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Abstract

This study provides evidence on the performance and labor market trajectories of sell-side equity analysts with prior experience or education in accounting. Analysts with work experience in accounting issue both more accurate earnings per share (EPS) forecasts and more profitable sell recommendations, particularly if they possess substantial public accounting experience. This result highlights the unique value of pre-analyst experience that combines accounting and business knowledge, but also a competitive edge in focusing on bad news. Supporting this interpretation, we find that former auditors ask more accounting-related and less positively toned questions during earnings calls. They also play a significant monitoring role, as suggested by the higher quality and more conservative earnings of the firms they cover. Regarding labor market trajectories, former auditors are marginally more likely to achieve "All Star" analyst recognition and exhibit longer tenure in the profession. Overall, our findings highlight the strengths and limitations of accounting expertise in sell-side research in terms of information processing and career outcomes.

Keywords: Analysts; Auditors; Information Processing; Monitoring; Labor Market

JEL: G10; G14; M41; M42

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"*You have to understand accounting and you have to understand the nuances of accounting. It's the language of business and it's an imperfect language, but unless you are willing to put in the effort to learn accounting - how to read and interpret financial statements - you really shouldn't select stocks yourself.*" - Warren Buffett

I. INTRODUCTION

Analysts play a prominent role as information intermediaries, particularly since their forecasting outputs shape market expectations of future earnings and the pricing of securities in capital markets (Bradshaw et al., 2017; Kothari et al., 2016). As financial statements grow increasingly complex, the demands on financial professionals to interpret and analyze this information have intensified, underscoring the importance of specialized expertise (Hoitash et al., 2021). While prior literature shows how the quality of forecasts and other outputs relates to different analyst characteristics (Bratten and Larocque, 2023), including their credentials (De Franco and Zhou, 2009) and prior industry experience (Bradley et al., 2017a), the role of accounting knowledge remains underexplored. This study investigates whether analysts with prior accounting training and experience differ in their performance and examines their labor market trajectories. By addressing this gap, we aim to inform both academic inquiry and practical application, particularly for students and young professionals navigating career paths in finance. Understanding how accounting expertise intersects with sell-side research provides critical insights into the factors that shape analysts' effectiveness and their professional careers.

Ex ante, it is not clear whether accounting knowledge or experience can yield a competitive edge in sell-side equity research. On the one hand, we expect accounting knowledge to help analysts understand financial statements and firms' reporting choices, thus enhancing the soundness of their research and models that support their forecasts and recommendations (Brown et al., 2015). Furthermore, even if from a reporting perspective, those with work experience in accounting can develop an in-depth understanding of either their employer and industry for corporate accountants, or the firms they previously audited and the industry in which they specialized for former auditors. Echoing this view, in a Wall Street Journal opinion piece, KPMG's CEO Paul Knopp states that "*no profession goes deeper into understanding the nature, risks, and opportunities of an industry than public accounting*" (Knopp, 2024).

On the other hand, however, extant research indicates that work experience in accounting may limit or even be detrimental to investment analyses (Griffith et al., 2015; Vera-Munoz, 1998). Also, insofar as a specialization in accounting during one's studies or work experience comes at the expense of other (e.g., product market) knowledge and skills that are valuable in sell-side research, those with accounting expertise may possibly underperform their peers. It thus remains an empirical question whether and how analysts with accounting knowledge and work experience differ from other analysts in their forecasting and stock recommendation quality.

Addressing this tension, we first provide evidence on the prevalence of accountants[1] in the analyst population. Using a hand-collected biographical dataset on 6,480 sell-side analysts over the period 1997 to 2019, we identify their accounting work experience and education by analyzing their LinkedIn profiles. We find that accountants issue 14.57% of the total annual one-year ahead EPS forecasts in the Institutional Broker Estimate System (I/B/E/S) during our sample period. In terms of coverage characteristics, accountants are more likely to follow firms with lower R&D expenditures but more subsidiaries. Their industry coverage resembles that of other analysts.

We next examine the forecast accuracy of analysts with an accounting background based on a sample of more than 318,000 earnings forecasts on about 7,700 unique firms. Our results indicate that, on average, accountants do not differ from other analysts in terms of earnings per

[1] For brevity, we use the term "accountants" to refer to analysts with schooling or work experience in accounting.

share (EPS) forecast accuracy. However, when we break down analysts' accounting background between education, certification, and work experience, we find that those with accounting work experience issue significantly more accurate EPS forecasts than the average analyst. The estimates are economically meaningful: the average former accountant's EPS forecast is 6.72 percentage points (pp) more accurate, compared to 3.6 pp for analysts with prior industry experience (Bradley et al. 2017a). This result is robust to using various controls for analyst education and experience (e.g., MBA and Ivy League status or pre-analyst experience) as well as firm controls and different sets of fixed effects, which we use in virtually all of our analyses. While we find similar results when we extend the EPS forecast horizon to two or three years, accounting experience is not associated with significantly greater revenue or cash flow forecast accuracy. When we examine the dynamic time-series in consensus forecast accuracy around coverage initiations and terminations by accountants, we find no pre-event trends for either, but a significant increase in consensus forecast accuracy following coverage initiations. This result suggests that accountants contribute to an improvement of the information environment when they start covering stocks.

We further test whether accountants differ from other analysts in terms of recommendation profitability. While forecast accuracy generally translates into recommendation profitability (Ertimur et al., 2007), recommendations rely on additional inputs and skills that are not necessarily acquired or nurtured in accounting. Using calendar-time portfolio risk-adjusted returns to assess analysts' stock recommendation profitability, we find accountants' recommendations to be no more profitable than those made by their peers, and even less so for sell recommendations. However, when we again separate accounting education, certification, and work experience, we find that former accountants issue more profitable sell recommendations, amounting to a sizeable six-month risk-adjusted outperformance of 3.45 percentage points. In contrast, analysts with a

CPA or accounting education issue less profitable sell recommendations. Also, no accountant subgroup differs from the average analyst in terms of buy recommendation profitability. Overall, the results indicate that former accountants outperform other analysts in terms of forecasting and sell recommendation accuracy. An explanation for former accountants' asymmetric recommendation outperformance may be that their skills better translate to detecting bad news than good news.[2]

To better understand the specific mechanisms underlying our main results, we perform in-depth tests. First, we disaggregate accounting work experience between public accounting and corporate accounting, and accounting knowledge between higher education (i.e., bachelor's or master's degrees in accounting) and CPA credentials. We find that former auditors—who make up the bulk of analysts with accounting work experience—drive our main results. Second, we find that former accountants' superior forecasting ability and sell recommendation profitability increase with the length of their accounting work experience, which mitigates concerns relating to omitted variable bias.[3] We also document that analysts with prior audit experience do not considerably benefit from covering firms that are audited by their former employer (hereafter "connected former auditors"). In fact, both connected and non-connected former auditors issue more accurate EPS forecasts and profitable sell recommendations.

[2] Consistently, we show that forecasts of analysts with work experience in accounting are relatively less timely (although by less than four days) and less 'bold'. Further, their recommendations are both less optimistic and less extreme.

[3] The results are also robust to a propensity score matching approach. Further, we collect information on whether analysts previously worked for audit firms in branches other than auditing (e.g., consulting). Such analysts have a similar career pathway to former auditors, mitigating concerns of unobserved analyst heterogeneity, such as lingering connections, employer preferences, or on-the-job learning. They should also develop similar business knowledge (from an external viewpoint), but not accounting experience. Using a placebo test, where we replace former auditors with their non-auditor colleagues, we find that only former auditors issue more accurate forecasts and sell recommendations. This result confirms the joint importance of accounting and business knowledge (along with professional skepticism) in explaining former auditors' superior forecasting and monitoring ability.

We additionally study former accountants' monitoring role and information gathering practices in earnings conference calls as potential channels explaining their superior forecasting and recommendation performance. Building on previous literature on the monitoring role of analysts (e.g., Irani and Oesch, 2013; Chen et al., 2015; Bradley et al., 2017b), we examine the earnings quality as well as the incidence of financial restatements and shareholder lawsuits in the firms they cover. Using a research design similar to Bradley et al. (2017b), we find that firms covered by former accountants report lower discretionary accruals and more conservative earnings and are less likely to restate their financials. In contrast, coverage by analysts with accounting knowledge is only associated with more conservative earnings. We find no association between former accountant coverage and securities lawsuits.

Regarding analysts' behavior in earnings conference calls, we find that former accountants use less positive tone and ask more accounting-related questions than other analysts on the same calls. Combined, these additional results are consistent with our main findings and suggest that former accountants' performance stems from (i) their combined accounting and business knowledge and (ii) their ability to elicit more negative information from management.

Finally, we provide supplemental evidence on the labor market trajectories of analysts with an accounting background. They are more likely to hold an MBA but less likely to have graduated from an Ivy League university. They also tend to work for larger brokerage firms but are no more likely to begin their careers as associate analysts. Additionally, accountants are not more likely to be ranked as "All Star" analysts by *Institutional Investor* magazine or to transition to larger brokerage firms during their careers. However, former professional accountants, particularly auditors, tend to have longer tenures in I/B/E/S and are marginally more likely to achieve 'All Star' status. While labor market success is challenging to measure with publicly available data, our evidence suggests that former professional accountants outperform the average sell-side analyst in metrics linked to compensation and job retention (e.g., Groysberg et al., 2011).

Our paper primarily contributes to the growing literature on the association between sell-side analysts' characteristics and their outputs. While early studies focus on data observable within I/B/E/S, such as experience and portfolio complexity (Clement, 1999), more recent literature leverages the online availability of analysts' CVs to collect their educational and professional backgrounds. Bradley et al. (2017a) provide evidence confirming survey data from institutional investors and analysts (Brown et al., 2015) according to which knowledge about the industries of the firms that analysts cover is valuable. De Franco and Zhou (2009) find that CFA charterholders issue timelier and bolder forecasts. While industry experience and CFA certification are both prevalent among sell-side analysts, we examine a unique and considerable subset of analysts with accounting education and work experience. Our evidence indicates that an accounting background is increasingly prevalent. It also highlights the importance of joint accounting expertise and business knowledge acquired by experienced former auditors, as evidenced by their forecast accuracy, sell recommendation profitability, and the higher earnings quality of covered firms. At the same time, our results also point to limitations of accounting knowledge for sell-side analysts, given the lack of outperformance by analysts with accounting backgrounds other than former auditors. We thereby add to a limited string of papers that study analysts' professional and educational background. Importantly, we contribute to this literature by leveraging earnings conference calls to provide insights into the information-gathering practices of accountants, highlighting these practices as a channel that shapes their information outputs.

Our study also contributes to two other strands of literature. The first is concerned with the monitoring role of analysts (e.g., Yu, 2008; Chen et al., 2015; Christensen et al., 2021). Few studies, such as Bradley et al. (2017b), directly explore the link between monitoring and analyst characteristics. We provide new evidence that former auditors enhance monitoring of GAAP violations and earnings quality. The second strand addresses the value of accounting expertise in capital markets. Prior research shows that boards with accounting expertise improve financial reporting quality (Krishnan, 2005), especially when paired with industry expertise (Cohen et al., 2014), while CFOs with accounting expertise face tradeoffs (Hoitash et al., 2016; Bernard et al., 2021). Our study extends this literature by focusing on the accounting expertise of external stakeholders—specifically, sell-side analysts.

Finally, our findings have practical implications. The forecasting and recommendation performance of former auditors offer valuable insights for investors and recruiters. Additionally, their labor market trajectories highlight a successful career path from public accounting to sell-side equity research for business students and young professionals.

II. LITERATURE AND HYPOTHESES

A subset of the literature on sell-side equity research explores analysts' attributes that are associated with the quality of their output. The early literature, likely in part due to data availability, focuses on differences observable within the analyst population in terms of general experience, firm-specific experience, and breadth of coverage. This evidence indicates that more experienced analysts issue more accurate forecasts (Clement, 1999; Clement et al., 2007; Mikhail et al., 1997; Bratten and Larocque, 2023) whereas those with more complex portfolios issue less accurate forecasts (Clement, 1999). More recent studies investigate attributes that are either innate to the analyst or at least arguably independent of their profession (such as culture, gender, and physical appearance, see Kumar, 2010; Cao et al., 2020; Cao et al., 2024; Li et al., 2020).

Most closely related to our study is Bradley et al. (2017a), who show that pre-analyst industry work experience is associated with higher forecasting accuracy and informativeness when analysts cover firms in their industry of experience. De Franco and Zhou (2009) also document that CFA-credentialed analysts issue timelier and bolder forecasts—including before passing the exam—which is consistent with signaling rather than a knowledge acquisition effect. Nevertheless, a longstanding literature documents analysts' failure to process accounting information in a timely manner (e.g., Ali et al., 1992; Abarbanell and Bushee, 1997). Hence, ex ante it is unclear what role, if any, accounting knowledge—both in and of itself and in conjunction with other skills—plays in shaping analysts' forecasting behavior. Accordingly, we are interested in whether sell-side analysts with an accounting background differ in their outputs from other analysts.

We expect accounting knowledge to be a valuable skill in equity research. Analysts with an accounting background should be more familiar with companies' financial reporting discretion and better understand the mapping of current accruals into future earnings. Brown et al. (2015) find that analysts consider consistency of reporting choices and exclusion of special or one-time issues when they assess the quality of firms' earnings, suggesting that accountants may have a competitive advantage.[4]

Beyond accounting knowledge, as evidenced from schooling or a CPA, work experience as an accountant can give an analyst potentially valuable real-world practical knowledge. This is especially true for public accountants, who likely develop a deeper understanding of the industries and firms they cover (Christensen et al., 2016), which is highly valued in sell-side research. We also expect accountants to be skilled at eliciting information from management, which translates

[4] Financial statement analysis is also the second most weighty topic on the CFA Level 1 exam and accounts for about 20% of Level 1 readings (UWorld Finance), pointing to its importance for financial analysis.

into better research outputs among sell-side analysts (Yezegel, 2023) and could facilitate access to management, a critical role of sell-side analysts (Brown et al., 2015).

Alternatively, however, accountants may also underperform as sell-side analysts. First, while accountants may be particularly skilled at verifying and interpreting reported numbers, forecasting requires the analyst to incorporate knowledge about the firm and industry from various sources. Second, accountants do not perform valuations per se. In fact, auditors rely heavily on valuation experts to audit fair value measurements (Martin et al., 2006) and often fail to incorporate data from various sources to question management estimates (Griffith et al., 2015). Third, an excessive focus on financial statements may be detrimental to a sound business analysis. For instance, Vera-Munoz (1998) finds that, in a business context, decision-makers with higher accounting knowledge are more likely to ignore opportunity costs than those with low accounting knowledge. However, conversely, Graham et al. (2017) find that managers with a CPA license are more likely to use the correct tax rate in corporate decision making. Lastly, while accounting knowledge and experience are potentially helpful, they may come at the expense of other valuable sources of expertise due to time constraints and career path dependency.

Thus, overall, we leave the relative performance of analysts with an accounting background in terms of earnings forecasts and recommendation profitability as empirical questions and present our two hypotheses in their null form.

H1: Sell-side analysts with accounting expertise do not differ from other analysts in earnings forecast accuracy.

H2: Sell-side analysts with accounting expertise do not differ from other analysts in recommendation profitability.

III. DATA, METHODOLOGY, AND SUMMARY STATISTICS

III.1 Data

We construct our sample using the I/B/E/S detail history file, which includes sell-side analysts' EPS forecasts for U.S. firms from 1997 to 2019. To ensure data accuracy, we exclude observations with sequencing errors (46,966 records), non-USD forecasts (2,612,343), anonymized analysts (8,039), and missing firm identifiers, forecasts, or actuals. We focus on annual EPS forecasts with horizons of one to 12 months before earnings release, dropping 17,277,692 observations. To avoid duplicate forecasts, we retain only the latest forecast per analyst per day (24,791 dropped) and per year, resulting in 19,056 analysts issuing 835,156 forecasts for 13,947 firms.

