Uncovering Accounting Misreporting: The Role of Analysts' revised estimates in Detecting AAER Companies' Practices

Abstract

Once a firm has reported its earnings, some analysts revise their ex-ante EPS forecast, based on the new information, to issue their own revised EPS estimate (ex-post). This research documents whether analysts can identify misreporting practices (fraud and earnings management), using a comprehensive sample of US fraudulent restating firms (AAERs dataset). The research relies on an original dataset over the period 2001-2022, which enables us to extract both 'originally reported earnings (i.e. *misreported earnings*) and 'restated' earnings (i.e. *corrected* earnings), required by the SEC. The empirical analysis is based on a sample of 1,663 cases of fraudulent firms with an equal number of non-fraudulent control firms. The findings indicate that the direction of analysts revised EPS estimate (ex-post) adjustment moves closer to the *corrected earnings.* This suggests that financial analysts exhibit a capacity to identify certain misreporting practices in companies engaging in fraud. This detection ability becomes apparent when analysts integrate financial data from earnings reports into their assessments.

Keywords: Analyst forecasts, accounting fraud, misstatements, misreporting.

1. Introduction

Earnings estimates issued by financial analysts serve as a vital channel through which market participants form expectations about firm performance. These estimates are not static; they are revised over time in response to new information, particularly around earnings publication (Barron, et al., 2002; Aubert, F. & G, Grudnitski, 2012, 2014). Financial analysts typically forecast earnings **(1)** for fiscal year t (see Figure 1), before companies publish their results in year t + 1. Once the earnings are released, analysts shift their focus to forecasting earnings for the following year (t + 1), providing forward-looking information to market participants. At the same time, they update the FactSet database with their own revised version of actual earnings for year t **(2)**. These figures reflect analysts' private adjustments, made by revising their latest estimates based on the newly available financial statements. These post-earnings publication revisions help brokers produce more accurate estimates, especially when they factor in discretionary reporting choices and earnings management practices. The revised ex-post EPS[1] represent what analysts consider the "true" earnings, partially adjusted for management discretion and often differs from the earnings per share (EPS) officially reported by the company. While much of the literature has focused on the accuracy of analysts' initial forecasts (ex-ante EPS) or the impact of earnings surprises, less attention has been paid to the revisions made after earnings publication (revised ex-post EPS), but before other major corporate events, such as fraud revelations.

This study examines analyst forecast behavior in a unique and high-risk setting: a sample of firms subject to Accounting and Auditing Enforcement Releases (AAERs) by the U.S. Securities and Exchange Commission. These cases involve companies where financial reporting fraud was later detected and sanctioned. Essentially, at the time of the earnings

[1] We use the word estimate instead of forecast to cite the estimation of actual EPS.

publication, fraud has not yet been publicly disclosed. Thus, analysts operate with incomplete information but are reacting to financial results that may already contain signals of irregularity or manipulation. Analysts revised ex-post EPS**,** updated after considering the reported earnings, but before the fraud becomes known, represents a decisive data point for assessing whether and how analysts internalize potentially misstated information (see Figure 1).

After fraud is detected, firms involved in this practices restated their earnings. In this context, we compare analysts' ante- and post-earnings publication EPS estimates, to the original GAAP published earnings (*misreported earnings*) and the restated earnings (*corrected earnings)* (see figure 1). While analyst forecasts are typically based on adjusted or "Street" earnings that exclude non-recurring items, our objective is not to test absolute forecast accuracy, but to assess whether the direction of forecast revision moves closer to the GAAP earnings following the earnings restatement. This allows us to infer whether analysts incorporate the available financial signals of fraud, into their expectations, and whether they exhibit any sensitivity to red flags embedded in the reported results. We argue that this adjustment process also implicitly incorporates signals related to misreporting practices such as earnings management and fraud, enabling analysts to move closer to estimating the firm's underlying, *corrected* earnings. By focusing on a period between the earnings publication and the fraud detection, this study provides insight into analysts' informational processing under uncertainty and potential manipulation. It also contributes to the broader literature on analyst behavior, earnings quality, and the timeline of fraud detection.

Financial analysts either do not anticipate the full impact of misreporting practices or include some portion of them in their earnings estimates. Analysts' ability to detect earnings manipulations is somewhat limited (Young & Peng, 2013). Analysts are more likely to react severely and quickly to firms with more egregious frauds due to lower detection costs and higher reputational risks. The presence of fictitious transactions, frauds that move a firm from a loss to a profit, and other severe fraud types increase the likelihood of severe analyst action (Young & Peng, 2013). Fraud can lead to increased uncertainty and risk, affecting analyst forecasts. The dispersion of analyst forecasts increases, which proxies for heightened uncertainty (Hribar & Thorne Jenkins, 2004). Analysts may revise downward their estimates of firm value and credibility, leading to a decline in stock prices and increased costs of capital (Dechow, et al., 1996). Analysts often rely on financial indicators and patterns to detect potential fraud. Companies that meet or beat analyst forecasts or inflate reported revenue are more likely to be committing fraud, even when there is no evidence of previously managed earnings (Perols & Lougee, 2011).

Research indicates a link between misreporting practices, aggressive earnings management and subsequent financial fraud. Firms engaging in extensive earnings manipulations may resort to fraudulent practices to sustain misstated financials when legitimate options are exhausted. For instance, Perols & Lougee, (2011), find that firms managing earnings through discretionary accruals over multiple years are more likely to commit fraud to offset accrual reversals or meet financial targets. In the same direction, Kamarudin, et al., (2012) affirm that firms with aggressive financial reporting (measured by less timely loss recognition and lower asymmetric timeliness of earnings) are significantly more likely to engage in corporate fraud.

Firms can use earnings management to dissimulate fraud. Managers can smooth earnings to hide deteriorating performance, buying time to fix underlying issues or avoid negative market reactions. Earnings management can create a false sense of firm stability. Firms that engage in earnings management create a consistent earnings trend that makes the company seem stable, reducing scrutiny from investors, auditors, or regulators (Ramos do Nascimento & de Souza

Gonçalves, 2024). The ability of analysts to separately detect earnings management and fraud is essential. While detecting fraud is inherently more challenging, analysts can still raise red flags when they observe inconsistencies that are not supported by a firm's fundamentals or financial disclosures. In contrast, signs of earnings management are often more subtle but detectable, such as unusual accrual patterns, shifts in discretionary spending, or deviations from industry benchmarks. For instance, Burgstahler and Eames (2003) point out that analysts have some ability to identify firms that may have engaged in earnings management policies to avoid small earnings declines.

Based on a matched sample of 1'663 fraudulent misstatements and 1'663 non-fraudulent control firms, over the period 2001-2022. The empirical analysis exhibits, first that the difference between analysts' revised ex-post EPS and the "*corrected earnings*" is lower (and statistically significant) than the difference between the revised ex-post EPS and the "*misreported earnings*", which indicates that analysts are moving towards restated earnings. Second, the *fraud* component is significantly and negatively associated with the direction of analysts' correction (ex-ante EPS forecast minus revised ex-post EPS). These results suggest that analysts are able to detect some accounting manipulations for fraudulent companies, when they incorporate financial information from earnings reports. The remainder of this paper is organized as follows. Section 2 summarizes previous literature that deals with analyst estimates and the AAERs dataset. Section 3 presents the study's research design. The empirical results are discussed in Section 4, followed by the conclusion.

2. Background and hypothesis development

2.1 Analysts ex-ante EPS forecast and revised ex-post EPS.

Earnings surprises – so called "forecast errors" in empirical studies and capital markets based accounting research – are usually determined by comparing analyst earnings forecasts to the equivalent earnings published by the firm. Unlike other empirical analyses in financial reporting that investigate the properties (quality, accuracy or dispersion) of analyst earnings forecasts, our study emphasizes an alternative approach, the revised ex-post EPS also called 'convergent consensus'.

The 'convergent consensus' is the *ex-post* estimate that is calculated after the firm has published its realized earnings (Bessler & Stanzel, 2009; Aubert & Grudnitski, 2014)(see Figure 1). Beaver et al. (2008) argue that annual earnings announcements generate more information in the form of a full set of consolidated and individual financial statements, more detailed corporate analysis is available, then there is the potential that analysts will gather more information as a result. Analysts can use this information to accurately adjust their last estimate. Therefore, the 'convergent consensus' should be of interest for investors because, they refer to the "true" annual earnings per share of a company that is a good proxy for the "partially-*correct*" earnings (Abarbannel & Lehavy, 2003a,b).

Analysts often revise their estimates following the earnings publication, believing that share prices do not fully incorporate the information contained in the earnings reports. Earnings publication can provide new information that may not be fully reflected in the stock prices, persuading analysts to revise their estimates to exploit market inefficiencies. Analysts are more likely to revise their estimates for firms with larger earnings surprises, as the magnitude of the earnings surprise increases, the frequency of estimates revisions within the three days after the announcement also rises, Yezegel (2015). Analysts believe that markets are relatively efficient, they adjust their estimates based on price-to-value assessments derived from private insights or new information and they have confidence in their superior ability to generate information through the analysis of public data. Altınkılıc & Hansen (2009) find that forecast revisions are prompted by corporate events, such as earnings publication, which often disclose firm-specific information about earnings and investments just hours before the revisions are announced. This indicates that firm management is the primary reliable source of information for analysts. If market prices fully incorporate earnings information, public earnings should not lead to recommendation changes. However, if analysts can interpret earnings information more effectively than the market, they might identify instances where market prices overreact or underreact to earnings.

