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OCI information and analysts' forecast accuracy: Evidence from US commercial banks[☆]

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ABSTRACT

This study investigates whether financial analysts accurately incorporate other comprehensive income (OCI) and its components into earnings per share (EPS) forecasts. Using a sample of 200 of the US's largest commercial banks from 2011 to 2020, our findings suggest that only OCI available for sale securities (AFS) and OCI Currency exhibit a positive and significant relationship with forecast accuracy, while cash flow hedges increase forecast error. Furthermore, additional robustness tests are conducted, revealing that large OCI AFS securities enhance analysts' forecast accuracy as financial analysts have expertise in interpreting these figures. In addition, the accounting standard update (ASU 2016–01) leads to decline in forecast accuracy. Moreover, OCI debt securities negatively impact forecast accuracy. However, analysts have gained more experience and insight into forecasting cash flow hedges and foreign currency translation, compared to the challenges posed by understanding ASU 2016–01.

1. Introduction

This study explores whether other comprehensive income (OCI) and its components enhance the accuracy of analysts' earnings forecasts for commercial US banks, specifically after the adoption of the accounting standard update (ASU) 2011–05, which prohibited the disclosure of OCI items in the stockholder's equity to be reported in income statements [Financial Accounting Standards Board (FASB), 2011]. This accounting regulation attempts to improve the transparency and comparability of firms' financial statements. Furthermore, our study considers the reporting accounting update under ASU 2016–01, being effective for fiscal years beginning after December 15, 2017, that requires the recognition of changes in the fair value of equity securities in income instead of OCI statement (FASB, 2016). Since these two-accounting guidance present interesting research opportunities, our study extends prior research conducted following the Statement of Financial Accounting Standards (SFAS) 130 (FASB, 1997) to examine the impact of ASU 2011–05 and ASU 2016–01 on OCI usefulness in a recent unexplored period (2011–2020) by delving into whether financial analysts consider OCI information to issue accurate earnings forecasts.

Practically, this context is intriguing due to ongoing debates among bank regulators regarding the recommendations of Basel III for

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Tier 1 Capital, which includes more components of accumulated other comprehensive income (AOCI). Given this regulatory shift, understanding the impact of OCI on financial analysis becomes crucial. Financial analysts, who provide forecasts and recommendations, rely on comprehensive and accurate financial information to make informed decisions. The inclusion of AOCI in Tier 1 Capital under Basel III means that analysts must now consider OCI's effects when evaluating a bank's financial stability and performance (Black, 2016).

An article published in the Financial Times[1] in 2018 by a financial analyst from The Swedish Society for Financial Analysts states, *"it is quite easy to handle the impact of fair value information. Information requirements are extensive, but the effects on investment decisions are in most cases marginal. What analysts struggle with is understanding the business models of today's companies, which have become more and more complex without any help from fair value accounting.*"

Prior conclusions highlight the implications of OCI and its components on both firm performance and valuation (e.g., Dhaliwal et al., 1999; Chambers et al., 2007; Kanagaretnam et al., 2009; Dong et al., 2014; Campbell, 2015; Bratten et al., 2016; Boulland et al., 2019; Anderson et al., 2023). However, it is still unclear whether financial analysts can assess the usefulness of OCI, which is frequently regarded as a transient measure, specifically when standard-setters attempt to revise the reporting location of OCI information several times. In addition, the role of OCI in assessing firm performance is complicated because of potential differences across the four key components of OCI (Yen et al., 2007): unrealized gains and losses on available-for-sale securities (OCI AFS), foreign currency translation adjustments (OCI Currency), gains and losses on cash flow hedging (OCI Hedge), and pension-related adjustments (OCI Pension).

Critics of OCI reporting argue that OCI comprises temporary earnings and merely introduces noise into reported income (Edinger et al., 2018), thereby reducing the usefulness of income information for financial statement users. On the other hand, proponents of OCI reporting contend that it captures a firm's value creation (Veltri et al., 2018), potentially enhancing the information's usefulness related to income figures (Biddle and Choi, 2006; Edinger et al., 2018). In a recent study of Durocher et al. (2024), the authors argue that auditors recognize OCI as a crucial mechanism for maintaining the integrity of fair value accounting. They metaphorically describe OCI as a "necessary evil," and a "parking lot" for addressing fair value-related issues and anomalies.

Hereafter, this study builds on the extant literature by providing conclusions on whether financial analysts incorporate aggregate OCI and its components into their earnings forecasts. Doing so, analysts could include OCI information to increase forecast accuracy as long as it is considered as value-relevant and presented in a salient location in income statement.

We expand earlier contemporary research on non-financial firms (Anderson et al., 2023) to cover US commercial banks from 2011 to 2020 due to the significant role of OCI, specifically AFS, in these institutions (e.g., Boulland et al., 2019). Our focus on banks is motivated by several key factors, beyond the scarcity of recent literature on this specific sector. Firstly, banks are pivotal to the economic system, with their performance influencing not only stock markets but entire economies, as evidenced by the 2008 financial crisis. This impact extends to the wealth of both investors and depositors. Additionally, these banks hold a large portion of OCI AFS, which accounts for 15–18 % of banks' total assets (e.g., Laux and Leuz, 2010; Barth et al., 2017; Dong and Zhang, 2018). Dong et al. (2014) emphasize that even securities typically regarded as highly liquid can face substantial price pressures when financial institutions engage in concentrated and synchronized trading. This trend is particularly noticeable for banks at the end of accounting periods, influenced by factors like financial statement adjustments and other related activities.

Generally, Banks are closely monitored by financial analysts and face high scrutiny from stakeholders. Prior research indicates that analysts' forecasts are influenced by the information environment and uncertainty, which vary across setting (Lehavy et al., 2011). We argue that the accounting complexity of certain OCI items increases uncertainty, leading to lower forecast accuracy and more herding behaviour (Dichev and Tang, 2009). However, in a high-information environment like the US, some OCI items may be better assimilated, improving forecast accuracy.

For our empirical analysis, we used two proxies of forecast accuracy and we considered the last median consensus forecasts to identify the common forecast ability of financial analysts. To ensure the robustness of the results, we performed additional tests. First, we examined whether large AFS amounts help financial analysts issue less biased forecasts. A large amount of AFS can be a signal for managers' discretionary behaviour; hence, financial analysts may consider it to help them produce accurate forecasts. Second, we re-examined the impact of OCI information on forecast accuracy while considering ASU 2016–01.

