IFRS 9 Adoption, Financial Analysts Earnings Forecast Accuracy: Evidence from European Banks

Abstract

This paper investigates the impact of the enforcement of the International Financial Reporting Standard (IFRS) 9-Financial Instruments on financial analysts' ability to translate and interpret accounting information into forward-looking information. Specifically, the paper examines whether the switch to IFRS 9 has an impact on financial analysts' ability to forecast earnings accurately. Using a sample of banks in Europe spanning 2012 to 2021, we employ panel data models and the difference-in-difference (diff-in-diff) technique to test the hypothesis of the impact of IFRS 9 enforcement on analysts' earnings forecast accuracy. The findings reveal that IFRS 9 enforcement is associated with more accurate financial analysts' earnings forecasts. These findings are robust to changes in model specification. Overall, the results are consistent with the notion that IFRS 9 enforcement has informational benefits and thus has improved the quality of financial reports. The findings contribute to the ongoing debate on the economic consequence and usefulness of IFRS 9 enforcement as one of the earliest to focus on financial analysts who represent a major user of accounting and financial information.

Keywords: IFRS 9 enforcement; Analysts' earnings forecasts; Europe

1. Introduction

The mandatory adoption of International Financial Reporting Standards (IFRS) 9-Financial Instruments in Europe and around the world represents perhaps the most significant accounting regulatory change sequel to the 2007 and 2008 global financial crisis. Commencing on 1st January 2018, firms in particular banks in all IFRS-compliant jurisdictions were mandated to prepare their financial statements per the requirements of the novel accounting standards on financial instruments. The development of IFRS 9 was anchored on the inherent weaknesses of the previous International Accounting Standard (IAS) 39. To address concerns about the shortfalls of IAS 39, the International Accounting Standard Board (IASB) published the final version of IFRS 9-Financial Instruments after a series of revisions to the initial exposure draft following consultation with key stakeholders and market participants. Therefore IFRS 9 replaced IAS 39 and became effective in the financial year beginning on January 1st 2018. Supporting the conceptual framework of the IASB (2008) that the main purpose of financial statements is providing financial information that is "useful to present and potential equity investors, lenders and other creditors in decision making as providers of capital", IFRS 9 seeks to provide more forward-looking information which is envisaged to be decision-useful to the primary users of the financial statements.

IFRS 9 is still in the early years of adoption and as result, literature on the post-adoption effects is very nascent and scarce. Timeliness is one of the desirable attributes of decision-relevant financial information. Accordingly, Kim et al. (2021) focused on the effect of shifting from the incurred loss model to the expected credit loss model on the timeliness of loan loss recognition and find that the switch to the expected credit loss model significantly improves loan loss recognition timeliness. Corroborating the above, Oberson (2021) examined the credit risk relevance of loan impairment under IFRS 9 for CDS pricing and also shows that the shift to the ECL model improves the timeliness of loan loss recognition. He further finds evidence that the loan loss provision under IFRS 9 is incrementally more relevant than under IAS 39 for the pricing of CDS. Consistent with the above findings, Yaghobee and Zick (2019) demonstrate that the impairment model under IFRS 9 leads to a more timely recognition of loan loss provisions due to the inclusion of forward-looking information compared to the previous accounting standard (IAS 39). López-Espinosa et al. (2021) also find evidence that expected credit loss provisions are more predictive of future bank risk than the incurred credit loss provisions. Different from the above studies, Taylor and Aubert (2022) recently compared the income smoothing nexus of IFRS 9 adoption between European banks and Sub-Saharan African (SSA) banks. Their findings show mixed evidence of higher and decreased income smoothing in European banks and SSA banks respectively.

IFRS 9 adoption is a significant game-changer for firms in particular financial institutions and is of great interest to different users of financial statements[1]. More so, IFRS 9 seeks to provide forward-looking information which is expected to be decision-useful to various users of financial statements. López-Espinosa et al. (2021) opine that to the extent that loan losses under the ECL are based on expected rather than realized or actual losses, provisions estimated under the ECL approach should be more informative about bank risk than those under the ICL approach. Nevertheless, they acknowledge that provisioning under the ECL is confronted with two key challenges. First, including forward-looking risk assessments in asset valuation is a difficult process; the ECL approach necessitates a significant data collection effort as well as competence in the execution of complex risk models. Second, when compared to the ICL technique, the ECL approach necessitates more discretion and judgment during the modeling process. As a result of measurement error and/or opportunism, the ECL technique may result in less informative LLP reporting. We dwell on an important group of users of financial information; financial analysts. Since financial analysts are sophisticated financial statement users and serve as information intermediaries (Schipper, 1991) in the financial markets, understanding the association between IFRS 9 adoption and the quality of decisions made by financial analysts is an important research question. Analysts use financial statements as one of the primary inputs for their activities. In particular, Barker and Imam (2008) opine that the earnings reported by a firm are one of the most important items used by financial analysts. Consequently, analysts' forecast accuracy is expected to reflect the quality of reported earnings information (Jiao et al., 2012). Thus, assessing analysts' forecast properties following the enforcement of IFRS 9 enables us to evaluate the informational quality of IFRS 9 more specifically on the quality of reported earnings. However, the few nascent literature on IFRS 9 adoption has focused on the effects of IFRS adoption from either creditors' or investors' perspectives. A priori, it remains an open question whether the adoption of IFRS 9 is relevant to financial analysts who represent another key user of financial statements.

Different from the few extant literature on IFRS 9 adoption (Kim et al., 2021; Oberson, 2021; Yaghobee and Zick, 2019; López-Espinosa et al., 2021; Taylor and Aubert, 2022) this paper is one of the earliest to examine the informational benefit of IFRS 9 enforcement to financial analysts by exploiting whether the accuracy of analyst earnings forecasts in the European banking industry improves following the enforcement of IFRS 9. Using a comprehensive sample of commercial banks in Europe spanning the period 2012 to 2021, the research employs panel data models and

[1] "IFRSs are primarily aimed at investors and creditors. And we really need to know what you—the primary users of financial statements—want." Ian Mackintosh (Vice-chairman of IASB), August 5, 2011

the difference-in-difference (diff-in-diff) technique to test the hypothesis of the impact of IFRS 9 enforcement on analysts' earnings forecast accuracy.

We document an improvement in financial analysts' ability to forecast earnings accurately following the enforcement of IFRS 9 in Europe. These findings remain robust to different model specifications. These findings suggest that IFRS 9 which is more forward-looking in nature and imposes extensive mandatory disclosure requirements on preparers of financial statements enriches the informational environment of financial analysts and thereby increases the accuracy of their forecasts. Regarding analysts' forecast dispersion, though the findings reveal a decrease in dispersion among analysts surrounding the enforcement of IFRS9, nevertheless, it is not significant. Thus, we do not document strong evidence of a decrease in analysts' forecast dispersion post-IFRS 9 enforcement. This study extends the nascent literature on IFRS 9 adoption. More importantly, the findings are relevant to stakeholders such as the IASB, regulators, and capital market participants and significantly contribute to the ongoing debate on the economic consequence and usefulness of IFRS 9 enforcement as one of the earliest to focus on financial analysts who represent a major user of accounting and financial information.

The rest of the paper is structured as follows. In section 2, we present the theoretical framework, a review of literature and the development of the hypothesis. Section 3 describes the data and methodology. Section 4 entails the discussion of the results. Section 5 concludes the paper.

2.0 Institutional Background of IFRS 9 adoption

Historically, loan loss provisions for banks have been estimated based on the "incurred credit loss" model, which required the creation of loan loss provisions if objective evidence of impairment exists (e.g., as a result of one or more events occurring after the asset's initial recognition and adversely affecting the expected future cash flows of the loans). However, the financial crisis of 2007-2008 engendered widespread perception that the ICL model under IAS 39 usually led to insufficient and late provisions, accumulating excessive losses in the financial system. Gaston and Song (2014) argue that the "too little, too late" approach under IAS 39 might have resulted in "procyclicality" (i.e., a magnifying of an economic cycle's oscillations by increasing the relationship between the financial sector and the real economy). This assertion was further shared by high-level institutions who extensively criticized the “too little, too late provisioning” under ILM of IAS 39 (G20, 2009; Financial Stability Forum, 2009; Financial Crisis Advisory Group, 2009; European Central Bank, 2017; Basel Committee for Bank Supervision, 2009). In response to the extensive criticism of the ILM under IAS 39 and the clarion call to reform the regulatory standard on financial instruments to address the procyclicality in the financial system by incorporating more forward-looking information, the International Accounting Standard Board (IASB) began a project on the development of IFRS 9-Financial instruments. The development of IFRS 9 was in three phases; classification and measurement of financial assets, impairment and hedge accounting. The publication of the Exposure Draft ED/2009/7 Financial instruments: Classification and Measurement by the IASB on July 14 2009 was the commencement of the much-needed reforms on financial instruments sequel to the financial crisis. As the development of IFRS 9 was on a piecemeal basis, the IASB released an updated version of IFRS 9 as and when each stage was completed, with early voluntary adoption of the updated version permitted. The IASB published the final version of IFRS 9 after a series of changes based on discussions and interactions with relevant stakeholders, completing the IASB's principal reaction to the accounting regulatory change highlighted by the 2007-2009 financial crisis. Following amendments to the prior draft version, the original effective date of 1 January 2013 was changed to 1 January 2015. With the permission of an earlier application, the mandatory effective date was amended from the yearly periods commencing on January 1st, 2015 to January 1st, 2018. However, it is important to note that banks did not embrace the earlier application due to the complexities and challenges of transitioning to this standard, which required a significant change in the business models of the banks.