After earnings are released, analysts redirect their attention to forecasting earnings for the next year, offering forward-looking insights to market participants. Simultaneously, they update the FactSet database[2] with their own revised version of historical earnings (revised ex-post EPS). This adjusted EPS represents what analysts believe the earnings should have been, incorporating their private assessments based on the newly disclosed financial statements. This approach is supported by findings from Min & Zach, (2024)[3] . We adopt an alternative method for measuring forecast errors. Following Bessler and Stanzel (2009), we use broker actuals, also referred to as the "convergent consensus", to assess if analysts incorporate new information in their previous forecast, after earnings publication, in the case of fraudulent firms.

- Insert Figure 1 about here –

[2] In some databases, such as I/B/E/S and *Value Line*, analyst earnings estimates are adjusted for items that may have been excluded by the provider. In contrast, FactSet actuals uses (rather than alters) post-earnings announcement analyst earnings estimates, when constructing the ‘convergence consensus’.
[3] This study uses Visible Alpha as database, which contains analysts’ financial models. The authors document that uncertainty about the past firms’ results, plays a significant role in shaping analysts’ information environment for future forecast. This uncertainty is mitigated by analysts’ proper estimates about the past.

The ex-post estimates are combined into what Factset calls a "convergent consensus"[4], which is typically the median (or mean) estimate and is available between one and several weeks after the publication of firms' results. Even though it is common practice for analysts to revise their estimates when a firm publishes its results, differences between the revised ex-post EPS (convergent consensus) and a firm's reported results may occur because of the manner in which analysts interpret the new information contained in a firm's published financial reports and because of the treatment of non-recurring, exceptional items or discretionary financial reporting choices. To estimate the revised ex-post EPS, analysts may have to carry-out several adjustments. Indeed, they may use the same methodology when forecasting future EPS for several companies in similar industries, whatever their specific accounting practices. Analysts may also compute the relevance and persistence of some extraordinary items, but also for discretionary accruals. Abarbanell and Lehavy (2003a).

2.2 AAER database and misreporting practices

The Security Exchange Commission (SEC) started issuing Accounting and Auditing Enforcement (AAERs) in 1982. The dataset of AAER currently consists of a total of 3.255 SEC AAERs. The AAER database provides a valuable venue for research on earnings management as all cases reported under AAER are confirmed cases of earnings management. One major use of the AAER database has been the research of statistical models to predict future accounting misstatements. Beneish (1997) was the first study, using a modified Jones (1995) model, to find that the ability of the discretionary accruals model to predict earnings management is significantly enhanced by adding a past stock performance variable. In a follow-up study, Beneish (1999) used indexes calculated entirely from financial statement ratios and estimated

[4] Convergent consensus is updated up to 100 days post the fiscal period report date. Source: Factset.

a probit regression from his sample to compute the probability of manipulation and then validated the model's efficacy using the AAERs data. Dechow et al. (2011) developed a sequential prediction model to calculate the F-score, which is used by a vast literature as an ex-ante predictor of a firm's earnings manipulation probability.

Following the estimation of the F-score by Dechow et al. (2011), Hui et al. (2014) further improved the fraud detection model using a combination of accruals (e.g., working capital), risk (e.g., earnings volatility), and other control variables (e.g., leverage, total assets). More recently, Bertomeu et al. (2021) use machine learnings technique to merge information from accounting, capital market, governance, and auditing data to detect material misstatements. Their training dataset and out of the sample prediction dataset both rely on the AAERs database as the identification of actual accounting misstatements. In summary, prior literature has been using the AAER database extensively as a reliable indicator of actual occurrences of earnings manipulation. Following this stream of literature, we also rely on the AAER database in this study to investigate whether and how the property of analyst forecast changes when we know revised ex-post EPS for firms that have committed fraud.

2.3 Analyst detecting misreporting practices

One of the important topics in financial analysts' research in accounting is whether financial analysts exclude from their estimates, *misreported* earnings, when they issue earnings forecasts. Misreporting in accounting refers to the intentional presentation of financial information in a way that misleads users of financial statements. It can take various forms, earnings management and fraud are generally involved, distorting the true financial position or performance of a company. Regulators such as the SEC (U.S.), consider misreporting a violation of financial reporting standards (e.g., US GAAP).

Evidence on analysts ability of detecting misreporting practices provides diverse results. Hribar & Jenkins (2004) show that analysts do not anticipate the consequence of earnings manipulation that leads to accounting restatements later. Analysts face challenges in detecting fraud due to limited time and resources, which can lead to oversight of red flags, as seen in the Enron scandal. Simple ratio analyses could have signaled issues, but these were often ignored in the face of rising stock prices (Barsky, et al., 2003). The detection of fraud is complicated by the difficulty in accessing relevant information and the delayed judicial ascertainment of fraudulent events, which can occur many years after fraud has been committed. Studies have shown that total accruals analysis is a consistent instrument for detecting fraud, particularly in the context of earnings management. D'Amico & Mafrolla, (2013) compare the relevance of fraud influencing total accruals in fraud firms against a peer group of non-fraud firms, the presence of fraud has been identified as a statistically significant element in explaining earnings management through total accruals.

Analysts often react to suspected fraud by revising their estimates downward or dropping coverage of the firm. This behavior is more pronounced in cases of egregious fraud, where the costs of detection are lower and the reputational risks for analysts are higher (Young & Peng, 2013). Young and Peng (2013), using an AAER sample between 1995 and 2009, find that analysts have a higher probability of dropping coverage rather than just revising down their recommendations for firms that they suspect have committed accounting fraud. Their research also suggests that analysts' actions may be useful in determining accounting fraud. Despite these capabilities, detecting fraud is challenging. Analysts may face conflicts of interest, such as investment banking relationships, which can bias their estimates. On the other hand, fraudulent firms often employ sophisticated methods to disguise fraudulent activities, making it difficult to distinguish between authentic and manipulated financial data. Other analysts measures can bring meaningful insights in fraud detection, for instance, analysts' avoidance of fraud is linked to their ability to affect the transparency of information and the attention of investors, which can reduce the likelihood of fraudulent activities (Hui, et al., 2020). Economic rationale suggests that analysts are rewarded by issuing accurate analyst forecasts in comparison to actual earnings. However, the analyst might be overly motivated by the incentive to be "accurate" so that they strategically adjust their earnings forecasts to be close to the "*misreported*" earnings rather than the "*corrected*" earnings. The AAER database provides a great venue to investigate whether analysts forecast detect *misreporting* practices, as all reported cases in AAER database are confirmed to have misreporting practices in their earnings.

Forecasts are part of an analyst's track record; unrevised or inaccurate projections harm their credibility (Altınkılıc & Hansen, 2009). If an analyst leaves a forecast unchanged despite newly available earnings data, after earnings publication, it can appear unresponsive or negligent, especially if peers revise their estimates. These revisions reflect analysts' interpretation of the quality and sustainability of the earnings, their alignment with the company's evolving narrative, and their own accountability to investors. In the context of AAER firms, where the earnings may later be revealed as fraudulent, post-announcement revisions allow us to observe how analysts incorporate financial signals that are, in hindsight, misleading. This moment captures a unique window into analyst judgment under uncertainty and the subtle signals that may precede fraud detection. Therefore,

H1a: Analysts' revised ex-post EPS moves towards "*corrected earnings*"

Higher levels of earnings management reduce the quality of public market information, affecting the comparability, reliability, and truthfulness of accounting information. This makes it difficult for analysts to detect earnings manipulations and adjust their forecasts accordingly. Du, et al., (2024) state that companies with higher degrees of earnings management tend to receive less attention from analysts, this is because analysts prefer to focus on companies with higher disclosure quality. Burgstahler & Eames (2003) show that analysts can identify earnings management policies to avoid small earnings declines. Analysts, who rely heavily on publicly disclosed information, find it challenging to detect and adjust for earnings manipulations, leading to less accurate forecasts (Embong & Hosseini, 2018). Aggressive financial reporting practices are a precursor to corporate fraud, with fraud firms showing distinct reporting behaviors compared to non-fraud firms. Other factors as the instability of a company's organizational structure, characterized by frequent changes in management, can also lead to earnings management practices, which are often precursors to fraud (Suryandari, et al., 2019). Such instability can create opportunities for earnings manipulation as new leaders may attempt to influence financial results to align with their strategic goals and dissimulate fraud or to present a favorable financial position (Suryandari, et al., 2019). For example, Chu et al. (2019) show that when management consistently beats analyst forecast for an extended period, they tend to move from within GAAP earnings management to out of GAAP earnings manipulations. Hong et al. (2014) find that analysts following, and earnings management are jointly determined, with analysts more likely to follow firms with lower accrual-based earnings management due to a better information environment. Most existing studies focus on earnings manipulation aimed at meeting or exceeding analyst forecasts, without considering whether analysts account for this manipulation when revising their own forecasts. Therefore,

> H2: Analysts' revised ex-post EPS incorporates more indicators of misreporting than their initial ex-ante forecast.

