falls below the control group with regards to average absolute forecast error.

Figure 6. Visual Representation of IFRS 9 Impact on Average Absolute Forecast Error



To understand if there really exists an effect from the introduction of IFRS 9, we run our DID regressions, which are summarized in Table 12.

Table 12. Absolute Forecast Error DID Regression Summary

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.2549	0.0282	9.0470	< 2e-16	***
IFRS	-0.0241	0.0165	-1.4560	0.1455	
GROUP	-0.0397	0.0198	-2.0100	0.0446	*
IFRS:GROUP	0.0622	0.0245	2.5410	0.0111	*
MCAP	0.0000	0.0000	-2.2290	0.0259	*
PB	0.0639	0.0167	3.8320	0.0001	***
ASSETS	0.0000	0.0000	-0.8430	0.3993	
ROE	-0.5232	0.2068	-2.5300	0.0115	*
FOLLOWING	-0.0020	0.0015	-1.3120	0.1899	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The table output above shows that there is a positive treatment effect of ~0.06 (6.22%), based on the interaction coefficient. This effect is significant at the 5%-level, meaning that the conditional probability of a Type I error (false positive, i.e., rejecting a correct null hypothesis) is less than 5%. We therefore reject the null hypothesis of no intervention effect on absolute forecast error.

Fig. 7 illustrates a steep shift as the forecast dispersion for the treatment group surges above that of the control group after the IFRS 9 adoption. It also seems as though the differences were converging in the period prior to the intervention and then diverges afterward.

Figure 7. Visual Representation of IFRS 9 Impact on Forecast Dispersion

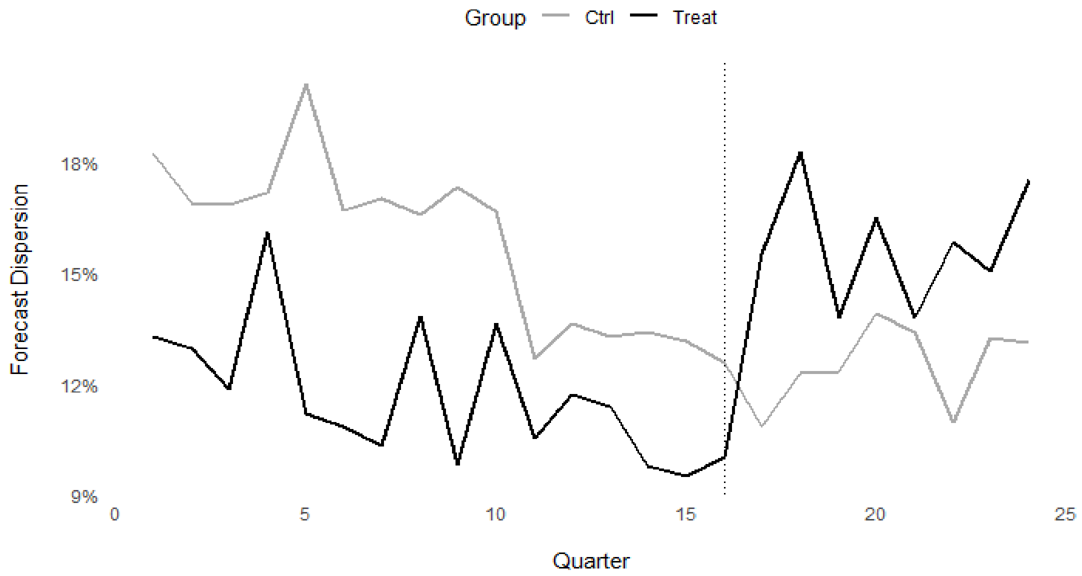


Table 13. Forecast Dispersion DID Regression Summary

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.1646	0.0120	13.7520	< 2e-16	***
IFRS	-0.0325	0.0068	-4.7610	0.0000	***
GROUP	-0.0325	0.0084	-3.8650	0.0001	***
IFRS:GROUP	0.0703	0.0106	6.6540	0.0000	***
MCAP	0.0000	0.0000	-1.5390	0.1241	
PB	0.0109	0.0070	1.5510	0.1211	
ASSETS	0.0000	0.0000	-2.8900	0.0039	**
ROE	-0.0919	0.0814	-1.1290	0.2592	
FOLLOWING	-0.0004	0.0006	-0.6830	0.4946	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The table output above shows that there is a positive treatment effect of ~0.07 (7.03%), based on the interaction coefficient. This effect is significant at the 0.1%-level. We therefore reject the null hypothesis of no intervention effect on forecast dispersion.