This study makes several contributions to the literature. First, it builds on studies examining the informativeness of OCI information (e.g., Dhaliwal et al., 1999; Kanagaretnam et al., 2009; Dong et al., 2014; Campbell, 2015; Bratten et al., 2016; Anderson et al., 2023). Furthermore, our study provides evidence of the importance of reporting location of OCI items. Our findings are valuable for accounting information users because they can enhance the quality of analysts' forecasts post-ASU 2011–05. Recognizing unrealized gains and losses in income statements rather than equity statements was a good step by the FASB to increase the transparency and visibility of financial reporting.

Additionally, our study builds on prior studies that focus on financial analysts' behavior and forecast accuracy. For instance, Black and Neururer (2024) put evidence that analysts provide at least some information about future OCI in their Book value per share forecasts. Other studies have examined the associations between forecast accuracy and mandatory disclosure (Huang et al., 2022), governance mechanisms (Fredj and Gana, 2023), and herding behaviour (Choi, 2022). Regarding accounting measures, it is worth knowing how analysts react to OCI information and whether they use it as input to issue their forecasts simply because investors often rely on analysts' forecasts and recommendations to make investment decisions. Thus, these forecasts may be affected by analysts'

1 Effects of fair value are quite easy for an analyst to handle (2018): From Peter Malmqvist, Stockholm, Sweden

behaviour or predispositions toward some accounting information (the functional fixation hypothesis), which indirectly conditions the reaction of market participants to OCI and CI information. Indeed, this study allows for renewed reflections on the usefulness of OCI information.

Section 2 reviews the background and develops the hypotheses. Section 3 describes the research design. Section 4 presents descriptive statistics, and Section 5 presents the empirical results. Finally, Section 6 discusses additional sensitivity tests, and Section 7 concludes the paper.

2. Literature review

The FASB defines Comprehensive Income (CI) as "*any changes in equity during a period that bypass those arising from investments by owners and distributions to owners*." Under SFAS 130, the FASB initially required reporting CI separately in financial statements as net income (NI) and OCI (FASB, 1997). OCI information is publicly available; it is reported in annual and quarterly reports and is not included in Net income (NI) until its recognition.

This study's theoretical framework is based on the semi-strong efficient market hypothesis (Fama, 1970), which states that stock prices reflect all publicly available information. Under the efficient market hypothesis, the reporting location of the information is irrelevant. ASU 2011–05 does not suggest new fair value information but introduces a new reporting location. ASU 2011–05 changed the location of OCI from shareholder equity to income statements. Thus, under the efficient market hypothesis, financial statement users are indifferent. However, at less than full market efficiency, reporting may influence users' reactions and analysts' valuations.

Moreover, the related theoretical framework for this study is linked to fair value debate. With reference to efficient market theory, fair values are assumed to reflect market prices; therefore, prices reflect unbiased expectations about future cash flows, enhancing predictability (Milburn, 2008). Proponents of fair value accounting argue that fair value measurement provides market participants with timelier and more value-relevant information than other accounting approaches (i.e., historical cost accounting). Fair value estimates can predict future performance (e.g., Barth, 2007). Similarly, Penman (2007) postulates that fair value conveys value on the balance sheet, which in turn better reflects equity value. Furthermore, Georgiou (2018) concludes that analysts are more cautious about fair value changes and are more willing to undertake additional assessments of fair value figures to evaluate firm's performance.

In contrast, opponents of fair value contend that fair value accounting makes firms' financial information less reliable and comparable. Indeed, certain fair value measurements may result in increased earnings volatility, increased opportunities for management discretion in financial reporting (Fargher and Zhang, 2014), and increased complexity in the forecasting process, which requires the implementation of effective systems that can capture, estimate, and record fair value disclosure (PwC, 2010).

Other studies have examined the impact of CI and OCI reporting formats. Hirst and Hopkins (1998) and Maines and McDaniel (2000) find that presenting OCI separately from changes in shareholders' equity enhances transparency and reduces earnings management. Specifically, clear CI and AFS reporting helps mitigate differences in analysts' stock price judgments between firms that manage earnings and those that do not. Maines and McDaniel (2000) also argue that nonprofessional investors can better assess CI volatility when OCI is presented separately. In contrast, Chambers et al. (2007), using archival data, find that including OCI items in the statement of shareholders' equity increases their usefulness.

Moreover, the reporting location of OCI and its components helps financial analysts better recognize managers' engagement in upward earnings smoothing. Prior research suggests that banks may recognize AFS gains and losses to smooth reported earnings (Barth et al., 2017). Bamber et al. (2010b) argue that managers who use aggressive earnings management avoid more transparent OCI presentations. Hunton et al. (2006) explicitly state that managers are more likely to become involved in earnings management when OCI components are reported in the statement of changes in equity. The requirements under ASU 2011–05 prohibit the inclusion of OCI in stockholders' equity, which improves both the comparability and transparency of financial statements and reveals managers' discretion. Therefore, increased transparency may enhance forecast accuracy.

Several studies suggest that some OCI components can predict firm performance. Kanagaretnam et al. (2009) find that OCI disclosure enhances the usefulness of financial statements for Canadian firms. Bratten et al. (2016) also show that OCI, particularly AFS securities, is positively related to future profitability in bank holding companies. Boulland et al. (2019) similarly find that banks' unrealized gains and losses on AFS securities predict future earnings changes. However, other studies conclude that CI does not provide a better performance summary than NI (Barton et al., 2010; Dhaliwal et al., 1999), as OCI items tend to have low persistence in future NI (Jones and Smith, 2011) and are influenced by market conditions, making them harder to use for forecasting. Additionally, most OCI items stem from non-core activities, requiring advanced technical knowledge to interpret.

A related underlying discussion in this study is the value relevance of OCI. Conclusions regarding the value relevance of OCI are contradictory. A stream of research supports the value relevance of aggregate OCI and its components (e.g., Biddle and Choi, 2006; Chambers et al., 2007; Kanagaretnam et al., 2009; Huang et al., 2021). Other studies do not show significant evidence of the value relevance of OCI, supporting the contention that OCI items are transitory and more strongly linked to short-term fluctuations (Black, 2016; Banks et al., 2018).

