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IAS 39 Reclassification Choice and Analyst Earnings Forecast Properties

Abstract

In October 2008, the International Accounting Standards Board amended IAS 39 to allow banks to retroactively reclassify financial assets that previously were measured at fair value to amortized cost. By reclassifying financial assets, a bank can potentially avoid recognizing the unrealized fair value losses and thereby increase its income and regulatory capital during a market downturn. We examine the implications of the reclassification decision by banks for the properties of financial analyst earnings forecasts during 2008-2009, when economic conditions were highly volatile. We find that the reclassification choice during the financial crisis reduced analyst forecast accuracy and increased forecast dispersion. We also find that the observed decline in analyst forecasting ability is limited to the year of adoption when the economic environment was highly volatile.

IAS 39 Reclassification Choice and Analyst Earnings Forecast Properties

1. Introduction

Many politicians and bankers have argued that the pro-cyclicality resulting from the use of fair value accounting hastened and exacerbated the recent financial crisis. Responding to the numerous calls to reduce the use of fair value accounting (Laux and Leuz, 2009; Bischof et al., 2010), the International Accounting Standards Board (IASB), in October 2008, amended IAS 39 to allow banks to use measurements other than fair value for non-derivative financial assets if they have the ability and intention to hold such assets for the foreseeable future (IASB, 2008). This amendment gives banks the option to retroactively reclassify financial assets that previously were measured at fair value using alternative measurements, and to recognize the related reclassification gains and losses in income or in other comprehensive income. By reclassifying financial assets, a bank can avoid recognizing these unrealized fair value losses and thereby increase its income as well as its regulatory capital during a market downturn.

Given the discretion in non-derivative financial asset reporting afforded by the amendment to IAS 39, a question of interest is whether banks use this discretion to unbiasedly communicate the assessment of their ability and intention to hold such assets for the foreseeable future or to accomplish their earnings and capital management objectives. If banks faithfully communicate such information, then reclassification of their non-derivative financial assets following the amendment should benefit users of financial statements in assessing the future performance of banks. Alternatively, if banks distort this information to accomplish other objectives (such as capital or earnings management), then the reclassification of financial assets adds noise to the information available to users of financial statements.

In this study, we focus on the implications of the amendment to IASB 39 for one important group of financial statement users, namely financial analysts, because financial analysts play an important role as information intermediaries in the capital market. By collecting and analyzing information, financial analysts reduce information asymmetry (Healy and Palepu, 2001) and improve market efficiency (Barth and Hutton, 2004). We examine how the reclassification choice permitted under the new accounting rule affects the ability of analysts to forecast earnings in a period of high economic volatility. Whereas the information advantage possessed by analysts allows them to make superior forecasts (Brown et al., 1987), their success is constrained by the quality of the data they use and the level of future uncertainty (Graham and Dodd, 2008).

In an information environment with heightened uncertainty, such as during the financial crisis, it is unclear ex-ante whether the information uncertainty associated with the decision to reclassify financial instruments increases the complexity of analysts' forecasting task, or whether financial analysts can use their information advantage and superior forecasting ability to maintain the quality of their forecasts. Using a sample of international (UK, Continental European, Australian, Asian and Middle Eastern/African) banks, we contribute to the literature by investigating whether the decisions by banks that reclassify their non-derivative financial assets following the amendment to IAS 39 aid or impede financial analysts in forecasting earnings.

Specifically, we investigate whether analyst forecast properties (forecast accuracy and forecast dispersion) are systematically related to the reclassification choice when analysts issue forecasts of one-year-ahead earnings following the release of the actual earnings impacted by the reclassification. Because the IAS 39 reclassification choice is an endogenous choice, it is possible that the same factors driving the choice may also influence analyst forecast performance. Hence, we control for this potential endogeneity by using the Heckman two-stage procedure in our empirical analyses. Our results show that analyst forecast accuracy decreases and analyst forecast dispersion increases when analysts issue forecasts for the following year, immediately after they observe the actual earnings impacted by the reclassification. These results hold even after controlling for factors, such as firm size, forecast horizon, analyst following, and other characteristics that have been shown to affect analyst forecast properties.

In additional analysis, we investigate whether the decline in forecast accuracy and increase in dispersion persists in the post adoption year. Because financial analysts are sophisticated players in the capital market, it is ex-ante unclear whether the change in the information environment subsequent to the IAS 39 amendment continues to systematically impede their ability to forecast earnings. Our results show that, in fiscal year 2010 when the economic environment became less volatile, analyst forecast properties are not associated with the reclassification choice. This result implies that the deterioration in analysts' forecasting ability is only transitory in the year of high uncertainty when firms made the one-time election in 2008. The reclassification choice elected by firms during this period of high volatility creates difficulty for analysts in issuing earnings forecasts, but this difficulty tapers off when the economic condition improves.

Our research contributes to two streams of accounting literature: fair value accounting choice and analyst earnings forecasts. First, we extend the fair value accounting choice literature by studying how the IAS 39 reclassification choice affects a subset of financial statement users, namely financial analysts. Prior studies examine the characteristics of banks that reclassify and the factors that influence their reclassification choice (Bischof et al., 2010; Kholmy and Ernstberger, 2010; Paananen et al., 2010; Fiechter, 2010; Quali and Ricciardi, 2010). These studies largely provide evidence of earnings and capital management motivations when banks reclassify assets out of fair value accounting. Unlike those studies, we document the implications of the reclassification choice for financial analysts, an important group of financial statement users.

Second, our study contributes to the analyst forecast literature by showing how a specific accounting choice (the IAS 39 reclassification option) during a period of high economic instability can affect analyst forecast properties. Our research complements prior studies documenting that analyst forecasting ability decreases with greater economic complexities during stable economic conditions (e.g., Haw et al. (1994) in the case of mergers; Plumlee (2003) in the case of tax law changes; Ho et al. (1995) in the case of options listing). Our study differs from these prior studies in that we investigate the effects of an accounting policy change during a highly volatile economic environment on the forecasting ability of financial analysts. Our research provides valuable evidence for policy makers that the reclassification elected by banks during the financial crisis period imposed temporary difficulty to analysts when they issued forecasts.

