**Do Sell-Side Analysts’ Qualifications Mitigate the Adverse Effects of Accounting Reporting Complexity?**

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While there is broad recognition that the financial reports are overly complex, regulators acknowledge that there is no solution in sight (FASB 2017). Complexity introduces challenges in collecting, interpreting, and analyzing information for investment decisions. Analysts are sophisticated intermediaries who can potentially alleviate the adverse effects of complexity (FASB 2010). It is unclear, however, whether analysts are also challenged by complexity. Addressing this question, we find that accounting reporting complexity (ARC) is associated with lower analysts’ performance. Further, we find that this association is driven by the complexity of the disclosed information in the footnotes, rather than the seemingly more important accounting information that is recognized on the face of the financial statements. Next, we find that while analysts’ general experience does not help alleviate complexity, analysts’ firm-specific experience, industry focus, and CFA certification do. Using a new approach for measuring analysts’ account-specific expertise we find that expertise in fair value, derivatives and pension accounts is more valuable than other types of qualifications in attenuating the negative effects of complexity in these accounts. Overall, this study underscores the importance of analysts’ qualifications and the need to simplify the disclosures in the notes to the financial statements.

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# Introduction

Regulators and standard setters have long recognized that financial reporting has become overly complicated (SEC 2008; FRC 2009), leading to several initiatives to simplify the financial reports (e.g. FASB 2016). Although efforts are underway, these work-in-progress initiatives are not expected to fully resolve accounting complexity in the near future. Recognizing the complex nature of financial statements, FASB states that sophisticated advisers can help investors “understand information about complex economic phenomena” (FASB 8, 2010). Sell-side financial analysts are considered among the most sophisticated users of financial information. Their role is to analyze, interpret and disseminate information to less knowledgeable market participants. As such, financial analysts can potentially alleviate the adverse consequences of accounting reporting complexity. Yet, it is possible that analysts also struggle when financial reports are complex, especially if they lack the requisite qualifications. In this study, we examine the association of accounting reporting complexity (hereafter, ARC) with analysts’ performance and whether certain analysts’ qualifications allow analysts to better cope with complexity.

 Following the speech of the SEC commissioner (SEC 2006) about the complexity of the financial reports, the SEC formed the Advisory Committee on Improvements to Financial Reporting (ACIFR hereafter, SEC 2008) with a mandate to reduce the complexity of the financial reporting system. We rely on the ACIFR report and define the user-centric aspect of ARC as: the difficulty for financial statement users to understand and analyze detailed economic activities and firm performance from the accounting disclosures in 10-K filings. ARC is calculated as the count of disclosed accounting concepts in annual XBRL (eXtensible Business Reporting Language) 10-K filings.[[1]](#footnote-1),[[2]](#footnote-2) Past research suggests that the need to analyze more information contributes to task complexity (e.g., Steinmann 1976; Campbell 1988; Bonner 1994). Consistently, we surmise that the disclosure of more accounting information complicates the work of financial analysts because consuming more information requires a broader and more diverse knowledge of accounting standards and regulations.[[3]](#footnote-3)

 Using a sample of 8,361 firm-year observations between 2011 and 2014 we document the following results. First, as predicted, we find that higher ARC is associated with lower forecast accuracy, higher forecast dispersion, and lower market reaction to recommendation revisions.[[4]](#footnote-4),[[5]](#footnote-5) While we expect complexity to be negatively associated with analysts’ performance, these results are not trivial and previous literature documents inconsistent results with respect to other complexity measures, perhaps because past measures were not directly derived from accounting disclosures. For example, Lehavy, Li, and Merkley (2011) and Dunn and Nathan (2005) find that the number of business segments is associated with lower analyst performance whereas Loughran and McDonald (2014) and Duru and Reeb (2002) fail to find a similar association. Furthermore, while Lehavy et al. (2011) document that lower readability, measured by the Gunning (1952) Fog index, is associated with lower analyst performance, Loughran and McDonald (2014) fail to find a significant association. Our analyses control for other complexity measures such as firm segments, the Fog index and the length of the 10-K (Li 2008) and we find that ARC exhibits a more consistent association with analyst performance than these measures.[[6]](#footnote-6)

An important aspect of financial reporting complexity, unaddressed by prior archival literature, is whether analysts are most affected by the complexity of the financial statements, the complexity of the disclosed information in the notes, or both. It is likely that analysts will be more effected by the complexity of the recognized information on the financial statements because this information is perceived to be more relevant (FASB 1984) than the disclosed information. We examine this question by exploiting a unique feature of ARC that allows for its disaggregation into complexity emanating from the face of the financial statements and from the notes.[[7]](#footnote-7) We find that the complexity of the disclosed information in the notes rather than the salient recognized information in the financial statements is associated with lower forecast accuracy and higher forecast dispersion. Both aspects of complexity, however, are associated with lower market reaction to recommendation revisions.