With reference to analysts' behaviour, financial analysts tend to have reference points, which makes their forecasts less objective. According to rational inattention theory (Sims, 2003), financial analysts must decide which information to carefully consider and disregard due to the various provided information. Truong (2018) postulates that analysts suffer from attention constraints that affect their forecasting abilities.

According to prior conclusions, we predict that OCI (and some of its components) have forecasting ability; first because OCI gains and losses can predict operating cash flows (Kanagaretnam et al., 2009) and second because OCI profits and losses can well represent the economic positions of the firm (Chambers et al., 2007; Goncharov and Hodgson, 2011; Jones and Smith, 2011; Dong et al., 2014;

Huang et al., 2021).

Hereafter, we address each of the four OCI components independently, as each item reflects different economic features, consistent with previous findings that establish different linkages between individual OCI components, market pricing, and future cash flow.

OCI AFS refers to the fair value changes in AFS securities net of the realized gains and losses resulting from the reclassification of unrealized gains and losses from OCI to NI. We argue that *OCI AFS* can be related to future earnings through three different channels. First, the realization of current fair value changes in the subsequent period affects both cash flow and earnings. For instance, Dong et al. (2014) use a sample of commercial banks and argue that *OCI AFS* and reclassified unrealized gains and losses of AFS predict one-year ahead reclassification.[2] Second, the fair value changes in AFS reflect firm AFS holdings' positions, which might be tied to future earnings and cash flows.[3] Third, it is obvious that the more AFS comprises a large portion of firm assets, the greater will be the effects of fair value changes on future earnings and financial conditions.[4]

OCI Currency captures the foreign currency translation adjustments for the current period, which can be linked positively to one-year ahead earnings for several reasons. First, this adjustment captures the exchange rate movement. Pinto (2001) highlights that short-run exchange rate trends have an enduring effect, implying that current-period currency changes can predict one-year ahead exchange rate directions. Second, the OCI Currency reflects firms' economic exposure to exchange rate movements.

OCI Hedge captures current fair value adjustments on cash flow hedges. According to Campbell (2015), fair value changes in cash flow hedges predict earnings when a related hedge expires. Specifically, the accumulated adjustments in the hedge derivatives of a given year t can predict the two-year-ahead gross profit. Therefore, there is no directional relationship between OCI Hedge and earnings forecasts in the subsequent period. Prior findings suggest a negative association between cash flow hedges and future earnings and that investors are not likely to anticipate this association. Campbell et al. (2015) find that analysts do not correctly consider unrealized gains and losses on cash flow hedging in their two or three-year ahead earnings forecasts because they revise their errors after the expiration of hedges.

OCI Pension captures the fair value changes of defined pension plan. Studies have reported mixed results regarding the value relevance of OCI Pension. Thus, no directional relationship exists between OCI Pension and earnings forecasts in the subsequent period.

These OCI components reflect unrealized fair value changes driven by market factors and, hence, are beyond management control (Chambers et al., 2007; Bamber et al., 2010a). This implies that the effects of OCI components on future earnings are highly uncertain. Zhang (2006) postulates that information uncertainty slows down the incorporation of new information into analysts' forecasts and increases forecast error. Furthermore, OCI items are from non-core activities requiring analysts to possess advanced technical knowledge and expertise.

However, OCI information reflects fair value measurement and can provide market participants with timelier and more value-relevant information than other accounting approaches (historical cost accounting) (Georgiou, 2018). Deol (2014) finds that aggregate OCI, AFS, and Hedge are significantly negatively linked to analysts' earnings errors, implying that aggregate OCI and some of its individual items are useful for analysts. Edinger et al. (2018) argue that OCI gains and losses reduce uncertainty among market participants and are considered in firms' stock prices. Arthur et al. (2019) find that cash flow hedge and foreign currency translation adjustments are negatively linked to forecast accuracy, whereas AFS securities exhibit a positive association with forecast accuracy and analyst following.

Allini et al. (2022) conduct an experiment with 29 CFA Institute analysts and find that fair value has a significant impact on analysts' decisions. Indeed, financial analysts exhibit a great aversion toward unrealized losses, whereas they prefer firms that have unrealized gains in OCI. In addition, according to the authors, CFA Institute analysts are likely to associate OCI with default risk, suggesting that higher default risk is attributed to companies reporting unrealized losses and vice versa. Furthermore, Black and Neururer (2022) use a sample of financial firms from 2009 to 2018 and find that analysts incorporate OCI disclosure into their book value per share forecasts, and investors react to this information. Based on prior empirical studies, the key hypothesis can be formulated as follows:

H1. OCI information is significantly linked to analyst forecast error.

In this hypothesis, we seek to investigate the potential relationship between OCI and forecast error, thereby exploring the underlying factors influencing this relationship. We aim to identify which specific components of OCI might contribute to exacerbating forecast errors and, conversely, which items might mitigate them. Building on this, the sub-hypotheses focusing on specific OCI components provide a deeper exploration of how specific components within OCI contribute to analysts' forecasting challenges. They are formulated as follows:

[2] Different from Dong et al. (2014), Anderson et al. (2023) focus more on current unrealized fair value changes rather than realized items already recorded in net income and use a sample of non-financial firms rather than banks, implying that this setting has infrequent trading of AFS and therefore immaterial reclassification compared to banks.

[3] In fact, when the firm holds equity securities, it implies that an increase in fair value results from an increase in stock prices for the investee companies, which affects potential dividend revenue and cash flows. Similarly, in cases where AFS are debt securities, fair value changes in debt securities refer to changes in the value of the underlying debt securities, which include future interest and principal payments.

[4] For instance, a rating downgrade of marketable securities by rating agencies logically incurs losses that affect financial conditions, income, and even the ability to pay dividends.

- *H1.1: Available for sale securities adjustments in OCI positively and significantly impact forecast accuracy.*
- *H1.2: Foreign currency translation adjustments in OCI positively and significantly impact forecast accuracy.*
- *H1.3: Cash flow hedges adjustments in OCI negatively and significantly impact forecast accuracy.*
- *H1.4: Fair value changes of defined pension plan are not statistically significant with forecast accuracy.*

3. Data and methodology

Our sample includes 200 of the largest US commercial banks listed on NASDAQ, NYSE, and AMEX over the period 2011–2020. We begin the sample in 2011 to capture the reporting changes introduced in ASU 2011–05, which is assumed to add more transparency and comparability to financial statements. Our sample period ends in 2020. This timeframe was chosen to avoid the effects of the COVID-19 pandemic, which began in late 2019 and peaked in 2020, potentially impacting analysts' ability to issue accurate forecasts in subsequent years. By concluding the study period in 2020, we mitigate the distortions caused by the pandemic's unprecedented effects on financial markets and the impact of OCI information on analyst forecast accuracy.