From our sample, we extract unique analyst identifiers (ANALYS) and merge them with the I/B/E/S recommendations file to obtain analysts' initials and last names. After removing entries with missing names, brokerage identifiers, or analyst teams, 15,490 analysts remain. To identify analysts' educational and professional backgrounds, we leverage LinkedIn. Since LinkedIn searches require full names, we manually search Google using analysts' initials, last names, brokerage firms, and covered firms. We then locate LinkedIn profiles based on names, brokerage firms, and employment dates (using the earliest forecast announcement date). We identify profiles for 9,380 analysts, collecting details from their profile headers and the "About", "Experience", "Education", and "Licenses & certifications" sections. To ensure accuracy, we verify profiles based on name similarity, company affiliation, and employment dates.

As a last step, we drop observations with missing LinkedIn data, missing current analyst controls, missing lagged firm controls, and missing proportional mean absolute forecast error (defined below), resulting in the removal of 516,476 observations. The resulting final sample consists of 318,680 analyst-firm-year observations for 6,480 unique analysts and 7,387 unique firms. Table OA1 in the online appendix provides a comprehensive step-wise description of our sample construction process. Table A1 lists the detailed steps of our LinkedIn profile selection process. In Table OA2 in the online appendix, we compare firms covered by analysts that can be found on LinkedIn to firms covered by analysts without LinkedIn accounts. Both types of firms show almost identical fundamentals. We conclude that sample selection is unlikely to pose a significant issue for our study.[5]

III.2 Methodology

To test our first hypothesis regarding the relative performance of analysts with accounting expertise in earnings forecasting, we estimate the following ordinary least squares (OLS) regression model at the analyst-firm-year level:

$$PMAFE_{i,j,t} = \alpha_0 + \beta_1 Accountant_{j,t} + \beta_2 A_{i,j,t} + \beta_3 F_{j,t-1} + FEs + \varepsilon \quad (1)$$

where i, j, and t index analyst, firm, and year, respectively. *PMAFE* is the proportional mean absolute forecast error established by Clement (1999), which is calculated as the difference between analyst i's absolute forecast error (AFE) for firm j in year t and the mean absolute forecast error for firm j in year t, divided by the mean absolute forecast error for firm j in year t. This gives an analyst's forecast accuracy relative to all other analysts covering the same firm at the same time. Negative values of *PMAFE* indicate better than average earnings forecasts. In additional analyses, we calculate *PMAFE* using two- and three-year ahead instead of one-year ahead EPS forecasts, and sales and cash flow per share (CPS) forecasts instead of EPS forecasts.

[5] They have identical mean values and similar standard deviations for book-to-market ratio, leverage, R&D, and return on assets, indicating that the firms are similar in terms of risk, profitability, and valuation by the stock market. Firms covered by analysts with LinkedIn accounts are slightly larger and have slightly lower stock returns. Further, the characteristics of analysts following both types of firms are almost identical.

Our independent variable of interest, *Accountant*, is an indicator variable that is equal to one if analyst i has accounting expertise. We define accounting expertise as work experience in accounting obtained prior to becoming a sell-side analyst and/or knowledge in accounting. Work experience in accounting includes both, public accounting and corporate accounting experience. Accounting knowledge includes university education in accounting and certifications in accounting, such as a chartered public accountant (CPA). Figure 1 illustrates our custom classification of accountants. The regression coefficient of interest is β_1, where a negative (positive) coefficient indicates that accountants perform better (worse) than average, meaning they issue more (less) accurate earnings forecasts compared to other analysts.

We control for both analyst and firm characteristics. Regarding the former, we include proxies for analysts' abilities (Mikhail et al., 1997; Mikhail et al., 2003; Clement, 1999; Clement and Tse, 2003). These are analysts' experience providing forecasts for the firm (*Firm experience*), analysts' experience providing forecasts for any firm (*General experience*), number of industries (*Number of industries*) and firms covered by analysts (*Number of companies*), and the number of days between the forecast and actual announcement (*Forecast timeliness*). We also control for analysts' CFA certifications (*CFA*), MBA degrees (*MBA*), doctorates (*PhD*), and top school status (*Ivy League*) as well as for the number of years analysts worked before becoming a sell-side analyst (*Pre-analyst experience length*). Regarding firm characteristics, we control for book leverage, book-to-market ratio, firm size, intangibles to total assets, research and development expenses to total assets (R&D), return on assets, stock return over the past 12 months, and the number of analysts issuing forecasts for the firm. Firm controls enter our regressions with a one-year lag to avoid simultaneity bias. All continuous variables are winsorized at the 1st and 99th percentiles. Table A2 in the appendix provides detailed variable definitions.

To further mitigate concerns of omitted variable bias, we include varying sets of fixed effects in our analysis. Our most saturated regression model contains broker, firm, and year fixed effects. This approach allows us to compare analysts' forecast accuracy across brokerage houses, covered firms, and time, thereby further reducing concerns about unobserved heterogeneity. Standard errors are double-clustered at the analyst- and year-levels.[6]

To test our second hypothesis regarding the relative performance of analysts with accounting expertise in recommendation profitability, we estimate the following OLS regression model at the analyst-firm-year level:

$$AR_{i,j,t} = \alpha_0 + \beta_1 Accountant_{j,t} + \beta_2 A_{i,j,t} + \beta_3 F_{j,t-1} + FEs + \varepsilon \tag{2}$$

where i, j, and t index analyst, firm, and year, respectively. We focus on recommendation changes rather than levels, because changes contain more predictive power (e.g., Jegadeesh et al., 2004). To that end, we assign recommendations to either a *calendar-time sell portfolio* or a *calendar-time buy portfolio* as outlined in Cohen et al. (2010). The *calendar-time sell (buy) portfolio* includes all stocks that are downgraded (upgraded) relative to prior recommendations, as well as stocks for which analysts initiate, resume, or reiterate their coverage with a "Hold", "Sell", or "Underperform" ("Strong Buy" or "Buy") recommendation. These portfolios are updated when analysts add or drop a stock, or when the outstanding recommendation becomes stale, i.e., analysts' coverage of firm j is inactive for at least one year. We use three different measures for abnormal stock returns (*AR*). The first measure, *DGTW return*, is the characteristic-adjusted return of Daniel et al. (1997). The second, *BHAR(1, 30)*, and third measure, *BHAR(1, 180)*, represent the buy-and-

[6] We choose double-clustering because residuals plausibly exhibit both time-series (i.e., correlation across years for a given analyst) and cross-sectional dependence (i.e., correlation across analysts in a given year). In this regard, Petersen (2009) shows that additionally clustering on the time dimension can enhance inference validity in panel datasets, if the number of panel years is not too small (certainly above ten, see also Cameron et al., 2011). Since our panel spans 23 years, double clustering appears appropriate. However, our results are robust to alternative clustering.

hold abnormal returns over the (1, 30) and (1, 180) trading days following stock recommendations, respectively, calculated using the Fama-French three-factor model with an additional momentum factor.

Our independent variable of interest, *Accountant*, is defined as in equation (1). The interpretation of the regression coefficient β_1 varies depending on the portfolio being analyzed. For the calendar-time sell portfolio, a negative (positive) coefficient indicates that accounting analysts issue more (less) profitable sell recommendations compared to other analysts. Conversely, for the calendar-time buy portfolio, a positive (negative) coefficient suggests that accounting analysts issue more (less) profitable buy recommendations than other analysts.

We control for the same analyst and firm characteristics as in equation (1), except for *Forecast timeliness,* as this variable is forecast-specific. As before, all continuous variables are winsorized at the 1st and 99th percentiles. Table A2 in the appendix provides detailed variable definitions. We include firm and recommendation-month fixed effects. Standard errors are double-clustered at the analyst- and year-levels.

III.3 Summary Statistics

Table 1 presents a summary of key descriptive statistics at the analyst-firm-year level. The sample mean of our main dependent variable measuring one-year ahead EPS forecast accuracy (*PMAFE*) is 24%, with the variable exhibiting significant variation. The means of our alternative accuracy measures based on two- and three-year ahead EPS forecasts (*PMAFE 2-year* and *PMAFE 3-year*) and sales and CPS forecasts (*PMAFE Sales* and *PMAFE CPS*) are 7.93% and 9.09%, and 42.77% and 63.98%, respectively. Our dependent variables measuring abnormal returns, i.e., *DGTW return*, *BHAR(1, 30)*, and *BHAR(1, 180)* have means of -0.35%, -0.65%, and -9.90%, respectively.

The sample means of our key independent variables, *Accountant*, *Accounting work experience,* and *Accounting knowledge*, are 14.57%, 4.17%, and 13.81%, respectively. Hence, nearly 15% of forecasts are issued by analysts with prior work experience and/or knowledge in accounting. Further, the shares of forecasts issued by analysts with *CFA* certification, *MBA*, *PhD*, and *Ivy League* degree are about 23%, 48%, 5%, and 18%, respectively. On average, analysts have 3.83 years of work experience prior to becoming sell-side analysts. The average sell-side analyst has covered a firm for an average of 2.74 years (*Firm experience*) and has been issuing forecasts for 11.79 years (*General experience*), covering an average of 3.28 industries and 13.29 firms. The average *Forecast timeliness* is 123.98 days. Overall, our analyst characteristics are in line with prior literature (e.g., Bradley et al., 2017a, 2020).

In untabulated tests, we conduct a determinants analysis, regressing the indicator variable *Accountant* on analyst and firm characteristics. We find most of the analyst characteristics to be comparable across accountants and other analysts, although a few differences are noteworthy. Accountants are more likely to hold an *MBA* degree and less likely to graduate from an *Ivy League* university. When they join the sell-side profession, accountants are no more likely to start at the associate level. However, accountants generally work for larger brokerage houses than their peers. Accountants are also more likely to cover firms with lower *R&D* expenses and more subsidiaries compared to firms covered by other analysts. Our subsequent regression analyses control for such differences and other unobserved sources of heterogeneity across covered firms.

IV. EMPIRICAL RESULTS

IV.1 Accountants' Forecast Accuracy

We first examine whether analysts with accounting expertise differ from other analysts in the accuracy of their EPS forecasts (H1). Panel A of Table 2 presents our coefficient estimates of equation (1). In column (1), we present results from a regression with broker*year as well as firm fixed effects. Results in column (2) are from a regression containing broker, firm, and year fixed effects. The regressions in columns (3) and (4) mirror columns (1) and (2) in terms of fixed effects structures, but break the *Accountant* indicator down into its components *Accounting work experience* and *Accounting knowledge* (see also Figure 1).[7]

The results in columns (1) and (2) show that the coefficient on *Accountant* is insignificant**,** irrespective of the fixed effects structure employed. This indicates that accountants do not differ from other analysts in terms of forecast accuracy. Yet, *Accountant* is a broad construct that combines two distinct attributes of accounting expertise: work experience and knowledge. We therefore decompose *Accountant* in the regressions in columns (3) and (4). In both specifications, we find a negative coefficient on *Accounting work experience*, which is significant at the 5% level. The coefficient on *Accounting knowledge* however is insignificant. F-tests show that the difference between the two coefficients is statistically significant in both specifications. The results suggest that analysts with accounting knowledge do not outperform other analysts. Analysts with work experience in accounting, however, do significantly outperform both the average analyst as well as analysts with knowledge in accounting, who serve as a different counterfactual.

Our control variables are also in line with economic intuition and prior literature. For instance, analysts who have spent more time in the analyst profession issue more accurate earnings forecasts (variable *General experience*). Also, the longer the distance between the earnings forecast and the announcement of the actual earnings, the less accurate the prediction (variable *Forecast timeliness*), consistent with, e.g., Cooper et al. (2001) and Shroff et al. (2014). Finally,

[7] In untabulated tests, we alternatively use industry*year fixed effects, and the regression specification employed in Bradley et al. (2017a) with de-meaned analyst controls and no fixed effects. Our results remain qualitatively similar.

earnings forecasts issued for firms with greater analyst coverage are more accurate (variable *Analyst following*), indicative of a richer information environment.

Next, we test whether the superior forecasting ability of analysts with accounting work experience persists over longer periods and holds for alternative measures of firm performance. In Panel B of Table 2, we replace the dependent variable *PMAFE* with the corresponding two-year ahead (column (1)) and three-year ahead (column (2)) EPS forecasts, as well as with analysts' estimates on sales (column (3)) and cash flow per share (CPS, column (4)). All regressions contain the same set of control variables as in Panel A (not displayed for brevity) as well as broker, firm, and year fixed effects. The results in columns (1) and (2) suggest that the superior forecast ability of analysts with work experience in accounting persist over the 2-year and 3-year periods. While the effect loses economic significance over time (from 6.72% in Panel A to 3.51% for *PMAFE 2-year* and 3.09% for *PMAFE 3-year*), it is still both statistically and economically significant in both specifications. Additionally, the insignificant coefficient on *Accounting knowledge*, which differs from *Accounting work experience* (as evidenced by the corresponding F-tests), confirms our earlier conclusion that the superior forecast ability of analysts with accounting expertise is driven by practical (accounting and industry) experience. We find no significant coefficients on our accounting analyst variables when we explain sales and cash flow per share estimates in columns (3) and (4), which points to the limits of accounting background in forecasting.

To strengthen our inference, we examine changes in consensus forecast accuracy around the initiation and termination of research coverage by accountants. Specifically, we employ a stacked difference-in-differences (DiD) approach at the firm-year-level to address concerns raised in recent literature regarding staggered DiD designs (e.g., Cengiz et al., 2019; Baker et al., 2022). For coverage initiations by accountants, firms are classified as treated if they are not covered by accountants in years t-3 to t-1, but receive coverage from accountants in years t to t+3. Conversely, for coverage terminations, firms are identified as treated if they are covered by accountants in years t-3 to t, but lose coverage by accountants in years t+1 to t+3. In both instances, suitable control firms are those that remain uncovered by accountants throughout t-3 to t+3, operate in the same two-digit SIC industry as the treated firm in year t-1, and have an analyst following in year t-1 that differs by no more than five analysts from the treated firm. We then estimate dynamic time-series regressions, using the consensus forecast accuracy as the dependent variable. The key explanatory variables are the interaction terms between *Treatment_initiation* and *Treatment_termination* with year-specific indicators capturing the period around coverage initiation and termination, respectively. The regressions also include the same firm controls as in previous analyses, along with event-specific firm and event-specific year fixed effects to account for unobserved heterogeneity. Figures 2A and 2B report 90% confidence intervals for these estimates (calculated using robust standard errors clustered at the event-level) for coverage initiations and coverage terminations, respectively. While we find no evidence of pre-event trends, Figure 2A reveals a significant increase in consensus forecast accuracy following coverage initiations by accountants. Consistent with our prior regression results, this finding suggests that accountants enhance the information environment when they begin covering stocks.

IV.2 Accountants' Recommendation Profitability

As a second key analysis, we examine whether accountants differ from other analysts in terms of the profitability of their stock recommendations (H2). We use abnormal returns following an analyst's most recent stock recommendation during the fiscal year as a proxy for recommendation profitability. We measure abnormal returns via the variables *DGTW return* as well as *BHAR(1,30)* and *BHAR(1,180)*, which we regress on the variable *Accountant* and subsets thereof. Regressions include fixed effects for firm and recommendation month as well as analyst and firm controls (as before), which are not reported for brevity. We conduct the regressions separately for calendar-time sell and calendar-time buy portfolios.