8.3. Summary of Results

In this study, we compare two groups of banks, one European treatment group and one U.S. control group. Moreover, the quarterly time-series data is divided into two periods, a pre-intervention period prior to the introduction of IFRS 9 and a post-intervention period after the introduction. We initially establish that the parallel trends assumption holds true in the pre-intervention period as we accept the null hypothesis of equal slopes for both dependent variables. After this, we run the difference-in-differences regressions for both absolute forecast errors and forecast dispersion.

The treatment effect as measured by the interaction coefficient is the focal point of this study. The coefficient is interpreted as follows. If the interaction coefficient positive, we can conclude that the dependent variable is affected to a greater degree in the treatment group than the control group as a result of the intervention (see Table 5a). For example, the interaction coefficient for absolute forecast error is 6.22%. This implies that the absolute forecast errors for the treatment group increased 6.22% more than the control group after the introduction of IFRS 9. A similar interpretation is made for the interaction term of 7.03% for forecast dispersion.

9. Discussion

The results of our study suggest that the absolute forecast errors and forecast dispersion for the European treatment group increased more than its U.S. counterpart did after the implementation of IFRS 9. With regards to IABS's Conceptual Framework, the deterioration of forecast accuracy implies that the predictive and confirmatory value has likewise weakened. As predictive and confirmatory value are the components that define relevance, we argue the relevance of the credit loss information has also declined. While we believe that these effects of IFRS 9 on forecast accuracy are interesting findings in themselves, they raise some important questions on the wider practical implications of the new framework. We conclude that the key objective of higher decision usefulness in new standards was not achieved in the post-intervention period studied. Evidently, it has become more difficult for analysts to forecast credit losses.

However, our results may not reflect a true long-term deterioration but simply an initial effect. The IFRS 9 adoption distorts average absolute forecast errors particularly in the early post-intervention quarters and later settles at a level below the control group. This effect is in line with the research presented by Ball (2006), which states that the accumulated confirmatory value of past forecasts becomes obsolete once new standards are adopted. Given the significant changes that the new standard brought about, it may entail a learning period for the analysts. In part, analysts must retrain themselves on the forecasting implications of the standard. Moreover, they must learn how to interpret the credit quality of the analyzed banks with the new information at hand (Ball, 2006).

Towards the later quarters of the post-intervention period, the average absolute forecast error for the European treatment group decreases sharply. A few disclaimers are warranted here. First, average absolute forecast error as observed visually in Fig. 6 mainly serves an illustrious purpose and differs from the difference-in-differences effect on absolute forecast errors. Moreover, since this measure represents the mean for all banks for the respective quarters, firm differences could potentially be large. Secondly, only the first eight subsequent quarters after the intervention are observed. It is possible that changes after 2019 follow a different trend. Nonetheless, in the final quarters of the observed period, the average absolute forecast error for the European group falls below that of the US group. This potentially implies that the predictive and confirmatory values are recovering after the initial adoption period. This would in turn support Ball's (2006) notion about the analyst adjustment period.

Besides the discussed analyst learning period, there might exist other factors that contribute to the observed effect. For example, given the systemic importance of the banking sector, it could be reasoned that IFRS 9 seeks to improve the informational value of credit losses, rather than seeking to improve their inherent predictiveness.

Moreover, it is not particularly obvious that the new framework has reduced reporting complexity. The rule-based format of IAS 39 created less ambiguity regarding the calculation of credit losses. The more principle-based framework of IFRS 9 is still considered rather complex and infers greater individual interpretation. It is plausible that this reduces comparability and makes it more difficult for analysts to understand how different variables impact the banks' internal credit loss models.

Concerning average forecast dispersion, the results differ from those observed with average absolute forecast error. The purpose of including analyst dispersion in this study is to capture how well-synchronized analysts are in estimating credit losses. With lower dispersion, analysts' estimates are closer in range and the conclusion could be that there is less guesswork included in the estimates. If that is the case, then it could be argued that lower dispersion implies greater predictive value. As is now obvious, forecast error and forecast dispersion are two highly comparable and interdependent measures of forecast accuracy.