The novel standard on financial instruments mandatorily replaced IAS 39 and was implemented for the first time for the annual reports corresponding to the 2018 financial year. Though under IFRS 9 changes to financial instruments accounting were introduced in three phases (1) Classification and measurement, (2) impairment, and (3) hedge accounting (EY, 2017). Nevertheless, the key difference between IAS 39 and IFRS 9 is the Expected credit loss model for credit loss recognition which replaces the incurred loss model under IAS 39. Addressing the general concerns of lack of loan loss recognition timeliness, the expected credit loss model under IFRS 9 is more forward-looking and proactive in nature as it incorporates historical information, current information and future events in the estimation of credit losses. Entities are obliged to utilize all available relevant information without undue cost to obtain. Therefore the ECL model under IFRS 9 recognizes both incurred loan losses and projected losses from expected defaults in provisioning decisions (Gebhardt and Novotny-Farkas, 2011). Due to the incorporation of forward-looking information, the ECL model under IFRS 9 is more stochastic in nature and places the onus on managers who are required to make reliable estimates of future events.

The ECL model in IFRS 9 categorizes financial instruments into three stages; stage 1, stage 2 and stage 3 financial instruments respectively. For stage 1 financial instruments, a 12-month expected credit loss is recognized as loan loss provisions at the origination of a loan. The stage 1 category, therefore, represents financial instruments with either no or low credit risk at the time of recognition. At each subsequent measurement, the banks re-evaluate the credit risk of the loans based on past, present, and future information using point-in-time estimation. The loan is categorized into Stage 2 if there is a significant increase in credit risk (SICR). At this stage, the full lifetime expected credit loss is recognized. Stage 2 financial instruments are those that exhibit significant deterioration in credit quality following initial recognition. If there is a further increase in credit risk to the extent that the loan is impaired, it is classified as a stage 3 financial instrument with a full lifetime expected credit loss recognized.

The forward-looking expected credit loss which represents a drastic shift from the backward-looking incurred loss thrives on a point-in-time estimate using input parameters such as the probability of default (PD), exposure at default (EAD) and loss given default (LGD). The expected credit loss under IFRS 9 is therefore given by:

$$ECL = PD * EAD * LGD$$

2.1 Theoretical framework

2.1.1 Disclosure theory

In general, IFRS imposes higher disclosure requirements than are typically necessary for financial statements prepared under local GAAP. More crucially, there are heightened disclosure obligations imposed on financial statement preparers in the context of IFRS 9 adoption. Because it integrates forward-looking information, the ECL model under IFRS 9 is more stochastic. For example, the primary input parameters for estimating predicted credit loss, such as the probability of default (PD), exposure at default (EAD) and loss given default (LGD), are based on point-in-time (PiT) assessments and necessitate a large number of forecasts, managerial judgment, and discretion. Opportunistic activities can make use of this natural discretion. IFRS 9 requires management to give clear and adequate information about potential risks to mitigate the impact of the aforesaid. Market discipline is expected to improve as a result of the enhanced disclosure requirement for detailed information on credit losses, as current and potential investors will have access to a richer set of both quantitative and qualitative financial data of firms to help them assess their financial health properly. We propose that if the new disclosures required by IFRS 9 contain meaningful and credible information, analysts' valuations based on financial statements prepared under IFRS 9 may incrementally improve. Earlier studies have linked the concept of rationality to accounting disclosures. Verrecchia (1983) posits that if managers possess relevant information, they will disclose it. Dye (1986) argues that the announcement of any information is dependent on how proprietary information will be affected. Dye (1986, p. 331) proceeds to define proprietary information “as the information whose disclosure reduces the present value of the cash flows of the firm endowed with the information.” He further suggests that investors may not necessarily assume the worst. However, they may assume that any undisclosed information is proprietary and by so doing, managers are protecting the investors. Sabac et al. (2005) suggest that further disclosures on firm-specific characteristics increase the relevance of accounting information. Byard and Shaw (2003) show that the greater the quality of corporate disclosures, the higher the precision of both analysts’ public (common) and private (idiosyncratic) information. Prior studies argue that more accurate forecasts are an indication of a firm with a better information environment. For instance, Lang and Lundholm (1996) find evidence that firms with better disclosure have lower analyst forecast errors. Similarly, Hope (2003) show that firms that exhibit better disclosure policies and enforcement mechanism have a high analyst forecast accuracy. Obviously, if enhanced and better disclosures enhance analysts’ understanding of an entity’s performance and prospects, then it presupposes that analysts’ forecast accuracy should improve around mandatory IFRS 9 adoption. Accordingly, dwelling on the theory for the impact of enhanced disclosures on analysts’ activities, it can be argued that if the forward-looking ECL model and the additional disclosures required under IFRS 9 contain relevant and reliable information and thus improves analysts’ information environment, then ceteris paribus, analysts’ valuations based on financial statements prepared and disclosed under IFRS 9 may be incrementally improved.

2.2 Literature Review

2.2.1 Analysts forecast properties and financial reporting quality

For analysts, financial statement data is a valuable source of information (Barker & Imam, 2008; Barron et al., 2002; Schipper, 1991). As a result, changes in accounting data are reflected in the properties of analysts' estimates. Manifold stream of research has examined the relationship between changes in disclosure and analyst decision-making. For example, Lang and Lundholm (1996) document that increased disclosure levels is linked to improved analyst coverage and prediction accuracy. Analogously, Hope (2003) discovers that firm-level disclosures are linked to analyst forecast accuracy. Focusing on the effects of cross-listings on analysts' forecasts, Lang et al. (2003) demonstrate that due to the stringent disclosures on the US exchange, analysts' coverage and forecast accuracy increases for non-US firms listed on the US exchange. Dwelling on the effects of regulatory accounting standards on analysts' forecast accuracy, Ashbaugh and Pincus (2001) find evidence to suggest an improvement in analysts' forecast accuracy following the adoption of international financial reporting standards. They further find that this effect is more pronounced when there are significant differences between the previous local standard (GAAP) and the international standard (IFRS). Consistent with the above, we assume that the quality and the volume of disclosures in a firm's financial report impact analysts' decisions making which is reflected in their earnings forecasts. Analysts are among the primary users of financial information which enables us to examine the much-touted forward-looking approach and enhanced disclosures on the quality of analysts' decisions in terms of their forecast accuracy.

2.2.2 IFRS 9 and financial reporting quality

The transition from incurred loan loss model under IAS 39 to the expected credit loss model under IFRS 9 was heralded to be a significant game-changer in the financial reports of firms. As IFRS 9 incorporates forward-looking information and imposes more mandatory disclosures about financial instruments, IFRS 9 is claimed to be a high-quality and robust financial instruments accounting standard that would engender more transparent financial reports to enhance market discipline. Regulators and standard setters argue that given the forward-looking nature of IFRS 9, the primary users of the financial statements such as investors, analysts, creditors will accrue more benefits from its adoption. This optimism seems to be supported by the capital markets as Onali and Ginesti (2014) document positive reactions to events surrounding the introduction of IFRS 9. Their findings further suggest that investors perceive the new regulatory standard as shareholder wealth-enhancing.