Table 3, Panel A, presents the results for the calendar-time buy portfolio. In brief, none of the coefficients of interest are statistically significant. That is, former accountants—irrespective of education or prior work experience—neither outperform nor underperform other analysts in terms of buy recommendation profitability. The asymmetric results with respect to sell vs. buy recommendations suggests that analysts with work experience in public or corporate accounting tend to be more skilled at detecting bad news than good news.

Table 3, Panel B, presents the results for the calendar-time sell portfolio. Column (1)shows that analysts with an accounting background perform significantly worse than other analysts in terms of DGTW returns, while columns (3) and (5) indicate no significant difference in buy-and-hold-returns. However, breaking the *Accountant* indicator into *Accounting work experience* and *Accounting knowledge* clarifies the result. In columns (2), (4), and (6), work experience in accounting is linked to more profitable sell recommendations, while accounting education is associated with lower profitability. F-tests confirm these differences at the 5% level or better. Overall, former accountants' superior forecasting translates into more profitable sell recommendations, both relative to the average analyst and relative to analysts with accounting knowledge.

To further validate our findings, we conduct a robustness test using propensity score matching to address potential concerns that differences in analyst forecast accuracy and recommendation profitability may be driven by selection effects rather than accounting expertise itself. Specifically, we estimate a logit model predicting an analyst's likelihood of having an accounting background (*Accountant*), using observable analyst characteristics such as *Firm experience, General experience, Number of industries, Number of companies*, and *Pre-analyst experience length*. We then implement a nearest-neighbor matching based on the estimated propensity scores to construct a sample of analysts with comparable backgrounds, ensuring that differences in performance are not merely the result of systematic differences in career trajectories or coverage patterns. Overall, our results continue to hold using propensity score matching (see Table OA3 in the online appendix). Since matching also reduces heterogeneity on unobservable covariates, this evidence also helps mitigate concerns of omitted variable bias that may persist despite our large set of controls for analyst education and experience.

IV.3 Heterogeneity in Accounting Backgrounds

Next, we decompose accounting work experience and knowledge further. Specifically, we break down *Accounting work experience* into public accounting work experience (*Auditor*) and corporate accounting work experience (*Corporate accountant*), and *Accounting knowledge* into *Accounting education* and accounting certification (*CPA*). We use this decomposition to shed further light on the differences in forecast accuracy and recommendation profitability among analysts with versus without accounting expertise.

Panel A of Table 4 presents summary statistics of the various components. With means of 3.76% (versus 0.63%), most analysts with accounting work experience obtained their skills as auditors in public accounting, while accounting education is mostly due to college education (12.95% versus 2.86% for CPAs). We then apply this decomposition to the model specifications in Table 2, Panel A, for forecast accuracy, and Table 3, Panel B, for sell recommendation profitability. The respective regression results are shown in Panel B of Table 4.

In line with our previous results, we find the coefficients on *Accounting knowledge* and its components, i.e., *Accounting education* and *CPA*, to be insignificant when used to explain our measure of forecast accuracy, *PMAFE* (see columns (1) – (3)). When we decompose *Accounting work experience* into its components *Auditor* and *Corporate accountant*, the results in column (1) show that the significant outperformance of analysts with accounting experience is driven by analysts with prior work experience in public accounting (significant at the 1% level). Conversely, the coefficient on *Corporate accountant* is negative, but not significant at conventional levels. In column (2) of Panel B, we substitute these two variables with the number of years analysts have spent gaining work experience in public or corporate accounting, respectively. The results show that analyst forecast accuracy improves with work experience in both cases. While both coefficient estimates are similar in terms of economic significance, the length of work experience is statistically significant at the 1% level for auditors (*Auditor length*), but only weakly significant for corporate accountants (*Corporate accountant length*). The positive and linearly increasing association between forecast accuracy and the length of work experience in accounting further mitigates endogeneity concerns since any omitted variable would have to show a similar pattern.

Lastly, we break the *Auditor* indicator further down into *Connected* and *Not connected auditors,* depending on whether the respective analyst used to (not) work at the audit firm that is currently auditing the firm covered. We thereby attempt to capture aspects of private information flowing from the auditor, specifically its employees, to the connected analyst. The results in column (3) show that the superior forecasting ability of analysts with experience in public accounting is likely not driven by such private information, as both variables show negative and statistically significant coefficients. As evidenced by the F-test, the difference between these two variables is not statistically significant.

With regards to recommendation profitability, the results on sell recommendations in columns (4) to (6) display a similar picture. The higher profitability of sell recommendations issued by analysts with accounting expertise is driven by work experience in public accounting, with profitability increasing in the number of years for which an analyst gained experience as auditor (column (5)). In line with the results on forecast accuracy, this result does not seem to be driven by private information, as C*onnected* and *Not connected auditor* do not display statistically different coefficients.

In sum, former auditors significantly outperform the average analyst, whereas others with accounting experience or knowledge do not. Regarding the economic significance of our results, the estimates in column (1) suggest that—for the same firm-year—analysts who are former auditors issue earnings forecasts that are, on average, 7.49 percentage points more accurate than those issued by other analysts from the same broker.

To ensure the robustness of our findings with regards to former auditors, we conduct several placebo tests. Specifically, our results could be driven by a general *audit firm effect* rather than the specific skills acquired by analysts with public accounting experience. To test this, we run OLS regressions in which we replace our key variable, *Auditor*—which equals one if an analyst has worked in an audit-related position at an audit firm (and zero otherwise)—with a new indicator variable, *Non-auditor*. This variable equals one if an analyst was employed in a *non-audit* role at an audit firm. If our previous results were merely capturing an audit firm effect rather than skills gained through auditing experience, we would expect to see similar effects for *Non-auditor*. However, as shown in Table OA4 in the online appendix, the coefficients on *Non-auditor* are not statistically significant. This evidence suggests that the superior forecast accuracy and more profitable sell recommendations identified earlier stem from the specialized skills developed through auditing experience, rather than a general audit firm affiliation and potentially related covariates, such as lingering connections, employer preferences, or on-the-job learning.

V. CHANNEL ANALYSES

V.1 Accountants' Monitoring Role

The idea that sell-side analysts act as external monitors of firms dates back to Jensen and Meckling (1976). While some evidence supports their monitoring role (e.g., Moyer et al., 1989; Yu, 2008; Kelly & Ljungqvist, 2012), few studies examine the skills that enhance their effectiveness. Bradley et al. (2017b) find that analysts with industry experience are stronger monitors, while Chen et al. (2015) suggest that frequent financial tracking and management interactions facilitate monitoring. We expect analysts with accounting expertise to have an edge in these tasks and exhibit greater professional skepticism, making them more likely to constrain managerial discretion.

To test whether accountants differ from other analysts in terms of monitoring, we consider several firm-level measures. First, we gather information on the incidence of financial restatements based on firms filing 8-K forms from Audit Analytics (*Restatements*). Second, we obtain settled and ongoing shareholder securities lawsuits from the Stanford Securities Class Action Clearinghouse (*Litigation*).[8] Third, we follow Yu (2008) and calculate firms' *Discretionary accruals* as the residual from cross-sectional regressions of total accruals on changes in sales, and on the level of property, plant, and equipment within industry-years. Fourth, we measure accounting conservatism using the variable *C-Score* based on Khan and Watts (2009). These metrics assess analysts' monitoring role by linking to managerial behavior and reporting quality. Restatements and litigation signal monitoring failures, discretionary accruals capture earnings

[8] We thank Cornerstone Research and Stanford Law School for sharing the data with us. The views expressed in the paper are views of the authors and do not represent in any way the views of Cornerstone Research or Stanford Law School.

management, and the C-Score reflects conservative reporting practices. Together, these measures capture explicit violations and subtle reporting shifts, aligning with analysts' potential influence in constraining managerial discretion and enhancing transparency.

Panel A of Table 5 presents summary statistics for the dependent variables alongside selected independent variables. The mean values for *Restatement* (4.15%) and *Litigation* (1.82%) indicate that these are rare events. Since our multivariate regressions contain firm fixed effects to account for unobservable firm characteristics, the model specifications for these two dependent variables are restricted to firms that experienced at least one restatement or litigation event during the sample period.

Given that our main results thus far are driven by analysts with work experience in (public) accounting, we directly examine disaggregated results. Specifically, our primary variable of interest in Panels B and C of Table 5 is the total number of analysts following a firm, categorized into former auditors, corporate accountants, analysts with university-level accounting education, CPAs, and other analysts without accounting background.[9] We estimate linear probability models to test whether analyst characteristics are linked to a firm's likelihood of financial misreporting in a given year, as measured by the dependent variables *Restatement* and *Litigation* in columns (1) and (2), respectively. In addition, we use the dependent variables *Discretionary accruals* and *C-Score* in columns (3) and (4). Analyst and firm controls are the same as in previous analyses. All regressions contain firm and year fixed effects, standard errors are clustered by firm.

[9] Our results are qualitatively similar if we follow Yu (2008) and Bradley et al. (2017b) and use residual analyst following (estimated separately for former auditors, corporate accountants, analysts with university education in accounting, CPAs, and other analysts) as our main proxy for analyst following. Residual analyst following is defined as the component of analyst following uncorrelated with cash flow volatility, external financing, firm size, return on assets, and total assets growth.

As before, we first regress these dependent variables on the variables breaking accounting expertise down into work experience (*Accounting work experience following)* and accounting knowledge (*Accounting knowledge following*). The results are presented in Pabel B of Table 5. We find the number of analysts with *accounting work experience* to be significantly negatively related to the incidence of financial restatements and the use discretionary accruals, and positively related to our measure of accounting conservatism, *C-Score*. Except for the dependent variable *C-Score*, we find no such effect for analysts with *accounting knowledge.*

In a second step, we employ similar model specifications in Panel C of Table 5, but break *Accounting work experience following* and *Accounting knowledge following* down further, into *Auditor following* and *Corporate Accountant following,* as well as *Accounting education following, CPA following,* and *Other analysts following*. The regression results in Panel C suggest that firms covered by (more) former auditors are significantly less likely to commit financial misreporting. Particularly, the coefficient on *Auditor following* is negative and statistically significant at the 1% level in column (1). In terms of the economic magnitude, the coefficient suggests that a one-unit increase in *Auditor following* is associated with a decrease of 1.61% in the average firm's probability to make a material restatement. As before, we do not find evidence of a systematic relation between analyst backgrounds and the probability of firms facing securities litigation (column (2)). However, the results in columns (3) and (4) again show that the findings in Panel B are driven by analysts with work experience in public accounting, with *Auditor following* being negatively related to the use of discretionary accruals and positively related to accounting conservatism. Overall, the results in Table 5 suggest that analysts with work experience in accounting, particularly former auditors, play a monitoring role, which may also explain their ability to issue more profitable sell recommendations.

V.2 Accountants' Behavior on Earnings Conference Calls

When preparing earnings forecasts and stock recommendations, analysts use earnings calls to gather information and engage with management. These calls provide insight into how analysts with and without accounting backgrounds prioritize information. If work experience and training shape analysts' thinking, this should be reflected in their language and the types of questions they ask. Accounting analysts' questions may help explain their greater EPS forecast accuracy and more profitable sell recommendations. To investigate this, we analyze the extent to which their questions contain accounting-related terms, assuming this focus enhances forecast accuracy and financial monitoring. We also examine the tone of their questions to better understand their role in issuing profitable sell recommendations and constraining managerial discretion.

We obtain all full-text quarterly earnings conference call transcripts available through Capital IQ from 2005 to 2019 for the firms in our final sample that are covered by former accountants. We keep the final copy of each transcript that is edited, proofed, or audited (*transcriptpresentationtypeid* = 5), and focus on full text related to analysts' questions (*speakertype* = 3 and *transcriptcomponenttypeid* = 3 or 8). We then identify questions posed by analysts with accounting expertise using a name-matching algorithm that cross-references analyst names from LinkedIn and Capital IQ (*transcriptpersonname*).

To assess the extent to which conference call questions are accounting-related, we use the number of accounting-related words (*Accounting words*) in an analyst's question.[10] These words are identified through manual classification using the Loughran and McDonald master dictionary (the full list is provided in Table OA6 in the online appendix). The tone of analysts' questions is

[10] We omit the word "guidance" when counting the number of accounting words in an analyst's question.

measured as the difference between positive and negative words (*Tone*), which are determined using the sentiment word list from Loughran and McDonald.[11] We further control for the analyst's number of spoken words (*Question length*). Before we use these variables in our analyses, we summarize the dataset at the analyst-call level. That is, if an analyst speaks multiple times during a call, we aggregate the total word count, the number of accounting-related words, and tone across all statements. Then, to run regressions at the analyst-firm-year level consistent with our baseline regressions, we calculate analysts' average total word count, number of accounting-related words, and tone across all quarterly conference calls for the firm-year they participated in. Panel A of Table 6 presents summary statistics for the three variables. The average tone of analysts' questions on conference calls for a firm-year is positive, and their questions on conference calls for a firm-year, on average, contain 2.6 accounting words and 157 words in total.

Panel B of Table 6 presents the results of OLS regressions of *Tone* and *Accounting words* on *Accounting work experience* and *Accounting knowledge* (columns (1) and (3)), as well as their individual components (columns (2) and (4)). All regressions include firm and year fixed effects, with standard errors being clustered at the firm-level. Columns (1) and (3) show that analysts with accounting work experience use significantly more negative and accounting-related words. The breakdown of these variables further reveals that the increased use of accounting-related words is primarily driven by analysts with an audit background. In contrast, questions from analysts with corporate accounting experience or an accounting education contain fewer accounting-related words (column (4)).

[11] We eliminate the word "question" from the list of negative words. Further, we adjust for negations and do not count the word "good" if it is followed by "morning", "afternoon", "evening", or "day" or the word "efficiency" if it is followed by "ratio".

Taken together, these findings align with our main results and further support the notion that analysts with accounting work experience—especially those with a background in public accounting—place greater emphasis on accounting information and adopt a more pessimistic tone in their questioning. These patterns may help explain why analysts with accounting work experience and former auditors in particular produce more accurate earnings forecasts, contribute to stronger financial reporting oversight, and issue more profitable sell recommendations.

VI. ACCOUNTANTS' LABOR MARKET OUTCOMES

We extend our main analyses by examining the career trajectories of analysts with accounting expertise. If the quality of their earnings forecasts and (sell) recommendations is systematically linked to their accounting background, these factors may also shape their labor market outcomes. Specifically, we analyze three career indicators: "all-star" recognition, the likelihood of advancing to a larger brokerage house, and tenure in the profession. Groysberg et al. (2011) find that "all-star" status is a strong predictor of analyst compensation, while Hong and Kubik (2003) identify upward mobility to a larger brokerage house as a favorable career outcome.

We hand-collect data on all-star analysts for the period 1997 to 2010 from the Institutional Investor's magazine and extend it until 2014 with data by Bill Mayew.[12] Then, we define the indicator *All Star* as one if an analyst is ranked as an all-star analyst in a year, and zero otherwise. *Time-to-promotion* measures the number of years it takes for an analyst to advance to a larger brokerage, determined by comparing broker size quintiles. Similarly, *Time-to-leave-IBES* captures the number of years until an analyst issues her final forecast in the I/B/E/S database. We regress these three dependent variables on analyst characteristics from our previous analyses, with results

[12] We thank Baozhong Yang for sharing Bill Mayew's data with us.

presented in Panel B of Table 7. As before, our primary variables of interest are the indicators for accounting work experience and knowledge. For specifications where *All Star* is the dependent variable (columns (1) and (2)), we use OLS regressions at the analyst-year level, including a control for the one-year lag of *All Star*. A positive (negative) coefficient suggests that accountants are more (less) likely to attain all-star status. To analyze analysts' transitions to larger brokerage houses (columns (3) and (4)) and their tenure in the profession (columns (5) and (6)), we employ survival analyses using a Cox proportional hazard model at the analyst-broker pair and analyst-level, respectively. In these models, a positive (negative) coefficient indicates that the event of interest—either job transitions or departures from I/B/E/S—occurs sooner (later).