To address our primary objective, we examine whether analysts’ qualifications can moderate the effect of accounting complexity and increase forecast accuracy of individual analysts. Past research documents the benefits of general and firm-specific experience and industry knowledge (Clement 1999; Mikhail, Walther, and Willis 1997; Kadan et al. 2012), yet we are unaware of research that examines whether these benefits vary with firm complexity. Using 113,073 analyst-firm-year observations, we examine this question using four measures that capture analysts’ qualifications. These include general experience (tenure as analyst in years), firm-specific experience (number of years the analyst covered the firm), industry focus (the inverse of number of industries the analyst cover) and Chartered Financial Analyst© (CFA) certification.[[8]](#footnote-8) Similar to previous studies (Clement 1999), we find that general experience is associated with greater accuracy. Such experience, however, fails to attenuate the negative effect of ARC. In contrast, analysts with more firm-specific experience, greater industry focus and a CFA certification issue more accurate forecasts, particularly when firms are more complex. Overall, these results suggest that not all types of qualifications are equally beneficial for analysts who cover complex firms.

We further explore whether the complexity attributed to specific account categories that are inherently difficult to understand influence the performance of financial analysts and whether analysts’ expertise in these specific accounts can mitigate this effect. Previous studies use novel measures to capture detailed account specific complexity (Picconi 2006; Magnan, Menini, and Parbonetti 2015; Chang, Donohoe, and Sougiannis 2016). Guided by these studies, we construct ARC measures in three categories of particularly complex accounts: fair values, derivatives and pensions. We compute these account-specific complexity measures by counting the reported accounting concepts (XBRL tags) in each account category. Different from previous studies, this approach for measuring ARC in these accounts is uniform across accounts, is not sample or event specific, and can be extended to other accounts. Constructing these account-specific proxies for complexity underscores an important advantage of ARC, because this is unattainable with measures of readability or other complexity measures that lack an accounting context. As predicted, we find that complexity in fair value, derivatives, and pension is associated with lower forecast accuracy.

Since companies can be complex along certain dimensions of accounting and simple along others, we present a new approach that is not used by prior research for measuring analysts’ expertise in specific accounts. We measure the degree of analyst expertise based on the count of the number of account-specific XBRL tags that analysts cover across their portfolio of firms. We conjecture that analysts who cover more account-specific XBRL tags gain expertise in these accounts, consistent with the notion of learning by doing (Arrow 1962).[[9]](#footnote-9) This approach for measuring analysts’ account specific expertise cannot be easily accomplished without XBRL data.[[10]](#footnote-10) We find that analysts’ expertise in fair value, pensions and derivatives attenuates the detrimental effect of complexity in these accounts. We further examine whether less nuanced qualifications in the form of general experience, firm-specific experience, industry focus, and a CFA certification are also instrumental in alleviating complexity of specific accounts. We find that general experience provides no benefit to analysts when specific accounts are more complex. In contrast, firm specific experience helps analysts handle complexity in all three accounts, industry focus helps analysts in fair value and pensions but not derivatives and CFA certification helps analysts with complexity in fair value and derivative but not in pension, which is consistent with material covered by the certification requirements. Importantly, we note that account specific expertise remains significant after controlling for other types of analyst expertise, and, in most cases, the effect of the more nuanced account specific expertise is greater than that of other qualifications.

Finally, in additional analysis, we examine whether certain information environment attributes that go beyond the individual analyst qualifications, can also alleviate the effects of complexity. We find that when more analysts cover a firm, the forecasts of individual analysts are more accurate among firms with greater ARC. In contrast, greater analyst effort, measured as the number of forecasts, does not alleviate the effects of complexity. Interestingly, while Guay, Samuels, and Taylor (2016) find that managers are more likely to increase the frequency of their earnings guidance when the company is complex, we find that heightened guidance fails to improve analyst performance when the company is complex.

Our study contributes to the accounting literature in several ways. First, we show that the new measure of ARC is inversely associated with analysts’ performance. Importantly, using a unique feature of ARC we document that the complexity from the disclosed rather than the more reliable and salient recognized financial information drives the negative analysts’ performance outcomes. This evidence was not documented by prior studies that examine recognition versus disclosure of financial information (Schipper 2007; De Franco, Wong, and Zhou 2011). These results suggest that analysts are unaffected by the complexity in the financial statements, perhaps because of the low volume, better information structure in the form of tables, or because analysts invest more time in analyzing these common statements. In contrast, our results show that analysts struggle when the disclosed information in the footnotes is complex. These findings are important to regulators working on simplifying the financial reports and suggest that improvements to the voluminous and unstructured nature of the disclosed information in the notes may have greater impact.

Second, while past research shows, and our results corroborate, that reporting complexity influence analyst performance, we are unaware of research that examines circumstances under which such negative effects are attenuated. Our results show that only certain types of analyst qualifications are instrumental when the financial reports are complex. Third we extend prior literature that uses different methods to measure the complexity of specific accounts (Gu and Wang 2005; Chang et al. 2016) by offering a unified method that is based on the FASB U.S. GAAP XBRL taxonomy to quantify account specific complexity. This method is systematic, objective, and consistent across different accounts, and can be extended to other accounts, samples, periods, and settings. Other researchers can use this method and examine account-specific complexity in different contexts. We show that analyst performance declines when certain accounts are more complex. Finally, we propose a new approach to measure analysts’ account specific expertise and demonstrate that this form of expertise is especially beneficial when specific accounts are more complex.