Since the implementation of IFRS 9 was just recent, the extant literature on its true effect is very scarce. The most empirical literature on IFRS 9 focused on the day one transitional effect on 1st January 2018 while the emerging stream of empirical literature examines whether the mandatory adoption of IFRS 9 is associated with improvement in financial reporting quality. These studies investigate different aspects of IFRS 9 depending on how they measure earnings quality. Akin (Dechow et al., 2010), we distinguish the studies that focus on the timeliness of loan loss provision under IFRS 9 from those that examine the value relevance of IFRS 9 and the income smoothing behavior of banks. Examining the informative content of IFRS 9 based on loan loss recognition timeliness, studies such as (Kim et al., 2021; Oberson, 2021; Yaghobee and Zick, 2019) show that the switch from incurred loss model to the expected credit loss model improves the timeliness of loan loss recognition. López-Espinosa et al. (2021) also find evidence that expected credit loss provisions are more predictive of future bank risk than the incurred credit loss provisions. Studies (Yaghobee and Zick, 2019; Mechelli & Cimini, 2021) that also empirically examine the association between IFRS 9 and stock market data likewise document that IFRS 9 is more value relevant to investors than IAS 39. Different from the above studies, Taylor and Aubert (2022) recently compared the income smoothing nexus of IFRS 9 adoption between European and Sub-Saharan African (SSA) banks. They report mixed evidence of higher and decreased income smoothing in European banks and SSA banks respectively. Macchioni et al. (2021) also document more aggressive income-smoothing behavior among European banks, supporting the findings of Taylor and Aubert (2022). From the above literature, it is very apparent that empirical studies on the effects of IFRS 9 on the forecast properties of financial analysts who are key users of financial information are barely available. We make a novel contribution to the literature on IFRS 9 adoption with a different approach by inferring the effect of mandatory IFRS 9 adoption on analysts' information environment. In particular, we examine the impact of IFRS 9 on analysts' forecast accuracy from their use of financial reports prepared under IFRS 9. As argued by (Dechow et al., 2010), this approach is synonymous with return-based research as earnings quality is inferred from the impact on the information users. Accordingly, this study focuses on analysts' use of IFRS 9 financial information rather than investors' reactions. Given that analysts' forecasts are predominantly geared toward earnings, while investors may as well respond to market information other than earnings, our study has some advantages compared to return-based studies. Also, in comparison with the few nascent literature on the properties of earnings under IFRS 9, our study has an advantage as it captures changes in the use of earnings information for decision-making.

2.3 Hypotheses development

Financial analysts are seen as essential information intermediaries within capital markets since investment practitioners and advisors use financial analysts' earnings forecasts for future stock valuation and portfolio selections (Beaver, 1998; Capstaff et al., 1995). Financial statements, in particular, are the primary source of information for analysts when estimating an entity's future earnings (Givoly and Lakonishok, 1984; Capstaff et al., 1995). Analysts incorporate both available public and private information in their forecasting activities. The expected credit loss model under IFRS 9 incorporates forward-looking information and also enjoins management to make more disclosures in their financial statements regarding the various assumptions under the estimation of ECL, the models employed, the input parameters used such as the probability of default, exposure at default, loss given default among others. Entities must also explain how they determine if credit risk has increased significantly over time. Credible information about the carrying amount of financial instruments must be provided consistently to enable users of financial statements such as investors and analysts to understand the primary drivers of change in the amount of credit losses: whether the change is induced by changes in credit risk or changes in lending volumes. The forward-looking information and the additional mandatory disclosures ensure that IFRS 9 adoption provides a high-quality set of both quantitative and qualitative financial information relevant to decision-making. After the mandatory adoption of IFRS 9, public financial statement information is likely to increase in quality and quantity. This may reduce the weight of private information in analysts' forecasts, which may lead to increased analysts' forecast accuracy (Lang & Lundholm, 1996).

Thus, if financial statement transparency improves under IFRS 9 as a result of the forward-looking information and extensive mandatory disclosure requirements, analysts will have access to more reliable information both quantitatively and qualitatively, and the tasks involved with validating the accuracy of financial statement information would be decreased (Ho et al., 2007; Tong, 2007).

According to previous research, analysts utilize financial statement data, particularly earnings, to forecast a company's future profitability (Barker & Imam, 2008; Schipper, 1991). Thus, analysts' ability to forecast earnings is likely to improve as the quality of financial statement data improves. Following this logic, since the primary objective of this research is to examine the effect of mandatory IFRS 9 adoption on analysts' earnings forecast accuracy in Europe, we expect that the mandatory adoption of IFRS 9 in Europe is positively related to analysts' forecast accuracy. Accordingly, we formulate our hypothesis as follows:

H1: Analysts' earnings forecasts have become more accurate post-IFRS 9 enforcement in Europe.

3.0 Research Methodology

3.1 Data

We draw our sample banks from 32 countries in Europe. Our initial sample consists of firms' and analysts' data from 2012 to 2021. We drop all non-banking firms in our sample and restrict our sample to only banks. This is because, unlike non-financial firms, significant proportions of banks' financial statements are predominantly financial instruments. IFRS 9 adoption is thus projected to have more enormous effects on banks than non-banking firms. All firm-level variables including analyst consensus forecasts are retrieved from the Factset Fundamentals database. Consistent with prior literature, we define analysts' consensus forecasts as the means of all available analysts' earnings forecasts at any given time. This study employs the final consensus analyst forecast before the actual earnings announcement as the latest forecast is more informative since it incorporates all available information in the market prior to the release of the actual earnings.

Given that IFRS 9 is mandatory in Europe since 2018, a control group of banks previously reporting under IAS 39 but have not adopted IFRS 9 and are still applying IAS 39 is difficult to find in Europe. Consequently, a direct control group made up of banks in Europe that did not adopt IFRS 9 when it became mandatory and is currently reporting under IAS 39 cannot be employed in this study. Researchers such as Hail and Leuz (2007) encountered similar issues when investigating the capital markets benefits of mandatory IFRS adoption in the EU due to the unavailability of an obvious control group of firms to be used as a benchmark. Cheong et al. (2010) also encountered a similar problem when examining the impact of IFRS adoption on analysts' accuracy in the Asia-Pacific region and thus elected a control group of firms from a non-IFRS adopting country outside the Asia-Pacific. We argue that the results of Cheong et al. (2010) could be influenced by the heterogeneity between the Asia-Pacific region and the other region where the control sample was drawn from. Consequently, we adopt an alternative approach and include a control sample of banks in Europe that do not report under IFRS and thus have not adopted IFRS 9. This group of banks has never reported under IFRS when it became mandatory in 2005 and continues to report under their domestic GAAP. Subsequently, these banks did not switch accounting standards in 2018 when IFRS 9 became mandatory. Consistent with Daske et al. (2008) and Horton et al. (2013) we control for the impact of potentially confounding events using this group of non-IFRS adopting banks as our control sample. Horton et al. (2013) opine that any change in forecast accuracy for non-adopting firms is likely to reflect the impact of concurrent economic and regulatory changes but not the effect of IFRS adoption. Out of the total observations of 1651 and 1653 for the forecast error and the dispersion sample, the test sample consists of 1532 observations and 1534 observations for the forecast error sample and the dispersion sample respectively. The control sample is 119 observations for both the forecast error and dispersion sample respectively. The small number of observations for the control group does not permit the estimation of different regressions for both the test and control samples separately. Accordingly, a more suitable approach in the form of difference-in-difference (diff-in-diff) estimation is adopted for this analysis. The final data spans a period of 10 years, segregated into pre-IFRS 9 (2012-2017) and post-IFRS 9 (2018-2021). Table 1 highlights the distributions of observations within the sample period in each country.