Odd-numbered columns report results where accounting background is categorized into *Accounting work experience* and *Accounting knowledge,* while even-numbered columns further distinguish between *Auditor*, *Corporate accountant*, *Accounting education*, and *CPA* certification. In columns (1) and (2), where *All Star* status is the dependent variable, only the *Auditor* indicator is statistically significant (at the 10%-level) suggesting that analysts with public accounting work experience are more likely to attain all-star recognition. In contrast, columns (3) and (4) show that none of our key variables are statistically significant in the hazard models for *Time-to-promotion*, indicating that analysts with accounting expertise are neither more nor less likely than their peers to advance to a larger brokerage house. However, they do tend to be employed by larger brokerage firms on average. Finally, in columns (5) and (6), the coefficients for *Accounting work experience* and *Auditor* are negative and statistically significant, suggesting that analysts with accounting experience remain in the profession longer, as reflected in their extended presence in I/B/E/S.

Taken together, these findings indicate that analysts with accounting experience achieve slightly better career outcomes, particularly in terms of professional recognition and job retention.

These results align with their demonstrated advantage in forecasting accuracy, reinforcing the notion that accounting expertise contributes to superior analyst performance.[13]

VII. CONCLUSION

This study examines the implications of accounting expertise for information processing, monitoring, and career trajectories in equity research. Our findings indicate that analysts who are former accountants exhibit superior forecasting accuracy and issue more profitable sell recommendations compared to the average analyst. These analysts also play a monitoring role, as evidenced by the higher financial reporting quality of the firms they cover and their use of more accounting-focused and less optimistic language in earnings conference calls. Importantly, these effects are driven by analysts with substantial public accounting experience rather than those with only an accounting degree, CPA certification, or corporate accounting background. We also find some evidence that former (public) accountants are more likely to attain an all-star analyst status and stay longer in the profession.

In addition to advancing academic research on the role of analysts' education and job experience as well as financial market efficiency, our study has important implications for practitioners. As the demand for financial expertise grows, our findings suggest that public accounting provides a valuable foundation for a successful transition into sell-side research. Prospective finance professionals may view auditing as a viable entry point into equity research, while brokerage firms and institutional investors can leverage these insights in hiring and

[13] Besides not observing analyst compensation, another limitation of our analyses is that we cannot reliably classify the labor market outcomes of analysts who leave I/B/E/S. However, for descriptive purposes, we examine the LinkedIn profiles of former auditors who do. We find that 65% of them leave the sell-side profession and, of those, 51% join the buy-side.

evaluating analyst performance. Additionally, our results underscore the growing competition for accounting talent between public accounting firms and financial institutions.

Our study comes with limitations. Chief among them is the reliance on self-reported LinkedIn data, which may introduce selection bias in analysts' disclosed education and experience, which our tests and sets of fixed effects may not fully account for. Additionally, while our findings suggest that former auditors contribute to improved financial reporting oversight, we cannot fully disentangle whether this effect results from direct monitoring or firms' strategic responses to analyst scrutiny. Future research could explore these mechanisms in greater detail.

Overall, our findings provide new insights into the role of accounting expertise in sell-side equity research, illustrating both its advantages and limitations in shaping analysts' performance and career trajectories.

APPENDIX

TABLE A1: LinkedIn Profile Selection

This table illustrates the step-wise screening process for selecting the correct LinkedIn profile for an I/B/E/S analyst. In the end, the process results in a unique link between an I/B/E/S analyst and a LinkedIn profile.

Step	
1	Drop all LinkedIn profiles where the analyst name similarity score (I/B/E/S vs. LinkedIn) is below 60%, the company name similarity score (I/B/E/S vs. LinkedIn) is below 60%, and the employment date range does not match even with a 1-year grace period (earliest I/B/E/S forecast announcement date vs. LinkedIn employment range).
2	Manually check LinkedIn profiles with an analyst name similarity score between 60% and 90%. Drop those where the name is wrong. Keep those where the last or first name is abbreviated, or where the last name is different due to marriage.
3	Create a similarity score that is the mean of the analyst name similarity score, company name similarity score, and an exact (without 1-year grace period) employment date range indicator that is equal to one if the earliest I/B/E/S forecast announcement date lies within the start and end date of the job experience at the I/B/E/S company in the LinkedIn profile, and zero otherwise.
4	If there is more than one job experience in a LinkedIn profile that fits the IBES search criteria, keep the last job experience after sorting by similarity score, analyst name similarity score, company name similarity score, and exact employment date range indicator in ascending order.
5	If a LinkedIn profile is matched to more than one I/B/E/S analyst, keep the last analyst after sorting by similarity score, analyst name similarity score, company name similarity score, and exact employment date range indicator in ascending order.
6	If there is more than one LinkedIn profile for an I/B/E/S analyst, keep the last profile after sorting by similarity score, analyst name similarity score, company name similarity score, and exact employment date range indicator in ascending order.

TABLE A2: Variable Definitions

This table provides detailed variable definitions. I/B/E/S data items are reported in upper case letters, italics and parentheses. Compustat data items are reported in lower case letters, italics and parentheses. All non-I/B/E/S and non-Compustat data sources are provided.

Accountant	Indicator variable that is equal to one if analyst i has accounting work experience and/ or accounting knowledge, and zero otherwise. Source: https://www.linkedin.com.
Accounting education	Indicator variable that is equal to one if analyst i obtained a bachelor's, master's and/ or MBA degree in accounting, and zero otherwise. Source: https://www.linkedin.com.
Accounting education following	The number of analysts with university education in accounting following firm j in year t. Accounting education following is winsorized at the top and bottom 1 percent level.
Accounting knowledge	Indicator variable that is equal to one if analyst i has accounting knowledge, i.e., has university education in accounting and/ or obtained a CPA certification before becoming an analyst, and zero otherwise. Source: https://www.linkedin.com.
Accounting knowledge following	The number of analysts with accounting knowledge following firm j in year t. Accounting knowledge following is winsorized at the top and bottom 1 percent level.
Accounting words	The average number of accounting words spoken by analyst i during all quarterly conference calls of firm j in year t. Table OA6 in the online appendix provides the list of accounting words. Source: Loughran and McDonald master dictionary at https://sraf.nd.edu/loughranmcdonald-master-dictionary/.
Accounting work experience	Indicator variable that is equal to one if analyst i has accounting work experience, i.e., worked as an auditor and/ or as a corporate accountant before becoming an analyst, and zero otherwise. Source: https://www.linkedin.com.
Accounting work experience following	The number of analysts with accounting work experience following firm j in year t. Accounting work experience following is winsorized at the top and bottom 1 percent level.
All Star	Indicator variable that is equal to one if analyst i is ranked as all-star during year t, and zero otherwise. Source: Data from 1997 to 2010 was hand-collected from the Institutional Investor's (II) magazine. We thank Baozhong Yang for sharing the All-Star analyst ratings by the II magazine for the period from 2010 to 2014 with us.
Analyst following	The number of analysts following firm j in year t. Analyst following is winsorized at the top and bottom 1 percent level.
Auditor	Indicator variable that is equal to one if analyst i is a former auditor, i.e., worked in an audit-related position at an audit firm before becoming an analyst, and zero otherwise. Source: https://www.linkedin.com. We classify a job position as audit-related if the job title contains the words audit, accountant, accounting, assurance, cpa or ca(sa) [whitelist], and not the words intern, trainee, restructuring, valuation, or tax [blacklist]. We additionally consider the job description if the job title does not contain a word from the whitelist and the blacklist. Hence, we classify a job position also as audit-related if the job description contains the words audit, accountant, accounting, assurance, cpa or ca(sa) [whitelist], and not the words intern, trainee, restructuring, valuation, tax, auditcore, audit support, accounting software, IT, accounting processes, or accounting practice [blacklist].

	We use (*au*) to include the following audit firms (and their predecessors): Arthur Andersen, PriceWaterhouseCoopers, Ernst & Young, KPMG, Deloitte, BDO, BKD, CliftonLarsonAllen, Crowe Horwath, Grant Thornton, CohnReznick, McGladrey, PKF, Plante & Moran, Spicer Oppenheim. We further perform an internet search and additionally include the following audit firms: Norrie stokes, CLB Coopers, Blackman Kallick, Fuller Landau, UHY, Gumbiner Savett, Hergott Duval Stack, Hein & Associates, ATA, S.B. Billimoria & Co., K.S. Aiyar, Mazars, Bentleys, Sharp & Tannan, Goldstein Golub Kessler, Coehn Weisinger Smallberg. For some analysts, the job title and/ or job description is either ambiguous or includes both whitelist and blacklist words. Thus, all audit firm employees are manually checked and based on that some analysts are manually coded as being former auditors.
Auditor following	The number of analysts who are former auditors following firm j in year t. Auditor following is winsorized at the top and bottom 1 percent level.
Auditor length	The number of years that analyst i worked as an auditor. The variable is set to zero for all other analysts.
Average AFE	The mean absolute forecast error (AFE) of forecasts issued by analysts for firm j in year t. The absolute forecast error is the difference between analyst i's forecast and the announced actual. Average AFE is winsorized at the top and bottom 1 percent level.
BHAR(1, 30)	Buy-and-hold abnormal returns calculated using the Fama-French 3-factor model plus momentum with an estimation window of 180 trading days, a gap of 9 trading days between the end of the estimation window and the stock recommendation announcement date, and an event window beginning one trading day after and ending 30 trading days after the stock recommendation announcement date. BHAR(1, 30) is winsorized at the top and bottom 1 percent level.
BHAR(1, 180)	Buy-and-hold abnormal returns calculated using the Fama-French 3-factor model plus momentum with an estimation window of 180 trading days, a gap of 9 trading days between the end of the estimation window and the stock recommendation announcement date, and an event window beginning one trading day after and ending 180 trading days after the stock recommendation announcement date. BHAR(1, 180) is winsorized at the top and bottom 1 percent level.
Book-to-market	Total stockholders' equity (*seq*) scaled by the market value of equity, i.e., the product of annual fiscal price close (*prcc_f*) and common shares outstanding (*csho*). Negative values as well as zero values of the market value of equity and total stockholders' equity are set to missing. Book-to-market is winsorized at the top and bottom 1 percent level.
Broker size	The number of analysts employed at the I/B/E/S brokerage house (*ESTIMATOR*) in year t. Broker size is winsorized at the top and bottom 1 percent level.
Cash flow volatility	Standard deviation of firm j's operating activites net cash flow (*oancf*) scaled by lagged total assets (*at*). Cash flow volatility is winsorized at the top and bottom 1 percent level.
CFA	Indicator variable that is equal to one if analyst i obtained a chartered financial analyst certification, and zero otherwise. Source: https://www.linkedin.com.

Connected auditor	Indicator variable that is equal to one if analyst i is a former auditor and used to work at the audit firm that is currently auditing covered firm j, and zero otherwise.
Corporate accountant	Indicator variable that is equal to one if analyst i is a corporate accountant, i.e., worked in an accounting-related position at a non-audit firm before becoming an analyst, and zero otherwise. Source: https://www.linkedin.com. We classify a job position as accounting-related if the job title contains the words audit, accountant, or accounting [whitelist], and not the words intern, trainee, tax, equity research, portfolio, fund, investment, analyst, derivative, trust, technology, and investigations [blacklist]. We do not classify job positions as accounting-related if the employer is an investment bank or brokerage, if the employer is a university or foundation, or if the employment is shorter than a year.
Corporate accountant following	The number of analysts who are corporate accountants following firm j in year t. Corporate accountant following is winsorized at the top and bottom 1 percent level.
Corporate accountant length	The number of years that analyst i worked as a corporate accountant. The variable is set to zero for all other analysts.
CPA	Indicator variable that is equal to one if analyst i obtained a certified public accountant (CPA) or chartered accountant (CA) certification, and zero otherwise. Source: https://www.linkedin.com. Specifically, we search whether analyst i's LinkedIn profile mentions the following: Certified public accountant/ CPA/ certified practicing accountant, Chartered accountant/ CA/ ca(sa)/ chartered professional accountant/ ACA/ ACCA/ FCA/ FCCA, Certificate in accounting, Certificate in accountancy, or Qualified accountant.
CPA following	The number of analysts with a CPA following firm j in year t. CPA following is winsorized at the top and bottom 1 percent level.
C-score	Firm-year measure of conservatism calculated following Khan and Watts (2009). It is based on an annual cross-sectional Basu (1997) regression model, specifying the asymmetric earnings timeliness coefficient as a linear function of firm-specific characteristics (size, market-to-book and leverage). C-score is winsorized at the top and bottom 1 percent level.
DGTW return	The monthly abnormal return for firm j on trading day t calculated following Daniel et al. (1997). From each stock's raw return, the return on a value-weighted portfolio of all CRSP firms in the same size, (industry-adjusted) market-to-book ratio and one-year momentum quintile is subtracted. We use the Fama-French 48-industry classification and update the 125 characteristic portfolios at the end of June of each year t. DGTW return is winsorized at the top and bottom 1 percent level.
Discretionary accruals	Discretionary accruals are calculated following Yu (2008), who uses a modified version of the Jones model (Jones, 1991; Dechow et al., 1995), which estimates discretionary accruals from cross-sectional regressions of total accruals on changes in sales (*sale*) and on property, plant, and equipment (*ppegt*) within industry-years. The magnitude of firm j's discretionary accruals is indicated as a percentage of lagged total assets (*at*). Discretionary accruals is winsorized at the top and bottom 1 percent level.
External financing	Sum of net cash received from equity and debt issuance (*sstk* + *dltt* + *dlc* - *dltt*_lag1y - *dlc*_lag1y) scaled by lagged total assets (*at*). External financing is winsorized at the top and bottom 1 percent level.

Firm experience	The number of consecutive years for which analyst i follows firm j as of year t. Firm experience is winsorized at the top and bottom 1 percent level.
Firm size	The natural logarithm of 1 plus total assets (*at*). Firm size is winsorized at the top and bottom 1 percent level.
Forecast boldness	The absolute deviation of analyst i's EPS forecast for firm j in year t from the average of those issued by all other analysts covering firm j in year t. Forecast boldness is winsorized at the top and bottom 1 percent level.
Forecast timeliness	The number of days between the forecast and actual announcement. Forecast timeliness is winsorized at the top and bottom 1 percent level.
General experience	The number of consecutive years for which analyst i follows any firm as of year t. General experience is winsorized at the top and bottom 1 percent level.
Intangibles	Intangible assets (*intan*) scaled by total assets (*at*). Negative as well as zero values of total assets are set to missing. Intangibles is winsorized at the top and bottom 1 percent level.
Ivy League	Indicator variable that is equal to one if analyst i studied at an Ivy League university, and zero otherwise. Source: https://www.linkedin.com.
Leverage	The sum of long-term debt (*dltt*) and total debt in current liabilities (*dlc*) scaled by total assets (*at*). Negative as well as zero values of total assets are set to missing. Leverage is winsorized at the top and bottom 1 percent level.
Litigation	Indicator variable that is equal to one if firm j has at least one litigation in fiscal year t, and zero otherwise. Source: We thank Cornerstone Research and Stanford Law School for sharing data on settled and ongoing shareholder securities lawsuits from the Stanford Securities Class Action Clearinghouse (https://securities.stanford.edu/) with us.
MBA	Indicator variable that is equal to one if analyst i obtained a MBA degree, and zero otherwise. Source: https://www.linkedin.com.
Non-auditor	Indicator variable that is equal to one if analyst i is a non-auditor, i.e., worked at an audit firm but not in an audit-related position, and zero otherwise. Source: https://www.linkedin.com.
Not connected auditor	Indicator variable that is equal to one if analyst i is a former auditor and used to work at another audit firm than the one that is currently auditing covered firm j, and zero otherwise.
Number of companies	The number of firms followed by analyst i in year t. Number of companies is winsorized at the top and bottom 1 percent level.
Number of industries	The number of industries (two-digit SIC) followed by analyst i in year t. Number of industries is winsorized at the top and bottom 1 percent level.
Other analysts following	The number of analysts who are not classified as accountants following firm j in year t. It is calculated as the difference between *Analyst following*, *Auditor following*, *Corporate accountant following*, *Accounting education following*, and *CPA following*. Other analysts following is winsorized at the top and bottom 1 percent level.
Past return	CRSP value-weighted index-adjusted buy-and-hold abnormal return over the fiscal year t in which the earnings forecast was issued. Past return is winsorized at the top and bottom 1 percent level.
PhD	Indicator variable that is equal to one if analyst i obtained a doctorate such as a PhD, JD, or MD, and zero otherwise. Source: https://www.linkedin.com.