Initially, we include 305 listed banks. Ranking the initial sample based on total assets in 2012, we eliminate banks with low total assets. The asset size in our sample ranges from $820.5 million to $2.1 trillion, indicating that our size-based selection is not particularly restrictive. We require that the sample banks be listed on the NYSE, AMEX, or NASDAQ and have complete and available data for all relevant variables. We then merge the IBES and Compustat databases and delete banks missing the necessary variables to measure analysts' forecast accuracy. Finally, our sample is drawn from 200 of the largest US commercial banks, and we obtain 2000 firm-year observations. Data regarding bank specific variables were extracted from the Compustat WRDS database, whereas variables on analysts' forecasts were obtained from the Thomson Reuter I/B/E/S Detail History file. Table 1 presents the sample selection process.

While testing the link between OCI and its items with analysts' forecast accuracy, we use the one-year-ahead consensus EPS forecast for the models discussed below.

$$ACCi,t+1 = \alpha + \beta 1OCIi,t + \beta 2SIZEi,t + \beta 3MTBi,t + \beta 4Lossi,t + \beta 5Voli,t + \beta 6Followi,t \quad + \beta 5AOCIi,t + \varepsilon i,\ t \tag{1}$$

$$\begin{aligned} ACCi,t+1 = {} & \alpha + \beta 1AFSi,t + \beta 2Currencyi,t + \beta 3Hedgei,t + \beta 4Pensioni,t + \beta 5Lossi,t + \beta 5Voli,t \quad + \beta 6Followi,t \\ & + \beta 6SIZEi,t + \beta 7MTBi,t + \beta 8AOCIi,t + \varepsilon i,t \end{aligned} \tag{2}$$

We use two alternatives to gauge the accuracy of analysts' earnings forecasts and we employ the median consensus EPS forecast for both of them. As advanced by Gua and Wu (2013), the median forecast is assumed to be more accurate than the mean because of earnings skewness. First, following Embong and Hosseini (2018) and Li and Zhang (2022), we measure accuracy as the absolute value of the difference between actual earnings and consensus earnings forecasts scaled by the stock price at the end of the prior fiscal year. Second, following Hutira (2016), we measure forecast error to indicate analysts' bias and is calculated as the difference between the actual earnings and median forecast for period (t) divided by the actual earnings.

Furthermore, we focus on one-year forecasts for a couple of reasons. In fact, using one-year-ahead earnings forecasts creates a balance between forecast accuracy and forecast horizon. While longer-term projections may encompass the gradual influence of OCI components, they also tend to be more uncertain and susceptible to errors due to OCI's volatility and transitory nature. This shorter projection timeframe captures the immediate effects of these factors on near-term earnings, enhancing the relevance of our analysis. Moreover, the most recent consensus forecast carries greater weight and influence in decision-making processes for investors.

Moreover, in line with previous research, we incorporated several control variables into our analysis. Specifically, we controlled for bank size (Size) by incorporating the natural logarithm of bank assets at the end of year t to account for the varying magnitudes and complexities of different banks within our sample.

Additionally, we factored in growth by including the market-to-book (MTB) ratio and the accumulated Other Comprehensive Income (AOCI) at the beginning of period t. The MTB ratio provides insights into the market's valuation of a bank relative to its book value, allowing us to examine the influence of growth expectations on analysts' forecast accuracy. Consistent with prior research by Anderson et al. (2023), we control for AOCI at the beginning of period t to account for the impact of cumulative OCI on analysts' forecast accuracy.

To account for whether the bank reports a loss, we introduce a dummy variable (LOSS) set to one if the bank reports an EPS loss and zero otherwise (Campbell et al., 2015). This adjustment is crucial considering the established difficulty analysts face in forecasting for loss-making firms, as highlighted in prior studies (Brown et al., 2013), which anticipate larger revisions to forecasts for such entities.

We also include the volatility (Vol) of the preceding 12 quarters of earnings, following the methodology proposed by Anderson et al. (2023) to control for earnings dispersion. Furthermore, we integrate a natural logarithm for the number of analysts following the bank. This consideration is essential as analyst coverage has been found to positively correlate with forecast accuracy, reflecting varying disclosure levels and competition among analysts (Hope, 2003; Choi and Zang, 2006). Table 2 provides the definitions of all variables used in our regressions.

Table 1
Sample selection.

	Bank-year (2011–2020)
Initial Sample (305)	*3050*
Less: Banks showing low total assets	*200*
Less: Banks lacking necessary variables to calculate analysts' forecast accuracy	*850*
Final Sample	*2000*

This table presents the sample selection process. Initially 305 listed banks were included. Ranking the initial sample based on total assets in 2012, we eliminated banks with low total assets. We then merged the IBES and Compustat databases and deleted banks lacking the necessary variables to calculate analysts' forecast accuracy. Finally, our sample was drawn from 200 of the largest US commercial banks, and we obtained 2000 firm-year observations.

Table 2
Variables definitions.

Variables	Measures	Data Sources	Citations
Dependent Variables			
ACC	The absolute value of the difference between actual earnings and consensus earnings forecasts scaled by the stock price at the end of the prior fiscal year	Manually measured	Embong and Hosseini (2018) and Li and Zhang (2022)
Error	The difference between the actual earnings and median forecast for period (t) divided by the actual earnings.	Manually measured	Hutira (2016)
Independent variables			
OCI	Total other comprehensive income per share	CRPS and manually collected for lacking data	Dong et al., (2014)
AFS	Unrealized gains and losses on available-for-sale securities per share		Bratten et al., (2016); Boulland et al., (2019)
Currency	Foreign currency translations adjustments per share		Anderson et al. (2023)
Hedge	Adjustments to the cash flow hedges per share		Campbell, (2015)
Pension	Pension-related adjustments per share		Anderson et al. (2023)
Control variables			
Size	The natural logarithm of total assets at the end of year	Compustat	Anderson et al. (2023); Choi and Zang (2006)
MTB	Market-to-book ratio at the end of year	Compustat	Anderson et al. (2023); Choi and Zang (2006); Goncharov and Hodgson (2011)
Vol	Standard deviation of the prior 12 quarters on net income	Manually measured	Embong and Hosseini (2018) and Li and Zhang (2022)
AOCI	Accumulated other comprehensive income per share at the beginning of year t	Compustat	Boulland et al., (2019)
Loss	Dummy variable that equals one if EPS<0	Manually measured	Embong and Hosseini (2018) and Li and Zhang (2022); Hutira (2016)
Follow	Natural logarithm of the number of analysts following the bank	I/B/E/S	Hope (2003); Choi and Zang (2006)

We do not consider the timeframe between the forecast date and the fiscal year-end, as the final consensus forecast typically occurs after the fiscal year has ended and is usually less than 30 days before the earnings announcement date.