3. 2 Empirical Model

To investigate whether the adoption of IFRS 9 in Europe in 2018 has impacted the accuracy of analysts' forecasts, the study employs panel regression models. We follow prior literature (Ashbaugh & Pincus, 2001) and employ the reverse of accuracy, namely forecast error, to measure the accuracy of analysts' forecasts. Forecast error is measured as the absolute value of the difference between mean consensus earnings forecast and actual earnings, scaled by the stock price at the end of December one year before the forecasted year. The equation below describes the accuracy of analyst forecasts.

$$AFE_{t;i} = \frac{\text{Consensus Forecast}_{t,i} - \text{Actual EPS}_{t,i}}{P_{t-1}} \qquad \text{equation (1)}$$

Next, using panel fixed effect and difference in difference (diff-in-diff) technique, we perform multivariate regressions where we focus on the relation between analysts' forecast accuracy and the mandatory IFRS 9 adoption among European banks. Following prior literature, we estimate the regression models below. Equation (2) is the baseline regression model. Equation (3) introduces our main variable of interest (IFRS9) and also includes an additional control variable (COVID) to control for the recent Covid-19 induced economic uncertainty on analysts' earnings forecast accuracy. Equation (4) builds on equation (3) by including the interaction term, IFRS9*PASTEARN

$$AFEt,i = \alpha + \beta 1PASTEARN_{t,i} + \beta 2ANAF_{t,i} + \beta 3CAR_{t,i} + \beta 4SIZE_{t;i} + \beta 5LEV_{t,i} + \beta 6PROFIT_{t,i} + \varepsilon_{t,i} \qquad \text{equation (2)}$$

$$AFEt,i = \alpha + \beta 1PASTEARN_{t,i} + \beta 2ANAF_{t,i} + \beta 3CAR_{t,i} + \beta 4SIZE_{t;i} + \beta 5LEV_{t,i} + \beta 6PROFIT_{t,i} + \beta 7IFRS9_{t,i} + \beta 8COVID_{t,i} + \varepsilon_{t,i} \qquad \text{equation (3)}$$

$$AFEt,i = \alpha + \beta 1PASTEARN_{t,i} + \beta 2ANAF_{t,i} + \beta 3CAR_{t,i} + \beta 4SIZE_{t;i} + \beta 5LEV_{t,i} + \beta 6PROFIT_{t,i} + \beta 7IFRS9_{t,i} + \beta 8COVID_{t,i} + \beta 9IFRS9*PASTEARN + \varepsilon_{t,i} \qquad \text{equation (4)}$$

The explanation of the variables for the study is outlined below.

Past Earnings (PASTEARN): Prior studies (Kong et al., 2021; Lee & So, 2017) document that past performance influences analysts' forecast properties in particular their forecast accuracy.

Consistent with this argument, we follow prior literature and include lagged earnings (prior year's earnings) to control for the effect of a firm's past performance on analysts' forecast accuracy. Given that past performance improves analysts' ability to forecast future earnings more accurately, we expect a negative relation between this variable and forecast error.

Analyst following (ANAF): The number of analysts following is argued in literature as one of the factors that influence a firm's disclosure quality and hence analysts' forecast properties. Lang and Lundholm (1996) assert that when firm-level disclosures improve, the number of analysts following the firm increases. In line with this, Lys and Soo (1995) show that analysts following a firm have a positive relation with forecast accuracy. They contend competition among analysts heightens as the number of analysts following a firm increases. Thus, analysts will have a higher incentive for more accurate forecasts. We therefore, expect that as the number of analysts following a firm increases, analysts' forecasts will thereby improve. In contrast, it is expected that the link between analysts' following and forecast dispersion will be negative as there can be wide variation in analysts' forecasts for a single firm when several analysts follow that particular firm. To control for this effect in our analysis, we employ the number of analysts' forecasts included in the final consensus forecast.

Capital Adequacy (CAR); Capital adequacy is included to control for the financial strength of the banks in the sample. Analysts' earnings forecasts are more likely to be accurate for banks that are financially sound and stable relative to others. In this context, it is expected that capital adequacy will be positively correlated with forecast accuracy.

Bank size (SIZE): Extant literature suggests that analyst forecast properties vary systematically with firm size. For instance, (Lang and Lundholm, 1996; Lang and Lundholm, 1993) opine that large firms are associated with more disclosures which enhances the accuracy of analysts' forecasts. Also, prior studies (Hope, 2003) employ firm size to control for other firm-specific characteristics such as management incentives which are not directly observable. Following previous studies (Ashbaugh and Pincus, 2001), we include firm size measured by the natural logarithm of the total assets at the end of the year to control for the possible size effect on analysts' forecast accuracy.

Leverage (LEV): Banks by the nature of their operations are inherently highly levered entities, nevertheless, the degree of leverage might vary from one bank to another. We follow prior literature (Kong et al., 2021; Byard et al., 2011; Hao et al., 2022) and include leverage as the measure of the debt burden of the banks. We measure leverage as the ratio of total debts to total assets. Consistent with literature (Kong et al., 2021; Byard et al., 2011; Hao et al., 2022), a positive association is expected between leverage and forecast error.

PROFIT: Extant literature (Choi et al. 2013; Barniv et al., 2022) argues that analyst earnings forecasts are more accurate for profit-making firms than loss-making firms as positive earnings are more informative than losses. Supporting the above, (Collins et al., 1999; Hayn, 1995) also document that losses are more transitory in nature and hence are less informative. Higher informative content of reported financial information is more likely to positively influence analysts' forecast properties. That is, higher informative content of a firm's financial information and disclosures will improve analysts' forecast accuracy and reduce forecast dispersion of analysts.

We control for this possible effect by using a dummy variable coded one in the years the firms report positive earnings and zero in the years the firms report losses.

IFRS 9: IFRS 9 is a binary indicator variable that takes the value of 1 post-IFRS 9 enforcement (2018 to 2021) and 0 otherwise (2012 to 2017). It is the main variable of interest. If the enforcement of IFRS 9 is associated with an improvement in analysts' ability to forecast earnings accurately, then a negative association is expected between this variable and the measure of forecast accuracy (forecast error).

Covid-19 (COVID): COVID is a dummy variable that takes the value of 1 for years corresponding to the outbreak of the Covid-19 pandemic (2020-2021) and 0 otherwise (2012-2019). Literature argues that uncertainties induced by crises affect analysts' forecast accuracy. In the specific context of the Covid-19 pandemic, recent studies such as (Hao et al., 2022; Anglin et al., 2021: Bilinski, 2021) document that the pandemic-induced uncertainties increased forecasting difficulties which resulted in less accurate forecasts by financial analysts. A positive relation is therefore expected for this variable.

The table below summarizes the definition of the variables.

Table 2. Summary of variables definition

Variable	Definition
AFE	AFE is analyst forecast error measured as the absolute value of the difference between mean consensus earnings forecast and actual earnings, scaled by the stock price at the end of December one year before the forecasted year
PASTEARN	PASTEARN is the prior year's earnings preceding the analyst's forecast
ANAF	ANAF is the number of analysts following the firm measured as the number of estimates contained in consensus forecasts
CAR	CAR measured as the ratio of total equity to total assets
SIZE	SIZE is the natural logarithm of total assets
LEV	LEV is leverage which is the ratio of total debt to total assets
PROFIT	PROFIT is an indicator variable that equals 1 for years the firm reports positive earnings and 0 otherwise
IFRS9	IFRS9 is an indicator variable that equals 1 for years after 2005 and 0 otherwise
COVID	COVID is a dummy variable that equals 1 for years after 2019 and 0 otherwise to control for the pandemic-induced uncertainties

4. Results

4.1 Descriptive statistics

Table 3 presents the descriptive statistics for the forecast error sample (Panel A) and the dispersion sample (Panel B). Both earnings forecasts accuracy and dispersion average about 3% and 2% of stock prices which is consistent with prior studies (Jiao et al., 2012; Bae et al., 2008). Panel A further shows that the mean of forecast error is positive for earnings forecast accuracy (0.03370). Extant literature argues that positive signs for forecast error (FE>0) signal that on average, managers tend to underestimate actual earnings. The dispersion sample in Panel B reveals a similar result. Analyst following measured by the natural logarithm of the number of analysts following the firm has a mean of 1.03895 and 1.03769 in the forecast error sample and the dispersion sample respectively. The mean bank size measured as the natural logarithm of total assets has a mean of about 9.69% in both the forecast error sample and the dispersion sample. Comparing other variables in both samples (forecast error and dispersion), it is observed that the means of all other independent variables are not greatly different.

Table 3. Descriptive statistics

Panel A: Forecast Error sample					
Variable	Obs	Mean	Std. Dev	Min	Max
AFE	1,651	0.03370	0.10623	0.00002	0.88867
PASTEARN	1,651	1.87555	14.18232	-42.83691	324.85780
ANAF	1,651	1.03895	1.07765	0.00000	3.43399
CAR	1,651	0.14764	0.17907	-0.34747	0.96916
SIZE	1,651	9.69213	2.63625	0.69740	14.43443
LEV	1,651	0.20738	0.15577	0.00000	0.90868
PROFIT	1,651	0.91036	0.28576	0.00000	1.00000
IFRS9	1,651	0.46275	0.49876	0.00000	1.00000
COVID	1,651	0.22774	0.41950	0.00000	1.00000
Panel B: Dispersion sample					
DISPERSION	1,653	0.01726	0.03688	0.00000	0.23963
PASTEARN	1,653	1.87400	14.17383	-42.83691	324.85780
ANAF	1,653	1.03769	1.07761	0.00000	3.43399
CAR	1,653	0.14788	0.17940	-0.34747	0.96916
SIZE	1,653	9.68701	2.64029	0.69740	14.43443
LEV	1,653	0.20726	0.15571	0.00000	0.90868
PROFIT	1,653	0.91047	0.28560	0.00000	1.00000
IFRS9	1,653	0.46340	0.49881	0.00000	1.00000
COVID	1,653	0.22868	0.42011	0.00000	1.00000

Descriptive statistics of the variables: AFE is the absolute forecast error (Actual Earnings-Consensus Mean Forecast| /Stock Price$_{t-1}$); PASTEARN: lagged earnings per share; ANAF: the natural logarithm of the number of analysts following the firm; CAR is capital adequacy ratio calculated as (Total equity/ Total assets); SIZE: the natural logarithm of total assets; LEV is leverage calculated as (total debt/total assets); PROFIT: an indicator variable denoted by 1 for profit-making firms and 0 for loss-making firms; IFRS9; an indicator variable taking the value of 1 post-IFRS 9 adoption and 0 otherwise; COVID; a dummy variable corresponding to 1 during the period of the Covid-19 crisis and 0 otherwise; DISPERSION: the absolute value of the difference between the highest forecast and the lowest forecast deflated by the stock price at the end of December of the year preceding the forecasted year.