The rest of this paper is structured as follows. We develop the hypotheses in the next section, present the research design in section three, describe the data in section four, discuss the results in section five, and present our conclusions in section six.

2. Hypotheses

IAS 39 requires banks to classify their equity and debt security assets into the following three broad categories: held for trading, available for sale, and held to maturity. Loans are classified as "held for trading" and "loans and receivables". Held-for-trading loans and securities are recorded at fair value and changes in fair value recognized each period in income. Available-for-sale securities are also fair valued; however, changes in fair values are not recognized in income but, instead, are recorded directly in shareholders' equity through 'other comprehensive income'. Held-to-maturity securities and loans and receivables are accounted for on an amortised cost and accrual basis (IASC, 2009).

In 2005, banks were given the option to fair value specific financial assets and liabilities (such as available-for-sale assets and repos) on an instrument-by-instrument basis to eliminate accounting mismatches and to reduce earnings volatility. Although the effective date for the fair value option was 2006, banks were given the choice to early adopt in 2005 (IASB, 2004). Consistent with the underlying intention of the fair value option, Fiechter (2011) finds banks that stated explicitly that they elected the fair value option to reduce accounting mismatches experienced a reduction in earnings volatility relative to banks that did not explicitly state their intent.

Other studies propose and test motivations other than efficiency improvement for choosing the fair value option for financial securities. For example, using a US bank sample, Song (2008), Henry (2009) and Chang et al. (2011) find that early adopters of the fair value option do so to manage earnings. Guthrie et al. (2011) find similar results for a sample of early adopting international banks.

Many bank regulators, bank managers, and politicians blame fair value accounting for having accelerated the recent financial crisis (e.g., Financial Stability Forum, 2009). In response to the excessive pressure and in light of the difficult economic climate, the IASB introduced an amendment to IAS 39. This amendment allows banks to reclassify financial assets (other than those elected under the fair value option) out of fair value if they have the intention and ability to hold these assets. Three possible reclassifications are allowed: (i) from "held for trading" to "available for sale", (ii) from "held for trading" to "held to maturity" or "loans and receivables", and (iii) from "available for sale" to "held to maturity" or "loans and receivables". Prior to the IAS 39 amendment in 2008, there were stringent criteria that had to be met for reclassification (IASB, 2008).

Recent research has investigated the underlying motivations for reclassifying some financial assets. For example, Fiechter (2010), Kholmy and Ernstberger (2010) and Bischof et al. (2010) document that reclassifying banks avoided substantial fair value losses, and reported an increase in profitability and higher regulatory capital, after the reclassification. Similarly, Paananen et al. (2010; 2011) find that banks with more exposures to fair value measurement are more likely to reclassify due to either liquidity or capital concerns. Broadly speaking, these studies suggest that banks' reclassification choice is related to earnings or capital management motivations.

Our study builds on these prior studies on fair value accounting choice by examining how the fair value accounting choice affects the forecasting ability of financial analysts. Financial analysts play a prominent role as information intermediaries in the securities market (Schipper, 1991). The incentives of analysts to make accurate earnings forecasts are well established in the literature. Analysts with greater earnings forecast accuracy are more likely to be ranked in *Institutional Investor* (Stickel, 1992; Jackson, 2005), less likely to be fired (Mikhail et al., 1999), and more likely to be promoted (Hong et al., 2000). To the extent that financial analysts are more sophisticated, have greater ability and aptitude to process relevant information and assess the fundamentals of the banks they follow, the reclassification decision by banks during a period of volatile economic environment should not severely impede their earnings forecasting ability.

However, it is also well known that analysts' ability to make accurate earnings forecasts is lower in an environment of high uncertainty. Analyst forecast properties have been studied in a number of contexts that increase forecasting complexity, including mergers (Haw et al., 1994), changes in tax law (Plumlee, 2003), options listing (Ho et al., 1995), insider trading (Lustgarten and Mande, 1998), and equity offerings (Das et al., 2006; Lin and McNichols, 1998). The general finding of these studies is that analyst forecast accuracy decreases as forecasting complexity increases.

On the one hand, the application of the IAS 39 amendment rule during the financial crisis period may create difficulties and complexities which affect analysts' ability to assess a bank's true earnings performance. On the other hand, to the extent that reclassification reduces earnings volatility created by measuring assets and liabilities differently, it can improve the usefulness of financial statements,[1] which suggests that the reclassification decision should aid analysts in their forecasting efforts. We investigate whether the decision by banks to reclassify certain non-derivative financial assets under the amended IAS 39 enhanced or diminished certain properties of financial analysts' annual earnings forecasts. Ex-ante, it is unclear how the reclassification choice would affect analyst forecast accuracy in the financial crisis period, hence we state our first hypothesis in null form as:

H1: The reclassification choice by banks is not related to analyst earnings forecast accuracy during the financial crisis period.

[1] Consistent with this argument, Fiechter (2011) finds banks that chose the fair value option under IAS 39 have lower accounting mismatches and exhibit lower earnings volatility than banks that did not choose this option. The accounting rules excluding the fair value option create potential accounting mismatches between assets and liabilities. An asset may be marked-to-market while the liability funding the asset is accounted for at historical cost. In this scenario, the fair value option allows a bank to elect the liability for fair valuation so as to eliminate accounting mismatches between the asset and liability. Thus the fair value option, by its nature, is used to reduce accounting mismatches and to reduce earnings volatility which is likely to be greater during the crisis period because the differences between fair value and historical cost accounting earnings are likely to be larger.

Earnings forecast dispersion shows the extent to which analysts disagree on a firm's future earnings potential. This disagreement arises due to uncertainties about the information environment (Imhoff and Lobo, 1992) and the lack of objective information that analysts can use to arrive at a consensus on a firm's earnings performance (Herrmann and Thomas, 2005). The different accounting treatments of reclassifications among the different categories of "held for trading", "available for sale", "held to maturity", and "loans and receivables", may create uncertainties among analysts on the scale of adjustments they should make to their earnings forecasts, especially in a period of volatile economic environment. Ex-ante, for reasons stated above, it is unclear how the reclassification choice during the crisis period would affect the dispersion of analyst forecasts. Hence, we state the second hypothesis in null form as:

> **H2:** The reclassification choice by banks is not related to analyst earnings forecast dispersion during the financial crisis period.