In our model specifications, we acknowledge that the relationship between analysts and managers is a two-way association where both parties can influence each other's actions.[5] Managers may respond to analysts' forecasts by adjusting their actions, such as selling AFS securities, to align with analysts' projections, as highlighted in prior research (Barth et al., 2017). On the other hand, analysts' forecasts are influenced by the information disclosed by managers.

To address the potential endogeneity issue arising from this two-way association, we employ the dynamic panel system generalized methods of moments (GMM) in our analysis. By using the GMM approach, we can obtain more robust and reliable estimates of the relationships between analysts' forecast accuracy and OCI information. Furthermore, all the variables except Loss are winsorized at

[5] For instance, managers can sell AFS to meet analysts' forecasts (Barth et al., 2017).

1 % and 99 % levels to avoid the influence of outliers.

4. Empirical results

4.1. Descriptive statistics

Table 3 presents the descriptive statistics, with Panels (A), (B), and (C) presenting the analysts' forecast variables, OCI components, and the battery of control variables. The median forecast error presents a mean of 0.002, and it varies between −2.97 and 1.69. The mean forecast accuracy is 0.024, with a maximum of 0.225. For our sample, the mean OCI per share is 0.00129. The OCI Pension and OCI AFS showed the largest standard deviations, implying substantial variation. Bank size (Ln total assets) varies between 11.83 and 17.17, indicating that our sample is heterogeneous and includes banks of different sizes.

Table 4 presents the Pearson correlations for the main variables in our analysis, revealing the following univariate links. Aggregate OCI and almost OCI items are linked to analysts' forecast accuracy, which is consistent with analysts' willingness to consider OCI and its items and incorporate them into their projections. The Vif test confirms the absence of multicollinearity problem.[6]

4.2. The impact of OCI information on analysts' EPS forecast accuracy

Hereafter, consistent with H1, we assess whether OCI information is associated with analysts' forecast accuracy (error). Table 5 presents the results of estimating Eq. (1) and (2). Both accuracy measures yielded similar results.

Focusing on aggregate OCI, our results show that aggregate OCI is positively (negatively) associated with forecast errors (forecast accuracy). This result suggests that analysts do not fully incorporate OCI information into their earnings forecasts. Based on the transient nature of OCI information, forecast accuracy is less assured. Thus, H1 is verified assuming that aggregate OCI negatively and significantly influences forecast accuracy.

With regards to different OCI items, Table 5 reveals that Hedge exhibits a positive (negative) relationship with forecast error (accuracy). AFS and Currency attain positive (negative) signs with forecast accuracy (forecast error). However, we fail to provide evidence on the link between Pension and analysts' forecast accuracy.

Our findings indicate that AFS securities and Currency holdings serve to reduce uncertainty, thereby facilitating financial analysts in issuing more precise forecasts. This aligns with prior research. For instance, Boulland et al. (2019) find that analysts don't revise their forecasts based on AFS holdings, and they are generally slow to react to unrealized gains and losses in their earnings forecasts. Dong and Zhang (2017) as well as Barth et al. (2017) suggest that these securities are used to smooth income by strategically timing the realization of unrealized AFS gains and losses into earnings.

Moreover, according to the CFA Institute's studies, unrealized gains or losses for short-term horizon AFS securities have a more accurate predictive value than realized gains or losses when these securities are sold. Indeed, we provide evidence that AFS items are worthy of analyst attention for performance, risk analysis, and valuation. Thus, H1.1 is supported.

Furthermore, as shown in Table 5, cash flow hedges are negatively associated with EPS forecast accuracy. Indeed, fair value changes in cash flow hedges cannot predict one-year earnings unless the related hedge expires. Campbell et al. (2015) document that financial analysts find it difficult to interpret the information provided by unrealized gains and losses on cash flow hedges and that this problem can be mitigated if managers provide additional and forward-looking disclosures in this area. Moreover, owing to the immaterial cash flow hedge amounts, it is difficult for analysts to discern a link between cyclical changes in the macroeconomic environment and cash flow hedge gains or losses in US banks. Our results are consistent with Bratten et al. (2016) and Arthur et al. (2019). The latter find that cash flow hedges increase uncertainty and make it harder for analysts to predict future income. Furthermore, forecasting cash flow hedges is not easy. Specifically, analysts need to evaluate bank risk exposure, its magnitude, and how hedges against risk exposure are managed. For instance, Chang et al. (2016) argue that, although financial analysts have financial expertise, they misjudge the earnings implications of derivative activity. Thus, H1.3 is supported.

Additionally, we find that Currency translations enhance analysts' forecast accuracy. Hence, currency may be associated with analysts' earnings forecasts even though the recognition of Currency itself is not directly related to operating income. Thus, H1.2 is supported. However, and based on Table 5, we fail to provide evidence on the link between Pension and analysts' forecast accuracy, supporting our hypothesis H1.4.

In summary, our findings offer strong support for our hypothesis, revealing a significant association between OCI and forecast error. Notably, while AFS securities and Currency holdings positively impact forecast accuracy, cash flow hedges have a dampening effect. This indicates analysts' adept incorporation of this data into their forecasts, signalling a thorough grasp of how OCI items influence financial performance.

[6] Provided once required.