4.2 Bivariate Analysis

Table 4 reports the correlation matrix and the variance inflation factor for the variables employed in the study. It is observed that prior year's earnings (PASTEARN) are negatively and significantly related to both measures of analysts' earnings forecast accuracy (forecast error and forecast dispersion). This suggests that a firm's prior year performance is associated with analysts' ability to forecast future earnings more accurately. Consistent with literature (Jiao et al., 2012), analysts' coverage measured by the number of analysts following is negatively correlated with forecast error and positively correlated with forecast dispersions. Capital adequacy ratio used to proxy for the strength of the banks is negatively and significantly correlated with both forecast error and dispersion. This indicates analysts' earnings forecast accuracy improves for healthy and well-capitalized banks. Panel A shows that the association between IFRS 9 dummy with forecast error is negative albeit not significant. However, Panel B reports that IFRS 9 dummy is negatively and significantly correlated with forecast dispersion, suggesting that forecasts are more accurate after the enforcement of IFRS 9. The expectation that forecasts are more accurate when firms are more profitable (Choi et al. 2013), is supported by the negative and significant correlation between profit and the two measures of forecast accuracy (forecast error and dispersion) respectively. We document a positive and significant association between the variable SIZE and the pair of measures for analyst forecast accuracy. An indicator variable COVID, included to control for the effects of the COVID-19-induced uncertainty on analysts' earnings forecast accuracy shows a contrasting relationship between forecast error and dispersion. While it is positively correlated with forecast error, it is negatively correlated with forecast dispersion. However, this relationship is not significant. This may suggest that crises-induced uncertainties affect all analysts alike and hence their forecasts are not widely dispersed. In line with prior research (Kong et al., 2021; Byard et al., 2011; Hao et al., 2022), we also document a positive relationship between the measures of forecast accuracy and leverage. From observation, the correlations are relatively small implying that multicollinearity is not likely to be an issue in the multivariate regressions. Nevertheless, we estimate the variance inflation factor (VIFs) to determine the severity of multicollinearity in the subsequent regression analyses. As can be observed from Table 4, all the VIFs are below 2, indicating our regression analyses are devoid of multicollinearity issues.

Table 4: Correlation analysis

Correlation between independent and dependent variables

Panel A: Forecast Error sample

	AFE	PASTEARN	ANAF	CAR	SIZE	LEV	PROFIT	IFRS9	COVID	VIF
AFE	1									
PASTEARN	-0.1110***	1								1.01
ANAF	-0.0244	-0.0458*	1							1.25
CAR	-0.0666***	-0.0326	-0.2810***	1						1.79
SIZE	0.0496**	0.0204	0.3749***	-0.6532***	1					1.94
LEV	0.0348	0.0088	0.1919***	0.3351***	0.3351***	1				1.16
PROFIT	-0.3090***	0.0234	0.0163	-0.0526**	-0.0526**	-0.0265	1			1.01
IFRS9	-0.0251	0.0138	-0.2110***	-0.0368	0.0194	-0.0366	0.0659	1		1.58
COVID	0.0032	0.0158	-0.1434***	-0.0183	0.5851***	-0.0334	0.0288	0.5851	1	1.52

Panel B: Dispersion sample

	DISPERSION	PASTEARN	ANAF	CAR	SIZE	LEV	PROFIT	IFRS9	COVID	VIF
DISPERSION	1									
PASTEARN	-0.1275***	1								1.01
ANAF	0.4062***	-0.0458*	1							1.25
CAR	-0.1600***	-0.0326	-0.2810***	1						1.79
SIZE	0.2189***	0.0204	0.3749***	-0.6532***	1					1.94
LEV	0.1332	0.0088	0.1919***	-0.3218***	-0.6532***	1				1.16
PROFIT	-0.3108***	0.0234	0.0163	0.0165	-0.0526**	-0.0265	1			1.01
IFRS9	-0.0912***	0.0138	-0.2110***	-0.0368	0.0194	-0.0366	0.0659	1		1.58
COVID	-0.0277	0.0158	-0.1434***	-0.0183	0.0194	-0.0334	0.0288	0.5851	1	1.53

AFE is the absolute forecast error (Actual Earnings-Consensus Mean Forecast/Stock Price$_{t-1}$); PASTEARN: lagged earnings per share; ANAF: the natural logarithm of the number of analysts following the firm; CAR is capital adequacy ratio calculated as (Total equity/ Total assets); SIZE: the natural logarithm of total assets; LEV is leverage calculated as (Total debt/Total assets); PROFIT: an indicator variable denoted by 1 for profit-making firms and 0 for loss-making firms; IFRS9; an indicator variable taking the value of 1 post-IFRS 9 adoption and 0 otherwise; COVID; a dummy variable corresponding to 1 during the period of the Covid-19 crisis and 0 otherwise; DISPERSION: the absolute value of the difference between the highest forecast and the lowest forecast deflated by the stock price at the end of December of the year preceding the forecasted year. *, ** and *** denote significance at 10%, 5% and 1% respectively.

4.3 Regression Results

Table 5 reports the results of the regression analysis for analyst forecast accuracy measured by the reverse of forecast accuracy (forecast error). Model 1 depicts the results of the baseline model. From Model 1, the coefficient of PASTEARN is negative and significant, which intuitively suggests that prior year's earnings improve analysts' forecast accuracy of future earnings. Consistent with prior literature (Jiao et al., 2012; Masoud, 2017), analysts following (ANAF) also show a negative and significant relation with forecast error, which suggests that the number of analysts following a firm is positively associated with analysts' forecast accuracy. Supporting the findings of Choi et al. (2013), our results show that analysts' forecast accuracy improves for profit-making firms. The baseline results further show that SIZE has a positive and significant effect on forecast error, corroborating the findings of (Masoud, 2017). Model 2 presents the regression results with the IFRS 9 indicator variable which is the main variable of interest. Another control variable (COVID) is included to control for the effects of the Covid-19 induced economic uncertainty on analyst forecast abilities as the sample period includes observations from the Covid-19 period. In Model 2, all the variables maintain the signs of the coefficient and statistical significance in the baseline model except for analysts following (ANAF) which increases in statistical significance. The main variable of interest in Model 2 (IFRS9) shows a negative and significant effect on analyst forecast error. Consistent with prior literature on analyst forecast accuracy in the adoption of IFRSs in general, the findings suggest analysts' forecast accuracy increases on average by 0.9% of stock price after the enforcement of IFRS 9 in 2018. The positive COVID variable implies that the economic uncertainty induced by the Covid-19 crisis decreases analysts' forecast accuracy, though the relationship is not significant. In Model 3 the variable of interest is the interaction of past earnings with IFRS 9 (PASTEARN*IFRS9). The interaction term of PASTEARN exhibits a negative and significant association with forecast error, further corroborating the findings in Model 2 that IFRS 9 enforcement is associated with an improvement in analysts' earnings forecast accuracy. Overall, the findings from the multivariate regression imply that the enforcement of IFRS 9 has increased the quality of reported earnings as shown in the improvement of analysts' earnings forecast accuracy and more consensus about the interpretation of firms' financial reports among financial analysts. The findings further suggest that IFRS 9's robust requirement due to its forward-looking nature, timelier recognition of credit losses and extensive mandatory disclosures has more predictive power than the rigid and restrictive nature of IAS 39 as it improves the predictive accuracy of analyst earnings forecast. Our findings on the predictive power of IFRS 9 thus corroborate López-Espinosa et al. (2021) who examined a different aspect of IFRS 9 enforcement and concluded that IFRS 9 is more predictive of future bank risk than IAS 39.