3. Research design

3.1. Analyst forecast properties

Following prior studies (e.g., Lang and Lundholm, 1996; Behn et al., 2008), we measure analyst forecast accuracy as follows:

$$Accy_t = (-1)\frac{|Forecast_t^{t-1} - Eps_t|}{\mathrm{Price}_{t-1}}$$

where $Accy_t$ denotes forecast accuracy, $Forecast_t^{t-1}$ refers to mean forecast of period t earnings made during the period starting three months after the prior year (t-1) actual earnings announcement date, Eps_t refers to earnings per share in time t, and $Price_{t-1}$ is share price at the end of the prior fiscal year.[2] We compute forecast accuracy for fiscal year 2009, after the release of actual 2008 earnings, which incorporate the effects of the reclassifications, but before release of 2009 actual earnings. Thus, our measure of forecast accuracy reflects the extent to which the assessment of a bank's 2009 economic performance is affected by the reclassifications in its 2008 earnings.

We measure analyst forecast dispersion as follows:

$$Disp_t = \frac{Std(Forecast_t)}{Price_{t-1}}$$

where $Disp_t$ denotes forecast dispersion and $Std(Forecast_t)$ refers to the standard deviation of analyst earnings forecasts at time t. Similar to forecast accuracy, forecast dispersion is calculated for fiscal year 2009.

3.2. Models for testing hypotheses

We estimate the following regression to test the association between reclassification choice and analyst forecast accuracy:

$$\begin{aligned} Accy &= \alpha_0 + \alpha_1 IASamend + \alpha_2 Size + \alpha_3 Surprise + \alpha_4 Loss + \alpha_5 Nana \\ &+ \alpha_6 Fin\_stability + \alpha_7 Horizon + \alpha_8 Stdroe + \alpha_9 Eps + \alpha_{10} Comlaw + \alpha_{11} Disc + \varepsilon \end{aligned} \tag{1}$$

where

Accy	=	forecast accuracy;
IASamend	=	indicator variable that equals one if the bank reclassifies its financial assets, and zero otherwise;
Size	=	natural logarithm of equity market value;
Surprise	=	current year's earnings minus prior year's earnings deflated by stock price;
Loss	=	indicator variable that equals one if earnings are negative, and zero otherwise;
Nana	=	natural logarithm of the number of analysts following the bank;

[2] To clarify, consider a bank with fiscal year-end in December 2008 and whose actual earnings were released in March 2009. If the analyst following the bank issues the first forecast for 2009 earnings within the three months after March 2009, we use that forecast to compute forecast accuracy. To be consistent with the EPS forecast measure, we use actual earnings from the I/B/E/S Detail file.

Fin_stability	=	natural logarithm of (ROA+CAR)/σ(ROA), where ROA is earnings divided by assets, CAR is capital-asset ratio, and σ(ROA) is standard deviation of ROA. ROA and capital-asset ratio are calculated as the mean over 2003–2007, and σ(ROA) is the standard deviation of ROA estimated over the same period. Higher *Fin_stability* implies greater financial stability;
Horizon	=	natural logarithm of the mean forecast horizon;
Stdroe	=	standard deviation of earnings over 2003 to 2007;
Eps	=	earnings per share;
Comlaw	=	indicator variable that equals one if the legal origin is common law, and zero otherwise (La Porta et al., 1998). The common law countries include Australia, Hong Kong, Ireland, Singapore, South Africa, and UK; the rest are code law countries;
Disc	=	Disclosure index reported in La Porta et al. (2006), which is based on questionnaire surveys of lawyers in 49 countries on the securities laws applicable to an offering of shares listed in each country's largest stock exchange in December 2000.

Our main variable of interest is *IASamend*, an indicator variable that equals 1 if the bank reclassifies its financial assets, and 0 otherwise. To the extent that the reclassification decision reduces the predictability of earnings, we expect to observe lower forecast accuracy, suggesting that the coefficient on *IASamend* should be negative. On the other hand, if the reclassification eliminates accounting mismatches, resulting in lower earnings volatility (Fiechter, 2011), we expect to observe higher forecast accuracy, suggesting that the coefficient on *IASamend* should be positive.

We winsorize all continuous variables (except log-transformed variables) at the 1% and 99% levels to remove the effect of extreme values. We estimate equation (1) with country-clustered standard errors to correct for cross-sectional dependence (Petersen, 2009). We control for other factors that have been shown to affect analyst forecast accuracy in prior studies. Following Lang and Lundholm (1996), we control for firm size (*Size*), analyst coverage (*Nana*) and earnings surprise (*Surprise*). Lang and Lundholm (1996) find a positive relation between size and analyst forecast accuracy for industrial firms. However, in the context of the current study, larger banks have more complex business operations, which make analyst forecasting less accurate. Consistent with Lang and Lundholm (1996), we expect wider analyst coverage to improve forecast accuracy and larger earnings surprise to reduce forecast accuracy.

We also control for earnings volatility (*Stdroe*) and accounting losses (*Loss*) because it is more difficult for analysts to forecast earnings of firms with a relatively larger change in earnings and with a loss (Lang and Lundholm, 1996; Hwang et al., 1996). We include the log of the number of days between the announcement of the consensus forecast and the announcement of actual earnings *(Horizon)* to control for the tendency for earnings forecasts to become more accurate as the earnings announcement date approaches (Clement, 1999; Brown et al., 1999). As in Behn et al. (2008), we control for financial stability of banks (*Fin_stability*) because financially stable firms tend to have more accurate forecasts.[3] We include earnings per share (*Eps*) in the regression model because Eames and Glover (2003) report that earnings level is related to forecast accuracy. We also control for legal origin since Chang et al. (2000) and Barniv et al. (2005) find that analyst forecasts are more accurate in common-law countries than in code-law countries. Common law countries generally have more effective corporate governance mechanisms, including stronger investor protection laws and inputs provided through higher-quality financial reporting systems. Lastly, we control for disclosure transparency (*Disc*) because Hope (2003) finds that analyst forecasts are more accurate in countries with higher accounting disclosure quality and stronger enforcement of accounting standards.