PMAFE	Proportional mean absolute forecast error (PMAFE) calculated as the difference between analyst i's absolute forecast error (AFE) for firm j in year t and the mean absolute forecast error for firm j in year t divided by the mean absolute forecast error for firm j in year t. The absolute forecast error (AFE) is the difference between analyst i's forecast and the announced actual. Negative values indicate better than average performance and positive values worse than average performance. PMAFE is winsorized at the top and bottom 1 percent level.
Pre-analyst experience length	The number of years that analyst i did not work as a sell-side analyst before becoming an analyst. Source: https://www.linkedin.com. Pre-analyst experience length is winsorized at the top and bottom 1 percent level.
Question length	The average number of words said by analyst i during all quarterly conference calls of firm j in year t.
R&D	Research and development expenses (*xrd*) scaled by total assets (*at*). Missing values of research and development expenses are set to zero. Negative as well as zero values of total assets are set to missing. R&D is winsorized at the top and bottom 1 percent level.
Rec. extremism	Indicator variable that is equal to one for “Sell” or “Strong Buy” recommendations, and zero otherwise. Larger values indicate that analysts issue more extreme recommendations.
Rec. optimism	Categorical variable that takes values between -2 (“Sell”) and +2 (“Strong Buy”) so that larger values indicate more analyst optimism.
Restatement	Indicator variable that is equal to one if firm j has at least one restatement in fiscal year t, and zero otherwise. Source: Audit Analytics.
Return on assets	Net income before extraordinary items (*ib*) scaled by total assets (*at*). Negative as well as zero values of total assets are set to missing. Return on assets is winsorized at the top and bottom 1 percent level.
Time-to-leave-IBES	The number of years until the analyst i last issues forecasts in the I/B/E/S database. This variable is right-censored, i.e., it is set to 23 (= 2019 – 1997) for analysts that are still in the I/B/E/S database at the end of our sample period.
Time-to-promotion	The number of years until analyst i moves up to a larger broker which is determined by comparing broker size quintiles. This variable is right-censored, i.e., it is set to 23 (= 2019 – 1997) for analysts that are still in the I/B/E/S database at the end of our sample period.
Tone	The average difference between positive and negative words spoken by analyst i during all quarterly conference calls of firm j in year t. Source: Sentiment wordlist from Loughran and McDonald master dictionary at https://sraf.nd.edu/loughranmcdonald-master-dictionary/.
Total assets growth	Growth rate of total assets (*at*) calculated by the change of assets scaled by lagged total assets. Total assets growth is winsorized at the top and bottom 1 percent level.
Treatment_initiation	Indicator variable that is equal to one if firm j is not covered by accountants in years t-3, t-2 and t-1, but covered by accountants in years t, t+1, t+2 and t+3. It is equal to zero for firms that are not covered by accountants in years t-3 to t+3, operate in the same two-digit SIC industry in year t-1 as the treated firm and have an absolute difference in analyst following as of year t-1 of maximum 5.
Treatment_termination	Indicator variable that is equal to one if firm j is covered by accountants in years t-3, t-2, t-1 and t, but not covered by accountants in years t+1, t+2 and t+3. It is equal to zero for firms that are not covered by accountants in years t-3 to t+3, operate in the same two-

	digit SIC industry in year t-1 as the treated firm and have an absolute difference in analyst following as of year t-1 of maximum 5.

REFERENCES

Abarbanell, J., and Bushee, B. (1997). Fundamental analysis, future earnings, and stock prices. *Journal of Accounting Research* 35(1), 1-24.

Ali, A., Klein, A., and Rosenfeld, J. (1992). Analysts' use of information about permanent and transitory earnings components in forecasting annual EPS. *The Accounting Review* 57(1), 183-198.

Baker, A. C., Larcker, D. F., and Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates?. *Journal of Financial Economics* 144(2), 370-395.

Bernard, D., Ge, W., Matsumoto, D., and Toynbee, S. (2021). Implied tradeoffs of chief financial officer accounting expertise: Evidence from firm-manager matching. *Management Science* 67(9), 5776-5799.

Bradley, D., Gokkaya, S., and Liu, X. (2017a). Before an analyst becomes an analyst: Does industry experience matter? *Journal of Finance* 72(2), 751-792.

Bradley, D., Gokkaya, S., Liu, X., and Xie, F. (2017b). Are all analysts created equal? Industry expertise and monitoring effectiveness of financial analysts. *Journal of Accounting and Economics* 63(2-3), 179-206.

Bradley, D., Gokkaya, S., and Liu, X. (2020). Ties that bind: The value of professional connections to sell-side analysts. *Management Science* 66(9), 4118-4151.

Bradshaw, M., Ertimur, Y., and O'Brien, P. (2017). Financial analysts and their contribution to well-functioning capital markets. *Foundations and Trends in Accounting* 11(3), 119-191.

Bratten, B., and Larocque, S. (2023). How do individual analyst characteristics affect analyst performance? *Journal of Financial Reporting* 8 (2), 1-21.

Brown, L. D., Call, A. C., Clement, M. B., and Sharp, N. Y. (2015). Inside the "black box" of sell-side financial analysts. *Journal of Accounting Research* 53(1), 1-47.

Cao, Y., Guan, F., Li, Z., and Yang, G. (2020). Analysts' beauty and performance. *Management Science* 66(9), 3799-4358.

Cao, Y., Hao, R., and Yang, G. (2024). National culture and analysts' forecasting. *Review of Accounting Studies* 29, 1147-1194.

Cameron, A. C., Gelbach, J. B., and Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business and Economic Statistics* 29(2), 238-249.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics* 134(3), 1405-1454.

Chen, T., Harford, J., and Lin, C. (2015). Do analysts matter for governance? Evidence from natural experiments. *Journal of Financial Economics* 115(2), 383-410.

Christensen, B., Glover, S., Omer, T., and Shelley, M. (2016). Understanding audit quality: Insights from audit professionals and investors. *Contemporary Accounting Research* 33(4), 1648-1684.

Christensen, T. E., Gomez, E., Ma, M., and Pan, J. (2021). Analysts' role in shaping non-GAAP reporting: Evidence from a natural experiment. *Review of Accounting Studies* 26, 172-217.

Clement, M. B. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics* 27(3), 285-303.

Clement, M., Koonce, L., and Lopez, T. (2007). The roles of task-specific forecasting experience and innate ability in understanding analyst forecasting performance, *Journal of Accounting and Economics* 44(3), 378-398.

Clement, M. B., and Tse, S. Y. (2003). Do investors respond to analysts' forecast revisions as if forecast accuracy is all that matters?. *The Accounting Review* 78(1), 227-249.

Cohen, J. R., Hoitash, U., Krishnamoorthy, G., and Wright, A. M. (2014). The effect of audit committee industry expertise on monitoring the financial reporting process. *The Accounting Review* 89(1), 243-273.

Cohen, L., Frazzini, A., and Malloy, C. (2010). Sell-side school ties. *Journal of Finance* 65(4), 1409-1437.

Cooper, R. A., Day, T. E., and Lewis, C. M. (2001). Following the leader: A study of individual analysts' earnings forecasts. *Journal of Financial Economics* 61(3), 383-416.

Daniel, K., Grinblatt, M., Titman, S., and Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of Finance* 52(3), 1035-1058.

De Franco, G., and Zhou, Y. (2009). The performance of analysts with a CFA® designation: The role of human-capital and signaling theories. *The Accounting Review* 84(2), 383-404.

Ertimur, Y., Sunder, J., and Sunder, S. V. (2007). Measure for measure: The relation between forecast accuracy and recommendation profitability of analysts. *Journal of Accounting Research* 45(3), 567-606.

Graham, J., Hanlon, M., Shevlin, T., and Shroff, N. (2017). Tax rates and corporate decision making. *Review of Financial Studies* 30(9), 3128-3175.

Griffith, E. E., Hammersley, J. S., and Kadous, K. (2015). Audits of complex estimates as verification of management numbers: How institutional pressures shape practice. *Contemporary Accounting Research* 32(3), 833-863.

Groysberg, B., Healy, P., and Maber, D. (2011). What drives sell-side analyst compensation at high-status investment banks? *Journal of Accounting Research* 49(4), 969-1000.

Hilary, G., and Menzly, L. (2006). Does past success lead analysts to become overconfident? *Management Science* 52(4), 489-500.

Hoitash, R., Hoitash, U., and Kurt, A. C. (2016). Do accountants make better chief financial officers? *Journal of Accounting and Economics* 61(2–3),414-432.

Hoitash, R., Hoitash, U., and Yezegel, A. (2021). Can sell-side analysts' experience, expertise and qualifications help mitigate the adverse effects of accounting reporting complexity? *Review of Quantitative Finance and Accounting* 57(3), 859-897.

Hong, H., and Kubik, J. D. (2003). Analyzing the analysts: Career concerns and biased earnings forecasts. *The Journal of Finance* 58(1), 313-351.

Irani, R., and Oesch, D. (2013). Monitoring and corporate disclosure: Evidence from a natural experiment. *Journal of Financial Economics* 109(2), 398-418.

Jegadeesh, N., Kim, J., Krische, S. D., and Lee, C. M. (2004). Analyzing the analysts: When do recommendations add value?. *The Journal of Finance* 59(3), 1083-1124.

Jensen, M. C., and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics* 3(4), 305-360.

Kelly, B., and Ljungqvist, A. (2012). Testing asymmetric-information asset pricing models. *Review of Financial Studies* 25(5), 1366-1413.

Khan, M., and Watts, R. L. (2009). Estimation and empirical properties of a firm-year measure of accounting conservatism. *Journal of Accounting and Economics* 48(2-3), 132-150.

Knopp, P. The dying language of accounting (2024). *Wall Street Journal*, December 10, available at https://www.wsj.com/opinion/the-dying-language-of-accounting-cpa-licensing-fede2e74.

Kothari, S. P., So, E., and Verdi, R. (2016). Analysts' forecasts and asset pricing: A survey. *Annual Review of Financial Economics* 8, 197-219.

Krishnan, J. (2005). Audit committee quality and internal control: An empirical analysis. *The Accounting Review* 80(2), 649-675.

Kumar, A. (2010). Self-selection and the forecasting abilities of female equity analysts. *Journal of Accounting Research* 48(2), 393-435.

Li, C., Lin, A. P., and Lu, H. (2023). The effect of social skills on analyst performance. *Contemporary Accounting Research* 40(2), 1418-1447.

Li, C., Lin, A. P., Lu, H., and Veenstra, K. (2020). Gender and beauty in the financial analyst profession: Evidence from the United States and China. *Review of Accounting Studies* 25, 1230-1262.

Li, Z., Wong, T. J., and Yu, G. (2020). Information dissemination through embedded financial analysts: Evidence from China. *The Accounting Review* 95(2), 257-281.

Martin, R. D., Rich, J. S., and Wilks, T. J. (2006). Auditing fair value measurements: A synthesis of relevant research. *Accounting Horizons* 20, 287-303.

Mikhail, M., Walther, B., and Willis, R. (1997). Do security analysts improve their performance with experience? *Journal of Accounting Research* 35, 131-157.

Mikhail, M. B., Walther, B. R., and Willis, R. H. (2003). The effect of experience on security analyst underreaction. *Journal of Accounting and Economics* 35(1), 101-116.

Moyer, R. C., Chatfield, R. E., and Sisneros, P. M. (1989). Security analyst monitoring activity: Agency costs and information demands. *Journal of Financial and Quantitative Analysis* 24(4), 503-512.

Peng, L., Teoh, S. H., Wang, Y., and Yan, J. (2022). Face value: Trait impressions, performance characteristics, and market outcomes for financial analysts. *Journal of Accounting Research* 60(2), 653-705.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22(1), 435-480.

Pope, P. F., and Wang, T. (2023). Analyst ability and research effort: non-EPS forecast provision as a research quality signal. *Review of Accounting Studies* 28(3), 1263-1315.

Shroff, P. K., Venkataraman, R., and Xin, B. (2014). Timeliness of analysts' forecasts: The information content of delayed forecasts. *Contemporary Accounting Research* 31(1), 202-229.

UWorld Finance. https://finance.uworld.com/cfa/financial-statement-analysis/.

Vera-Munoz, S. C. (1998). The effects of accounting knowledge and context on the omission of opportunity costs in resource allocation decisions. *The Accounting Review* 73(1), 47-72.

Yezegel, A. (2023). The value of eliciting information: Evidence from sell-side analysts. *The Accounting Review* 98(3), 459-486.

Yu, F. F. (2008). Analyst coverage and earnings management. *Journal of Financial Economics* 88(2), 245-271.

FIGURE 1: Classification of Accountants
This figure presents the classification of accountants we employ in this study.