3. Research design

3.1 Sample

We analyze annual accounting data for a selection of US listed firms during the period running from 2001 through 2022. We focus specifically on fraudulent restatements extracted from AAER and Audit Analytics databases. The original AAERs data set has been provided by the University of Berkeley-Haas School of Business (SEC filings), complemented manually for some missing years. After dropping firm-year observations due to missing FactSet and Reuters analysts' forecasts and due to missing both « originally-reported » and « restated » earnings, the final sample yield of 1,663 firm-year observations. To reduce the impact of outliers, a trimming method was used, removing all observations in the 1% tail of deflated values annually. A matched sample is constructed for the AAER' firms, using propensity score matching with EPS, Debt to Assets, Market to book and Industry as confounders. A complementary sample of 1,663 U.S. companies, which have neither restated their financial results nor been accused of earnings manipulation is created. In addition, ex-ante EPS forecast (analysts' EPS forecast before earnings publication) and revised ex-post EPS (analysts' EPS corrected forecast, three days after earnings publication) are retrieved from FactSet. Table 1 shows the composition of the final sample.

3.2 Variable measures

First, in order to investigate if analysts exclude *misreporting*[5] practices from their estimates. We first compare both estimates ex-ante forecast EPS and revised ex-post EPS to « originally-reported » (*misreported* EPS) and « restated » earnings (*corrected* EPS). For this purpose, several variables are computed.

[5] We use two proxies for misreporting practices: earnings management (discretionary accruals and real earnings management) and fraud.

The **ex-ante forecast error “originally-reported” ($EAFE_{OR}$)** is defined as:

[ex-ante EPS forecast – originally-reported EPS] / lagged stock price.

The **ex-ante forecast error “restated” ($EAFE_R$)** is defined as:

[ex-ante EPS forecast – restated EPS] / lagged stock price

The **ex-post forecast error ‘originally-reported’ ($EPFE_{OR}$)** is defined as:

[revised ex-post EPS – originally-reported EPS] / lagged stock price

The **ex-post forecast error “restated” ($EPFE_R$)** is defined as:

[revised ex-post EPS – restated EPS] / lagged stock price

If $EAFE_R > EAFE_{OR}$, we may conclude that analysts first estimate (ex-ante) is able to exclude some *misreporting practices.*

If $EPFE_R < EAFE_R$, we may conclude that analysts include new information after earnings publication and predict *corrected* earnings rather than *misreported* earnings.

Because analyst should adjust their latest forecast incorporating the earnings management component by analyzing the information conveyed by financial statements, when they make their revised ex-post EPS, they should predict thus the *corrected* earnings, in this case we can hypothesize that: $EPFE_R < EAFE_R$.

On a second analysis we explore the capability of analysts to identify and separate between earnings management and fraud, and the degree in which they incorporate these two misreporting practices into their estimates. For firms subject to Accounting and Auditing Enforcement Releases (AAERs), we treat the magnitude of the restatement as a proxy to the extent of fraud. These restatements, mandated by the SEC, are issued to correct fraudulent misstatements in the financial reports. Therefore, the size of the restatement reflects the amount of fraud addressed:

The **Fraud (FRAUD)** of AAER companies, defined as the amount of restatement:

[Original EPS – Restated EPS] / lagged stock price.

Analysts revise their ex-ante EPS forecast by incorporating new information from reported earnings, ultimately issuing updated revised ex-post EPS. Prior research (Yezegel, 2015) indicates that most of these revisions occur within three days following the earnings announcement, a period characterized by heightened demand for updated estimates. To assess analysts' ability to integrate new information, we calculate the magnitude of their estimates corrections. We posit that these corrections capture elements of both earnings management and fraud, reflecting analysts' efforts to approximate *corrected* earnings. The analysts' correction is defined as the difference between the initial ex-ante EPS forecast and the subsequent revised ex-post EPS.

The **analysts' correction**, 3 days after earnings' publication **(ANCORR)**, defined as:

[revised ex-post EPS – ex-ante EPS forecast] / lagged stock price.

To investigate whether analysts' corrections incorporate earnings management practices, such as discretionary accruals and real earnings management; we collect *corrected* financial data and begin by estimating discretionary accruals using Kothari, et al., (2005) model:

$$DACC = TAt - NDAt$$

Where TAt, is calculated as:

$$TA = (\Delta Current\ Assets - \Delta Current\ Liabilities - \Delta Cash\ and\ cash\ Equivalents + \Delta Short\ Term\ Debt - Depreciation\ and\ Amortization)$$

And NDAt as:

$$NDAt = \alpha 1 \left(\frac{1}{A_{it-}}\right) + \alpha 2 \left(\frac{\Delta Revenue_{it} - \Delta Receivables_{it}}{A_{it-1}}\right) + \alpha 3 \left(\frac{PPE_{it}}{A_{it-1}}\right) + \alpha 4 \left(\frac{ROA_{it}}{A_{it-1}}\right) + \varepsilon_{it}$$

Where, for firm i:

- A_{it-1} = Total assets in the previous period (Year t-1)
- $\Delta Revenue_{it}$ = Change in revenues from the previous period
- $\Delta Receivables_{it}$ = Change in accounts receivables from the previous period
- $PPEit$ = Property, plant, and equipment (Year t)
- ROA_{it}= Net income divided by Total Assets

Accruals earnings management involves adjusting accounting entries and estimates without affecting actual cash flows. Fraudulent firms may switch between accruals and real earnings manipulations based on the relative costs and benefits of each method. For instance, to meet analysts' forecasts or avoid regulatory costs, managers might choose the method that best aligns with their immediate goals. Then, we calculate real earnings manipulations included in the analysts' estimates, following previous research Cohen and Zarowin (2010), Roychowdhury, (2006) and Séverin & Veganzones, (2021), the following variables are calculated:

$$RM1: \quad \frac{CF_{it}}{TA_{it-1}} = \alpha 0 + \alpha 1 \frac{1_{it}}{TA_{it-}} + \alpha 2 \frac{Sales_{it}}{TA_{it-1}} + \alpha 3 \frac{\Delta Sales_{it}}{TA_{it-1}} + \varepsilon_{it}$$

$$RM2: \quad \frac{Prod_{it}}{TA_{it-1}} = \alpha 0 + \alpha 1 \frac{1_{it}}{TA_{it-1}} + \alpha 2 \frac{Sales_{it}}{TA_{it-1}} + \alpha 3 \frac{\Delta Sales_{it}}{TA_{it-1}} + \alpha 4 \frac{\Delta Sales_{it-1}}{TA_{it-1}} + \varepsilon_{it}$$

$$RM3_{it}: \quad \alpha \frac{DISEXP_{it}}{TA_{it-1}} = \alpha 0 + \alpha 1 \frac{1_{it}}{TA_{it-1}} + \alpha 2 \frac{Sales_{it}}{TA_{it-1}} + \varepsilon_{it}$$

Where, for firm i:

CF_{it} = cashflow in year t ;

TA_{it} = total assets in year t-1 ;

$Sales_{it}$ = sales in year t ;

$\Delta Sales_{it}$ = change in net sales between years t and t-1 ;

$\Delta Sales_{it-1}$ = change in net sales between years t-1 and t-2 ;

$Prod_{it}$ = cost of goods sold plus the change in the inventory in year t;

DISEXP = sum of advertising, R&D and S&GA expenses in year t.

We multiply residuals of RM1 and RM3 by minus one. Higher abnormal discretionary expenses decrease earnings. The same happens when firms offer discounts to boost sales, which increases sales volume but reduces cash flow from operations (CF). Therefore, we summarize the three calculated amounts for real earnings management into one unique variable: REM. Finally, we construct our model to test analysts' capability to assess both management and fraud components on the degree of the correction:

$$ANCOR_{it} = \alpha 0 + \alpha 1\, FRAUD_i + \alpha 2\, DACC_{it} + \alpha 3 REM_{\ it} + \alpha 4\, ES_{it} + Controls_{it} + \varepsilon_{it}$$

Where, for firm i:

$ANCOR_{it}$ = revised ex-post EPS – ex-ante EPS forecast / lagged stock price;

$FRAUD_{it}$ = Original EPS - Restated EPS / lagged stock price;

$DACC_{it}$ = Discretionary accruals ;

REM_{it} = Real Earnings Management;

ES_{it} = ex-ante EPS forecast - originally-reported EPS;

Previous literature (Rui, et al., 2016) confirms that analysts estimates are influenced by other components as earnings surprise, level of indebtedness, market capitalization, etc. We control this effects by calculating the variables described in Table 2.

4. Empirical results

4.1 Descriptive statistics and univariate test

Table 3 lists the mean, median, standard deviation as well as the maximum and minimum values of the independent variables. On average the fraud (FRAUD) is positive, this implies that AAERs' firms manipulate upward their earnings. However, $EAFE_{OR}$ (earnings surprise) mean is negative for both AAER and non AAER firms, which indicates that analysts estimate a higher EPS compared to *originally reported EPS* . Analysts' correction shows that on average analysts do higher corrections to AAER firms, on the contrary, for non AAER firms, analysts seem to downgrade slightly their estimate. After restatement, the decrease of EPS represents on average 2.5 %. On average 95% of the firms in the sample are listed on the NYSE or the NASDAQ, their average leverage is 16.5% (Leverage) and 2.9% are foreign firms (ADR). Table 4 exhibits correlation matrix, analysts' correction (ANCORR) is positively correlated with the amount of FRAUD (0.11) which indicates larger corrections in fraud cases. Moderately and positively correlated with ES (0.3269), this indicates that analysts align their corrections to their first estimate (ex-ante EPS forecast). FRAUD is positively correlated with ES (0.4733), which might suggest a higher amount of earnings manipulation leads to a higher forecast error. Fraud firms (FF) are negatively correlated with N. ANALYST (-0.4669), perhaps reflecting less analyst coverage for fraud firms.