The empirical evidence that we present has several important implications for regulators, standard-setters, investors, creditors, and brokerage houses. Regulators should take note of the adverse consequences of ARC on analyst performance. Our results suggest that even sophisticated financial statement users face challenges when financial reports are complex. Similarly, investors and creditors should be cautious when considering analyst forecasts for firms with complex accounting. Our results highlight both a challenge and an opportunity for brokerage houses and sell-side analysts. Additional investment directed towards understanding the nuances in complex accounting standards may help analysts issue more accurate forecasts and profitable recommendations. Further, the difficulties associated with processing complex accounting information and the importance of experience, expertise, industry focus, and a CFA certification should be considered in cost-benefit discussions and coverage decisions.

# Background

The first objective of this paper is to test the association between a relatively new measure of accounting reporting complexity (ARC) that is directly constructed from monetary accounting disclosures, and analyst performance. While prior research showed that ARC presents challenges for preparers, leading to financial reports that are more susceptible to errors and misapplications of GAAP (Hoitash and Hoitash 2018), this measure is untested in the context of financial statement users.

Accounting information is chiefly obtained from filings with the SEC and is one of the three primary sources used by analysts to prepare their reports (Ramnath, Rock, and Shane 2008). We surmise that the performance of financial analysts declines with ARC, measured as the number of XBRL tags (accounting concepts), for several reasons. First, like most business actors, analysts face economic resources constraints and therefore, as the amount of accounting disclosures increase, analysts need to exert greater effort to complete the forecasting task. Second, even with adequate resources, understanding a larger number of accounting concepts in the financial reports requires more in-depth knowledge of, already complex, authoritative accounting standards. In addition, when the disclosed accounting information is more voluminous and diverse, judgment quality may decline (Payne, Bettman, and Johnson 1988). Nevertheless, financial analysts are considered among the most sophisticated users of the financial reports and are known to have intimate knowledge of the firms they cover, as a result greater ARC may not influence their performance. At the outset, our investigation is aimed at testing the prediction of an inverse association between ARC and analysts' performance.

In an auxiliary analysis we examine whether the complexity of the recognized information that appear on the face of the financial statements, the disclosed information that appear in the notes, or both, are associated with analyst performance. While some evidence from the experimental literature suggests that information in the notes is harder to consume (Hirst and Hopkins 1998), statement of Financial Accounting Concepts No. 5 (FASB 1984) clearly states that the most relevant information needs to be recognized. Thus, analysts may perceive that recognized information is more important and put more weight on that information. As a result, there is reason to expect that analysts’ performance may be impacted more by the complexity of the recognized information. However, if analysts put more effort to process the recognized information, they may diffuse the negative effect of complexity. In addition, recognized information is typically formatted using standardized tables, which previous literature suggests are easier to consume (Linsmeier et al. 2002; Clar-Proell and Maines 2014). Taken together, the complexity of the recognized information may or may not influence analyst performance.

In contrast, the disclosed information in the financial statement notes is voluminous and less structured, necessitating greater data collection, analysis, and interpretation effort. Such detailed information may impose excessive cognitive load on analysts, and processing such information may not be cost effective (e.g., Schroder, Driver, and Streufert 1967; Shields 1983; Iyengar and Lepper 2000; Thaler and Benartzi 2004). This can impede analysts’ performance because of failure to incorporate relevant information into their forecasts. However, it is also plausible that analysts do not use the information in the financial statement notes or significantly discount it (Schipper 2007) and therefore whether or not disclosures in the notes are complex may not be relevant. Nevertheless, other studies suggested that information residing in the notes is highly useful (Shevlin 1991; Amir 1993; Wahlen 1994; Riedl and Srinivasan 2010) and analysts rely on the information in the notes to update their forecasts (De Franco et al. 2011). Since, we are unaware of archival research that examines this issue we do not have a clear prediction on how the complexity of the recognized information differs from the disclosed information in influencing analyst performance. Therefore, we do not pose a directional prediction and examine this issue as an empirical question.

# Hypotheses Development

## Can certain qualifications help analysts overcome the challenges associated with ARC?

Although we predict that complexity will adversely affect analyst performance, it is possible that certain analysts’ qualifications can help alleviate these adverse outcomes. Prior research find that certain analysts’ qualifications improve their performance, however, these findings do not consider accounting complexity. Since market participants rely on analysts for guidance, and accounting complexity is pervasive across many firms, understanding what types of analysts’ qualifications is instrumental in the presence of complexity is of outmost importance to market participants.

Prior research shows that on average, analyst forecast accuracy improves with experience. This research finds that general experience, defined as the number of years as a financial analyst (Clement 1999), and firm specific experience, defined as the number of years covering a specific firm (Mikhail et al. 1997), are each associated with greater forecast accuracy. This improved performance is attributed to analysts’ ability to more successfully incorporate macroeconomic trends and firm-specific information into their predictions. Nevertheless, when the financial statements are more complex it is possible that experience alone is insufficient to mitigate the adverse effects of complexity. In contrast, given that accounting complexity is often innate to firms and their specific economic activities, we predict that over time analysts can gain knowledge and experience that helps them effectively navigate complex financial reports and thus attenuate the negative performance consequences.