Table 3
Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A: Analysts' forecasts					
Error	2000	.002	.097	−2.97	1.69
Accuracy	2000	.024	.225	.017	3.13
Panel B: OCI and its components					
OCI	2000	.0012	.726	−.006	.0042
Currency	1884	−.0004	.210	−.0024	.0077
Hedge	2000	.0007	.032	−.0080	.0067
Pension	2000	.0005	.384	−.0002	.0006
AFS	2000	.0021	.791	−.0044	.0074
Panel C: Control variables					
Size	2000	15.43	1.572	11.836	17.173
AOCI	2000	.502	3.66	−7.33	5.98
Vol	2000	.181	.192	.012	.535
Follow	2000	1.060	.898	0	3.73
MTB	2000	1.59	.543	.757	2.340

This table presents descriptive statistics for all variables used in our models. Panels (A), (B), and (C) present analysts' forecasts, OCI components, and control variables, respectively. Note that we winsorized all continuous variables at 1 % and 99 % levels to avoid outlines. All variables are defined in Table 2.

Table 4
Pairwise correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Error	1.000							
(2) Accuracy	**−0.766***	1.000						
(3) AOCI	0.242*	0.262*	1.000					
(4) OCI	**0.366***	**−0.369***	**0.525***	1.000				
(5) Currency	**−0.161***	**0.230***	0.233*	0.047*	1.000			
(6) Hedge	**0.335***	**−0.386***	0.203*	0.423*	0.004	1.000		
(7) Pension	0.007	−0.012	0.007*	0.0327	0.003	0.0272	1.000	
(8) AFS	**−0.394***	**0.404***	**0.431***	**0.809***	0.036	0.362*	−0.036	1.000

This table presents pairwise correlations.
[*] represents the significance at the 5 % level. The variables are defined in Table 2.

5. Robustness checks

5.1. *Impact of large AFS amount and analysts' forecast error*

Based on prior studies (Abarbanell et Lehavy, 2003), a large amount of AFS may reduce uncertainty. Unrealized gains or losses are recognized in earnings once they are sold, a process that is known as "recycling," allowing managers to time the recognition of unrealized gains and losses in a strategic manner. Barth et al. (2017) and Dong and Zhang (2017) find that banks use AFS securities to smooth income by timing the period in which unrealized gains and losses are recycled. These authors also advance the idea that banks use selective AFS to manage regulatory capital (Barth et al., 2017) and to meet analysts' forecasts (Dong and Zhang, 2017). Fabrizi et al. (2021) suggest that such activities are more likely to occur in situations where capital ratios would otherwise limit banks' capacity to distribute resources to shareholders.

Thus, a large amount of OCI gains/losses would act as a signal of future reclassifications. Managers have discretion in dealing with current earnings. For instance, if a firm is doing well in the current year, managers may tend to defer gains recognition because they do not need to boost their current income. Furthermore, if a firm is doing poorly, managers may also defer loss recognition as they do not want to further depress its poor performance. Thus, managers may delay recognition of unrealized gains (losses) when the firm performs better (worse) than market expectations.

Overall, forecast accuracy for banks with high amounts of AFS will be significantly higher if analysts expect a firm to engage in earnings smoothing to prevent minor losses (or meet or beat the previous year's NI). Consequently, larger amounts of unrealized AFS profits and losses can reduce analysts' uncertainty and improve their forecast quality. Thus, we hypothesize that a large AFS amount may be positively related to analysts' EPS accuracy. In doing so, we build two subsamples; while the first subsample contains AFS observations that are greater than the 75th percentile, the second subsample contains AFS observations that are lower than the 25th percentile. Then we estimate Eq. (1).

The results presented in Table 6 reveal some interesting findings regarding the relationship between AFS securities and forecast accuracy for banks. Firstly, regarding column (1), we observe a positive and significant relationship between AFS securities and forecast accuracy, with a coefficient of 0.0132 and a p-value of less than 5 %. This suggests that banks with higher amounts of AFS securities tend to have more accurate forecasts, indicating that analysts are able to better incorporate and interpret the information

Table 5
Results on the relationship between analysts' forecast accuracy and OCI.

	(1)	(2)	(3)	(4)
VARIABLES	Error	Error	ACC	ACC
OCI	**0.0297*****		**−0.0407****	
	(0.0692)		(0.0168)	
AFS		**−0.0144*****		**0.0666*****
		(0.0248)		(0.0142)
Currency		**−0.0402*****		**0.0823*****
		(0.0508)		(0.0264)
Hedge		**0.0547***		**−0.0146***
		(0.0333)		(0.0192)
Pension		0.0166		−0.698
		(0.0329)		(0.195)
AOCI	**−0.245*****	**−0.109*****	0.0590	0.0128
	(0.0597)	(0.0190)	(0.0152)	(0.0889)
Size	**−0. 316*****	**−0.122*****	**0.464***	**0.164****
	(0.0975)	(0.0230)	(0.0243)	(0.0652)
MTB	0.462	**0.461****	**−0.195*****	**−0.251*****
	(0.0298)	(0.020)	(0.0239)	(0.0184)
Vol	0.058	0.582	**−0.0601****	−0.0366*
	(0.0644)	(0.0433)	(0.0300)	(0.0209)
Follow	**−0.235***	**0.206*****	**0.166***	**0.436****
	(0.0137)	(0.0774)	(0.0948)	(0.0758)
LOSS	**0.0174*****	**0.0156*****	**−0.0146*****	**−0.867*****
	(0.00212)	(0.00136)	(0.00142)	(0.0428)
Constant	−0.636***	−0.317***	0.457***	0.589***
	(0.0165)	(0.0369)	(0.0498)	(0.0323)
Observations	1835	1835	1835	1835
Number of id	200	200	200	200
AR (2)	0.476	0.477	0.470	0.369
Hansen test	0.489	0.482	0.492	0.428

This table presents the results for the relationship between aggregate OCI and its components with analyst forecast accuracy. We used two proxies to measure forecast accuracy (Accuracy and error). To control for endogeneity problem, we used the GMM panel estimator. Table 2 provides a description of each variable. Robust standard error in parentheses. Statistical significance at the 10 %, 5 %, and 1 % levels is denoted by *, **, and ***, respectively.

provided by AFS securities in their earnings projections.

On the other hand, the lack of a significant impact on forecast accuracy for lower AFS values suggests that analysts may not pay as much attention to smaller AFS holdings in their forecasting process. This could be due to the relative insignificance of these holdings in influencing overall financial performance or the complexity involved in interpreting smaller AFS amounts.

5.2. The impact of ASU 2016–01 on analysts' forecast error

ASU 2016–01 does not introduce new fair value information, but it requires that fair value changes available for sale of securities move from OCI to income (FASB, 2016), which may increase earnings volatility and reduce firms' ability to manage or smooth earnings. Campbell et al. (2023) investigate the capital market consequences linked to this reporting change for a sample of US public insurers and find a significant drop in firms' earnings response coefficient (ERC) resulting from a decrease in earnings persistence. In addition, the authors provide no evidence of changes in investors' evaluations of overall firm risk following the reporting change.