- Insert Table 3 and 4 about here –

Table 5 exhibits univariate tests of the dependent variables, for AAER firms compared to non AAER firms . In panel A (1), we observe that the absolute mean and median values of $EAFE_{OR}$ are below for non AAER firms, the analysis reveals that analyst ex-ante EPS forecast are more accurate for firms not involved in earnings manipulations. The difference compared to AAER firms is statistically significant at the 1% level for both median and mean values. In panel A (2), the revised ex-post EPS reflects a higher accuracy for medians for both AAER firms and not AAER firms, statistically significant at the 1% level. While on average, analysts seem to lower the gap towards *corrected earnings* for AAER firms compared to ex-ante EPS forecast. Means are significant at the 1% level.

When analysts' revised ex-post EPS and ex-ante EPS forecast for AAER firms are compared to *corrected earnings* (i.e. restated EPS) in panel B of Table 5 (3), we observe that the revised ex-post EPS is more closely aligned with *corrected earnings* (mean is significant at 1% level). This suggests that analysts adjust their initial estimates to account for potential earnings management practices and fraud, after the company has released its financial statements.

Panel B (4) of Table 5 presents a comparative analysis of revised ex-post EPS for AAER firms. The revised ex-post EPS is compared to *misreported earnings* and *corrected earnings*.

Results indicate that both the median and mean values of $EPFE_R$ are below those of the $EPFE_{OR}$. However, only the difference in medians is statistically significant at the 5% level. This reveals a significant pattern for AAER firms: analysts' revised ex-post EPS aligns more closely with *corrected earnings* than with *misreported* figures.

- Insert Table 5 about here –

Table 6 presents univariate statistics for absolute values. Earnings surprise, for AAER and non AAER firms, differ significantly at 1% level. We observe that there is a larger earnings surprise for AAER firms, analyst are more accurate for non AAER firms, this could be explained by the absence of the fraud component. In the case of analysts' correction which is the difference between the revised ex-post EPS and ex-ante EPS forecast, the statistics suggest that analysts do higher corrections to the initial estimate (ex-ante) for AAER firms. This could indicate that analyst see through some kind of fraud, as their correction is different compared to non AAER firms, mean and median are significant at 1% level.

Unexpectedly, the statistical analysis reveals that AAER firms show lower discretionary accruals in both mean and median measurements. This counterintuitive outcome suggests that firms subject to AAERs appear to have less earnings management through discretionary accruals than their non-AAER counterparts, contrary to what might be anticipated. This finding can be attributed to several factors, one is the reversal of accruals: fraudulent companies may have already reversed their discretionary accruals by the time fraud was detected. As companies must deal with the consequences of accruals reversing over time, they might have exhausted their ability to manage earnings through accruals and resorted to outright fraud, this has been confirmed by Ramos do Nascimento et al. (2024). Their research indicates that earnings management was more prevalent before fraud occurred than after its discovery. Companies engaging in high levels of earnings management eventually need to reverse discretionary accruals, potentially leading them to commit fraud to offset these reversals and achieve their financial objectives. Our study focuses on the year of fraud revelation, suggesting that AAER companies might have engaged in more aggressive earnings management in preceding years. An alternative explanation for the observed pattern could be a transition towards real activities manipulation, AAERs companies show a significatively higher mean and median than non AAER firms. The fraudulent companies might have moved beyond accrual-based earnings management to more severe forms of manipulation that are not captured by discretionary accruals measures. And overcompensation, fraudulent companies might be deliberately keeping their discretionary accruals low to avoid suspicion, effectively overcompensating in their attempt to appear legitimate.

- Insert Table 6 about here –

4.2 Multivariate analysis

Table 7 contains the results of the first OLS regression for the matched sample, i.e. that runs the amount of analysts' correction (ANCORR) as the independent variable (revised ex-post EPS – ex-ante EPS forecast) with several explanatory variables described in Table 2. The results indicate that the revised ex-post EPS adjustment made by the analysts towards the restated EPS is negatively associated with the discretionary accruals (significant at the 5% level). This shows that the lower discretional accruals, the higher the correction will be performed by the analyst. Analysts are highly over-optimistic when DACC (accrual manipulation) is high. They miss aggressive earnings manipulation.

In the case of the amount of fraud (FRAUD), it is negatively associated with the analysts' correction. This shows that analysts will only upgrade their first estimate for firms with less amount of Fraud. Analyst overreact when they detect something questionable after the publication of results.

The effect of being a fraudulent firm does not seems to be significant. This finding suggests that analysts do take into account, to some extent, the amount of fraud, differentiated from earnings management practices for both fraudulent and non fraudulent firms

The variable earnings surprise (ES) is positively and significantly associated with analysts' correction. This can be attributed to the following scenario. Analysts align with their original surprise. If there's a positive earnings surprise (originally reported EPS higher than ex-ante EPS forecast), analysts make significant corrections to their revised ex-post EPS. If there is a negative earnings surprise (originally reported EPS lower than ex-ante EPS forecast), analysts may need to make larger downward corrections to their revised ex-post EPS. The interaction variable ES*FF is also significant and positively associated, suggesting that analysts are more responsive, in the case of fraudulent firms, perhaps because they suspect something is wrong.

The magnitude of a company's size appears to positively correlate with the extent of analysts' corrections. As a company grows larger, it tends to attract more analyst coverage and disclosure more detailed information than smaller firms. This increased scrutiny often results in analysts making larger adjustments to their initial estimates. Overall, this result suggests that analysts' corrections include new information after the publication of results and adjust their first estimation to reflect *corrected* earnings, this process of adjustment suggests that analysts are refining their initial projections to better reflect the company's true financial performance, unaffected by potential earnings management.

- Insert Table 7 about here –

Table 8 presents the last regression using absolute values for variables ANCOR, FRAUD, DACC, REM and ES. We model the magnitude of analyst correction errors (i.e., how far off analysts were, regardless of direction). The variable FRAUD is positively and significantly (1% level) correlated with the magnitude of the correction, this means that the amount of fraud is associated with larger corrections. Analysts miss some of the manipulation in their Ex-ante estimate, leading to greater revised ex-post EPS corrections. The relationship between ES and the direction of the correction is confirmed, analysts align with their original surprise. The variable is positively and significantly (1% level) correlated. New insights emerge regarding the factors analysts consider in their revisions, with the variable LOSS showing significant positive correlation (at the 1% level) with the magnitude of analysts' corrections. Loss making firms might generally lead to larger analyst correction errors, likely due to unexpected earnings or unusual items. LogTA and MTB are negatively and significantly correlated, suggesting larger firms have smaller analysts' corrections.

- Insert Table 8 about here –

We divide the matched sample into two groups: companies where analysts's corrections (ANCORR) bring them "closer" to *corrected* earnings ($EPFE_R < EAFE_R$) and those where analysts remain "far" from *corrected* earnings. Analyst are closer to the *corrected* earnings for around 57% of the firms in the sample. We introduce a new variable FQuantile to measure the effects of the amount of fraud by quantile for fraudulent firms. Table 9 regression outcomes:

- Insert Table 9 about here –

Variable	**Closer** (EPFE$_R$ < EAFE$_R$)	**Far** (EPFE$_R$ > EAFE$_R$)	**Interpretation**
FRAUD	Negatively correlated (–0.14) ***	Positively correlated (0.22) ***	Significant and inverted signs: In "Closer", higher amount of fraud lead to less upgrades in the correction (analysts anticipated some of the fraud); in "Far", analysts underestimated manipulation, so their correction is optimistic in the case of fraud.
DACC	Not significant	Negative and significant (–0.48) ***	When analysts are far from *corrected* earnings, accrual manipulation (DACC) is associated with larger upgrades. In "Closer" cases, DACC seems not to influence analyst corrections.
REM	Not significant	Weakly positive (0.09)	REM has some influence in the "Far" group, analysts may account for some real manipulation.
ES	Positively correlated (0.24) ***	Negative and significant (–0.11) ***	Inverted signs: In "Closer", analysts' corrections align with their original surprise (they knew something). In "Far", analysts correct in the opposite direction, reinforcing their mistake.
FF	Positively correlated (0.01) **	Not significant	Being a fraudulent firm is positively associated with more accurate corrections only in the "Closer" group possibly because analysts see thought some earnings manipulation.
FQuintile	Negatively correlated (–0.01) ***	Not significant	Higher fraud magnitude is associated with more accurate analyst correction in "Closer" cases.

Table: **Dependent variable : Analysts' correction (ANCORR)**

Table 10 presents a more detailed regression analysis for AAER firms, focusing on analysts' estimate corrections as the dependent variable. The sample is segmented into quintiles to examine the relationship between the magnitude of earnings manipulation and the extent of analysts' EPS adjustments. The findings reveal that analysts take into account the size of the earnings surprise relative to their initial estimate when making corrections to their subsequent revised ex-post EPS. The earnings surprise (ES) variable shows a positive association with the magnitude of EPS correction (statistically significant at the 1% level across the quintiles where the amount of fraud is higher). This suggests that analysts tend to make align adjustments to their initial estimates when they perceive that their original estimates already predict the company's actual results. This approach allows analysts to account for potential earnings manipulations in their estimate revisions, as the gap between their initial estimate and the announced earnings can absorb any possible earnings manipulation.

The analysis reveals that the amount of fraud (FRAUD) is statistically significant and negatively correlated only for the fifth quintile, which represents the firms with the highest positive levels of manipulation. This finding suggests that analysts can detect fraudulent activities when they reach a substantial magnitude. As the scale of fraud increases, analysts make less significant revised ex-post EPS upgrades to their initial estimates. Additionally, the results indicate that analysts appear to factor in real earnings management (REM) when adjusting their estimates. This is evidenced by the negative correlation between REM and the revised ex-post EPS correction, which is statistically significant at the 1% level. These observations imply that analysts are more likely to revise their estimates downwards in response to larger manipulations and higher levels of real earnings management, particularly when the manipulation is extensive enough to be noticeable.