In addition to general and firm specific experience, several studies find that analysts’ industry knowledge is valuable (e.g. Piotroski and Roulstone 2004; Kadan et al. 2012; Bradley, Gokkaya, and Liu 2017).[[11]](#footnote-11) Brown et al. (2015) conduct extensive interviews with sell-side analysts and find that industry knowledge is the single most useful input into analysts’ earnings forecasts and stock recommendations. Consistently, Clement (1999) find that analyst performance is better when analysts cover fewer industries and thus exhibit greater industry focus. Industry knowledge can help analysts through several interrelated channels. First, analysts with industry knowledge can better understand how macro- and micro economic factors influence the firms they cover. Second, the type of economic transactions and accounting treatments are often comparable across companies within an industry, easing the information acquisition processing cost and increasing the quality of the work of the financial analyst. Third, throughout their careers, analysts create connections, these in turn can help analysts gain additional insights about the firms that they cover. While it is possible that analysts with greater industry focus will not be able to cope with accounting complexity, it is likely that they will successfully apply their knowledge to understand the industry specific accounting intricacies in a way that will attenuate the potential detrimental impact of accounting complexity on their forecast predictions.

Limited research also finds that analysts with a Chartered Financial Analyst© (CFA) certification outperform other analysts. De Franco and Zhou (2009) find that CFA Charterholders’ forecasts are timelier and more accurate. As the authors acknowledge, however, the results with respect to accuracy are mixed and sensitive to the research design. Similarly, Kang, Li, and Su (2017) find that CFA Charterholders have better recommendation performance. These results are attributed to the additional training imposed by the certification process. Nevertheless, it is unclear whether analysts with CFA credentials perform better when the firm’s accounting is complex. On the one hand, the certification process is not strictly focused on accounting topics. In contrast, the certification does require extensive financial statement analysis knowledge, which is primarily based on accounting disclosures. As such, we predict that a CFA certification would enhance analyst’s ability to cope with complex accounting.

Together, the abovementioned discussion of general experience, firm-specific experience, industry focus, and a CFA certification leads to our first hypothesis:

**H1:** The expected negative effect of accounting complexity on analysts’ performance is lower among analysts with stronger qualifications.

**Account-specific complexity and analysts’ qualifications**

While prior research examines how experience and industry focus in general are associated with analysts’ performance, the extant literature ignores how these analyst-specific qualifications help mitigate the complexity in specific accounts. Examining this issue is important because recent research shows that account specific complexity is negatively associated with analyst performance. For example, using a sample of banking firms, Magnan et al. (2015) report that level 2 fair value disclosures enhance forecast accuracy, while level 3 fair value disclosures increase forecast dispersion. Chang et al. (2016) examine the relation between analysts’ performance and derivatives and find that analysts’ earnings forecasts for new derivative users are less accurate and more dispersed. They conclude that accounting for derivatives creates a financial reporting challenge because they represent a complex financial contract. Finally, Picconi (2006) finds that analysts fail to fully incorporate and interpret information contained in pension disclosures. In addition to their intrinsic complexity, many of the abovementioned accounts are different across firms, further complicating the forecasting task. Overall, extant research suggests that analysts struggle to fully incorporate information in these complex accounts.[[12]](#footnote-12)

Examining how analysts’ qualifications moderate account specific complexity requires measurement that consistently captures complexity across specific accounts. Similar to the construction of ARC, which is based on the count of accounting concepts reported by firms in their annual filings, we count fair-value, derivative and pension related accounting concepts that are disclosed and use each count as a measure of account specific complexity. This approach for measuring complexity in each account is different from prior research because it is uniform across accounts, is not sample- or event specific, and it can be extended to various accounts.

Following prior literature, we predict that each of these account complexity measures will be inversely associated with analysts’ performance. Extending prior findings by recognizing the value of experience, we hypothesize that general experience, firm specific experience, industry focus and a CFA certification should each be beneficial to analysts who cover firms with greater account specific complexity. This leads to the following hypothesis:

**H2:** There is a negative association between account specific complexity and forecast accuracy and this effect is attenuated when analysts possess greater qualifications.

## Account specific analyst expertise

We argue that analysts can develop a higher level of technical accounting expertise because of the nature of the companies that they cover. Specifically, analysts who frequently encounter specific account categories that are inherently complex (e.g. derivatives, Chang et al. (2016)) can gain knowledge in these accounts, and thus develop account-specific forms of expertise which can help them improve their forecast accuracy. This form of experience can develop organically, over time, as analysts review their forecasts relative to realized company disclosures. In addition, analysts are more likely to rationalize the allocation of additional time to learn about complex accounting topics, because the potential knowledge gains can be used across their portfolio of coverage, thus allowing them to spread the fixed cost required to achieve expertise. This form of expertise is consistent with the learning-by-doing model proposed in a similar context by Mikhail et al. (1997). To date, past research has not examined this specific knowledge gain as a channel through which analysts can alleviate the observed inferior performance.

We predict that analysts who gain account specific expertise in fair-value, derivative, and pension accounts will perform better in companies where these accounts are complex. We formulate this prediction in the following hypothesis.