[3] Behn et al. (2008) include the financial distress measure from Zmijewski (1984). We replace this measure with the *Fin_stability* measure from Laeven and Levine (2009), which is a bank-specific measure of financial solvency. *Fin_stability* is calculated as the natural logarithm of return on assets (ROA) plus capital asset ratio (CAR)) divided by the standard deviation of return on assets (σ(ROA)). *Fin_stability* is the inverse of the probability of insolvency, with a higher score indicating lower probability of the bank going insolvent and greater bank stability (Laeven and Levine, 2009).

We estimate the following regression to test the association between reclassification choice and analyst forecast dispersion (*Disp*):

$$\begin{aligned} Disp &= \alpha_0 + \alpha_1 IASamend + \alpha_2 Size + \alpha_3 Surprise + \alpha_4 Fin\_stability + \alpha_5 Horizon \\ &+ \alpha_6 Stdroe + \alpha_7 Comlaw + \alpha_8 Disc + \varepsilon \end{aligned} \tag{2}$$

To the extent that the reclassification decision by banks increases the complexity of the forecasting task for financial analysts, we expect to observe higher dispersion of earnings forecasts for banks that reclassify relative to banks that do not reclassify financial assets, i.e., we expect a positive coefficient on *IASamend*. On the other hand, if the reclassification decision decreases the complexity of the forecasting task for financial analysts, we expect a negative coefficient on *IASamend*.

We estimate equation (2) with country-clustered standard errors to correct for cross-sectional dependence (Petersen, 2009). We include the same set of controls as in equation (1), with the exception of *Loss*, *Nana* and *Eps*, because the influence of these three variables on forecast dispersion lacks theoretical foundation (Behn et al., 2008).

3.3. Endogeneity between reclassification choice and analyst forecast properties

Given that the IAS 39 reclassification choice is an endogenous choice, it is possible that the same factors driving the choice may also influence analyst forecast performance. We use the Heckman two-stage procedure to control for this potential endogeneity in the IAS 39 amendment choice. We model the IAS 39 amendment choice in the first stage equation, drawing on prior research to identify the variables likely to influence the reclassification choice (Kholmy and Ernstberger, 2010; Quali and Ricciardi, 2010; Paananen, 2011). These variables include market-to-book ratio (*MTB*), leverage (*Lev*), size (*Size*), earnings per share (*Eps*), and a common law indicator (*Comlaw*). We add *Fin_stability* as the risk of bank insolvency is likely related to the reclassification choice. Lastly, we include disclosure quality index (*Disc*) to account for differences in disclosure quality across countries in our international bank sample.[4] Based on the prior literature, we expect positive coefficients on *Lev*, *Size* and *Loss* and a negative coefficient on *Eps*. Large banks, banks with higher leverage, and less profitable banks are more likely to opt for the reclassification choice to minimize the impact on their financial condition. We estimate the following selection model:

$$\begin{aligned} IASamend &= \alpha_0 + \alpha_1 MTB + \alpha_2 Lev + \alpha_3 Size + \alpha_4 Loss + \alpha_5 Fin\_stability \\ &+ \alpha_6 Eps + \alpha_7 Comlaw + \alpha_8 Disc + \varepsilon \end{aligned} \tag{3}$$

In the second stage, we re-estimate equations (1) and (2) after including the inverse Mills ratio from the first stage selection model.

4. Data and sample

We begin with the 478 banks from Bankscope that apply IFRS, since our study focuses on the accounting choice in IAS 39.[5] We obtain market data (i.e., market capitalization and stock prices) from Datastream. We obtain financial data (i.e., shareholder's equity, total assets, earnings per share and return on equity) either from Bankscope or, by hand-collection, from annual reports to calculate *Lev*, *Fin_stability* and *Stdroe*. We exclude banks with missing market and financial data (for example, because English versions of the annual reports are unavailable for a few European banks). We read the remaining bank annual reports to determine if a bank reclassified its financial assets under the 2008 IAS 39 amendment rule. When we apply these

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[4] We exclude the variables *MTB* and *Lev* that are used in the first stage selection model, from the second stage regression. Because these two variables are typically not used in the model with analyst forecast accuracy and dispersion as the dependent variable, there is no compelling reason to believe that they are related to analyst forecast properties. As suggested by Lennox et al. (2012), we perform sensitivity analyses on our first-stage selection model, with either *MTB* or *Lev* as the exclusion variable. The results are qualitatively similar.

[5] These countries include Australia, Austria, Bahrain, Belgium, Bermuda, Bulgaria, Croatia, Cyprus, Czech, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, Hungary, Ireland, Italy, Jordan, Kuwait, Lebanon, Liechtenstein, Luxembourg, Malta, Morocco, Oman, Netherlands, Norway, Peru, Poland, Portugal, Qatar, Romania, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Turkey, United Arab Emirates and UK.

criteria, the countries with data are limited to Australia, Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Netherlands, Norway, Singapore, South Africa, Spain, Sweden, Switzerland, Turkey and UK. The number of banks from these countries is 98.

We extract analyst forecast data from the I/B/E/S Detail files. Missing analyst forecasts, and the requirement of financial data availability for the prior five years for calculating *Fin_stability* and standard deviation of return on equity, further reduce the sample to 79 banks. Of these 79 banks, 40 chose the IAS 39 amendment and 39 did not.

5. Empirical Results

5.1. Descriptive statistics

In Table 1, we report the sample distribution and mean descriptive statistics of firm characteristics by country. Because reclassification data is not available for many banks, the number of banks in each country is relatively small, ranging from one (Cyprus, Singapore) to eight (Germany and Italy).[6] We observe considerable variation across countries in our two test variables, *Accy*, and *Disp*. Forecast accuracy is highest in South Africa, Australia and Hong Kong, and lowest in Ireland and Belgium. The dispersion of forecasts among financial analysts is greatest in Belgium, UK, and Ireland, and least in South Africa and Australia.