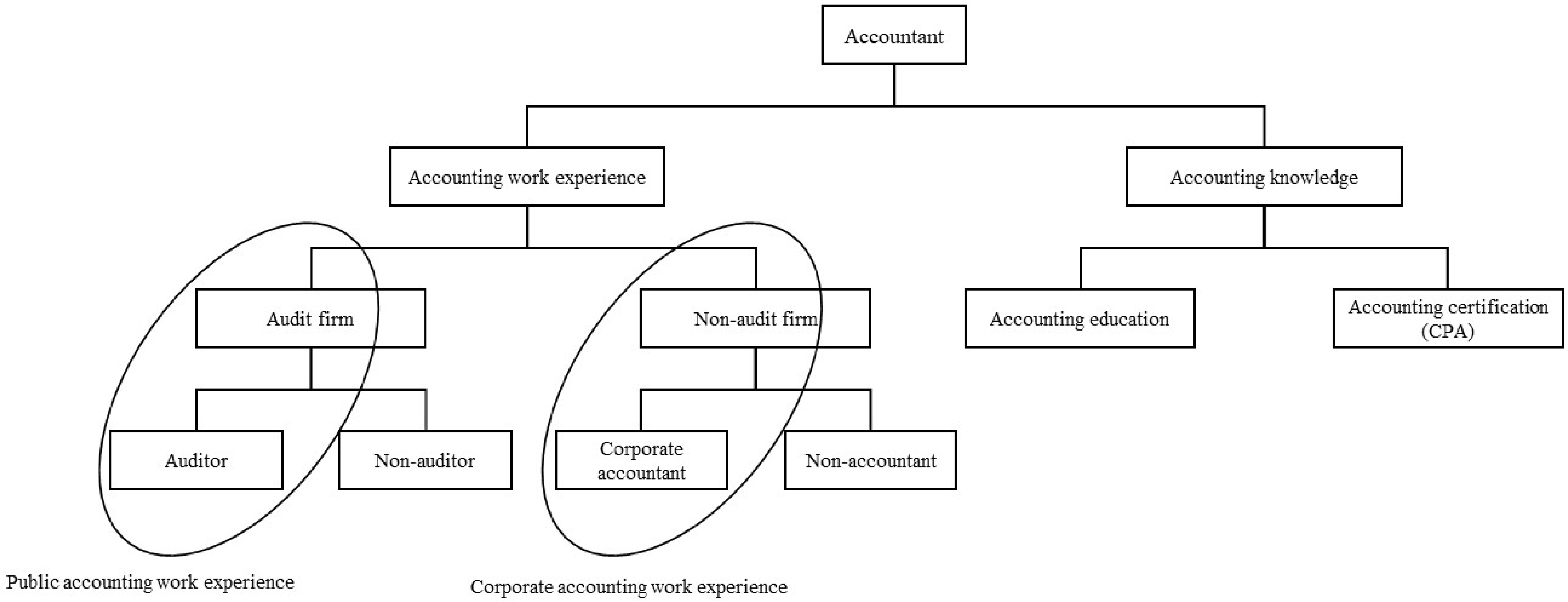

FIGURE 2: Changes in Absolute Forecast Error around Coverage Initiations and Terminations

This figure presents trends in firms' average absolute forecast error around the sample of accountant coverage initiations and accountant coverage terminations, using a stacked DiD design. Firms are identified as treated by an accountant coverage initiation if they are not covered by accountants in years t-3, t-2 and t-1, but covered by accountants in years t, t+1, t+2 and t+3. Firms are identified as treated by an accountant coverage termination if they are covered by accountants in years t-3, t-2, t-1 and t, but not covered by accountants in years t+1, t+2 and t+3. Control firms are not covered by accountants in years t-3 to t+3, operate in the same two-digit SIC industry in year t-1 as the treated firm, and have an absolute difference in analyst following as of year t-1 of at most 5. We interact the indicator variables *Treatment_initiation* and *Treatment_termination* with indicator variables for the respective years around the coverage change. All regressions include firm controls as before as well as event-specific firm fixed effects and event-specific year fixed effects. We report 90% confidence intervals based on robust standard errors clustered at the event-level.

Figure 2A: Coverage Initiations by Accountants

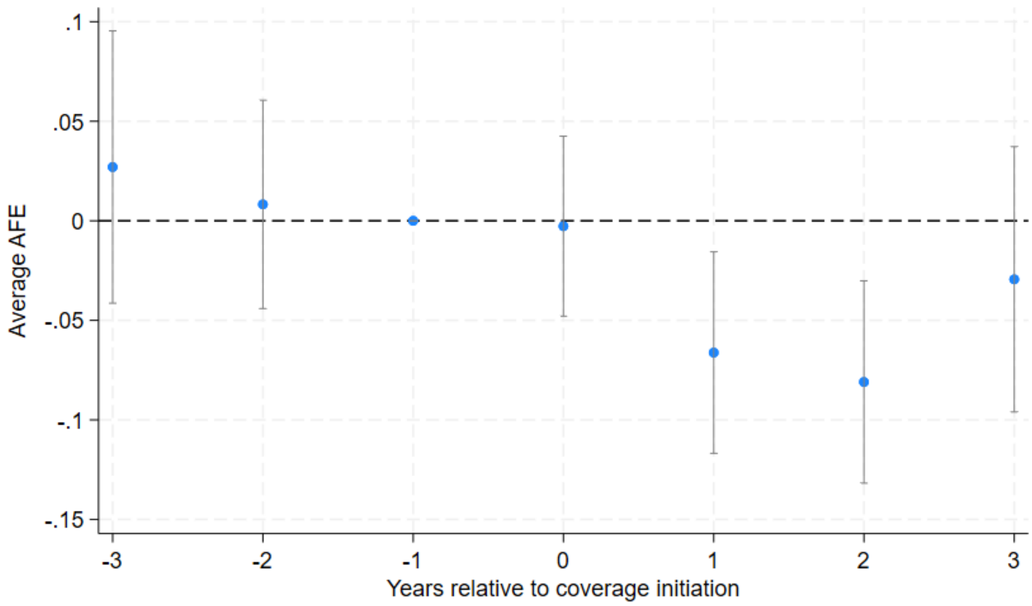

Figure 2B: Coverage Terminations by Accountants

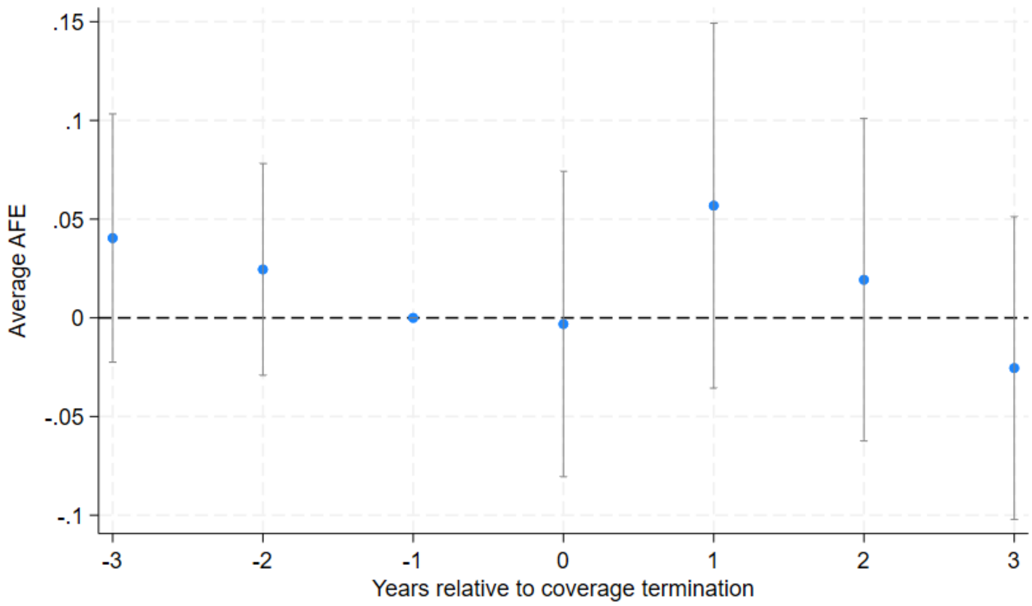

TABLE 1: Summary Statistics

This table reports analyst-firm-year level summary statistics for our final sample covering the period between 1997 and 2019. The sample comprises 318,680 analyst-firm-year observations for 6,480 analysts and 7,387 firms. We require forecasts to be annually and retain only the most recent forecast per fiscal period end date. A firm-year is required to be followed by at least two analysts. Data on the proportional mean absolute forecast error (PMAFE), on analyst characteristics, and on firm characteristics have to be available. *PMAFE* is calculated following prior literature (e.g., Bradley et al., 2017a) as the difference between the analyst's absolute forecast error for firm j at time t and the mean absolute forecast error for firm j at time t divided by the mean absolute forecast error for firm j at time t. Table A2 in the appendix provides detailed variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles.

	N	Mean	Percentile		
			25th	50th	75th
Dependent variables:					
PMAFE (%)	318,680	24.00	-60.94	-18.18	31.15
PMAFE 2-year (%)	288,011	7.93	-34.52	-3.79	24.66
PMAFE 3-year (%)	143,855	9.09	-28.44	-1.71	23.31
PMAFE Sales (%)	243,226	42.77	-66.75	-22.16	34.25
PMAFE CPS (%)	42,714	63.98	-58.88	-9.62	57.04
DGTW return (%)	226,425	-0.35	-6.11	-0.19	5.63
BHAR(1, 30) (%)	268,605	-0.65	-7.44	-0.65	6.07
BHAR(1, 180) (%)	268,616	-9.90	-29.56	-4.68	17.31
Analyst characteristics in t:					
Accountant (indicator, %)	318,680	14.57	0	0	0
Accounting work experience (indicator, %)	318,680	4.17	0	0	0
Accounting knowledge (indicator, %)	318,680	13.81	0	0	0
Firm experience (years)	318,680	2.74	0	2	4
General experience (years)	318,680	11.79	7	11	17
Number of industries (number)	318,680	3.28	2	3	4
Number of companies (number)	318,680	13.29	9	13	17
Forecast timeliness (days)	318,680	123.98	87	99	125
CFA (indicator, %)	318,680	22.74	0	0	0
MBA (indicator, %)	318,680	47.83	0	0	1
PhD (indicator, %)	318,680	5.21	0	0	0
Ivy League (indicator, %)	318,680	18.21	0	0	0
Pre-analyst experience length (years)	318,680	3.83	0	0	5
Firm characteristics in t-1:					
Firm size	318,680	8.06	6.73	8.02	9.36
Book-to-market (%)	318,680	50.33	23.73	40.51	65.57
Past return (%)	318,680	13.43	-19.23	1.64	28.27
Analyst following (number)	318,680	16.23	8	14	22
Leverage (%)	318,680	22.89	5.74	20.75	35.52
Intangibles (%)	318,680	18.12	1.30	9.70	29.84
R&D (%)	318,680	3.53	0.00	0.00	4.04
Return on assets (%)	318,680	2.47	0.80	3.95	8.08

TABLE 2: Forecast Accuracy

This table reports coefficient estimates from OLS regressions of the proportional mean absolute forecast error (PMAFE) on analysts' accounting expertise. The dependent variable *PMAFE* is calculated following prior literature (e.g., Bradley et al., 2017a) as the difference between the analyst's absolute forecast error for firm j at time t and the mean absolute forecast error for firm j at time t divided by the mean absolute forecast error for firm j at time t. *PMAFE* refers to analysts' one-year ahead EPS forecasts in Panel A and to analysts' two-year ahead or three-year ahead EPS forecasts, or to analysts' sales or cash flow per share (CPS) forecasts in Panel B. Regarding our independent variables of interest, *Accountant* is an indicator variable that equals one if the analyst has accounting work experience and/ or accounting knowledge, and zero otherwise. *Accounting work experience* and *Accounting knowledge*, are indicator variables that equal one if the analyst has accounting work experience and accounting knowledge, respectively, and zero otherwise. Table A2 in the appendix provides detailed variable definitions. In Panel B, we do not report coefficient estimates for the control variables for brevity. Standard errors are double-clustered at the analyst- and year-levels. P-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Forecast Accuracy of Accountants

Dependent variable:	PMAFE			
	(1)	(2)	(3)	(4)
Accountant	**-0.0194**	**-0.0200**		
	(0.2345)	**(0.2046)**		
Accounting work experience			**-0.0870*** **	**-0.0672*** **
			(0.0008)	**(0.0048)**
Accounting knowledge			**0.0051**	**-0.0014**
			(0.7784)	**(0.9387)**
F-test:			*-0.0921*** *	*-0.0659**
			(0.0132)	*(0.0638)*
Analyst controls in t:				
Firm experience	-0.0011	-0.0017	-0.0012	-0.0017
	(0.4645)	(0.2764)	(0.4536)	(0.2695)
General experience	-0.0079***	-0.0078***	-0.0079***	-0.0078***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Number of industries	0.0041	0.0044	0.0042	0.0045
	(0.3137)	(0.2909)	(0.3029)	(0.2843)
Number of companies	-0.0001	-0.0003	-0.0002	-0.0004
	(0.9135)	(0.7726)	(0.8856)	(0.7515)
Forecast timeliness	0.0073***	0.0074***	0.0073***	0.0074***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CFA	-0.0151	-0.0197	-0.0148	-0.0194
	(0.3251)	(0.1953)	(0.3363)	(0.2013)
MBA	-0.0000	-0.0033	-0.0014	-0.0044
	(0.9973)	(0.7468)	(0.8961)	(0.6670)
PhD	0.0342	0.0357	0.0336	0.0350
	(0.5608)	(0.5317)	(0.5675)	(0.5391)
Ivy League	-0.0071	-0.0079	-0.0072	-0.0081
	(0.6004)	(0.5623)	(0.5912)	(0.5531)
Pre-analyst experience length	0.0008	0.0011	0.0010	0.0013*
	(0.2782)	(0.1349)	(0.1925)	(0.0957)
Firm controls in t-1:				
Firm size	0.0104	0.0110	0.0102	0.0109
	(0.2401)	(0.1916)	(0.2463)	(0.1955)
Book-to-market	0.0175	0.0158	0.0179	0.0161
	(0.1451)	(0.1658)	(0.1377)	(0.1581)
Past return	-0.0001	0.0013	0.0000	0.0014
	(0.9842)	(0.8309)	(0.9997)	(0.8187)
Analyst following	-0.0105***	-0.0107***	-0.0105***	-0.0107***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Leverage	0.0254	0.0210	0.0263	0.0213
	(0.4504)	(0.5023)	(0.4332)	(0.4940)
Intangibles	-0.0107	-0.0156	-0.0111	-0.0162
	(0.8027)	(0.7240)	(0.7965)	(0.7160)
R&D	0.1369	0.1516	0.1357	0.1510
	(0.3092)	(0.2881)	(0.3129)	(0.2894)

Return on assets	0.1533***	0.1416***	0.1536***	0.1417***
	(0.0015)	(0.0038)	(0.0014)	(0.0037)
Broker*Year FE	Yes	No	Yes	No
Broker FE	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Observations	318,080	318,554	318,080	318,554
Adjusted R-squared	13.31%	12.44%	13.31%	12.44%

Panel B: Long-term EPS Forecast Accuracy and Non-EPS Forecast Accuracy

Dependent variable:	**PMAFE 2-year**	**PMAFE 3-year**	**PMAFE Sales**	**PMAFE CPS**
	(1)	(2)	(3)	(4)
Accounting work experience	-0.0351***	-0.0309*	-0.0166	-0.1836
	(0.0016)	(0.0567)	(0.7348)	(0.1712)
Accounting knowledge	0.0096	0.0062	-0.0308	-0.0391
	(0.2025)	(0.4395)	(0.3865)	(0.6888)
F-test:	*-0.0447****	*-0.0371**	*0.0142*	*-0.1444*
	(0.0053)	*(0.0898)*	*(0.8504)*	*(0.4500)*
Analyst and firm controls as before	Yes	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	287,933	143,778	243,158	42,659
Adjusted R-squared	3.94%	0.33%	12.07%	6.22%

TABLE 3: Recommendation Profitability

This table reports coefficient estimates from OLS regressions of abnormal returns to analysts' buy recommendations (Panel A) and analysts' sell recommendations (Panel B) on analysts' accounting expertise. Following Cohen et al. (2010), the calendar-time buy portfolio consists of all upgraded stocks and stocks for which analysts initiate, resume or reiterate their coverage with a "Strong Buy" or "Buy" recommendation. The calendar-time sell portfolio consists of all downgraded stocks and stocks for which analysts initiate, resume or reiterate their coverage with a "Hold", "Sell", or "Underperform" recommendation. The portfolios are updated when analysts add or drop a stock, or when the outstanding recommendation becomes stale defined by no activity for at least one year. The dependent variable *DGTW return* is calculated following Daniel et al. (1997) as the monthly abnormal return for firm j on trading day t. The dependent variables *BHAR(1, 30)* and *BHAR(1, 180)* are buy-and-hold abnormal returns calculated using the Fama-French 3-factor model plus momentum with an event window beginning one trading day after and ending 30 and 180 trading days after the stock recommendation announcement date, respectively. Regarding the independent variables of interest, *Accountant* is an indicator variable that equals one if the analyst has accounting work experience and/ or accounting knowledge, and zero otherwise. *Accounting work experience* and *Accounting knowledge*, are indicator variables that equal one if the analyst has accounting work experience and accounting knowledge, respectively, and zero otherwise. Table A2 in the appendix provides detailed variable definitions. All specifications include firm and recommendation-month fixed effects. We do not report coefficient estimates for the control variables for brevity. Standard errors are double-clustered at the analyst- and year-levels. P-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Buy Recommendation Profitability of Accountants