**H3:** The negative effect of account specific complexity on forecast accuracy is attenuated when analysts possess greater account specific expertise.

# Sample and Methodology

## Construction of accounting complexity

In 2009, the SEC passed the “Interactive Data to Improve Financial Reporting” rule, which requires companies to provide financial statement information in an XBRL format (SEC 2009).[[13]](#footnote-13) The SEC phased in the rule over three years based on company filing status. The rule requires companies to tag each numerical value in Item 8 of the 10-K filings. Each tag represents an accounting concept such as net inventory, raw materials, or net revenue. We rely on detailed tag-level XBRL data filed with the SEC to measure accounting complexity. We obtained the necessary XBRL data directly from the SEC filings using Python.[[14]](#footnote-14) The data includes all XBRL tag names, the period of each tag as well as a variable indicating whether the tag represents a monetary accounting concept.

We start with 13,499 XBRL filings of 10-K reports for fiscal years 2011-2014 and implement a number of filters, which we describe in Table 2 Panel A. Our final sample, after limiting the sample to observations with coverage in Compustat and imposing several other constraints, consists of 8,361 firm-year observations and 113,073 annual analyst earnings estimates.[[15]](#footnote-15) Table 2 Panel B indicates that the fiscal years between 2012 and 2014 are roughly equally represented in the final sample whereas fiscal year 2011 has less than half of the average number of firms for the period 2012-2014. The relatively small sample size for fiscal year 2011 is primarily due to the SEC’s phased implementation of the rule governing XBRL submissions.[[16]](#footnote-16)

## Overall Accounting Complexity

In XBRL filings, each concept is depicted by a tag that is numerical, textual, or date-oriented. Each tag in the XBRL U.S. GAAP taxonomy is assigned a name and a label and includes other attributes such as definition, data type (monetary or string), balance type (credit/debit), and period type (instant for balance sheet items, or duration for income statement items). The goal of the taxonomy is to define a universe of XBRL tags that enable companies to report all of their accounting concepts. In other words, it allows companies to present their traditional HTML filings in XBRL. Although the taxonomy is comprehensive (includes nearly 16,000 tags), companies may have unique disclosure needs that are unmet by the taxonomy. XBRL’s design, therefore, enables companies to extend the taxonomy and create unique tags (extensions) that meet their needs.

Our first test variable is a measure of accounting reporting complexity (*ARC*). The construction of *ARC* follows Hoitash and Hoitash (2018) and begins with all reported monetary XBRL tags in Item 8 of the 10-K filings. Each tag refers to accounting standards and regulations. More tags, therefore, suggest greater accounting complexity because more accounting knowledge is necessary to understand the financial reports. We only count distinct tags in each disclosure (statement/note/table) because tags that recur represent a similar accounting concept and do not increase the complexity. Tag repetition typically happens in comparable financial statements that firms are required to report. For example, the tag “NetIncomeLoss” will repeat three times in the income statement because it is disclosed for the current and the prior two years. In such instances, we only include the tag that refers to the current year. In the sensitivity section, we report that results are not sensitive to alternative construction heuristics of *ARC* such as counting all tags whether or not they repeat within a filing.

***Accounting Complexity Resulting from Recognition versus Disclosure***

A unique feature of *ARC* is the ability to disentangle the complexity emanating from the recognized (i.e. information in the face of the financial statements) and disclosed accounting information (i.e. information in the notes to the financial statements). We take advantage of this feature and decompose *ARC* into two mutually exclusive test variables, *ARC-FS* is the number of distinct tags that appear on the face of the financial statements, and *ARC-NOTES* is the number of distinct tags that appear in the notes to the financial statements.

***Account Specific Complexity and Account Specific Expertise***

Another important feature that differentiates *ARC* from other broad measures (e.g., the Fog Index) is that it is constructed based on specific accounting disclosures and, as such, it can be disaggregated to calculate the complexity of specific accounts. We use the FASB XBRL taxonomy and common search terms to measure complexity of three specific accounts (fair value, derivatives, and pensions). Specifically, we use the calculation link and the presentation link files provided by FASB.[[17]](#footnote-17) These files classify XBRL tags into various account categories. We rely on these files to extract a list of tags that appear in each account category (fair value, derivatives, and pensions) and remove duplicates. Some of the tags in these lists repeat frequently across different accounting categories (e.g., EPS).[[18]](#footnote-18) We remove these tags because we are unable to uniquely attribute them to specific categories. We further search for common terms that the taxonomy uses to describe tags in specific categories and classify taxonomy and extended tags to account categories.[[19]](#footnote-19) For example, the word “fairvalue” exists in 98% of the fair value tags in the taxonomy and thus is very helpful in identifying other fair value tags. We term the three new complexity variables as *ARC-FAIR*, *ARC-DERIV*,and *ARC-PENS.* Each variable represents the number of reported XBRL tags in its category. Using a similar method, we construct an analyst account specific expertise measure in fair value(*EXPRT-FAIR*), derivatives (*EXPRT-DERIV*), and pension (*EXPRT-PENS*). To capture these types of expertise we first calculate the sum of the tags reported by companies in the analyst’s portfolio of coverage in each of the three accounts.[[20]](#footnote-20) We then rank analysts based on this measure and classify those in the top 50 percentile as experts. We conjecture that greater exposure of analysts to these specific complex accounting concepts, increases their expertise.