[Insert Table 1]

Table 2, Panel A, presents descriptive statistics for the full sample of 79 banks. The mean (median) forecast accuracy (*Accy*) is -0.034 (-0.016), indicating that the mean (median) difference between analyst forecasts and earnings is three (two)

[6] Reclassification information is not available for other Singapore banks.

percent of lagged stock price. The mean (median) forecast dispersion (*Disp*) is 0.065 (0.035).

Table 2, Panel B reports mean and median values of the variables used in the regression, for banks that chose reclassification and banks that did not, and tests of differences in means and medians across these two groups of banks. The mean and median *Accy* for the reclassified banks (*IASamend* = 1) are significantly (at the 1% level) lower than for the banks that did not reclassify (*IASamend* = 0). We also find that the mean and median forecast dispersion (*Disp*) for the reclassified banks are significantly (at the 1% level) higher than the corresponding values for the non-reclassified banks.

In terms of the control variables, we find that reclassified banks are larger in size (*Size*), have greater earnings surprise (*Surprise*), are more likely to report losses (*Loss*), and are more closely followed by analysts (*Nana*). These significant differences suggest that controlling for these bank characteristics is important in our multivariate analysis.

[Insert Table 2]

We report Pearson correlations between the dependent, independent and control variables in Table 3. Forecast accuracy (*Accy*) and forecast dispersion (*Disp*) have a strong negative correlation of -0.61, showing that the average earnings forecast is less accurate when analysts have lower consensus on a bank's earnings. The negative (positive) correlations between *IASamend* and *Accy* (*Disp*) indicate that analyst forecasts are less accurate and have wider dispersion when banks choose to reclassify under the IAS 39 amendment option. Analyst forecasts are also less accurate and have wider dispersion when earnings surprise is larger and when banks incur losses as indicated by the negative (positive) correlation between *Surprise*, *Loss* and *Accy* (*Disp*).

[Insert Table 3]

5.2. IAS 39 amendment choice and analyst forecast accuracy/dispersion

We report the results for the first-stage selection model in table 4. The exclusion variables *MTB* and *Lev* are statistically significant. The results indicate that low growth banks and high leverage banks are more likely to have reclassified out of fair value. The coefficient on *Size* is positive and significant, suggesting that larger banks are more likely to reclassify. These results are largely consistent with prior literature. For example, Kholmy and Ernstberger (2010) report a significant negative coefficient on *MTB* and a positive coefficient on *Size*, and Paananen (2011) finds that the coefficient on the capital adequacy ratio (an inverse measure of leverage) is negative and significant. However, we find that the coefficients on *Loss* and *Eps* are statistically insignificant, similar to the findings in Paananen (2011). We include the inverse Mills ratio (*IMR*) from the selection model in the second-stage regression model.

[Insert Table 4]

The main multivariate results are shown in Tables 5 and 6. Table 5 presents forecast accuracy results for banks that opted to reclassify financial assets versus banks that did not opt for reclassification. In Model 1, we report the coefficients of our main variable, *IASamend*, and of the bank-level controls, but without including *IMR* as an additional independent variable. The coefficient on *IASamend* is negative and statistically significant at 5%, indicating that analyst forecasts are less accurate when banks reclassify assets from trading to available-for-sale/held-to-maturity or from available-for-sale to held-to-maturity categories under the IAS 39 amendment option. We next examine the economic size of the coefficient on *IASamend*. Banks that reclassify financial assets, compared to banks that do not, experience lower forecast accuracy of about 2.5% of lagged stock price. This reduction in forecast accuracy is non-trivial as it represents about 74% of the mean forecast accuracy (0.034) for the sample banks.

In Model 2, we include the *IMR* computed from the first-stage selection model as an additional independent variable. The coefficient on *IMR* is positive and significant, suggesting potential endogeneity between reclassification choice and analyst forecast accuracy.[7] Nevertheless, even after controlling for the potential endogeneity, the coefficient on *IASamend* is still negative and statistically significant at 10%.[8] Overall, the results reported in Table 5 are consistent with the view that the reclassification decision reduces the predictability of earnings, and hence weakens the ability of analysts to forecast accurately. The evidence suggests that forecast accuracy is lower for banks that reclassified their financial assets compared to banks that did not.

For the control variables, the coefficient on *Loss* is negative and significant while the coefficient on *Nana* is positive and significant, indicating that it is relatively more difficult for analysts to forecast loss-making banks and that more analyst coverage tends to improve forecast accuracy. These results are consistent with prior studies (e.g., Lang and Lundholm, 1996). For the country-level controls, consistent

[7] As suggested by Lennox et al. (2012), multicollinearity can arise even when the exclusion variables are valid. We therefore conduct diagnostic tests for multicollinearity and report the findings here. In Model 1, the variance inflation factor (VIF) for *IASamend* is 1.59. In Model 2, the VIFs for *IASamend* and *IMR* are 1.63 and 1.72, respectively. Overall, there is no strong evidence that multicollinearity is driving the results.

[8] The economic size of the coefficient on *IASamend* is non-trivial. The reduction in forecast accuracy for banks that reclassified compared to banks that did not is about 65% of the mean forecast accuracy (0.034) for the sample banks.

with prior studies (e.g., Chang et al., 2000; Barniv et al., 2005), the coefficient on *Comlaw* is positive, although it is statistically insignificant. The coefficient on *Disc* is positive and significant at 5% level, indicating that analyst forecasts are more accurate when the information environment in the country is richer. This result is consistent with the finding of Hope (2003).

[Insert Table 5]

We report the results for the relation between banks' reclassification choice and analyst forecast dispersion in Table 6. The key results largely mirror those of Table 5. The coefficient estimate on *IASamend* is positive and statistically significant at 5% in both Model 1 and Model 2 (i.e., without and with the inclusion of *IMR* as an additional independent variable in the regression model). The economic size of the coefficient on *IASamend* is non-trivial in both models. In Model 1, the forecast dispersion for banks that reclassify financial assets, compared to banks that do not reclassify, is larger by about 4.9% of lagged stock price. This larger dispersion represents about 75% of the mean forecast dispersion (0.065) for the sample banks. In Model 2, the larger dispersion represents about 65% of the mean forecast dispersion for the sample banks.[9]

Overall, the results reported in Table 6 show that analyst forecast dispersion is wider for banks that opted to reclassify under the IAS 39 amendment choice. The evidence is consistent with the view that the reclassification of non-derivatives impedes analyst forecasting ability.