Table 11 corroborates the previous findings by using quintiles based on the absolute magnitude of FRAUD, DACC, REM and ES and the absolute value of analysts' corrections (ANCORR) as the dependent variable. The results reinforce that analysts can detect fraudulent activities when they reach a substantial scale. Specifically, the manipulation variable (|FRAUD) shows a significant and negative relationship only for the fifth quintile, which represents the firms with the most extreme levels of manipulation. This suggests that analysts make fewer upgrade adjustments to their estimates when confronted with more substantial fraudulent activities. Additionally, the earnings surprise (ES) variable is negatively correlated with estimates corrections and statistically significant at the 1% level across most of quintiles. This pattern indicates that analysts incorporate new information after earnings publication and correct towards the earnings surprise when revising their initial estimates, regardless of the magnitude of manipulation.

- Insert Table 10 and 11 about here –

5. Conclusion

This research focuses on the use of the analysts' revised ex-post EPS (i.e. "convergence consensus") in order to measure the intrinsic quality of analysts' estimates activities by comparing their *ex-ante* forecast to their revised *ex-post* EPS. It also relies on the AAER data basis that identifies fraudulent companies but also provides the "correct" or "restated" earnings (i.e. without the fraud) the firms have to report (even though several months or years later). Using a matched sample of US listed firms of fraudulent and non-fraudulent firms, the empirical analysis reveals that the analyst's revised ex-post EPS is closer to the restated EPS (i.e. EPS without fraud) than to the originally reported EPS (i.e. fraudulent EPS). Besides, multivariate analysis exhibits that the overall analysts' correction (i.e. revised ex-post EPS compared to ex-ante EPS forecast) is negatively and significantly associated to the magnitude of the fraud.

This research makes a contribution to analyst literature in two ways. First, fraudulent companies may employ sophisticated earnings management techniques to manipulate their financial statements. These techniques can make it difficult for analysts to detect discrepancies, potentially leading to fewer corrections even as fraud increases. Yet, analysts are able, to some extent, to detect fraudulent accounting practices. Indeed, the revised ex-post EPS is more distant from the *misreported EPS* (originally reported EPS) than from the *corrected* (restated EPS). Second, analysts are also in the capacity to adjust their ex-ante EPS forecast as they take into account the magnitude of the fraud in their revised ex-post EPS, but for the largest fraud only (i.e. highest quintile of firm manipulation). The overlooked revised ex-post EPS warrants consideration by stakeholders, as it offers meaningful insights into a company's financial conduct and managerial decisions.

Figure 1. Estimated earnings, reported earnings and convergence consensus

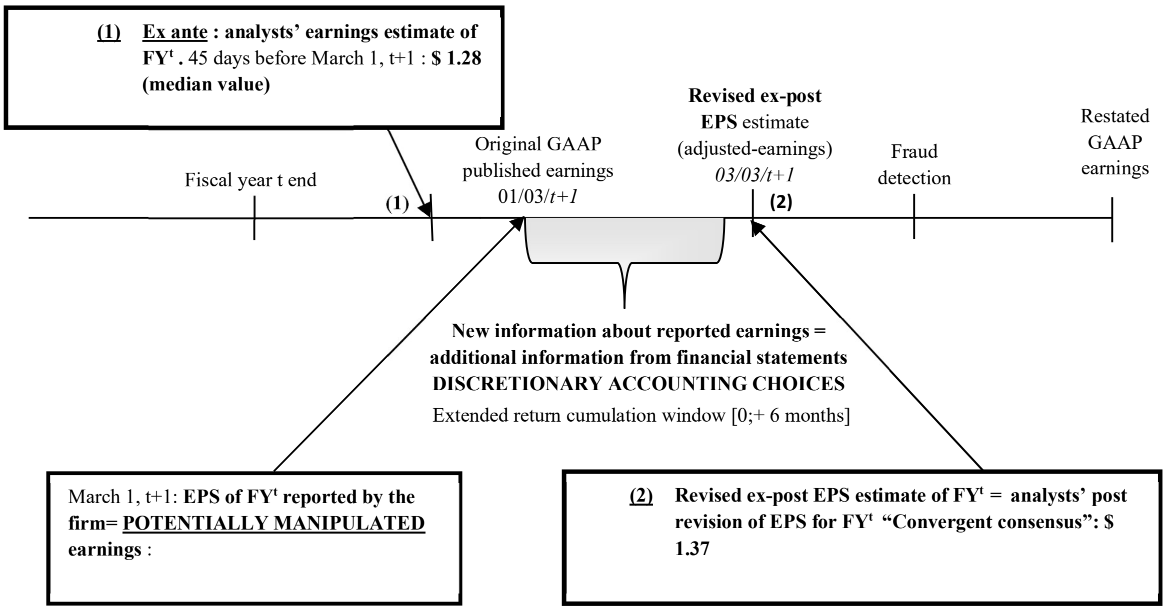

Table 1. Sample Construction

Industry	SIC Code	Number of non AAER firms	%	Number of AAER firms	%	Total
Agriculture	0000-1999	39	2.35%	73	4.39%	112
Manufacturing	2000-3569 and 3580-3999	526	31.63%	564	33.91%	1090
Technology	3570-3579 and 7370-7379	371	22.31%	174	10.46%	545
Transportation	4000-4799	114	6.86%	38	2.29%	152
Communication	4800-4899	65	3.91%	40	2.41%	105
Utilities	4900-4999	239	14.37%	91	5.47%	330
Wholesale and retail	5000-5999	131	7.88%	145	8.72%	276
Financial services	6000-6999	21	1.26%	313	18.82%	334
Services	7000-7369 and 7380-8999	149	8.96%	215	12.93%	364
Other	9000-9999	8	0.48%	10	0.60%	18
Total		1,663		1,663		3,326

Total AAER firms in SEC database	3,255
Firms not followed by analysts	(826)
Firms missing information	(776)
Total	1,663

Table 2. Variables Construction

Variable	Definition
$EAFE_{OR}$ (ES)	Originally-reported EPS - Ex-ante EPS forecast / lagged stock price.
$EAFE_{R}$	Restated EPS - Ex-ante EPS forecast / lagged stock price.
$EPFE_{R}$	Restated EPS – Revised ex-post EPS / lagged stock price.
$EPFE_{OR}$	Originally-reported EPS – Revised ex-post EPS / lagged stock price.
DACC	Discretionary accruals calculated according to Khotari (2005).
REM	Real Earnings Management calculated according to Cohen and Zarowin (2010).
ANCORR	Analysts' correction: revised ex-post EPS – ex-ante EPS forecast / lagged stock price.
FRAUD	Original EPS - Restated EPS / lagged stock price.
ES	Earnings surprise: ex-ante EPS forecast - originally-reported EPS / lagged stock price.
FF	Fraudulent firm: Binary variable that resumes companies being part of AAER sample.
ES*FF	Interaction variable earnings surprise * fraudulent firm
FQUANTILE	Quantile number based on the amount of Fraud.
LEVERAGE	Total debt / Total Assets.
LOSS	Binary variable with value 1 if the company has reported negative earnings in the present year.
ADR	Binary variable with value 1 if the company is a foreign company traded by an ADR.
N. ANALYST	Number of analysts following the company.
LogTA	Logarithm of Total Assets.
MTB	Market to book ratio: Total Equity/Market capitalization.

Table 3. Descriptive Statistics

AAER Firms

	EPS Original	EPS Restated	DACC	FRAUD (Restate amount)	LOSS	REM	Leverage	N . Analyst	EPFE$_{OR}$ Ex-post Forecast error Original EPS	EPFE$_{R}$ Ex-post Forecast error Restated EPS	EAFE$_{OR}$ (ES) Ex-ante Forecast error Original EPS	EAFE$_{R}$ Ex-ante Forecast error Restated EPS	Analysts' Correction	MTB	ADR
Count	1 663	1 663	1 663	1 663	1 663	1 663	1 663	1 663	1 663	1 663	1 663	1 663	1 663	1 663	1 663
Mean	1.5483	1.5093	-0.0012	-0.0025	0.2014	-0.7576	0.2159	2.7865	-0.0196	-0.0171	-0.0251	-0.0226	-0.0055	2.7148	0.0553
Std	15.3165	15.6611	0.0687	0.1123	0.4012	2.2988	0.1940	5.6090	0.1421	0.1267	0.1506	0.1301	0.0664	3.4198	0.2287
Min	-238.0000	-280.0000	-0.4291	-2.1143	0.0000	-16.3259	0.0000	0.0000	-1.7382	-1.8056	-1.9167	-1.8856	-1.2800	-17.5654	0.0000
25%	0.2226	0.1850	-0.2826	-0.0083	0.0000	-0.9685	0.0536	1.0000	-0.0219	-0.0180	-0.0257	-0.0243	-0.0029	1.4391	0.0000
50%	1.0900	1.0473	-0.0001	0.0000	0.0000	-0.1228	0.1772	1.0000	-0.0052	-0.0025	-0.0067	-0.0044	0.0004	2.1502	0.0000
75%	2.4008	2.3000	0.0002	0.0056	0.0000	0.0399	0.3199	1.0000	0.0001	0.0000	0.0020	0.0020	0.0028	3.5523	0.0000
Max	284.2344	252.4636	2.2510	1.8029	1.0000	16.0258	0.8905	47.0000	1.4000	1.6018	1.5376	1.2788	0.8149	20.3376	1.0000