## Research Design

Our research design centers on the analyses of two samples: firm-year and analyst-firm-year level. The first set of analyses examines our research question using firm-level attributes. The second set of analyses uses analyst-specific attributes to shed light on moderators of the relation between complexity and forecast accuracy.

## Firm-year Level Sample: Dependent variables

In the firm-year level analysis, we use three dependent variables to study ARC in relation to financial analysts’ performance. Specifically, we examine the accuracy of analysts’ earnings forecasts (*ACCURACY*), dispersion of analysts’ earnings forecasts (*FORDISP*), and the informativeness of their stock recommendation revisions (*RECVAL*). We calculate *ACCURACY* as the absolute value of reported earnings minus the median earnings forecast for the fiscal year, scaled by price, and multiplied by minus one so that higher values represent higher forecast accuracy.[[21]](#footnote-21) We measure *FORDISP* by calculating the standard deviation of analysts’ annual earnings estimates, scaled by the share price as of the end of the fiscal year. Higher values of *FORDISP* indicate greater disagreement among analysts. We multiply both *ACCURACY* and *FORDISP* by 100 to avoid overly small OLS coefficient estimates. We measure *RECVAL* by first calculating the three-day market reaction associated with each revision. We then exclude revisions that analysts issued within two days following earnings announcements,[[22]](#footnote-22) those that reiterate previous recommendation ratings, and those that were issued on days with conflicting recommendation revisions (e.g., one analyst issues an upgrade and another issues a downgrade).[[23]](#footnote-23) We multiply the market reaction for downgrades by minus one to align the returns of upgrades with downgrades.[[24]](#footnote-24) *RECVAL* is equal to the mean three-day market reaction for all revisions issued during the fiscal year. To the extent that analysts uncover and/or process information that is useful to their clients, the market reaction associated with their revisions will be higher.[[25]](#footnote-25)

## Firm-year Level Sample: Control variables

We control for a number of factors that prior research shows to be associated with the value of analysts’ recommendations and their forecast accuracy. Prior studies find attributes of the information environment to be strongly associated with analyst coverage and their performance (Bhushan 1989, O'Brien and Bhushan 1990, Lang and Lundholm 1996, Barth, Kasznik and McNichols 2001, Frankel, Kothari and Weber 2006, Lehavy et al. 2011). Firm size (*LOGMV*), institutional ownership (*IO*), growth potential (*B/M* and *GROWTH*), earnings volatility (*EARNVOL*) standard deviation of returns (*STDRET*)losing firms (*LOSS*),disclosure informativeness (*NEWS10K*), analyst following (*LOGFOLL\_FOR*), and forecast horizon (*LOGHORIZON*) are frequently used as proxies for the information environment as well as investors’ demand for information. We also control for analysts’ incentives to cover companies (*TURN*, *ADV*, *RND,* and *ROA*). Analysts’ and their employers’ incentives to provide research vary in relation to various firm-specific attributes. For example, brokerage firms consider companies with higher trading activity to be more lucrative for business because of the potential commission revenue that they can earn by covering them. In this respect, trading activity represents an incentive for analysts to cover companies and provide accurate earnings forecasts (Alford and Berger 1999, Barth et al. 2001).

Finally, we control for other complexity measures that were shown to be associated with analysts’ performance. Dunn and Nathan (2005) finds that the number of segments is detrimental to the performance of financial analysts whereas Loughran and McDonald (2014) find no association between a business segment index and forecast dispersion. Further, Duru and Reeb (2002) do not find an association between industrial diversification and forecast accuracy. Overall, results with respect to operating complexity are inconclusive, perhaps because these measures are highly aggregated. Nonetheless, we control for the number of segments and presence of foreign operations (*LOGSGMT, FOROPS*) in our regression analyses.

In addition to operating complexity, past research examines linguistic complexity as one feature that increases the difficulty to consume the reports. The most commonly used measure of linguistic complexity is the Gunning (1952) Fog Index of the financial reports (Li 2008) which measures the difficulty to understand text. Indeed, Lehavy et al. (2011) and Bozanic and Thevenot (2015) find that less readable reports are associated with poor analyst performance. In contrast, Loughran and McDonald (2014) criticize the use of the Fog index when measuring complexity in a financial context because words that are classified as complex by the Fog algorithm are straightforward to understand by intended audience of financial statement users.[[26]](#footnote-26) Indeed, they did not find significant association between analysts’ forecast dispersion and the Fog Index. Instead of using the Fog index, they suggest using the number of words in the 10-K to proxy for complexity and find that it is associated with greater analyst forecast dispersion. Following these studies, we control for *FOG10K* and *LOGWORDS*. Table 1 defines in detail the control variables that we use in the regression analyses.