[Insert Table 6]

[9] As before, we conduct diagnostic tests for multicollinearity. In model 1, the Variance-Inflation-Factor (VIF) for *IASamend* is 1.43. In model 2, VIFs for *IASamend* and *IMR* are 1.52 and 1.63, respectively. We thus conclude that multicollinearity is unlikely to drive our main results.

5.3. Sensitivity analysis

We perform several robustness checks and discuss the un-tabulated results in this section. In our first robustness check, we use an alternative measure to capture the effects of reclassification on financial statements. This measure, which we denote as *IAS39amount*, is the amount of financial assets reclassified from trading to AFS and from AFS to held-to-maturity, scaled by total assets. The overall results, although weaker, are largely consistent with the results in tables 5 and 6. In the forecast accuracy test, the coefficient on *IAS39amount* is negative and significant at the 1% level (two-tailed), suggesting that forecast accuracy decreases as the reclassified amount increases, consistent with the results reported in Table 5. In the forecast dispersion test, the coefficient on *IAS39amount* is positive, consistent with the results in Table 6, and indicates that forecast dispersion is larger for banks that reclassified a larger amount. However, unlike the results for *IAS39amend* in Table 6, the coefficient on *IAS39amount* is not statistically significant.

In our second robustness check, we repeat the same analysis for the post-adoption period, 2010. Our results show that, in the fiscal year 2010, both analyst forecast accuracy and dispersion are not significantly associated with reclassification choice. This finding is perhaps not surprising as the economic environment in the year 2010 is less volatile than in 2009, and indicates that the forecasting ability of analysts improves as the environment becomes more stable.[10]

In our main analysis, we compute forecast accuracy (and dispersion) for 2009, immediately after the release of actual 2008 earnings, which incorporate the

[10] Another reason that may partially explain the improvement in the analyst forecasting ability in 2010 relative to 2009 is that, in 2008, some assets were reclassified from trading to available-for-sale. Fair value changes of these assets were reclassified as Other Comprehensive Income (OCI), which are typically not used as inputs by analysts in making forecasts. In the subsequent year when economic conditions improve, these assets were sold and the fair value changes have been transferred from OCI to earnings, which will be used by analysts to make earnings forecasts.

effects of the reclassifications. Our third robustness check is to measure accuracy using the latest forecasts issued before the release of 2009 actual earnings to test our prediction. The results show that our inferences remain unchanged although the results are statistically weaker. The coefficients on *IAS39amend* for the forecast accuracy and forecast dispersion tests are both significant at 10% level (two-tailed), with *IMR* as an additional independent variable in the regression models.[11]

6. Conclusion

Our study examines how the choice by banks to use measurements other than fair value to reclassify non-derivative financial assets permitted under the amendment to IAS 39, affects the properties of financial analysts' earnings forecasts. We find that the reclassification choice reduced analyst earnings forecast accuracy and increased forecast dispersion one year following the reclassification. These results are robust to controlling for factors, such as firm size, forecast horizon, analyst following, and other characteristics that have been shown to affect analyst forecast properties, and also to controlling for the potential endogeneity in the IAS 39 amendment decision by banks. We also find the observed decline in analyst forecasting ability is limited to the year of adoption when the economic environment was highly volatile.

One interpretation of this evidence is that the reclassification reduces the ability of financial analysts to predict earnings during a period of heightened uncertainty induced by the financial crisis. However, as the economic conditions in the subsequent period improve, analysts understand and incorporate the reporting changes due to the IAS amendment rule in their earnings forecasts. This interpretation

[11] The coefficients (t-values) on *IAS39amend* for the forecast accuracy and forecast dispersion tests are -0.0155 (-1.79) and 0.0100 (1.86) respectively.

is supported by our finding that the deterioration in analyst forecasts is observed only in the first year of adoption when the banking sector was highly volatile, but not in the post-adoption year.

We recommend caution in interpreting the results of our study, because the relatively small sample size used limits the generalizability. Notwithstanding this caveat, the effects of the reclassification choice on earnings predictability by financial analysts provide interesting insights to regulators around the world in assessing the costs and benefits of the amendment to IAS 39. We document that the negative effect of the amendment rule on analyst behaviour is transitory and represents a one-time shock to analysts' forecasting ability without a long-lasting effect.