Non AAER Firms

	EPS Original	EPS Restated	DACC	FRAUD	LOSS	REM	Leverage	N . Analyst	EPFE$_{OR}$ Ex-post Forecast error Original EPS	EPFE$_{R}$ Ex-post Forecast error Restated EPS	EAFE$_{OR}$ (ES) Ex-ante Forecast error Original EPS	EAFE$_{R}$ Ex-ante Forecast error Restated EPS	Analysts' Correction	MTB	ADR
Count	1 663	1 663	1 663	1 663	1 663	1663	1 663	1 663	1 663	1 663	1 663	1 663	1 663	1 663	1 663
Mean	1.4716	1.4716	-0.0026	0.0000	0.1118	-0.0680)	0.1149	10.1720	-0.0086	-0.0086	-0.0082	-0.0082	0.0003	4.1586	0.0036
Std	11.9062	11.9062	0.0103	0.0000	0.3153	0.9212	0.1555	8.1491	0.0813	0.0813	0.0846	0.0846	0.0067	4.3949	0.0600
Min	-290.2247	-290.2247	-0.2414	0.0000	0.0000	-7.7325	0.0000	0.0000	-2.5935	-2.5935	-2.7623	-2.7623	-0.1688	-21.7650	0.0000
25%	0.3300	0.3300	-0.0030	0.0000	0.0000	-0.1826	0.0000	3.5000	-0.0066	-0.0066	-0.0076	-0.0076	-0.0004	2.0084	0.0000
50%	1.1100	1.1100	-0.0010	0.0000	0.0000	-0.0114	0.0386	8.0000	0.0000	0.0000	-0.0005	-0.0005	0.0004	3.2147	0.0000
75%	2.2586	2.2586	-0.0000	0.0000	0.0000	0.1274	0.1710	15.0000	0.0001	0.0001	0.0020	0.0020	0.0019	5.1789	0.0000
Max	331.2500	331.2500	0.0396	0.0000	1.0000	15.1490	0.7314	45.0000	0.3344	0.3344	0.3360	0.3360	0.0152	31.1856	1.0000

Table 3. Descriptive Statistics

Matched Sample															
									$EPFE_{OR}$	$EPFE_{R}$	$EAFE_{OR}$ (ES)	$EAFE_{R}$			
	EPS Original	**EPS Restated**	**DACC**	**FRAUD (Restate amount)**	**LOSS**	**REM**	**Leverage**	**N . Analyst**	**Ex-post Forecast error Original EPS**	**Ex-post Forecast error Restated EPS**	**Ex-ante Forecast error Original EPS**	**Ex-ante Forecast error Restated EPS**	**Analysts' Correction**	**MTB**	**ADR**
Count	3 326	3 326	3 326	3 326	3 326	3 326	3 326	3 326	3 326	3 326	3 326	3 326	3 326	3326	3326
Mean	1.5099	1.4904	-0.0019	-0.0013	0.1566	-0.4128	0.1654	6.4793	-0.0141	-0.0128	-0.0167	-0.0154	-0.0026	3.4367	0.0295
Std	13.7157	13.9088	0.0491	0.0794	0.3635	1.7845	0.1829	7.9095	0.1159	0.1065	0.1224	0.1099	0.0472	4.0027	0.1691
Min	-290.2247	-290.2247	-0.4290	-2.1143	0.0000	-16.3259	0.0000	0.0000	-2.5935	-2.5935	-2.7623	-2.7623	-1.2800	-21.7650	0.0000
25%	0.3046	0.2800	-0.2826	0.0000	0.0000	-0.4463	0.0030	1.0000	-0.0130	-0.0107	-0.0152	-0.0139	0.0023	1.7067	0.0000
50%	1.1000	1.0800	-0.0004	0.0000	0.0000	-0.0475	0.1099	3.0000	-0.0014	-0.0007	-0.0025	-0.0017	0.0004	2.6741	0.0000
75%	2.3000	2.2678	0.0000	0.0000	0.0000	0.0855	0.2758	10.0000	0.0001	0.0000	0.0020	0.0020	-0.0012	4.2594	0.0000
Max	331.2500	331.2500	2.2510	1.8029	1.0000	16.0258	0.8905	47.0000	1.4000	1.6018	1.5376	1.2788	0.8149	31.1856	1.0000

Table 4. Correlation Matrix

	ANCORR	DACC	REM	FRAUD	ES	FF	LEVERAGE	LOSS	ADR	N. ANALYST	LogTA	MTB
ANCORR	1											
DACC	-0.0312	1										
REM	0.0020	0.0944	1									
FRAUD	0.1084	0.0199	-0.0239	1								
ES	0.3269	0.0172	0.0191	0.4733	1							
FF	-0.0619	0.0145	-0.1724	-0.0159	-0.0689	1						
LEVERAGE	-0.0283	0.0825	0.0083	0.0153	-0.1096	0.2761	1					
LOSS	-0.1383	-0.0274	-0.0286	-0.1249	-0.3278	0.1233	0.0881	1				
ADR	-0.0117	0.0058	0.0291	0.0084	0.0332	0.1529	-0.05	-0.0262	1			
N. ANALYST	0.0420	0.0066	0.0817	0.0132	0.0161	-0.4669	-0.1121	-0.1513	0.1551	1		
LogTA	0.0430	0.0417	0.1042	-0.0134	-0.0029	0.0637	0.2638	-0.276	0.1993	0.4287	1	
MTB	0.0384	0.0189	0.0216	0.0037	0.0578	-0.1804	-0.2598	-0.0339	-0.0138	0.1328	-0.1054	1

ANCORR is based on revised ex-post EPS – ex-ante EPS forecast / lagged stock price. DACC represents discretionary accruals. REM stands for real earnings' management. FRAUD is calculated as Original EPS - Restated EPS / lagged stock price. ES is the Originally-reported EPS - Ex-ante EPS forecast / lagged stock price. FF is a binary variable that groups companies being part of AAER sample. LEVERAGE indicates Total debt / Total Assets. LOSS is a binary variable with value 1 if the company has reported negative earnings in the present year. ADR a binary variable with value 1 if the company is a foreign company traded by an ADR. N. ANALYST is number of analysts following the company. LogTA stands for Logarithm of Total Assets. MTB or Market to book ratio is equal to Total Equity/Market capitalization.

Table 5. Univariate statistics ex-ante forecast and revised ex-post EPS

Panel A

	(1) Ex-*ante* EPS forecast- *Misreported EPS*		**(2) Revised ex-*post* EPS – *Corrected EPS***	
Sample	**AAER[1]**	**Non AAER**	**AAER**	**Non AAER**
	$EAFE_{OR}$	$EAFE_{OR}$	$EPFE_{R}$	$EPFE_{OR}$
Mean	0.0251 >	0.0082	0.0171 >	0.0085
Median	0.0067 >	0.0005	0.0025 >	0.0000
Maximum	1.5376 >	0.3360	1.6018 >	0.3344
Minimum	1.9167 <	2.7623	1.8056 <	2.5934
Std. Dev.	0.1506 >	0.0846	0.1267 >	0.0812
Observations	1,663	1,663	1,663	1,663
	Test of equality	P-value	Test of equality	P-value
	t-test: -3.9799	0.0000***	t-test: -3.7679	0.0001***
	Wilcoxon/Mann-Whitney:	0.0000***	Wilcoxon/Mann-Whitney: 8.490	0.0000***

Panel B

	(3) Revised ex-post EPS estimate – Ex-ante EPS		**(4) Revised ex-post EPS – Ex-ante EPS forecast**	
Sample	**AAER**	**AAER**	**AAER**	**AAER**
	$EPFE_{R}$	$EAFE_{R}$	$EPFE_{R}$	$EPFE_{OR}$
Mean	0.0171 <	0.0226	0.0171 <	0.0196
Median	0.0025 <	0.0044	0.0025 <	0.0052
Maximum	1.6018 >	1.2788	1.6018 >	1.4000
Minimum	1.8056 <	1.8856	1.8056 >	1.7382
Std. Dev.	0.1267 <	0.1301	0.1267 <	0.1421
Observations	1,663	1,663	1,663	1,663
	Test of equality	P-value	Test of equality	P-value
	t-test : 3.3707	0.0004***	t-test : (0.5394)	0.5896
	Wilcoxon/Mann-Whitney:	0.3097	Wilcoxon/Mann-Whitney: 2.2109	0.0270**

[1] AAER represent firms that have received and Accounting and Auditing Enforcement Release, due to earnings manipulations.
EPFE (ex-post forecast error) and EAFE (ex-ante forecast error) are based on median values of convergent consensus using broker actuals 3 days after earnings publication. The ex-post forecast error restated ($EPFE_{R}$) is defined as = restated EPS- revised ex-post EPS / lagged stock price. The ex-post forecast error 'originally-reported' ($EPFE_{OR}$) is defined as = originally-reported EPS – revised ex-post EPS / lagged stock price. The ex-ante forecast error restated ($EAFE_{OR}$) is defined as = originally-reported EPS - ex-ante EPS forecast / lagged stock price. The ex-ante forecast error restated ($EAFE_{R}$) is defined as = restated EPS / ex-ante EPS forecast / lagged stock price. *,**.***, significance at 10%, 5% and 1% respectively.