***Analyst-firm-year Level Sample***

In the analyst-firm-year level sample, we focus exclusively on forecast accuracy as our performance measure.[[27]](#footnote-27) We examine the association between analysts’ forecast accuracy and general experience (*GEXP*), which is the natural logarithm of the number of years the individual worked as an analyst plus one, firm-specific experience (*FEXP*), which is the natural logarithm of the number of years the analyst covered the company plus one, industry focus (*INDFOCUS*), which is one divided by the number of industries the analyst covers and CFA designation (CFA), which is an indicator variable that equals one for analysts who have the Chartered Financial Analyst© credential. In order to collect data on analysts’ CFA credentials, we first used IBES’s recommendation file and the broker translation file to identify the name of each analyst and the broker the analyst worked for. We then accessed the Factset database and searched for personal information on each analyst. Based on the information that we found on Factset, we were able to determine, for nearly 80 percent of our sample, whether the analyst held a CFA certification. Finally, we examine whether forecast accuracy is associated with account-specific complexity (*ARC-FAIR*, *ARC-DERIV* and, *ARC-PENS*) and expertise (*EXPRT-FAIR*, *EXPRT-DERIV*, and *EXPRT-PENS*).

## Descriptive Statistics

Table 3 Panel A reports descriptive statistics for the final sample. The first section in Table 3 lists the three dependent variables used in the analyses. The mean (median) *ACCURACY* is -0.716 (-0.178). The interquartile range is between -0.515 and -0.059.[[28]](#footnote-28) The mean and median *ACCURACY* values indicate a left skewed distribution. This is primarily because, as in prior research (Lang and Lundholm 1996, Mikhail, Walther, and Willis 1999, Duru and Reeb 2002, Hope 2003, Dhaliwal et al. 2012), we compute the absolute value of forecast errors, which places the negative and positive values in the same quadrant. We winsorize all continuous variables (with the exception of log-transformed variables) at the bottom and top one-percentile to ensure that our results are not due to the influence of outliers. The mean (median) value for *FORDISP* is 1.239 (0.337). Similar to *ACCURACY*, *FORDISP* exhibits a skewed distribution (right-skewed). Finally, the mean (median) three-day (-1, +1) abnormal market reaction associated with revisions (*RECVAL*) is 3.198 (1.963) percent.

The next section in Table 3 presents descriptive statistics for the six variables that we use to measure accounting reporting complexity. The mean (median) *ARC*, which is the overall XBRL tag count, equals 386.977 (362).[[29]](#footnote-29) The following two variables represent the breakdown of *ARC* into *ARC-FS* (μ = 113.025) and *ARC-NOTES* (μ = 273.952). The final three variables, in this section capture account specific complexity. The mean (median) values for *ARC-FAIR*, *ARC-DERIV*, and *ARC-PENS* are 18.242 (12), 17.437 (13), and 26.729 (6), respectively. There is significant variation within the account specific complexity measures. For instance, the first and third quartile values for *ARC-PENS* equal 2 and 53. The final section in Table 3 Panel A, reports statistics on control variables used in our analyses and their descriptive statistics are consistent with prior research. Table 3 Panel B presents descriptive statistics on the analyst-firm-year level sample. The average analyst in our sample has 9.4 years of general and 4.5 years of firm-specific experience and covers an average of 1.75 industries.[[30]](#footnote-30) To help interpret the coefficient on the industry variable, we divide one by the number of industries and use this as a measure of the analyst’s industry focus (0.57).[[31]](#footnote-31) Also evident in Table 3 is that 33 percent of the financial analysts in our sample hold a CFA credential. Further, we identify that 61.9, 62.4, and 58.8 percent of the forecasts in our sample are issued by analysts who we classify as fair value, derivatives, and pensions experts, respectively. Finally, the average (median) forecast age for our sample is 109.661 (97) days.

# Empirical Results

## Accounting complexity and analysts’ performance

Table 4 presents the regression analysis results for validating ARC as a measure of complexity in the context of analysts, using three dependent variables: *ACCURACY*, *FORDISP*, and *RECVAL*. Column 1 shows a negative and significant association between *ARC* and forecast accuracy (*p* < 0.01). TI amhe -0.323 coefficient indicates that a single standard deviation increase in *ARC* is associated with a 0.12 decline in analysts’ forecast accuracy (*ACCURACY*). Placing this association in perspective, note that the interquartile range of *ACCURACY* is 0.456. In other words, a single standard-deviation change in *ARC* is associated with a variation in *ACCURACY* that is equal to approximately a quarter of the interquartile range, which is economically meaningful.

The second column of Table 4 shows a positive and significant association between *ARC* and forecast dispersion (*p* < 0.01). The estimated coefficient of 0.479 indicates a 0.175 increase in forecast dispersion per one standard deviation increase in *ARC*. This increase corresponds to approximately 20 percent of the interquartile range for forecast dispersion, which is economically important. The two models together suggest that greater *ARC* is associated with forecasts that are less accurate and more dispersed. Importantly, our analyses control for prior complexity measures such as firm segments, the Fog index and the length of the 10-K (Li 2008) and results show that ARC exhibits a stronger and more consistent association with accuracy and dispersion.