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Table 1

Mean values of bank characteristics by country

Country	No. of banks	*Accy*	*Disp*	*Size*	*Surprise*	*Loss*	*Nana*	*Fin_stability*	*Horizon*	*Stdroe*	*Eps*	*Comlaw*	*Disc*
Australia	3	-0.002	0.006	9.854	0.012	0.000	2.962	4.446	5.324	0.022	1.907	1.000	0.750
Austria	2	-0.016	0.040	9.315	0.151	0.000	3.322	3.258	5.133	0.038	2.420	0.000	0.250
Belgium	2	-0.120	0.183	9.491	0.281	0.500	3.257	3.908	5.187	0.025	-4.828	0.000	0.420
Cyprus	1	-0.014	0.041	8.344	0.141	0.000	2.708	2.195	5.193	0.118	0.576	0.000	0.330
Denmark	5	-0.060**	0.057	7.189	0.078	0.200	1.317	3.659	4.971	0.029	1.823	0.000	0.580
Finland	2	-0.018	0.028	9.265	0.046	0.000	2.916	4.306	5.375	0.046	0.902	0.000	0.500
France	4	-0.021*	0.022	9.667	0.044	0.000	2.773	3.672	5.201	0.047	2.569	0.000	0.750
Germany	8	-0.026***	0.051	7.568	0.161	0.125	2.704	3.127	5.215	0.074	1.705	0.000	0.420
Greece	3	-0.093	0.084	8.158	0.203	0.333	2.991	3.244	5.312	0.079	-0.783	0.000	0.330
Hong Kong	4	-0.003*	0.024	8.083	0.024	0.000	2.613	4.000	5.447	0.031	0.389	1.000	0.920
Ireland	2	-0.146	0.403	7.533	0.145	1.000	2.890	2.962	5.760	0.068	-1.696	1.000	0.670
Italy	8	-0.021***	0.027	8.368	0.056	0.000	2.789	3.698	5.250	0.083	0.554	0.000	0.670
Netherlands	3	-0.016	0.060	8.409	0.211	0.000	2.868	3.380	5.106	0.079	0.681	0.000	0.500
Norway	7	-0.045**	0.058	6.796	0.119	0.000	2.069	3.309	5.202	0.041	0.745	0.000	0.580
Singapore	1	-0.016	0.017	10.128	0.034	0.000	3.091	3.559	5.318	0.030	0.630	1.000	1.000
South Africa	3	-0.000*	0.000	9.484	0.000	0.000	2.538	3.501	5.295	0.050	1.258	1.000	0.830
Spain	6	-0.028**	0.038	9.481	0.051	0.000	3.086	3.486	5.225	0.042	1.615	0.000	0.500
Sweden	2	-0.066	0.072	9.453	0.341	0.500	3.496	3.990	5.290	0.027	0.371	0.000	0.580
Switzerland	6	-0.020**	0.027	8.293	0.185	0.167	2.792	2.990	5.257	0.069	6.967	0.000	0.670
Turkey	2	-0.016	0.035	9.027	0.015	0.000	2.697	2.549	5.193	0.260	0.340	0.000	0.500
UK	5	-0.042**	0.241	9.718	0.254	0.400	3.069	3.106	5.219	0.095	10.882	1.000	0.830

This table reports mean values of bank characteristic variables by country. Comlaw and Disc are country-level variables. Definitions of the variables are as follows:

Accy	Accuracy of analysts' earnings forecasts winsorized at 1% and 99% levels
Disp	Dispersion of analysts' earnings forecasts winsorized at 1% and 99% levels
IASamend	IAS 39 amendment choice indicator that equals 1 when selected, 0 otherwise
Size	Natural logarithm of equity market value
Surprise	Change in earnings deflated by stock price winsorized at 1% and 99% levels
Loss	Loss indicator that equals 1 when the bank earnings is negative, 0 otherwise
Nana	Natural logarithm of number of analysts following the bank
Fin_stability	Natural logarithm of [(return on assets plus capital assets) divided by standard deviation of return on asset over 2003 to 2007] winsorized at 1% and 99% levels.
Horizon	Natural logarithm of mean forecast horizon for 2009 earnings
Stdroe	Standard deviation of earnings over 2003 to 2007 winsorized at 1% and 99% levels
Eps	Earnings per share winsorized at 1% and 99% levels
Comlaw	Common law indicator that equals 1 for common law countries, 0 for code law countries
Disc	Disclosure requirement in equity offerings reported in La Porta 2006

***, **, * indicate (two-tailed) significance at 1%, 5% and 10%, respectively.

Table 2
Descriptive Statistics for the pooled sample

Panel A: Full sample descriptive statistics

Variable	Mean	Std. Dev.	Min.	Max.	Median	Skewness
Accy	-0.034	0.053	-0.267	-0.000	-0.016	-2.881
Disp	0.065	0.123	0.000	0.763	0.035	4.756
IASamend	0.506	0.503	0.000	1.000	1.000	-0.025
Size	8.501	1.835	4.253	12.203	8.344	-0.106
Surprise	0.118	0.165	0.000	0.654	0.049	1.964
Loss	0.127	0.335	0.000	1.000	0.000	2.246
Nana	2.711	0.937	0.000	3.912	2.944	-1.164
Fin_stability	3.450	0.883	1.458	5.090	3.548	-0.319
Horizon	5.241	0.198	4.127	6.242	5.236	-0.600
Stdroe	0.062	0.085	0.009	0.502	0.037	3.834
Eps	1.969	7.103	-10.394	36.675	0.747	3.581
Comlaw	0.228	0.422	0.000	1.000	0.000	1.298
Disc	0.607	0.169	0.250	1.000	0.580	0.110

Panel B: Descriptive statistics IAS 39 amendment adopters and non-adopters

Variable	*Adopters* (n=40)		*Non-adopters* (n=39)		Difference	
	Mean	Median	Mean	Median	t-stat	z-stat
Accy	-0.051	-0.020	-0.017	-0.011	2.883***	2.898***
Disp	0.102	0.050	0.027	0.019	-2.820***	-4.329***
Size	9.054	9.174	7.935	7.565	-2.830***	-2.677***
Surprise	0.189	0.110	0.045	0.020	-4.293***	-4.398***
Loss	0.250	0.000	0.000	0.000	-3.560***	-3.320***
Nana	3.077	3.332	2.336	2.565	-3.807***	-4.023***
Fin_stability	3.473	3.464	3.426	3.640	-0.233	-0.103
Horizon	5.257	5.236	5.226	5.252	-0.688	0.574
Stdroe	0.056	0.034	0.068	0.042	0.637	0.780
Eps	1.122	0.603	2.837	0.859	1.074	2.182**
Comlaw	0.200	0.000	0.256	0.000	0.591	0.594
Disc	0.589	0.580	0.625	0.580	0.930	0.808

This table reports descriptive ststistics for the variables used in the regressions. Detailed definitions of the variables are provided in Table 1. ***, **, * indicate (two-tailed) significance at 1%, 5% and 10%, respectively.