Table 6. Univariate statistics: earning surprise, analysts' correction, discretionary accruals and real earnings' management.

	|Earnings Surprise (ES)|		**|Analysts' correction (ANCORR)|**		**|Discretionary accruals (DACC)|**		**|Real Earnings Management (REM)|**	
	AAER[1]	**Non AAER**	**AAER**	**Non AAER**	**AAER**	**Non AAER**	**AAER**	**Non AAER**
Mean	0.0251 >	0.0082	0.0055 >	0.0003	0.0012 <	0.0026	0.7576 >	0.0680
Median	0.0067 >	0.0005	0.0003 <	0.0004	0.0001 <	0.0010	0.1229 >	0.0114
Maximum	1.5376 >	0.3360	0.8149 >	0.0152	2.2510 >	0.0397	16.0258 >	15.1490
Minimum	1.9167 <	2.7623	1.2800 >	0.1688	0.4291 >	0.2415	16.3259 >	7.7325
Std. Dev.	0.1506 >	0.0846	0.0664 >	0.0067	0.0687 >	0.0103	2.2988 >	0.9213
Observations	1,663	1,663	1,663	1,663	1,663	1,663	1'663	1'663
	Test of equality	P-value	Test of equality	P-value	Test of equality	P-value	Test of equality	P-value
	t-test: (3.9799)	0.0000***	t-test: 3.575203	0.0000***	t-test: 0.8383	0.4100	t-test: 11.355	0.0000***
	Wilcoxon/Mann-Whitney: 10.5651	0.000***	Wilcoxon/Mann-Whitney: (2.939)	0.0030***	Wilcoxon/Mann-Whitney: (13.251)	0.0000***	Wilcoxon/Mann-Whitney: 13.088	0.0000***

[1] AAER represent firms that have received an Accounting and Auditing Enforcement Release, due to earnings manipulations.

Earnings Surprise (ES) calculated as Originally-reported EPS - Ex-ante EPS forecast / lagged stock price. Analysts' correction is the revised ex-post EPS – ex-ante EPS forecast / lagged stock price. *,**.***, significance at 10%, 5% and 1% respectively.

Table 7. Matched Sample– Dependent variable: Analyst's Correction (ANCORR)

	Coeff		Coeff		Coeff		Coeff		Coeff	
INTERCEPT	-0.0099		-0.0098		-0.0104		-0.0102		-0.0108	
	(-0.5300)		(-0.5200)		(-0.5600)		(-0.5500)		(-0.5800)	
FRAUD			-0.0388	***			-0.0384	***	-0.0696	***
			(-3.4700)				(-3.4300		(-6.0000)	
DACC	-0.0376	**	-0.0369	**	-0.0373	**	-0.0366	**	-2.3800	**
	(-2.3600)		(-2.3200)		(-2.3400)		(-2.3000)		(0.0170)	
REM	-0.0003		-0.0004		-0.0003		-0.0004		-0.0005	
	(-0.6000)		(-0.6900)		(-0.6600)		(-0.7400)		-0.9300	
ES	0.1256	***	0.1378	***	0.1252	***	0.1374	***	0.0420	***
	(18.4400)		(18.0000)		(18.3800)		(17.9200)		(3.2100)	
FF					-0.0042		-0.0039		-0.0013	
					(-1.3700)		(-1.2700)		(-0.4200)	
ES*FF									0.1394	***
									(8.9300)	
LEVERAGE	0.0054		0.0065		0.0053		0.0063		0.0082	
	(1.0100)		(1.2000)		(0.9800)		(1.1700)		(1.5400)	
LOSS	-0.0019		-0.0018		-0.0018		-0.0017		-0.0003	
	(-0.7800)		(-0.7200)		(-0.7300)		(-0.6700)		(-0.1200)	
ADR	-0.0076		-0.0080		-0.0078		-0.0081		-0.0088	
	(-0.5400)		-0.5600)		(-0.5500)		(-0.5700)		(-0.6300)	
N. ANALYST	0.0000		0.0000		-0.0001		-0.0000		-0.0001	
	(0.0100)		(0.1000)		(-0.4500)		(-0.3300)		(-0.7600)	
LogTA	0.0021	*	0.0019	*	0.0023	**	0.0021	*	0.0023	**
	(1.9600)		1.8100)		(2.0900)		(1.9300)		(2.1800)	
MTB	0.0003		0.0003		0.0003		0.0003		0.0003	
	(1.4800)		(1.4400)		(1.5100)		(1.4700)		(1.3300)	
Observations	3 326		3 326		3326		3 326		3326	
R^2	0.1250		0.1280		0.1250		0.1290		0.1490	
R^2 adjusted	0.1130		0.1160		0.1130		0.1160		0.1370	

ANCORR is based on revised ex-post EPS – ex-ante EPS forecast / lagged stock price. DACC represents discretionary accruals. REM stands for real earnings' management. FRAUD is calculated as Original EPS - Restated EPS / lagged stock price. ES is the Originally-reported EPS - Ex-ante EPS forecast / lagged stock price. FF is a binary variable that groups companies being part of AAER sample. ES*FF interaction term for earnings surprise and fraud firm. LEVERAGE indicates Total debt / Total Assets. LOSS is a binary variable with value 1 if the company has reported negative earnings in the present year. ADR a binary variable with value 1 if the company is a foreign company traded by an ADR. N. ANALYST is number of analysts following the company. LogTA stands for Logarithm of Total Assets. MTB or Market to book ratio is equal to Total Equity/Market capitalization.

T values are indicated in parentheses (). *,**.***, significance at 10%, 5% and 1% respectively. Fixed effects year and industry included.

Table 8. Matched Sample– Dependent variable: │Analyst's Correction (ANCORR)│										
	Coeff		Coeff		Coeff		Coeff		Coeff	
INTERCEPT	0.0200		0.0201		0.0172		0.0205		0.0205	
	(1.1600)		(1.1700)		(1.1900)		(1.1900)		(1.2200)	
│FRAUD│			0.0390	***			0.0379	***	-0.0049	
			(3.5400)				(3.4300)		(0.0115)	
│DACC│	0.0079		0.0069		0.0153		0.0069		0.0069	
	(0.5100)		(0.4500)		(0.5100)		(0.4500)		(0.4600)	
│REM│	0.0002		0.0001		0.0006		0.0001		0.0001	
	(0.3400)		(0.2600)		(0.3300)		(0.2500)		(0.2300)	
│ES│	0.1595	***	0.1468	***	0.0066	***	0.1465	***	0.0394	***
	(24.3500)		(19.6800)		(24.1600)		(19.6400)		(3.2200)	
FF					0.0028		0.0037		-0.0009	
					(1.5700)		(1.3000)		(-0.3200)	
│ES*FF│									0.1629	***
									(10.9100)	
LEVERAGE	-0.0023		-0.0033		0.0049		-0.0030		-0.0024	
	(-0.4700)		(-0.6600)		(-0.4200)		(-0.6200)		(-0.5100)	
LOSS	0.0088	***	0.0086	***	0.0023	***	0.0085	***	0.0073	***
	(3.8800)		(3.7600)		(3.8400)		(3.7300)		(3.3000)	
ADR	-0.0003		0.0000		0.0131		0.0001		-0.0004	
	(-0.0200)		(0.0000)		(-0.0100)		(0.0100)		(-0.0400)	
N. ANALYST	0.0001		0.0001		0.0001		0.0002		0.0001	
	(0.7200)		(0.7900		(1.2000)		(1.1800)		(1.5600)	
LogTA	-0.0045	***	-0.0044	***	0.0010	***	-0.0045	***	-0.0045	***
	(-4.3400)		(-4.2900)		(-4.4700)		(-4.3900)		(-4.4900)	
MTB	-0.0005	***	-0.0005	***	0.0002	***	-0.0005	***	-0.0004	***
	(-2.6300)		(-2.6800)		(-2.6700)		(-2.7000)		(-2.6700)	
Observations	3 326		3 326		3326		3 326		3326	
R^2	0.2306		0.2336		0.2312		0.2340		0.2608	
R^2 adjusted	0.2203		0.2231		0.2207		0.2232		0.2502	

│ANCORR│ is the absolute value of revised ex-post EPS – ex-ante EPS forecast / lagged stock price. │DACC│ represents the absolute value of discretionary accruals. │REM│ stands for absolute value of real earnings' management. │FRAUD│ is calculated as the absolute value of Original EPS - Restated EPS / lagged stock price. │ES│ is the absolute value of Originally-reported EPS - Ex-ante EPS forecast / lagged stock price. FF is a binary variable that groups companies being part of AAER sample. LEVERAGE indicates Total debt / Total Assets. LOSS is a binary variable with value 1 if the company has reported negative earnings in the present year. ADR a binary variable with value 1 if the company is a foreign company traded by an ADR. N. ANALYST is number of analysts following the company. LogTA stands for Logarithm of Total Assets. MTB or Market to book ratio is equal to Total Equity/Market capitalization. Variables in | represent absolute values.