After the introduction of IFRS 9, the average forecast dispersion for the European treatment group rises sharply and stays at a high level throughout the study period (see Fig. 7). As such, there are no signs of a recovery to the pre-intervention mean. Meanwhile, the average forecast dispersion for the U.S. control group remains at the same approximate level as before the intervention. As IFRS 9 does not affect this group, such results are of course in line with expectations. IFRS 9 seems to make analysts less synchronized, and it is likely that it takes longer time for the re-accumulation of the confirmatory values to affect average forecast dispersion.

Considering previous research related to general IFRS adoption and forecast accuracy, our results stand out as forecast accuracy decreased after adoption. Given the explanation put forward in Ball (2006), the selected post-intervention measurement period could reasonably explain the results. However, our eight quarters of post-adoption data is not meaningfully shorter than most other relevant studies. What distinguishes our study however is the quarterly data employed. Quarterly data over only two years may be affected by an initial learning period to a higher degree. The effect on quarterly measures of forecast accuracy may also differ from annual forecasts. Therefore, the data granularity provides a potential explanation for why our study shows a decrease in forecast accuracy after the adoption of IFRS 9 when research concerning the general adoption of IFRS typically shows no decrease.

Our study is one of the first efforts to base the assessment of forecast accuracy on something else than share price, revenue, or earnings. As such, the description of the procedure by which analysts make forecasts as a "black box" put forward by Ramnath et al. (2008) is even more pronounced for credit loss provisions, as it has been the subject of less research. Also, credit loss provisions typically make up a relatively small portion of the income statement and the actual attention given to the specific line item by analysts remain unexplored.

10. Conclusion

The purpose of this study is to examine how the adoption of the expected credit loss model under IFRS 9 has affected the forecast accuracy of credit losses. We assert that the information provided under IFRS 9 is more extensive than under the prior standard. In contrast, the increased preparer judgment required under IFRS 9 may increase volatility and thus negatively affect the forecast accuracy. Our results indicate that the absolute forecast errors and forecast dispersion has increased after adoption. Accordingly, the results imply that the relevance and decision usefulness of the credit loss accounting has worsened.

Our results are in line with prior research that suggests that the adoption of new accounting standards renders information content in previous reports obsolete and thus reflects a reset of the confirmatory value. This is then manifested through the decrease in forecast accuracy which has been statistically validated. While only visually validated, our results also indicate an improvement in average absolute forecast error towards the end of the post-intervention period studied. This may suggest that analysts begin to adapt to the new information environment. However, such a recovery of the predictive and confirmatory values for average forecast dispersion does not occur during the same period. We also conclude that our findings may not reflect a true long-term deterioration of forecast accuracy. Thus, the results should be interpreted with care concerning the implications for decision usefulness given the limited post-adoption time frame.

Our study makes two primary contributions. First, we provide early evidence that the forecast accuracy of credit loss provisions has deteriorated after the adoption of IFRS 9. Correspondingly, our results imply that IASB's goal of improving decision usefulness when developing new reporting standards has not been achieved in the early period after adoption. Secondly, we add to the existing literature on analyst forecasting in relation to the adoption of new accounting standards by shedding light on our results in relation to prior findings regarding analysts' adaption to a new information environment.

10.1. Research Limitation and Suggestions for Future Research

The most apparent limitation to our study is the time frame post-adoption which in turn hinders us from drawing any conclusions on the long-term effect of IFRS 9 on the forecast accuracy of credit losses. As time passes and more data becomes available, a more thorough study that examines a longer post-adoption period will be possible. However, such a study will have to be conducted with a different control group since U.S. firms switch to the U.S. GAAP equivalent of IFRS 9 after January 1, 2020.

Furthermore, IFRS 9 was developed in response to criticism against the prior standard claiming that credit losses were recognized at a late stage during the financial crisis of 2008. Consistent with this, the two accounting standards are likely to differ the most in times when the credit loss provisions are higher than usual. Either in times of financial crises or simply due to low credit quality. It is mainly under these circumstances that IFRS 9 was developed to provide superior information compared to its predecessor. Given that the timeframe after the implementation has not included any major financial turmoil, the standard has arguably not been tested in the environment for which it was primarily designed. As such, a natural suggestion for future research is to test the forecasting properties of IFRS 9 during the early Covid-19 era.