Dependent variable:	**DGTW return**		**BHAR(1, 30)**		**BHAR(1, 180)**	
	(1)	(2)	(3)	(4)	(5)	(6)
Accountant	0.0003		-0.0003		-0.0085	
	(0.8629)		(0.8728)		(0.2769)	
Accounting work experience		-0.0028		-0.0000		-0.0098
		(0.3371)		(0.9988)		(0.4788)
Accounting knowledge		0.0013		-0.0006		-0.0046
		(0.4932)		(0.7609)		(0.5454)
F-test:		*-0.0040*		*0.0006*		*-0.0052*
		(0.3260)		*(0.8960)*		*(0.7570)*
Analyst and firm controls as before	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Recommendation month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	104,813	104,813	125,703	125,703	125,708	125,708
Adjusted R-squared	9.45%	9.45%	9.02%	9.02%	14.71%	14.70%

Panel B: Sell Recommendation Profitability of Accountants

Dependent variable:	**DGTW return**		**BHAR(1, 30)**		**BHAR(1, 180)**	
	(1)	(2)	(3)	(4)	(5)	(6)
Accountant	0.0055***		0.0025		0.0051	
	(0.0060)		(0.1197)		(0.4830)	
Accounting work experience		-0.0082***		-0.0050		-0.0345***
		(0.0061)		(0.1102)		(0.0055)
Accounting knowledge		0.0083***		0.0045**		0.0155**
		(0.0005)		(0.0248)		(0.0478)
F-test:		*-0.0165****		*-0.0095***		*-0.0500****
		(0.0006)		*(0.0365)*		*(0.0035)*
Analyst and firm controls as before	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Recommendation month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102,584	102,584	120,481	120,481	120,487	120,487
Adjusted R-squared	15.69%	15.71%	9.15%	9.15%	11.48%	11.50%

TABLE 4: Heterogeneity in Accounting Backgrounds

This table reports coefficient estimates from OLS regressions of the proportional mean absolute forecast error (PMAFE) abnormal returns to analysts' sell recommendations on analysts' accounting expertise, respectively. Panel A provides summary statistics for the independent variables of interest which are the various components of *Accounting work experience* and *Accounting knowledge*. Panel B presents regression results. The dependent variable in columns (1) to (3), *PMAFE*, is calculated following prior literature (e.g., Bradley et al., 2017a) as the difference between the analyst's absolute forecast error for firm j at time t and the mean absolute forecast error for firm j at time t divided by the mean absolute forecast error for firm j at time t. The dependent variable in columns (4) to (6), *DGTW return*, is calculated following Daniel et al. (1997) as the monthly abnormal return for firm j on trading day t. In columns (1) and (4), the independent variables of interest are *Auditor*, *Corporate accountant*, *Accounting education*, and *CPA*. *Auditor* (*Corporate accountant*) is an indicator variable that equals one if the analyst has public accounting (corporate accounting) work experience, and zero otherwise. *Accounting education* (*CPA*) is an indicator variable that equals one if the analyst obtained university education in accounting (a CPA certification), and zero otherwise. In columns (2) and (5), *Auditor* and *Corporate accountant* are replaced by *Auditor length* and *Corporate accountant length* both of which measure the length in years of the respective work experience. In columns (3) and (6), *Auditor* is replaced by *Auditor (not) connected*, indicator variables that equal one if the former auditor used to (not) work at the audit firm that is currently auditing the firm covered, and zero otherwise. Table A2 in the appendix provides detailed variable definitions. We do not report coefficient estimates for the control variables for brevity. Standard errors are double-clustered at the analyst- and year-levels. P-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Summary Statistics

	N	Mean	Percentile		
			25th	50th	75th
Auditor (indicator, %)	318,680	3.76	0	0	0
Corporate accountant (indicator, %)	318,680	0.63	0	0	0
Accounting education (indicator, %)	318,680	12.95	0	0	0
CPA (indicator, %)	318,680	2.86	0	0	0
Auditor length (years)	318,680	0.15	0	0	0
Corporate accountant length (years)	318,680	0.02	0	0	0
Connected auditor (indicator, %)	313,370	1.43	0	0	0
Not connected auditor (indicator, %)	313,370	2.96	0	0	0

Panel B: Accounting Backgrounds Decomposed

Dependent variable:	PMAFE			DGTW return (calendar-time sell portfolio)		
	(1)	(2)	(3)	(4)	(5)	(6)
Accounting work experience:						
Auditor	-0.0749***			-0.0128***		
	(0.0023)			(0.0001)		
Corporate accountant	-0.0596		-0.0603	-0.0019		-0.0023
	(0.1939)		(0.1944)	(0.7364)		(0.6979)
Auditor length		-0.0174***			-0.0026***	
		(0.0008)			(0.0001)	
Corporate accountant length		-0.0178*			-0.0013	
		(0.0860)			(0.4590)	
Connected auditor			-0.0765**			-0.0088*
			(0.0138)			(0.0672)
Not connected auditor			-0.0627**			-0.0099***
			(0.0110)			(0.0034)
F-test:			*-0.0138*			*0.0011*
			(0.6790)			*(0.8290)*
Accounting knowledge:						
Accounting education	-0.0081	-0.0085	-0.0117	0.0080***	0.0077***	0.0075***
	(0.6459)	(0.6279)	(0.5093)	(0.0009)	(0.0014)	(0.0018)
CPA	0.0285	0.0237	0.0270	0.0099***	0.0086**	0.0085**
	(0.3839)	(0.4547)	(0.4135)	(0.0091)	(0.0186)	(0.0151)
Analyst and firm controls as before	Yes	Yes	Yes	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes	No	No	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	No
Recommendation month FE	No	No	No	Yes	Yes	Yes
Observations	318,554	318,554	313,244	102,584	102,584	100,509
Adjusted R-squared	12.44%	12.44%	12.45%	15.72%	15.72%	15.85%

TABLE 5: Channel Analyses – Monitoring

This table reports coefficient estimates for analyses of accountants' monitoring role. Panel A provides summary statistics for the dependent variables, independent variables of interest as well as additional firm controls used in the analyses. Panels B and C present regression results. Across both panels, the dependent variable in column (1), *Restatement*, is an indicator variable that equals one if the firm has at least one restatement in the fiscal year, and zero otherwise. The dependent variable in column (2), *Litigation*, is an indicator variable that equals one if the firm has at least one litigation in the fiscal year, and zero otherwise. The dependent variable in column (3), *Discretionary accruals*, is calculated following Yu (2008) as the residual from cross-sectional regressions of total accruals on changes in sales and on property, plant and equipment within industry-years. The magnitude of a firm's discretionary accruals is indicated as a percentage of the lagged assets of the firm. The dependent variable in column (4), *C-score*, is a firm-year measure of conservatism that is calculated following Khan and Watts (2009). In Panel B, the independent variables of interest are the number of analysts with accounting work experience following the firm-year (*Accounting work experience following*) and the number of analysts with accounting knowledge following the firm-year (*Accounting knowledge following*). In Panel C, the independent variables of interest are the number of former auditors following the firm-year (*Auditor following*), the number of corporate accountants following the firm-year (*Corporate accountant following*), the number of analysts with university education in accounting following the firm-year (Accounting education following), and the number of CPAs following the firm-year (*CPA following*). All specifications further include the number of other analysts following the firm-year (*Other analysts following*). Following Bradley et al. (2017b), we include three additional firm controls, *cash flow volatility*, *external financing*, and *total assets growth*. Table A2 in the appendix provides detailed variable definitions. In columns (1) and (2) of Panels B and C, we exclude firms that are never subject to a restatement or litigation. All specifications include firm and year fixed effects. We do not report coefficient estimates for the control variables for brevity. Standard errors are clustered at the firm-level. P-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Summary Statistics

	N	Mean	Percentile		
			25th	50th	75th
Dependent variables:					
Restatement (indicator, %)	318,680	4.15	0	0	0
Litigation (indicator, %)	318,680	1.82	0	0	0
Discretionary accruals (%)	285,903	0.10	-2.58	0.44	3.54
C-score	267,946	-0.17	-0.01	0.11	0.21
Independent variables of interest:					
Accounting work experience following (number)	318,680	0.57	0	0	1
Accounting knowledge following (number)	318,680	3.24	0	1	4
Auditor following (number)	318,680	0.52	0	0	1
Corporate accountant following (number)	318,680	0.05	0	0	0
Accounting education following (number)	318,680	2.92	0	1	4
CPA following (number)	318,680	0.34	0	0	0
Other analysts following (number)	318,680	12.91	6	11	18
Additional firm controls in t:					
Total assets growth (%)	318,680	13.37	-1.04	6.41	18.02
Cash flow volatility (%)	317,734	8.90	2.74	5.05	9.28
External financing (%)	305,925	8.24	-0.20	1.92	7.96

Panel B: Accounting Background Following

Dependent variable:	**Restatement**	**Litigation**	**Discretionary accruals**	**C-score**
	(1)	(2)	(3)	(4)
Accounting work experience following	-0.0114**	0.0006	-0.0021***	0.1957**
	(0.0406)	(0.9432)	(0.0003)	(0.0175)
Accounting knowledge following	0.0019	0.0033	-0.0003	0.1263***
	(0.3465)	(0.2789)	(0.1188)	(0.0000)
F-test:	*-0.0133***	*-0.0027*	*-0.0018****	*0.0694*
	(0.0394)	*(0.8010)*	*(0.0044)*	*(0.4580)*
Other analysts following	0.0024	0.0045**	-0.0007***	0.0540***
	(0.1144)	(0.0394)	(0.0000)	(0.0000)
Analyst and firm controls as before	Yes	Yes	Yes	Yes
Additional firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	59,528	40,878	277,636	256,928
Adjusted R-squared	46.54%	23.20%	32.88%	11.14%

Panel C: Accounting Background Following Decomposed

Dependent variable:	**Restatement**	**Litigation**	**Discretionary accruals**	**C-score**
	(1)	(2)	(3)	(4)
Accounting work experience following:				
Auditor following	-0.0161***	0.0021	-0.0021***	0.1745*
	(0.0024)	(0.8191)	(0.0012)	(0.0545)
Corporate accountant following	-0.0369	-0.0835	-0.0021	-0.0740
	(0.3316)	(0.1067)	(0.5229)	(0.7576)
Accounting knowledge following:				
Accounting education following	0.0019	0.0040	-0.0003*	0.1232***
	(0.3873)	(0.2442)	(0.0903)	(0.0000)
CPA following:	0.0197***	0.0072	-0.0009	0.4343***
	(0.0095)	(0.6060)	(0.3138)	(0.0005)
Other analysts following	0.0027*	0.0049**	-0.0008***	0.0668***
	(0.0889)	(0.0286)	(0.0000)	(0.0000)
Analyst and firm controls as before	Yes	Yes	Yes	Yes
Additional firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	59,528	40,878	277,636	256,928
Adjusted R-squared	46.62%	23.43%	32.90%	11.26%

TABLE 6: Channel Analyses – Earnings Conference Calls

This table reports coefficient estimates for analyses of accountants' behavior on earnings conference calls. Panel A provides summary statistics for the dependent variables and the control variable used in the analyses. Panel B presents regression results. The dependent variable in columns (1) and (2), *Tone*, is the average difference between positive and negative words spoken by an analyst during all quarterly conference calls for a firm-year. The dependent variable in columns (3) and (4), *Accounting words*, is the average number of accounting words spoken by an analyst during all quarterly conference calls for a firm-year. Table OA6 in the online appendix provides the list of accounting words. We neglect the word "guidance" when counting the number of accounting words spoken by an analyst during a conference call. In columns (1) and (3), the independent variables of interest are *Accounting work experience* and *Accounting knowledge*. Both are indicator variables that equal one if the analyst has accounting work experience and accounting knowledge, respectively, and zero otherwise. In columns (2) and (4), the independent variables of interest are *Auditor*, *Corporate accountant*, *Accounting education*, and *CPA*. *Auditor* (*Corporate accountant*) is an indicator variable that equals one if the analyst has public accounting (corporate accounting) work experience, and zero otherwise. *Accounting education* (*CPA*) is an indicator variable that equals one if the analyst obtained university education in accounting (a CPA certification), and zero otherwise. All specifications further control for the *Question length*, which is the average number of words said by an analyst during all quarterly conference calls for a firm-year. Table A2 in the appendix provides detailed variable definitions. All specifications include firm and year fixed effects. Standard errors are clustered at the firm-level. P-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Summary Statistics

	N	Mean	Percentile		
			25^{th}	50^{th}	75^{th}
Tone (wordcount)	115,527	0.08	-1	0	1
Accounting words (wordcount)	115,527	2.60	1	2	4
Question length (wordcount)	115,527	156.91	102	142	194

Panel B: Accounting Background and Earnings Calls

Dependent variable:	**Tone**		**Accounting words**	
	(1)	(2)	(3)	(4)
Accounting work experience	-0.0474*		0.1425***	
	(0.0929)		(0.0010)	
Accounting knowledge	0.0283*		-0.0360	
	(0.0875)		(0.1294)	
Accounting work experience:				
Auditor		-0.0191		0.1621***
		(0.5831)		(0.0018)
Corporate accountant		-0.0501		-0.1959*
		(0.4826)		(0.0578)
Accounting knowledge:				
Accounting education		0.0406**		-0.0616**
		(0.0144)		(0.0135)
CPA		-0.0702		0.0681
		(0.1080)		(0.2340)
Question length	-0.0003**	-0.0003**	0.0169***	0.0168***
	(0.0201)	(0.0215)	(0.0000)	(0.0000)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	115,247	115,247	115,247	115,247
Adjusted R-squared	7.40%	7.40%	41.86%	41.87%

TABLE 7: Labor Market Outcomes

This table reports coefficient estimates for accountants' labor market outcomes. Panel A provides summary statistics for the dependent variables used in the analyses. Panel B presents regression results. Columns (1) and (2) of Panel B present OLS regression results. The dependent variable, *All Star*, is an indicator variable that equals one if an analyst is ranked as all-star during the year, and zero otherwise. Following Bradley et al. (2017a), we include lagged analyst controls as well as the one-year lag in *All Star*. Both columns include broker, firm and year fixed effects, and standard errors are double-clustered at the analyst- and year-levels. Columns (3) to (6) of Panel B present results from survival analyses using a Cox proportional hazard model. The unit of observation in columns (3) and (4) is an analyst-broker pair, and the unit of observation in columns (5) and (6) is an analyst. The dependent variable in columns (3) and (4), *Time-to-promotion*, is the number of years until the analyst moves up to a larger broker which is determined by comparing broker size quintiles. The dependent variable in columns (5) and (6), *Time-to-leave-IBES*, is the number of years until the analyst last issues forecasts in the I/B/E/S database. Both variables, *Time-to-promotion* and *Time-to-leave-IBES* are right-censored, i.e., they are set to 23 (= 2019 – 1997) for analysts that are still in the I/B/E/S database at the end of our sample period. We control for the analyst controls used in previous analyses as well as for broker size. In columns (1), (3) and (5), the independent variables of interest are *Accounting work experience* and *Accounting knowledge*. Both are indicator variables that equal one if the analyst has accounting work experience and accounting knowledge, respectively, and zero otherwise. In columns (2), (4) and (6), the independent variables of interest are *Auditor*, *Corporate accountant*, *Accounting education*, and *CPA*. *Auditor* (*Corporate accountant*) is an indicator variable that equals one if the analyst has public accounting (corporate accounting) work experience, and zero otherwise. *Accounting education* (*CPA*) is an indicator variable that equals one if the analyst obtained university education in accounting (a CPA certification), and zero otherwise. Table A2 in the appendix provides detailed variable definitions. We do not report coefficient estimates for the control variables for brevity. P-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Summary Statistics