Table 5: Regression results

Panel A: Forecast Error sample			
	Model 1	Model 2	Model 3
PASTEARN	-0.0007**	-0.0007**	-0.0007**
	(0.0003)	(0 .0003)	(0.0003)
ANAF	-0.0027*	-0.0040**	-0.0039**
	(0.0016)	(0.0020)	(0.0020)
CAR	0.0104	0.0180	0.0199
	(0.0368)	(0.0379)	(0.0374)
SIZE	0.0132*	0.0165*	0.0165*
	(0.0071)	(0.0096)	(0.0095)
LEV	0.0120	0.0078	0.0136
	(0.0391)	(0.0386)	(0.0395)
PROFIT	-0.0813***	-0.0802***	-0.0801***
	(0.0173)	(0.0173)	(0 .0171)
IFRS9		-0.0096*	-0.0065
		(0.0050)	(0.0047)
COVID		0.0045	0.0044
		(0.0049)	(0.0049)
PASTEARN*IFRS9			-0.0011*
			(0.0006)
Intercept	-0.0201	-0.0481	-0.0507
	(0.0708)	(0.0946)	(0.0934)
Obs	1651	1651	1651
F-statistic	5.09***	4.06***	3.71***
Adjusted R^2	5.52%	4.60%	4.39%

AFE is the absolute forecast error (Actual Earnings-Consensus Mean Forecast/Stock Price$_{t-1}$); PASTEARN: lagged earnings per share; ANAF: the natural logarithm of the number of analysts following the firm; CAR is capital adequacy ratio calculated as (Total equity/ Total assets); SIZE: the natural logarithm of total assets; LEV is leverage calculated as (Total debt/Total asset); PROFIT: an indicator variable denoted by 1 for profit-making firms and 0 for loss-making firms; IFRS9; an indicator variable taking the value of 1 post-IFRS 9 adoption and 0 otherwise; COVID; a dummy variable corresponding to 1 during the period of the Covid-19 crisis and 0 otherwise; PASTEARN*IFRS9: Interaction of lagged earnings with IFRS 9. *, ** and *** denote significance at 10%, 5% and 1% respectively. Robust standard errors are shown in parenthesis.

4.4 Sensitivity Analysis/Robustness Checks

The analysis above so far employs the mean consensus forecast. To ensure the robustness of our results, we follow prior literature (Cheong et al. 2010; Cotter et al., 2012) and employ the median of consensus forecast to calculate the forecast error, as it minimizes potential problems associated with mean calculations due to outliers. Given that certain companies may have a comparatively small number of analysts following them, the mean of forecast EPS may not be the best indicator of central tendency as the impact of one extreme forecast EPS can significantly affect a dataset with few observations. Specifically, EPS forecast that significantly deviates from the mean may be ascribed to the forecasting ability of individual analysts. Table 5 presents the multivariate regression results using median consensus forecasts. The results across all three models are consistent with the earlier regression estimates using the consensus mean forecast EPS. Our earlier findings are therefore not sensitive to the choice of mean EPS consensus forecast employed. Overall the results corroborate the earlier findings of an improvement in analysts' earnings forecast accuracy following the enforcement of IFRS 9. This is consistent with the assertion that the forward-looking nature of IFRS 9 and extensive mandatory disclosure requirements provide a richer set of both quantitative and qualitative financial information to assess the earnings potential of firms.

Table 6: Regression results with the median consensus forecast

Panel A: Forecast Error sample			
	Model 1	Model 2	Model 3
PASTEARN	-0.0007***	-0.0007***	-0.0007***
	(0.0003)	(0.0003)	(0.0003)
ANAF	-0.0028*	-0.0041**	-0.0040**
	(0.0016)	(0.0020)	(0.0019)
CAR	0.0112	0.0194	0.0210
	(0.0364)	(0.0373)	(0.0369)
SIZE	0.0129*	0.0164*	0.0165*
	(0.0071)	(0.0096)	(0.0095)
LEV	0.0097	0.0055	0.0104
	(0.0374)	(0.0369)	(0.0374)
PROFIT	-0.0788***	-0.0777***	-0.0776***
	(0.0164)	(0.0164)	(0.0163)
IFRS9		-0.0088*	-0.0061
		(0.0047)	(0.0046)
COVID		0.0032	0.0032
		(0.0048)	(0.0048)
PASTEARN*IFRS9			-0.0009*
			(0.0005)
Intercept	-0.0201	-0.0512	-0.0534
	(0.0704)	(0.0940)	(0.0928)

Obs	1651	1651	1651
F-statistic	5.62***	4.54***	4.18***
Adjusted R^2	5.89%	4.8%	4.61%

AFE is the absolute forecast error (Actual Earnings-Consensus Mean Forecast| /Stock Price$_{t-1}$); PASTEARN: lagged earnings per share; ANAF: the natural logarithm of the number of analysts following the firm; CAR is capital adequacy ratio calculated as (Total equity/ Total assets); SIZE: the natural logarithm of total assets; LEV is leverage calculated as (Total debt/Total Assets); PROFIT: an indicator variable denoted by 1 for profit-making firms and 0 for loss-making firms; IFRS9; an indicator variable taking the value of 1 post-IFRS 9 adoption and 0 otherwise; COVID; a dummy variable corresponding to 1 during the period of the Covid-19 crisis and 0 otherwise. PASTEARN*IFRS9: Interaction of lagged earnings with IFRS 9. *, ** and *** denote significance at 10%, 5% and 1% respectively. Robust standard errors are shown in parenthesis.

Proceeding with the robustness and sensitive test, we employ another measure of analysts' forecast accuracy which is forecast dispersion. We define analysts' forecast dispersion as the absolute value of the difference between the highest forecast and the lowest forecast deflated by the stock price at the end of December of the year preceding the forecasted year as shown in the equation below.

$$\text{Dispersion}_{t;i} = \frac{\text{Forecast}_{h,t,i} - \text{Forecast}_{l,t,i}}{P_{t-1,i}} \qquad \text{equation (5)}$$

Table 7 reports the results of the regression estimates using forecast dispersion. Consistent with the results of the forecast error, the results across all the models show that past earnings (PASTEARN) and profit-making firms (PROFIT) decrease forecast dispersion and hence increase analysts' forecast accuracy. Analyst following (ANAF) is positive and significantly related to forecast dispersion which suggests that as the number of analysts following a firm increases, there tends to be greater variation in analyst consensus forecast which supports prior literature (Jiao et al., 2012). The positive and significant coefficient of COVID implies that the Covid-19 induced uncertainties increase analysts' forecast dispersion and thereby reduce the accuracy of analysts' forecasts. Though the main variables of interest in Model 2 and Model 3 (IFRS9 and EARNINGS*IFRS9) show negative coefficients, they are not significant. While the negative coefficient may suggest that IFRS 9 provides a richer set of financial information due to the incorporation of forward-looking information and extensive disclosures in the company’s reports and thus analysts have become less dispersed in their forecast, it is insignificant. Thus, we do not find strong evidence of a decrease in analysts' earnings forecast dispersion following the enforcement of IFRS 9.

Table 7: Regression results with Forecast dispersion

Dispersion sample			
	Model 1	Model 2	Model 3
PASTEARN	-0.0003***	-0.0003***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)
ANAF	0.0116***	0.0118***	0.0118***
	(0.0011)	(0.0012)	(0.0012)

CAR	-0.0055	-0.0094	-0.0088
	(0.0088)	(0.0100)	(0.0101)
SIZE	0.0027	0.0009	0.0009
	(0.0020)	(0.0025)	(0.0025)
LEV	-0.0041	-0.0032	-0.0013
	(0.0132)	(0.0126)	(0.0125)
PROFIT	-0.0272***	-0.0270***	-0.0270***
	(0.0071)	(0.0071)	(0.0071)
IFRS9		-0.0014	-0.0004
		(0.0015)	(0.0017)
COVID		0.0044**	0.0044**
		(0.0022)	(0.0022)
PASTEARN*IFRS9			-0.0004
			(0.0002)
Intercept	0.0059	0.0235	0.0227
	(0.0209)	(0.0255)	(0.0255)
Obs	1653	1653	1653
F-statistic	19.84***	14.97***	13.35***
Adjusted R^2	25.19%	27.19%	26.55%

DISPERSION: the absolute value of the difference between the highest forecast and the lowest forecast deflated by the stock price at the end of December of the year preceding the forecasted year. PASTEARN: lagged earnings per share; ANAF: the natural logarithm of the number of analysts following the firm; CAR is capital adequacy ratio calculated as (Total equity/ Total assets); SIZE: the natural logarithm of total assets; LEV is leverage calculated as (Total debt/Total asset); PROFIT: an indicator variable denoted by 1 for profit-making firms and 0 for loss-making firms; IFRS9; an indicator variable taking the value of 1 post-IFRS 9 adoption and 0 otherwise; COVID; a dummy variable corresponding to 1 during the period of the Covid-19 crisis and 0 otherwise; PASTEARN*IFRS9: Interaction of lagged earnings with IFRS 9. *, ** and *** denote significance at 10%, 5% and 1% respectively. Robust standard errors are shown in parenthesis.