T values are indicated in parentheses (). *,**.***, significance at 10%, 5% and 1% respectively. Fixed effects year and industry included

Table 9. Matched Sample Revised ex-post EPS – *corrected* earnings
Dep. Var. ANCORR

	Closer		Far	
	Coeff		**Coeff**	
INTERCEPT	-0.0117		-0.0052	
	(-0.2700)		(-0.2900)	
FRAUD	-0.1432	***	0.2202	***
	(-9.4100)		(13.9700)	
DACC	-0.0099		-0.4821	***
	(-0.6300)		(-8.8500)	
REM	-0.0004		0.0013	*
	(-0.6500)		(0.0940)	
ES	0.2356	***	-0.1071	***
	(26.7000)		(-9.2100)	
Firm Fraud	0.0102	**	0.0047	
	(2.0300)		(0.8900)	
FQUINTILE	-0.0050	***	-0.0014	
	(-4.7200)		(-1.2400)	
LEVERAGE	0.0080		0.0010	
	(1.2200)		(0.1400)	
LOSS	-0.0060	*	-0.0021	
	(-1.9200)		(-0.6600)	
ADR	-0.0006		-0.0013	
	(-0.0300)		(-0.0900)	
N. ANALYST	-0.0001		-0.0002	
	(-0.3500)		(-1.0700)	
LogTA	0.0009		0.0025	
	(0.6800)		(1.6200)	
MTB	0.0004		0.0001	
	(1.4900)		(0.3100)	
Observations	1 885		1 441	
R^2	0.3480		0.2070	
R^2 adjusted	0.3310		0.1820	

ANCORR is based on revised ex-post EPS – ex-ante EPS forecast / lagged stock price. DACC represents discretionary accruals. REM stands for real earnings' management. FRAUD is calculated as Original EPS - Restated EPS / lagged stock price. ES is the Originally-reported EPS - Ex-ante EPS forecast / lagged stock price. FQUINTILE is the quantile number based on the amount of Fraud. LEVERAGE indicates Total debt / Total Assets. LOSS is a binary variable with value 1 if the company has reported negative earnings in the present year. ADR a binary variable with value 1 if the company is a foreign company traded by an ADR. N. ANALYST is number of analysts following the company. LogTA stands for Logarithm of Total Assets. MTB or Market to book ratio is equal to Total Equity/Market capitalization. Variables in | represent absolute values.
T values are indicated in parentheses (). *,**.***, significance at 10%, 5% and 1% respectively. Fixed effects year and industry included.

Table 10. Fraud quintiles AAER firms – Dependent variable: Analyst's Correction (ANCORR)

Quintile	1		2		3		4		5	
	Coeff		**Coeff**		**Coeff**		**Coeff**		**Coeff**	
Intercept	-0.0185		-0.0035		0.0048		-0.0423		-0.0533	
	(-0.2700)		(-0.1600)		(0.2200)		(-0.7100)		(-0.7800)	
FRAUD	-0.0059		-0.0384		1.1431		-1.1307		-0.1300	***
	(0.9110)		(-0.1000)		(0.5600)		(-0.8000)		(-3.4500)	
DACC	0.0045		-0.0169		0.0557		-0.3655	***	-0.1898	**
	(0.1200)		(-0.9100)		(0.5000)		(-4.7800)		(-1.7100)	
REM	-0.0024		-0.0020	**	0.0012		-0.0012		-0.0004	
	(0.2320)		(-2.5600)		(1.2200)		(-0.6600)		(-0.1900)	
ES	0.1142	**	-0.0530	***	-0.0214		0.3286	***	0.2943	***
	(2.5000)		(-5.1600)		(-1.2000)		(7.9600)		(10.6600)	
LEVERAGE	-0.0117		-0.0024		-0.0045		-0.0023		0.0757	
	(-0.4400)		(-0.3300)		(-0.6100)		(-0.1400)		(3.0900)	
LOSS	0.0033		-0.0185	***	-0.0167	***	0.0087		0.0169	
	(0.2500)		(-5.0800)		(-4.5000)		(0.8800)		(1.1900)	
ADR	-0.0335		-0.0196	***	-0.0172	**	0.0126		0.0014	
	(-0.3400)		(-2.6400)		(-2.1300)		(0.2300)		(0.0200)	
N. ANALYST	0.0004		0.0002		0.0003	*	0.0001		0.0005	
	(0.2800)		(0.9400)		(1.7800)		(0.0900)		(0.5700)	
LogTA	0.0024		0.0014		0.0023		0.0091	**	0.0110	*
	(0.3600)		(0.9100)		(1.6400)		(2.0900)		(1.8900)	
MTB	0.0016		0.0002		-0.0000		0.0005		-0.0005	
	(1.1000)		(0.4300)		(-0.1400)		(0.4800)		(-0.3900)	
Obs.	332		333		332		333		333	
R2	0.193		0.255		0.199		0.342		0.396	
R2 adjusted	0.076		0.153		0.082		0.247		0.309	

ANCORR is based on revised ex-post EPS – ex-ante EPS forecast / lagged stock price. DACC represents discretionary accruals. REM stands for real earnings' management. FRAUD is calculated as Original EPS - Restated EPS / lagged stock price. ES is the Originally-reported EPS - Ex-ante EPS forecast / lagged stock price. LEVERAGE indicates Total debt / Total Assets. LOSS is a binary variable with value 1 if the company has reported negative earnings in the present year. ADR a binary variable with value 1 if the company is a foreign company traded by an ADR. N. ANALYST is number of analysts following the company. LogTA stands for Logarithm of Total Assets. MTB or Market to book ratio is equal to Total Equity/Market capitalization.
T values are indicated in parentheses (). *,**.***, significance at 10%, 5% and 1% respectively. Fixed effects year and industry included.

Quantile	Variable	Obs.	Mean	Std.	Min	Max
1	FRAUD	332	-0.0778	0.1771	-2.1143	-0.0118
2	FRAUD	333	-0.0057	0.0030	-0.0118	-0.0013
3	FRAUD	332	-0.0001	0.0005	-0.0014	0.0009
4	FRAUD	333	0.0038	0.0021	0.0009	0.0088
5	FRAUD	333	0.0674	0.1453	0.0091	1.8029
Total		**1663**				

FRAUD is calculated as Original EPS - Restated EPS / lagged stock price.

Table 11. |Fraud| quintiles – Dependent variable: Analysts' Correction (ANCORR)

Quintile	1		2		3		4		5	
	Coeff		Coeff		Coeff		Coeff		Coeff	
Intercept	0.0055		-0.1685	***	-0.0118		-0.0690	**	-0.0286	
	(0.2800)		(-3.5600)		(-0.5300)		(-2.3800)		(-0.2900)	
|FRAUD|	-0.9588		2.5889		0.9058		0.0865		-0.0934	**
	(-0.3000)		(0.7200)		(1.1200)		(0.2100)		(-2.1200)	
|DACC|	0.0574		1.0816	***	0.0027		-0.2409	***	0.0322	
	(0.4200)		(7.9700)		(0.1100)		(-2.8600)		(0.5900)	
|REM|	-0.0006		-0.0033		-0.0006		-0.0005		0.0021	
	(-0.5700)		(-1.5400)		(-0.5600)		(-0.4200)		(0.6100)	
|ES|	-0.0687	***	-0.1091	**	-0.0976	***	0.0290		-0.2374	***
	(-3.6900)		(-2.3900)		(-6.8100)		(1.2500)		(-6.1600)	
LEVERAGE	-0.0033		0.0011		-0.0025		-0.0109		0.0304	
	(-0.4700)		(0.0600)		(-0.2800)		(-0.9400)		(0.9400)	
LOSS	-0.0065	*	-0.0141		-0.0150	***	-0.0143	**	-0.0064	
	(-1.9000)		(-1.3000)		(-3.0300)		(-2.1900)		(-0.3700)	
ADR	-0.0173	**	0.0104		-0.0137		0.0110		-0.0404	
	(-2.3100)		(0.1900)		(-0.5100)		(0.7700)		(-0.3900)	
N. ANALYST	0.0002		-0.0002		0.0001		0.0003		0.0007	
	(0.9600)		(-0.1800)		(0.2400)		(0.6500)		(0.3300)	
LogTA	0.0031	**	0.0128	***	0.0029		-0.0044		0.0098	
	(2.3000)		(2.6200)		(1.3700)		(-1.5700)		(1.0600)	
MTB	-0.0001		0.0005		-0.0003		0.0007		0.0021	
	(-0.2800)		(0.5200)		(-0.6300)		(1.2100)		(1.0800)	
Obs.	333		333		333		333		333	
R^2	0.2296		0.2774		0.3295		0.1837		0.2216	
R^2 adjusted	0.1180		0.1752		0.2324		0.0711		0.1084	

ANCORR is based on revised ex-post EPS – ex-ante EPS forecast / lagged stock price. DACC represents discretionary accruals. REM stands for real earnings' management. FRAUD is calculated as Original EPS - Restated EPS / lagged stock price. ES is the Originally-reported EPS - Ex-ante EPS forecast / lagged stock price. LEVERAGE indicates Total debt / Total Assets. LOSS is a binary variable with value 1 if the company has reported negative earnings in the present year. ADR a binary variable with value 1 if the company is a foreign company traded by an ADR. N. ANALYST is number of analysts following the company. LogTA stands for Logarithm of Total Assets. MTB or Market to book ratio is equal to Total Equity/Market capitalization.

T values are indicated in parentheses (). *,**.***, significance at 10%, 5% and 1% respectively. Fixed effects year and industry included.

Quantile	Variable	Obs.	Mean	Std.	Min	Max
1	|FRAUD|	333	0.0004	0.0003	0.0000	0.0011
2	|FRAUD|	333	0.0025	0.0009	0.0011	0.0041
3	|FRAUD|	333	0.0070	0.0019	0.0041	0.0108
4	|FRAUD|	332	0.0175	0.0047	0.0108	0.0276
5	|FRAUD|	332	0.1280	0.2156	0.0279	2.1143
Total		**1663**				

FRAUD is calculated as Original EPS - Restated EPS / lagged stock price.

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