	N	Mean	Percentile		
			25th	50th	75th
Allstar (indicator, %)	27,369	6.27	0	0	0
Time-to-promotion (years)	5,361	19.99	23	23	23
Time-to-leave-IBES (years)	4,069	9.55	1	4	23

Panel B: Career Trajectories of Analysts with Accounting Expertise

Dependent variable:	**All Star**		**Time-to-promotion**		**Time-to-leave-IBES**	
	(1)	(2)	(3)	(4)	(5)	(6)
Accounting work experience	0.0145		0.0549		-0.2082**	
	(0.1384)		(0.7233)		(0.0309)	
Accounting knowledge	-0.0017		-0.0555		0.0011	
	(0.7988)		(0.5395)		(0.9856)	
F-test:	*0.0162*					
	0.228					
Accounting work experience:						
Auditor		0.0179*		0.1111		-0.1910*
		(0.0925)		(0.4972)		(0.0887)
Corporate accountant		-0.0414		0.0770		-0.2439
		(0.1134)		(0.8997)		(0.2136)
Accounting knowledge:						
Accounting education		-0.0039		0.0743		-0.0244
		(0.6364)		(0.5349)		(0.6895)
CPA		0.0091		-0.4372		0.0937
		(0.5449)		(0.1293)		(0.4385)
Analyst controls and All Star in t-1	Yes	Yes	No	No	No	No
Analyst controls as before and Broker size	No	No	Yes	Yes	Yes	Yes
Broker FE	Yes	Yes	No	No	No	No
Firm FE	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	No	No	No	No
Observations	12,222	12,222	5,331	5,331	3,520	3,520
Adjusted R-squared	54.00%	54.01%				

ONLINE APPENDIX

TABLE OA1: Sample Construction

This table illustrates the step-wise sample construction process. I/B/E/S data items are reported in upper case letters, italics and parentheses.

	Analyst-Firm-Years	Unique Analysts	Unique Firms
I/B/E/S Detail History – Detail File with Actuals (retrieved May 25, 2022).	23,104,683	22,211	15,624
Drop erroneous observations:			
Forecast announcement date (*ANNDATS*) after actual announcement date (*ANNDATS_ACT*).	23,057,717	22,203	15,623
Require forecasts and actuals to be reported in USD.	20,445,374	19,678	14,749
Require the unique analyst identifier (*ANALYS*) to be non-zero.	20,437,335	19,677	14,745
Require firm identifiers (*TICKER*), forecasts (*VALUE*) and actuals (*ACTUAL*) to be non-missing.	20,301,445	19,613	14,534
Require forecasts to be annual.	3,159,643	19,056	13,947
Retain an analyst's most recent forecast per day (i.e., latest *ANNTIMS* per *ANNDATS*).	3,134,852	19,056	13,947
Retain an analyst's most recent forecast per year (i.e., latest *ANNDATS* per *FPEDATS*).	835,156	19,056	13,947
Drop observations with missing LinkedIn data.	410,929	6,989	11,900
Drop observations with missing current analyst controls, with missing lagged firm controls, and with missing proportional mean absolute forecast error (= Final sample).	318,680	6,480	7,387

TABLE OA2: Sample Selection

This table reports analyst-firm-year level summary statistics for firms covered by analysts that cannot be found on LinkedIn (Non-LinkedIn analysts) and for firms covered by analysts that can be found on LinkedIn (LinkedIn analysts). The latter represents our final sample. We require forecasts to be annually and retain only the most recent forecast per fiscal period end date. A firm-year is required to be followed by at least two analysts. Table A2 in the appendix provides detailed variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles.

	Non-LinkedIn Analysts			LinkedIn Analysts		
	N	Mean	SD	N	Mean	SD
Firm experience (years)	311,454	2.61	3.40	318,680	2.74	3.34
General experience (years)	311,454	11.47	6.41	318,680	11.78	5.89
Number of industries (number)	311,454	3.20	2.23	318,680	3.28	2.21
Number of companies (number)	311,454	12.80	7.46	318,680	13.29	7.06
Forecast timeliness (days)	311,454	130.72	81.93	318,680	123.98	76.49
Firm size	311,454	7.93	1.96	318,680	8.06	1.90
Book-to-market (%)	311,454	50.74	38.55	318,680	50.31	38.98
Past return (%)	311,454	15.51	64.63	318,680	13.62	60.62
Analyst following (number)	311,454	15.81	10.09	318,680	16.22	9.86
Leverage (%)	311,454	22.49	18.58	318,680	22.88	18.99
Intangibles (%)	311,454	15.53	18.88	318,680	18.10	20.43
R&D (%)	311,454	3.81	7.69	318,680	3.55	7.19
Return on assets (%)	311,454	2.23	13.07	318,680	2.46	12.52

TABLE OA3: Propensity-Score Matching

This table reports coefficient estimates for re-estimating our forecast accuracy and sell recommendation profitability OLS regressions using a propensity-score matched sample. To implement propensity-score matching, we estimate a logit model using *Accountant* as the dependent variable and *Firm experience*, *General experience*, *Number of industries*, *Number of companies*, and *Pre-analyst experience length* as independent variables. We then use nearest neighbor matching within a caliper of 0.3 using the propensity score. Table A2 in the appendix provides detailed variable definitions. We do not report coefficient estimates for the control variables for brevity. Standard errors are double-clustered at the analyst- and year-levels. P-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Sample:		Calendar-time sell portfolio		
Dependent variable:	**PMAFE**	**DGTW return**	**BHAR(1, 30)**	**BHAR(1, 180)**
	(1)	(2)	(3)	(4)
Accounting work experience	-0.0497**	-0.0091***	-0.0060*	-0.0468***
	(0.0343)	(0.0018)	(0.0769)	(0.0002)
Accounting knowledge	-0.0270	0.0061**	0.0027	0.0066
	(0.1448)	(0.0188)	(0.2688)	(0.4286)
F-test:	*-0.0227*	*-0.0152****	*-0.0086**	*-0.0534*
	(0.5180)	*(0.0015)*	*(0.0897)*	*(0.0018)*
Analyst and firm controls as before	Yes	Yes	Yes	Yes
Broker FE	Yes	No	No	No
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
Recommendation month FE	No	Yes	Yes	Yes
Observations	91,813	29,182	34,499	34,499
Adjusted R-squared	13.81%	19.32%	13.36%	14.56%

TABLE OA4: Placebo Tests

This table reports coefficient estimates for re-estimating our forecast accuracy and sell recommendation profitability OLS regressions. Instead of the indicator variable *Auditor*, that equals one if the analyst has public accounting work experience, i.e., worked in an audit-related position at an audit firm (and zero otherwise), we include the indicator variable *Non-auditor*. This variable equals one if the analyst worked in a non-audit-related position at an audit firm. Table A2 in the appendix provides detailed variable definitions. We do not report coefficient estimates for the control variables for brevity. Standard errors are double-clustered at the analyst- and year-levels. P-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Sample:		Calendar-time sell portfolio		
Dependent variable:	**PMAFE**	**DGTW return**	**BHAR(1, 30)**	**BHAR(1, 180)**
	(1)	(2)	(3)	(4)
Accounting work experience:				
Non-auditor	**-0.0271**	**-0.0031**	**0.0008**	**0.0127**
	(0.2175)	**(0.2124)**	**(0.7922)**	**(0.2755)**
Corporate accountant	-0.0428	0.0018	-0.0024	-0.0466
	(0.3401)	(0.7426)	(0.6131)	(0.1633)
Accounting knowledge:				
Accounting education	-0.0036	0.0078***	0.0052**	0.0168*
	(0.8435)	(0.0016)	(0.0165)	(0.0697)
CPA	0.0306	0.0044	-0.0074	-0.0146
	(0.5237)	(0.3232)	(0.1691)	(0.4445)
Analyst and firm controls as before	Yes	Yes	Yes	Yes
Broker FE	Yes	No	No	No
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
Recommendation month FE	No	Yes	Yes	Yes
Observations	306,558	98,593	115,567	115,573
Adjusted R-squared	12.53%	15.72%	9.23%	11.58%

TABLE OA5: Forecast Properties

This table reports coefficient estimates from OLS regressions of different forecast properties on analysts' accounting expertise. The dependent variable in column (1), *Forecast timeliness*, is the number of days between the forecast and actual announcement. The dependent variable in column (2), *Forecast boldness*, is calculated following Pope and Wang (2023) as the absolute deviation of analyst i's EPS forecast for firm j from the average of those issued by all other analysts covering firm j. The dependent variable in column (3), *Rec. optimism*, is a categorical variable that takes values between -2 ("Sell") and +2 ("Strong Buy") so that larger values indicate more analyst optimism. The dependent variable in column (4), *Rec. extremism*, is an indicator variable that equals one for "Sell" or "Strong Buy" recommendations, and zero otherwise. Larger values indicate that analysts issue more extreme recommendations. Table A2 in the appendix provides detailed variable definitions. All specifications include broker, firm and year fixed effects. We do not report coefficient estimates for the control variables for brevity. Standard errors are double-clustered at the analyst- and year-levels. P-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable:	**Forecast timeliness** (1)	**Forecast boldness** (2)	**Rec. optimism** (3)	**Rec. extremism** (4)
Accounting work experience	-3.7327**	-0.0116**	-0.0420**	-0.0164*
	(0.0312)	(0.0283)	(0.0450)	(0.0978)
Accounting knowledge	2.0383***	0.0040	0.0056	-0.0000
	(0.0026)	(0.1836)	(0.6468)	(0.9963)
F-test:	*-5.7710****	*-0.0156***	*-0.0477**	*-0.0163*
	(0.0048)	*(0.0364)*	*(0.0958)*	*(0.2070)*
Analyst and firm controls as before	Yes	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	318,554	317,638	273,890	273,890
Adjusted R-squared	7.78%	59.29%	21.67%	35.18%

TABLE OA6: List of Accounting Words

This table provides the list of accounting words used to calculate the number of accounting words spoken by an analyst during a firm's quarterly earnings conference call. The accounting words are identified by manually classifying words from the Loughran and McDonald master dictionary available at https://sraf.nd.edu/loughranmcdonald-master-dictionary/.

ACCOUNT	CASH	EXPENDITURE	MINORITY	REPORTABLE
ACCOUNTANT	CASHFLOW	EXPENDITURES	MULTIPLES	REPORTED
ACCOUNTANTS	CASHFLOW	EXPENSE	NET	REPORTING
ACCOUNTED	CASHFLOWS	EXPENSED	NETTING	REPORTS
ACCOUNTING	CASHFLOWS	EXPENSES	NOMINAL	RESERVES
ACCOUNTINGS	CHARGED	EXTRAORDINARY	NONACCRUAL	RESTATE
ACCOUNTS	CHARGES	FAS	NONACCRUALS	RESTATE
ACCRETION	COGS	FILED	NONAMORTIZATION	RESTATED
ACCRUAL	CONCERN	FILING	NONCASH	RESTATEMENT
ACCRUALS	CONDENSED	FILINGS	NONCONTROLLING	RESTATEMENTS
ACCRUE	CONSOLIDATE	FINANCIALS	NONFINANCIAL	RESTATES
ACCRUED	CONSOLIDATED	FISCAL	NONMARKETABLE	RETIREMENT
ACCRUES	CONSOLIDATING	FLOW	NONPENSION	RETIREMENTS
ACCRUING	CONTINGENCY	FLOWS	NONRECURRING	REVENUE
ACCUMULATED	CONTINGENT	FOOTNOTES	NONTAXABLE	REVENUES
ACTUARIAL	CONTRIBUTION	FORECASTING	OBLIGATIONS	SEC
ALLOWANCE	CONTRIBUTIONS	FORMA	OFFSETTING	SHEET
ALLOWANCES	CONTROLLER	FORWARDLOOKING	OUTFLOW	SHEETS
AMORTIZATION	COST	GAIN	OUTFLOWS	STANDARDS
AMORTIZATIONS	COSTS	GAINS	OUTSTANDING	STATEMENT
AMORTIZE	CUMULATIVE	GOODWILL	OVERESTIMATE	STATEMENTS
AMORTIZED	DEBIT	GOVERNANCE	PAYABLE	SURPLUS
AMORTIZES	DEDUCTED	GROSS	PAYABLES	TANGIBLE
ANALYST	DEDUCTIBLE	GUIDANCE	PENSION	TAX
ANALYSTS	DEDUCTION	IMPAIR	PENSIONS	TAXABILITY
ANNOUNCEMENT	DEDUCTIONS	IMPAIRED	PERIODIC	TAXABLE
ANNOUNCEMENTS	DEFER	IMPAIRMENT	POOLING	TAXATION
ASSET	DEFERRAL	IMPAIRMENTS	POSTRETIREMENT	TAXED
ASSETS	DEFERRALS	INCOME	PREPAID	TAXES
ASSURANCE	DEFERRED	INCOMES	PRETAX	TAXING
AUDIT	DELINQUENCY	INCUR	PROFIT	TRANSACTIONS
AUDITED	DELINQUENT	INCURRED	PROFITABILITY	TREASURY
AUDITING	DEPLETION	INDEMNIFIABLE	PROFITABLE	UNACCRUED
AUDITOR	DEPOSIT	INDEMNIFICATIONS	PROFITS	UNAMORTIZED
AUDITORS	DEPRECIATE	INDEMNIFIES	PROFORMA	UNAUDITED
AUDITS	DEPRECIATED	INDEMNITEES	PROVISION	UNCERTAINTIES
BALANCE	DEPRECIATES	INDEMNITOR	PROVISIONS	UNCERTAINTY
BALANCES	DEPRECIATION	INFLOW	QUALIFIED	UNCOLLECTIBLE
BANKRUPTCIES	DISCLOSED	INFLOWS	QUARTERLY	UNCOLLECTIBLES
BOOK	DISCLOSURE	INTANGIBLE	RATIO	UNCONSOLIDATED
BOOKKEEPING	DISCLOSURES	INTANGIBLES	RATIOS	UNDEPRECIATED
BOOKS	DISCOUNT	LEASES	RECEIPTS	UNDERESTIMATED
CAPITALIZATIONS	DISCOUNTED	LIABILITIES	RECEIVABLE	UNDISCOUNTED
CARRYBACK	DISCRETION	LIABILITY	RECEIVABLES	UNEARNED
CARRYBACKS	DISCRETIONARY	LOSS	RECLASSIFICATIONS	UNMARKETABLE
CARRYFORWARD	DOUBTFUL	LOSSES	RECOGNITION	UNREALIZED
CARRYFORWARDS	EARNING	LUMP	RECOGNIZE	UNRELEASED
CARRYFOWARD	EARNINGS	MARGIN	RECONCILIATION	VALUATION
CARRYFOWARDS	ESTIMATE	MARGINS	RECOVERABILITY	VALUATIONS
CARRYING	ESTIMATED	MARKETABLE	RECOVERIES	VALUE
CARRYOVER	ESTIMATES	MATERIAL	RECURRING	VIE
CARRYOVERS	EXCISE	MATERIALLY	RELEASEES	WITHHOLDINGS

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