Prior studies (Jiao et al., 2012; Tan et al., 2011) have documented that earnings are more difficult to forecasts for firms with more volatile performance than for firms whose financial performance is relatively stable. Thus, it is feasible that the earnings forecast accuracy for firms with more performance volatility will be lower and the dispersion is higher. As a further robustness check, we follow prior literature and control for performance volatility by including the standard deviation of return of equity in our analysis. Furthermore, we also include year-fixed effect and country-fixed effect to control for time-invariant characteristics and country-level factors that may affect the results. Table 8 presents the empirical results which control for performance volatility, year-fixed effects and country-fixed effects. From the forecast error sample, the sign of the coefficients of all the variables remains the same except for leverage which assumes a negative coefficient albeit insignificant. The interaction term (EARNINGS*IFRS9) which is the main variable of interest is negative and significant, suggesting that IFRS 9 adoption is associated with a decrease in analysts' earnings forecast error and thereby an improvement in the accuracy of earnings forecast by analysts. Thus after controlling for performance volatility, year-fixed effects and country-fixed effects, we document consistent evidence of an improvement in earnings forecast accuracy by analysts following the enforcement of IFRS 9. Turning to the dispersion sample, though IFRS9 variable which was negative but not significant in the earlier regression becomes significant. Nevertheless, the main variable of interest EARNINGS*IFRS9 is negative but not significant as documented in the earlier results. Consistent with the initial findings, we therefore, do not document strong evidence of a decrease in dispersion among analysts' earnings forecasts.

Table 8: Regression results including standard deviation

	Forecast error	Forecast dispersion
PASTEARN	-0.0009*	-0.0003
	(0.0005)	(0.0002)
ANAF	-0.0037*	0.0118***
	(0.0020)	(0.0012)
CAR	0.0168	-0.0126
	(0.0409)	(0.0114)
SIZE	0.0095	-0.0010
	(0.0090)	(0.0025)
LEV	-0.0041	-0.0050
	(0.0381)	(0.0124)
PROFIT	-0.0733***	-0.0279
	(0.0137)	(0.0068)
IFRS9	-0.0073	-0.0066*
	(0.0106)	(0.0038)
COVID	0.0004	0.0059*
	(0.0076)	(0.0030)
SD	0.1427**	0.0059
	(0.0657)	(0.0325)
PASTEARN*IFRS9	-0.0008*	-0.0003
	(0.0005)	(0.0002)
Intercept	0.0178	0.0490*
	(0.0915)	(0.0277)
Obs	1634	1636
F-statistic	3.35***	7.64***
Adjusted R^2	9.87%	26.89%
Year Fixed Effect	Yes	Yes
Country Fixed Effect	Yes	Yes

AFE is the absolute forecast error (Actual Earnings-Consensus Mean Forecast/Stock $Price_{t-1}$); DISPERSION: the absolute value of the difference between the highest forecast and the lowest forecast deflated by the stock price at the end of December of the year preceding the forecasted year. PASTEARN: lagged earnings per share; ANAF: the natural logarithm of the number of analysts following the firm; CAR is capital adequacy ratio calculated as (Total equity/ Total assets); SIZE: the natural logarithm of total assets; LEV is leverage calculated as (Total debt/Total asset); PROFIT: an indicator variable denoted by 1 for profit-making firms and 0 for loss-making firms; IFRS9; an indicator variable taking the value of 1 post-IFRS 9 adoption and 0 otherwise; COVID; a dummy variable corresponding to 1 during the period of the Covid-19 crisis and 0 otherwise; SD: standard deviation of return on equity; PASTEARN*IFRS9: Interaction of lagged earnings with IFRS 9. *, ** and *** denote significance at 10%, 5% and 1% respectively. Robust standard errors are shown in parenthesis.

5. Conclusion

This study draws on the mandatory enforcement of IFRS 9 (Financial Instruments) in European countries to investigate the impact of IFRS 9 adoption on earnings quality as reflected in the characteristics of financial analysts' forecasts, in particular, their earnings forecast accuracy. While recently, there has been a growing stream of empirical literature examining various financial accounting outcomes following the enforcement of IFRS 9 in IFRS compliant nations globally, we believe to the best of our knowledge that this is one of the first to study how IFRS 9 enforcement affects the earnings forecast accuracy of financial analysts who represent a sophisticated and a key user group of financial information. Employing fixed effect panel regression analysis and difference in difference (diff-in-diff) technique, we find that analysts' earnings forecasts have become more accurate post-IFRS 9 enforcement. This effect persists after controlling for factors such as firm size, number of financial analysts following, past performance, firm's financial strength, performance volatility, the Covid-19 economic uncertainty as well as country and year fixed effects. Regarding analysts' forecast dispersion, though the findings reveal a decrease in dispersion among analysts surrounding the enforcement of IFRS9, nevertheless, it is not significant. Thus, we do not document strong evidence of a decrease in analysts' forecast dispersion post-IFRS 9 enforcement.

Prior empirical studies on IFRS 9 adoption are mostly focused on examining the impact of IFRS 9 enforcement from creditors' and investors' perspectives. Different from these studies, we focus on financial analysts, important and primary users of financial information. Therefore, while the nascent stream of literature surrounding IFRS 9 adoption has documented various outcomes such as implications on banks' credit risk, earnings management and relevance to the stock markets, the implications of IFRS 9 enforcement on the earnings forecast accuracy of analysts remains unknown. Accordingly, this study makes a general contribution to the literature on IFRS adoption and specifically extends the nascent body of literature on IFRS 9 adoption by assessing analysts' earnings forecast accuracy in the context of IFRS 9 enforcement. The findings of this study are of fundamental interest to the current discussion on the economic consequences of IFRS 9 enforcement. Although it seems that IFRS 9 to some extent addresses some of the flaws of the previous accounting standard (IAS 39), it is nevertheless bereft of its weakness given its inherent flexibility and discretion. Thus the debate about the quality and economic usefulness of IFRS 9 continues. We believe that our study will be of interest to accounting academics, international standard setters, regulators and practitioners in countries that have implemented IFRS 9 or are in the process of doing so.

Finally, akin to any study, there are some limitations and thus the results must be interpreted with caution. We emphasize that this research does not provide a comprehensive assessment of the cost and benefit of IFRS 9 enforcement. While the study suggests that the enforcement of IFRS 9 has some informational benefits considering the improvement in analysts' decision-making regarding their forecast accuracy, the study does not access the cost implications of IFRS 9. Accordingly, the study is silent on whether these benefits outweigh the costs of IFRS 9 enforcement and must be interpreted as such.

References

Anglin, P., Cui, J., Gao, Y., & Zhang, L. (2021). Analyst Forecasts during the COVID-19 Pandemic: Evidence from REITs. *Journal of Risk and Financial Management*, *14*(10), 457.

Ashbaugh, H., & Pincus, M. (2001). Domestic Accounting Standards, International Accounting Standards, and the Predictability of Earnings. Journal of Accounting Research, 417-434.

Bae, K. H., Tan, H., & Welker, M. (2008). International GAAP differences: The impact on foreign analysts. *The Accounting Review*, *83*(3), 593-628.

Barker, R., & Imam, S. (2008). Analysts' perceptions of 'earnings quality'. Accounting and Business Research, 38(4), 313-329.

Barniv, R. R., Myring, M., & Westfall, T. (2022). Does IFRS experience improve analyst performance?. *Journal of International Accounting, Auditing and Taxation*, *46*, 100443.

Barron, O. E., Byard, D., & Kim, O. (2002). Changes in analysts' information around earnings announcements. The Accounting Review, 77(4), 821-846.

Basel Committee of Banking Supervision (BCBS) (2009). Guiding principles for the replacement of IAS 39.