Table 3
Pearson Correlation Matrix

	Accy	*Disp*	*IASamend*	*Size*	*Surprise*	*Loss*	*Nana*	*Fin_stability*	*Horizon*	*Stdroe*	*Eps*	*Comlaw*
Accy	1.00											
Disp	-0.61**	1.00										
IASamend	-0.32**	0.31**	1.00									
Size	0.09	0.07	0.31**	1.00								
Surprise	-0.30**	0.42**	0.44**	0.13	1.00							
Loss	-0.62**	0.59**	0.38**	0.06	0.40**	1.00						
Nana	0.15	0.11	0.40**	0.75**	0.24**	0.08	1.00					
Fin_stabilityy	0.27**	-0.15	0.03	0.20	-0.16	-0.24**	0.10	1.00				
Horizon	-0.24**	0.41**	0.08	0.21	0.04	0.21	0.31**	-0.02	1.00			
Stdroe	-0.13	0.04	-0.07	-0.05	0.06	0.08	0.04	-0.71**	0.03	1.00		
Eps	0.15	-0.19	-0.12	-0.07	-0.02	-0.33**	-0.12	-0.13	-0.16	0.12	1.00	
Comlaw	0.05	0.24**	-0.07	0.18	-0.07	0.16	0.08	0.09	0.34**	-0.05	0.12	1.00
Disc	0.17	0.04	-0.11	0.14	-0.16	-0.02	-0.03	0.15	0.21	-0.06	0.16	0.72**

This table reports correlations among the variables used in the regressions. Detailed definitions of the variables are provided in Table 1.
The number of observations is 79. ** indicates (two-tailed) significance at 5%.

Table 4
First stage selection model for IAS 39 amendment

Variable	Predicted Sign	Dependent Variable: IASamend	
		Coefficient	Wald-statistic
Intercept	?	-32.7353	(4.60)**
MTB	?	-2.0455	(6.35)***
Lev	+	33.4162	(4.21)**
Size	+	0.4230	(4.31)**
Loss	+	26.8731	(0.01)
Fin_stability	?	-0.1484	(0.11)
Eps	-	-0.0252	(0.13)
Comlaw	?	-0.0000	(0.00)
Disc	?	0.8338	(0.09)
Pseudo R^2		0.5870	
Obs.		79	

This table reports estimation results for the following probit model:

$$IASamend = \alpha_0 + \alpha_1 MTB + \alpha_2 Lev + \alpha_3 Size + \alpha_4 Loss + \alpha_5 Fin\_stability + \alpha_6 Eps$$
$$+ \alpha_7 Comlaw + \alpha_8 Disc + \varepsilon$$

where *MTB* is market-to-book ratio; *Lev* is leverage measured as debt divided by total assets. Each variable is winsorized at 1% and 99% levels. Other variables are as defined in Table 1. Wald chi-squares are reported in parentheses. ***, **, * indicate (two-tailed) significance at 1%, 5% and 10%, respectively.

Table 5
Association between IAS 39 amendment choice and Forecast Accuracy

Variable	Predicted Sign	Model 1		Model 2	
		Coefficient	t-statistic	Coefficient	t-statistic
Intercept	?	0.3433	(1.20)	0.3437	(1.22)
IASamend	-	-0.0246	(-2.06)**	-0.0220	(-1.94)*
Size	?	-0.0057	(-1.48)	-0.0058	(-1.72)*
Surprise	-	-0.0132	(-0.41)	-0.0129	(-0.38)
Loss	-	-0.0793	(-3.06)***	-0.0733	(-2.72)***
Nana	+	0.0300	(3.76)***	0.0344	(3.56)***
Fin_stability	+	0.0020	(0.37)	0.0035	(0.56)
Horizon	-	-0.0819	(-1.49)	-0.0863	(-1.56)
Stdroe	-	-0.0440	(-0.77)	-0.0572	(-0.87)
Eps	?	-0.0006	(-1.16)	-0.0004	(-0.86)
Comlaw	+	0.0085	(0.68)	0.0075	(0.59)
Disc	+	0.0618	(2.22)**	0.0625	(2.36)**
IMR	?			0.0028	(2.12)**
Adjusted R^2		0.5043		0.5136	
Obs.		79		79	

This table reports estimation results for the following model:

$$Accy = \alpha_0 + \alpha_1 IASamend + \alpha_2 Size + \alpha_3 Surprise + \alpha_4 Loss + \alpha_5 Nana + \alpha_6 Fin\_stability$$
$$+ \alpha_7 Horizon + \alpha_8 Stdroe + \alpha_9 Eps + \alpha_{10} Comlaw + \alpha_{11} Disc + \alpha_{12} IMR + \varepsilon$$

Detailed definitions of the variables are provided in Table 1. *IMR* is inverse Mills ratio derived from the first-stage probit regression in Table 4. t-statistics are reported in parentheses. ***, **, * indicate (two-tailed) significance at 1%, 5% and 10%, respectively.

Table 6
Association between IAS 39 amendment choice and Forecast Dispersion

Variable	Predicted Sign	Model 1		Model 2	
		Coefficient	t-statistic	Coefficient	t-statistic
Intercept	?	-1.0445	(-1.26)	-1.0469	(-1.27)
IASamend	+	0.0491	(2.21)**	0.0422	(2.14)**
Size	?	0.0012	(0.21)	0.0014	(0.26)
Surprise	-	0.2563	(1.42)	0.2495	(1.35)
Nana	+	-0.0257	(-1.63)	-0.0331	(-1.92)*
Fin_stability	+	-0.0135	(-0.95)	-0.0151	(-1.09)
Horizon	-	0.2327	(1.38)	0.2399	(1.42)
Stdroe	-	-0.0478	(-0.46)	-0.0208	(-0.20)
Comlaw	-	0.0856	(2.11)**	0.0848	(2.06)**
Disc	-	-0.1250	(-1.46)	-0.1249	(-1.48)
IMR	?			-0.0052	(-1.87)*
Adjusted R^2		0.3367		0.3380	
Obs.		79		79	

This table reports estimation results for the following model:

$$Disp = \alpha_0 + \alpha_1 IASamend + \alpha_2 Size + \alpha_3 Surprise + \alpha_4 Nana + \alpha_5 Fin\_stability + \alpha_6 Horizon$$
$$+ \alpha_7 Stdroe + \alpha_8 Comlaw + \alpha_9 Disc + \alpha_{10} IMR + \varepsilon$$

Detailed definitions of the variables are provided in Table 1. *IMR* is inverse Mills ratio derived from the first-stage probit regression in Table 4. t-statistics are reported in parentheses. ***, **, * indicate (two-tailed) significance at 1%, 5% and 10%, respectively.