Under ASU 2016–01, financial analysts should estimate the fair value of equity portfolios to forecast upcoming earnings. If the EPS estimate becomes more challenging after adopting ASU 2016–01, earnings forecast accuracy may decrease. Accounting information becomes less comparable and reliable, which decreases the forecasting ability of financial analysts (McGregor, 2022).

According to the market efficiency theory, market reactions should not be affected by adopting ASU 2016–01. However, ASU 2016–01 has gained several criticisms by showing that financial statement users are less capable of valuing information recorded in OCI. For instance, the press release for the fourth quarter of 2018 of Berkshire Hathaway's earnings states that the "*change in GAAP (ASU 2016–01) requiring recognition of unrealized gains/losses of our EQ investments in earnings instead of equity can be misleading to investors*" (Berkshire Hathaway, 2019). Overall, if analysts do not fully assimilate the change in equity securities treatment, they may misinterpret the results, which consequently decreases their ability to forecast earnings accurately.

ASU 2016–01 is effective for fiscal years beginning December 15, 2017. Consequently, once the amendment becomes effective, the OCI AFS will contain only unrealized gains and losses in debt securities. FASB (2016) argues that unrealized gains and losses in AFS are performance-related indicators that should be reported in earnings.

Hereafter, we include interaction terms $AFS \times ASU$, $Currency \times ASU$, $Hedge \times ASU$ and $Pension \times ASU$; where ASU is a dummy variable that takes the value of one in the post-ASU 2016–01 period for fiscal years beginning after December 15, 2017 and null otherwise. The model is formulated as follows:

Table 6
Analysts' forecast accuracy and large AFS amounts.

	(1)	(2)
VARIABLES	ACC	ACC
AFS	0.0132*	0.0472
	(0.0712)	(0.0143)
Currency	0.0368***	0.0263**
	(0.0104)	(0.0144)
Hedge	−0.0157*	−0.0104
	(0.0017)	(0.0012)
Pension	−0.0049	−0.0250
	(0.0068)	(0.0570)
AOCI	−0.0131	−0.0772
	(0.0111)	(0.0869)
Size	0.4372	0.5210
	(0.0285)	(0.0166)
MTB	−0.2852***	−0.2305***
	(0.0107)	(0.0531)
Vol	−0.0362	0.0992*
	(0.0372)	(0.0012)
Follow	0.7295***	0.2962***
	(0.0462)	(0.0398)
LOSS	0.0132***	0.0669***
	(0.0022)	(0.0018)
Constant	−0.4575	−0.4010
	(0.0065)	(0.0030)
Observations	545	562
Number of id	109	186
AR (2)	0.424	0.450
Hansen test	0.605	0.681

This table presents the results for the relationship between analyst forecast accuracy and AFS levels. Column (1) reports results for AFS that are greater than the 75th percentile. Column (2) reports results for AFS that are lower than the 25th percentile. To control for the endogeneity problem, we use the GMM panel estimator. Table 2 provides a description of each variable. Robust standard error in parentheses. Statistical significance at the 10 %, 5 %, and 1 % levels is denoted by *, **, and ***, respectively.

$$\begin{aligned} ACCi,t+1 = {} & \alpha1+\beta0ASUt+\beta1AFSi,t+\beta2AFS\times ASUi,t+\beta3Currencyi,t+\beta4Currency\times ASUi,t+\beta5Hedgei,t+\beta6Hedge \\ & \times ASUi,t+\beta7Pensioni,t+\beta8Pension \\ & \times ASUi,t+\beta9Lossi,t+\beta10Voli,t+\beta11Followi,t+\beta12SIZEi,t+\beta13MTBi,t+\beta14AOCIi,t+\varepsilon i,\ t \end{aligned} \tag{3}$$

In estimating model (3), the primary interest variables are the interaction terms ($\beta2,\ \beta4,\ \beta6$ and $\beta8$) between OCI components and ASU. These variables reflect an inter-temporal change in the impact of OCI items on forecast accuracy. Table 7 presents the underlying results.

Table 7 presents interesting results. First, the negative and significant coefficient of the dummy variable ASU indicates that after the implementation of ASU 2016–01, there is a statistically significant decrease in forecast accuracy compared to the period before the implementation. This negative effect might stem from increased complexity in financial reporting due to the changes brought by ASU 2016–01. Indeed, regulatory changes can sometimes introduce uncertainty, which could lead to less accurate predictions.

Furthermore, the positive coefficient of AFS suggests that higher levels of AFS positively influence forecast accuracy. Banks with more AFS investments tend to have more accurate forecasts. However, the negative coefficient of the interaction term with ASU suggests that after the implementation of ASU 2016–01, the positive impact of AFS on forecast accuracy becomes weaker or even reverses. In other words, the beneficial effect of AFS on forecast accuracy seems to be less pronounced or potentially negative after the regulatory changes introduced by ASU 2016–01, since the fair value of AFS is no longer reported in OCI but in NI and only AFS on debt securities remain in OCI.

Therefore, our results may also indicate that financial analysts do not fully incorporate OCI debt securities into their forecasting process after the adoption of ASU 2016–01. Banks may have incentives to hold AFS debt instruments to maintain regulatory capital. However, it is essential to recognize that holding debt instruments to maturity is a time-sensitive matter, as highlighted by Moyer (1990). As time progresses, the accounting treatment and implications of AFS securities may change, which can affect their significance in analysts' forecasting practices.

Furthermore, the negative and significant coefficient of the Hedge variable indicates that the presence of cash flow hedging activities is associated with decreased forecast accuracy. This suggests that banks engaging more in cash flow hedging might have more

Table 7
The effect of ASU 2016–01 on forecast accuracy.