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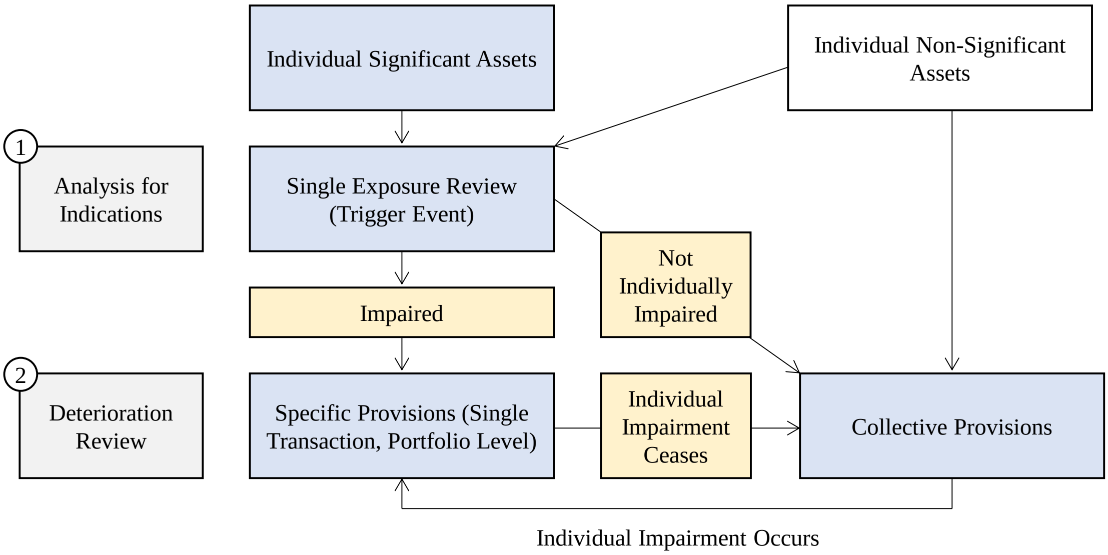
12. Appendices

Appendix I. IAS 39 Credit Loss Provision Framework (KPMG, 2007)



Appendix II. Illustrative Credit Losses Under IAS 39 (SEB, 2017)

	Q4
CCYm	**2017**
Provisions:	
Net collective provisions for individually assessed loans	(100)
Net collective provisions for collectively assessed loans	(50)
Specific provisions	(200)
Reversal of specific provisions	300
Net provisions	**(50)**
Write-offs:	
Total write-offs	(150)
Reversal of specific provisions utilized for write-offs	20
Write-offs previously not provided for	(130)
Recovered from previous write-offs	30
Net write-offs	**(100)**
Net credit losses	**(150)**

Appendix III. Illustrative Credit Losses Under IFRS 9 (SHB, 2018)

CCYm	Q1 **2018**
Provisions stage 1 & 2:	
The period's net provison stage 1	(20)
The period's net provison stage 2	(60)
Total	**(80)**
Provisions stage 3:	
The period's net provison stage 3	(120)
Reversals of stage 3 provisions to stage 1 & 2	70
Total	**(50)**
Write-offs:	
Actual loan losses for the period	(400)
Utilized share of previous provisions stage 3	300
Total	**(100)**
Recoveries	**40**
Net credit losses	**(190)**

Appendix IV. Illustrative Credit Losses Under US GAAP ILM (Wells Fargo, 2019)

CCYm	Q4 **2019**
Opening Loan Balance	10,000
Provision for Credit Losses	2,500
Interest Income on Impaired Loans	(150)
Loan Charge-Offs:	
Commercial	(900)
Consumer	(3,000)
Total Loan Charge-Offs	(3,900)
Loan Recoveries:	
Commercial	250
Consumer	1,200
Total Loan Recoveries	1,450
Net Loan Charge-Offs	(2,450)
Other	(100)
Closing Loan Balance	9,800

Appendix V. Illustrative Internal Risk Grades and Probability of Defaults (DNB, 2018)

	PD (%)		External Rating	
Risk class	From	To	Moody's	S&P
1	0.01	0.10	Aaa - A3	AAA
2	0.10	0.25	Baa1 - Baa2	BBB+ - BBB
3	0.25	0.50	Baa3	BBB-
4	0.50	0.75	Ba1	BB+
5	0.75	1.25	Ba2	BB
6	1.25	2.00		
7	2.00	3.00	Ba3	BB-
8	3.00	5.00	B1	B+
9	5.00	8.00	B2	B
10	8.00	*impaired*	B3 - Caa/C	B- - CCC/C