Beaver, W. (1998). Financial Reporting: An Accounting Revolution, 3rd ed., Prentice-Hall, Upper Saddle River, NJ.

Bilinski, P. (2021). Analyst information intermediation during the COVID-19 pandemic. *Available at SSRN 3807974*.

Byard, D., Li, Y., & Yu, Y. (2011). The effect of mandatory IFRS adoption on financial analysts' information environment. *Journal of accounting research*, *49*(1), 69-96.

Byard, D., & Shaw, K. W. (2003). Corporate Disclosure Quality and Properties of Analysts' Information Environment. Journal of Accounting, Auditing & Finance, 18(3).

Capstaff, J., Paudyal, K., & Rees, W. (1995). The accuracy and rationality of earnings forecasts by UK analysts. Journal of Business Finance & Accounting, 22(1), 67-85.

Cheong, C. S., Kim, S., & Zurbruegg, R. (2010). The impact of IFRS on financial analysts' forecast accuracy in the Asia-Pacific region: The case of Australia, Hong Kong and New Zealand. *Pacific accounting review*.

Choi, Y. S., Peasnell, K., & Toniato, J. (2013). Has the IASB been successful in making accounting earnings more useful for prediction and valuation? UK evidence. *Journal of Business Finance & Accounting*, *40*(7-8), 741-768.

Collins, D. W., Pincus, M., & Xie, H. (1999). Equity valuation and negative earnings: The role of book value of equity. *The Accounting Review*, *74*(1), 29-61.

Cotter, J., Tarca, A., & Wee, M. (2012). IFRS adoption and analysts' earnings forecasts: Australian evidence. *Accounting & Finance*, *52*(2), 395-419.

Daske, H., Hail, L., Leuz, C., & Verdi, R. (2008). Mandatory IFRS reporting around the world: Early evidence on the economic consequences. Journal of accounting research, 46(5), 1085-1142.

Dechow, P., Ge, W., & Schrand, C. (2010). Understanding earnings quality: A review of the proxies, their determinants and their consequences. Journal of accounting and economics, 50(2-3), 344-401.

Dye, R. A. (1986). Proprietary and nonproprietary disclosures. Journal of Business, 331-366.

ECB (2017): SSM thematic review on IFRS 9 Assessment of institutions' preparedness for the implementation of IFRS 9.

EY (2017). Financial Instruments, A summary of IFRS 9 and its effects.

Financial Crisis Advisory Group. (2009). Report of the financial crisis advisory group.

Financial Stability Forum. (2009, April 2). Report of the financial stability forum on addressing procyclicality in the financial system.

Gaston, E., & Song, M. I. (2014). Supervisory roles in loan loss provisioning in countries implementing IFRS. International Monetary Fund.

Gebhardt, G. U., & Novotny-Farkas, Z. (2011). Mandatory IFRS adoption and accounting quality of European banks. Journal of business finance & accounting, 38(3-4), 289-333.

Givoly, D., & Lakonishok, J. (1984). The quality of analysts' forecasts of earnings. Financial Analysts Journal, 40(5), 40-47.

G20. (2009). London summit – Leader's statement 2 April 2009.

Hail, L., & Leuz, C. (2007). Capital market effects of mandatory IFRS reporting in the EU: Empirical evidence. Available at SSRN 1511671.

Hao, R., Xue, J., Yau, L. N. B., & Zhang, C. (2022). Analyst forecasting during COVID-19 pandemic. *Managerial Auditing Journal*.

Hayn, C. (1995). The information content of losses. *Journal of Accounting and Economics*, *20*(2), 125-153.

Ho, L. C. J., Liu, C. S., & Schaefer, T. F. (2007). Analysts' forecast revisions and firms' research and development expenses. Review of Quantitative Finance and Accounting, 28(3), 307-326.

Hope, O. K. (2003). Disclosure practices, enforcement of accounting standards, and analysts' forecast accuracy: An international study. Journal of accounting research, 41(2), 235-272.

Horton, J., Serafeim, G., & Serafeim, I. (2013). Does mandatory IFRS adoption improve the information environment?. Contemporary accounting research, 30(1), 388-423.

IASB (2008). International financial reporting standards. International Accounting Standards Board, London.

Jiao, T., Koning, M., Mertens, G., & Roosenboom, P. (2012). Mandatory IFRS adoption and its impact on analysts' forecasts. International review of financial analysis, 21, 56-63.

Kim, J. B., Ng, J., Wang, C., & Wu, F. (2021). The effect of the shift to an expected credit loss model on loan loss recognition timeliness. Available at SSRN 3490600.

Kong, D., Lin, Z., Wang, Y., & Xiang, J. (2021). Natural disasters and analysts' earnings forecasts. *Journal of Corporate Finance*, *66*, 101860.

Lang, M., & Lundholm, R. (1993). Cross-sectional determinants of analyst ratings of corporate disclosures. Journal of accounting research, 31(2), 246-271.

Lang, M. H., Lins, K. V., & Miller, D. P. (2003). ADRs, analysts, and accuracy: Does cross listing in the United States improve a firm's information environment and increase market value?. Journal of accounting research, 41(2), 317-345.

Lang, M. H., & Lundholm, R. (1996). Corporate Disclosure Policy and Analyst Behavior. The Accounting Review, 71(4), 467-492.

Lee, C. M., & So, E. C. (2017). Uncovering expected returns: Information in analyst coverage proxies. *Journal of Financial Economics*, *124*(2), 331-348.

López-Espinosa, G., Ormazabal, G., & Sakasai, Y. (2021). Switching from incurred to expected loan loss provisioning: Early evidence. Journal of Accounting Research, 59(3), 757-804.

Lys, T., & Soo, L. G. (1995). Analysts' forecast precision as a response to competition. *Journal of Accounting, Auditing & Finance*, *10*(4), 751-765.

Macchioni, R., Prisco, M., & Allini, A. (2021). Expected credit losses and managerial discretion: current practices and future challenges. Expected credit losses and managerial discretion: current practices and future challenges, 111-134.

Masoud, N. (2017). The effects of mandatory IFRS adoption on financial analysts' forecast: Evidence from Jordan. *Cogent Business & Management*, *4*(1), 1290331.

Mechelli, A., & Cimini, R. (2021). The effect of corporate governance and investor protection environments on the value relevance of new accounting standards: the case of IFRS 9 and IAS 39.

Oberson, R. (2021). The Credit-Risk Relevance of Loan Impairments Under IFRS 9 for CDS Pricing: Early Evidence. European Accounting Review, 30(5), 959-987.

Onali, E., & Ginesti, G. (2014). Pre-adoption market reaction to IFRS 9: A cross-country event-study. *Journal of Accounting and Public Policy*, *33*(6), 628-637.

Şabac, F., Scott, T. W., & Wier, H. A. (2005). An investigation of the value relevance of alternative foreign exchange disclosures. Contemporary Accounting Research, 22(4), 1027-1061.

Schipper, K. (1991). Analysts' forecasts. Accounting Horizons, 5, 105–121.

Tan, H., Wang, S., & Welker, M. (2011). Analyst following and forecast accuracy after mandated IFRS adoptions. *Journal of accounting research*, *49*(5), 1307-1357.

Taylor, D., & Aubert, F. (2022). IFRS-9 adoption and income smoothing nexus: A comparison of the post-adoption effects between European and Sub-Saharan African Banks. Journal of Accounting and Taxation.

Tong, H. (2007). Disclosure standards and market efficiency: Evidence from analysts' forecasts. Journal of International Economics, 72(1), 222-241.

Verrecchia, R. E. (1983). Discretionary disclosure. Journal of Accounting and Economics, 5, 179-194.

Yaghobee, Y., & Zick, T. (2019). The Value Relevance of the Expected Credit Loss Model under IFRS 9. Available at SSRN 3719414.

Appendix

Table 1: Sample distribution by country

Country	Forecast error sample	Dispersion sample
Austria	24	24
Belgium	9	9
Bulgaria	16	16
Croatia	2	2
Cyprus	8	8
Czech republic	14	14
Denmark	64	65
Estonia	2	2
Finland	22	22
France	72	72
Germany	85	86
Greece	48	48
Hungary	9	9
Iceland	3	3
Ireland	18	18
Italy	163	163
Lithuania	9	9
Macedonia	2	2
Netherlands	43	43
Norway	231	231
Poland	96	96
Portugal	14	14
Romania	28	28
Russia	44	44
Serbia	7	7
Slovenia	3	3
Spain	75	75
Sweden	65	65
Switzerland	143	143
Turkey	75	75
Ukraine	8	8
United Kingdom	249	249
Total	1651	1653