	(1)	(2)
VARIABLES	ACC	Error
ASU	−0.114*	0.0315*
	(0.0740)	(0.00381)
AFS	0.014**	−0.0582**
	(0.0310)	(0.0277)
AFSxASU	−0.0965**	0.0542*
	(0.0436)	(0.0284)
Hedge	−0.0228***	0.0524*
	(0.0413)	(0.0786)
HedgexASU	0.0403***	−0.0132*
	(0.0692)	(0.00867)
Pension	−0.0108	0.00358
	(0.0204)	(0.00193)
PensionxASU	−0.0115	−0.00789*
	(0.0533)	(0.00438)
Currency	0.0307***	−0.0642*
	(0.0868)	(0.0532)
CurrencyxASU	0.0511***	−0.00201*
	(0.0195)	(0.0105)
AOCI	0.0207	−0.0253
	(0.0149)	(0.0177)
Size	−0.0208	0.0238
	(0.0329)	(0.0252)
MTB	−0.0101***	0.0192*
	(0.0184)	(0.0844)
Vol	−0.00127	0.00224
	(0.00403)	(0.00150)
Follow	0.0244	−0.0377*
	(0.0772)	(0.000391)
LOSS	−0.0234***	0.0204***
	(0.00154)	(0.00501)
Constant	0.0317***	0.0456**
	(0.0561)	(0.0421)
Observations	1724	1724
Number of id	193	193

This table presents results for the relationship between analysts forecast accuracy and OCI components for the periods before and after ASU 2016–01. To control for the endogeneity problem, we use the GMM panel estimator. Table 2 provides a description of each variable. ASU is a dummy variable that equals 1 for the year ASU 2016–01 is implemented. Robust standard error in parentheses. Statistical significance at the 10 %, 5 %, and 1 % levels is denoted by *, **, and ***, respectively.

complex financial arrangements, making it harder to accurately predict their financial outcomes. However, our results suggest a positive and significant coefficient of the interaction term; implying that the negative impact of cash flow hedge on forecast accuracy is less pronounced or even reversed after the implementation of ASU 2016–01.

This change in relationship can be explained by the initiative made by the FASB, which publishes an Accounting Standards Update (ASU) on August 28, 2017, with the goal of enhancing accounting for hedging operations. The updated standards likely provide financial analysts with clearer and more reliable information on cash flow hedges, making it easier for them to incorporate the effects of unrealized gains and losses on their forecasts.

Finally, the positive and significant coefficient of the Currency variable indicates that foreign currency translation activities have a positive influence on forecast accuracy. This implies that companies with high level of Currency tend to have more accurate forecasts. Moreover, our results suggest a positive and significant coefficient of the interaction term between Currency and ASU implying that the positive impact is even stronger after the implementation of ASU 2016–01. One possible explanation is that US banks are likely to adopt more robust risk management strategies related to currency fluctuations. This heightened focus on risk management could lead to more accurate forecasts as banks better account for currency-related impacts. The regulatory changes brought about by ASU 2016–01 could have prompted US banks to adopt a more careful and diligent approach to financial reporting overall. This mindset shift could extend to foreign currency translation practices, indirectly contributing to better forecast accuracy. Similar to previous results presented in Table 5, our analysis did not find any robust significant evidence suggesting that the Pension has an impact on forecast accuracy.

6. Conclusion

Our study examines the usefulness of OCI and its components by analysing the relationships between OCI items and analysts' forecast accuracy and error. We use a sample of the 200 largest US commercial banks over the period 2011–2020 and gauged main OCI components: AFS, Hedge, Currency, and Pension. Our findings provide interesting insights. We document that OCI AFS and OCI Currency exert a significant positive impact on forecast accuracy, whereas Hedge exhibits a significant negative sign on forecast accuracy. Hence, our study provides a caveat against considering OCI items as having similar implications or usefulness.

To ensure the robustness of our results, we perform two additional tests. First, our results suggest that large AFS amounts are associated with forecast accuracy, implying that analysts have gained expertise in dissimulating this information. Second, we examine the impact of ASU 2016–01 on analysts' forecast accuracy and several noteworthy results are found. The implementation of ASU 2016–01 has adversely contributed to forecast accuracy. ASU 2016–01's negative impact might stem from the initial complexities and adaptation challenges it introduced.

More intriguingly, the interaction between Currency and ASU 2016–01 further strengthens the positive effect after the ASU 2016–01. Similarly, the interaction between the cash flow hedge and ASU 2016–01 reveals a positive and significant effect, indicating that the positive impact of cash flow hedge on forecast accuracy is amplified after the regulatory changes. However, the positive effect of AFS on forecast accuracy seems to be less pronounced or even negative in the post-ASU period compared to the pre-ASU period. Moreover, the impact of the Pension on forecast accuracy is found to be non-significant. These findings collectively underscore the intricate interplay of diverse factors affecting forecast accuracy. They reflect also a realistic scenario where the familiarity and historical trends associated with Hedge and Currency could provide analysts with better tools and insights for accurate forecasting, whereas adapting to new accounting standards like ASU 2016–01 might take more time due to its novel and intricate nature. This is a valuable perspective to consider when discussing the varying impacts of these factors on forecast accuracy.

Regarding policy implications related to the ongoing debate about the usefulness of OCI, our results suggest that OCI conveys valuable information to analysts, helps reduce information asymmetry, and improves the informativeness of earnings reports. This paper adds to the existing literature in the banking industry by documenting the impact of income measures on this behaviour. Regulators may need to revise accounting standards to enhance the transparency and comparability of OCI reporting, especially considering the impact of ASU 2016–01 on earnings' usefulness. Investors should focus on OCI and CI for better insights into a company's financial health and future cash flows. Additionally, bank managers should recognize that OCI provides deeper insights into the company's overall financial well-being and future prospects, influencing strategic decision-making. Prioritizing transparency in reporting OCI components is crucial, as they contain valuable information and exhibit usefulness. Transparent disclosures help investors and stakeholders better understand the company's financial status and risk exposure. Moreover, these findings support the Basel III approach of including accumulated other comprehensive income in Tier 1 Capital, countering criticisms by showing that OCI captures firm-specific risk.

Our study highlights the importance of how financial analysts, as experts, interpret and dissimulate banks' disclosures related to non-operating activities. An investigation conducted by McDonough et al. (2020) underscores the need for further exploration into how fair value disclosure can lead to reduced information-processing costs. Building on this premise, the current study aims to address a critical question: whether information based on fair value influences the predictive abilities of analysts. This inquiry holds significant implications for regulators, standard-setters, and investors and still warrant further investigation.

CRediT authorship contribution statement

Imen Fredj: Writing – original draft, Methodology. **Marjène Gana:** Supervision. **Samir Trabelsi:** Visualization, Validation.

Data availability

The data that has been used is confidential.

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