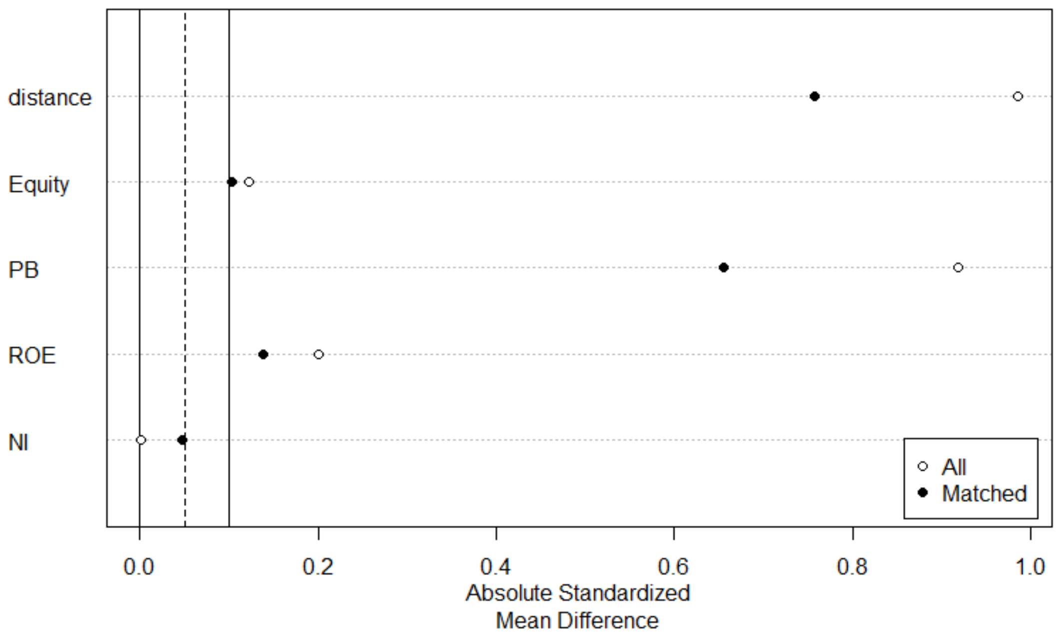
	Loans			
CCYm	Stage 1	Stage 2	Stage 3	Total
Risk grade based on probability of default				
1-4	1,000,000	300		1,000,300
5-7	300,000	40,000		340,000
8-10	25,000	35,000		60,000
Credit Impairment			30,000	30,000
Total	**1,325,000**	**75,300**	**30,000**	**1,430,300**

Appendix VI. Pre-Matching Object and Matching Command

$$> \text{matchit}(\text{GROUP} \sim \text{EQUITY} + \text{PB} + \text{ROE} + \text{NI}, \text{method} = \text{"NULL"}, \text{distance} = \text{"glm"})$$

$$> \text{matchit}(\text{GROUP} \sim \text{EQUITY} + \text{PB} + \text{ROE} + \text{NI}, \text{method} = \text{"nearest"}, \text{distance} = \text{"glm"})$$

Appendix VII. Before and After Matching Variable Distribution



Appendix VIII. Banks Sampled by Matched Pairs

Pair	European Bank	US Bank
1	ABNAMRO	Citizens
2	BancaMonte	Fulton
3	BancoBpm	CIT
4	BancoSabadell	Peoples
5	BancoSantander	Citi
6	Bankia	PNCFS
7	Barclays	CapitalOne
8	BBVA	MT
9	BNPParibas	Prosperity
10	CaixaBank	NYCB
11	Commerzbank	Regions
12	CreditAgricole	Associated
13	CreditSuisse	Sterling
14	DanskeBank	BOK
15	DeutscheBank	HancockWhitney
16	DNB	TCF
17	ErsteGroup	PacWest
18	INGGroep	Comerica
19	IntesaSanpaolo	Wintrust
20	Lloyds	Simmons
21	Nordea	BankUnited
22	NatWest	Valley
23	SEB	Frost
24	Socgen	MS
25	Swedbank	Pinnacle
26	Handelsbanken	USBancorp
27	UBS	UnitedBank
28	Unicredit	OldNational
29	Bankinter	UMB
30	JyskeBank	BofA
31	BPER	FifthThird
32	Ringkjoebing	EastWest
33	CreditoEmilano	KeyCorp
34	Sydbank	Synovus
35	SparNord	FirstMidwest
36	BancoPiccolo	FNB
37	SparebankenVest	Ally
38	Sbanken	JPM
39	Liberbank	Umpqua