We next turn to an analysis of the informativeness of stock recommendation revisions to test whether accounting complexity favorably or adversely affects analysts’ ability to identify mispriced securities. Column 3 of Table 4 shows a negative and significant association between *ARC* and *RECVAL* (p< 0.01) suggesting that the informativeness of analysts' revisions is lower when the accounting is complex. The -0.899 *ARC* coefficient suggests a 33 basis point decrease in the market reaction to revisions, per one standard deviation increase in *ARC*. Given that the mean *RECVAL* is 3.2 percent, this corresponds to a roughly ten-percent decrease in the value of revisions per standard deviation increase in *ARC,* which is economically meaningful. These results are interesting because, a priori, it is unclear whether, greater *ARC* would provide a comparative advantage to financial analysts over investors and therefore increase the value of recommendation revisions, or as we find, their recommendation would be discounted due to high ARC.

 In the next set of analysis, we decompose the total number of tags (*ARC*) into the complexity of the recognized accounting information (i.e. the number of tags in the financial statements, *ARC-FS*) and the complexity of the disclosed accounting information (i.e. the number of tags in the notes, *ARC-NOTES*). This analysis is intended to help us isolate the source of complexity. Table 5 Column 1 shows that *ARC-FS* is not significantly associated with *ACCURACY* whereas the coefficient on *ARC-NOTES* is negative and significant (p<0.01). Similarly, in Column 2, we find that the coefficient on *ARC-NOTES* is positive and significantly associated with *FORDISP* (p<0.01) whereas the coefficient on *ARC-FS* is not. Finally, in Column 3, we find that the coefficient on both *ARC-FS* and *ARC-NOTES* is negative and statistically significant at the ten and five percent significance levels, respectively.

 We next turn to the analyst-firm-year level sample to further explore the relation between accounting reporting complexity and analysts’ performance. Table 6 reports the regression of analysts’ forecast errors on *ARC*, *ARC-FS*, and *ARC-NOTES* using data at a granular level (i.e. forecast level). The estimation results in Column 1 shows a negative association between *ARC* and analysts’ forecast errors (*p* < 0.05). In Column 2, we find that the coefficients on *ARC-FS* is not significant whereas in Column 3 the coefficient on *ARC-NOTES* is negative and significant (*p* < 0.05). Finally, in Column 4 we observe that the coefficient on *ARC-NOTES* remains negative and significant when included with *ARC-FS*. Overall, the results in tables 5 and 6 suggest that the complexity of the disclosed, rather than the recognized, accounting information is the primary source of complexity that adversely affects analysts’ performance. These results are important and suggest that future initiatives to simplify financial reports should focus on disclosed accounting information. Further, since *ARC-NOTES* is driving our results we use it as the primary measure of accounting complexity in the remainder of our analysis.

## Analyst experience and industry focus

 The findings reported in tables 5 and 6 show that accounting reporting complexity is inversely associated with analysts’ performance. We next test our first hypothesis that examines whether analyst experience, industry focus, and credential (i.e. CFA) mitigate the adverse effects that are associated with complexity. In order to examine variation across analysts in terms of experience and industry focus, we estimate analyst-firm-year level models and focus on forecast accuracy.

 Table 7 presents four models that include general experience (*GEXP*), firm-specific experience (*FEXP*), industry focus (*INDFOCUS*) and Chartered Financial Analyst credential (*CFA*) measures and their interactions with *ARC-NOTES*.[[32]](#footnote-32) Column 1 shows that *GEXP* is positive and significant (p< 0.01), suggesting that forecast accuracy increases with general experience. However, the coefficient on the interaction variable, *ARC-NOTES X GEXP*, is not statistically significant suggesting that general experience does not moderate the negative effect of complexity. Column 2 shows that firm-specific experience (*FEXP*) is not statistically significant. Different from Column 1, the coefficient on the interaction variable *ARC-NOTES X FEXP* is positive and significant (p< 0.01) suggesting that firm specific experience is particularly valuable when *ARC-NOTES* is high. The standardized coefficient on *ARC-NOTES X FEXP* (untabulated for brevity), indicates that a standard deviation increase in the interaction variable is associated with a reduction in forecast error that equals 2.4 percent of the standard deviation of the dependent variable. In Column 3, we examine the relation between analysts’ industry focus and their forecast accuracy. We find that the coefficient on the interaction variable, *ARC-NOTES X INDFOCUS*, is positive and significant (p< 0.01); this implies that analysts who concentrate on fewer industries (i.e. covering fewer industries) perform better, in particular, among firms with greater accounting reporting complexity. A standard deviation increase in the interaction variable is associated with a 0.026 standard deviation increase in the forecast error variable. Finally, in Column 4, we find that analysts who hold CFA credentials issue more accurate forecasts as evidenced by the positive coefficient on *CFA* (*p* < 0.01). Further, we find that the coefficient on the interaction *ARC-NOTES X* *CFA* is positive and significant (*p* < 0.1), which indicates that analysts who hold CFA credentials perform better at dealing with accounting reporting complexity (*ARC-NOTES*). Overall these results provide support for H1 and suggest that analysts with firm-specific experience and industry focus as well as those who hold a CFA are better positioned to handle accounting reporting complexity.

## Account specific analyst expertise

 We next examine whether account specific expertise (i.e., fair value, derivatives, and pensions) helps analysts forecast earnings for companies wherein these accounts are more complex. Table 8 Panels A, B, and C present the estimation results of the analysis with fair-value, derivative, and pension complexity, respectively, and accounting specific expertise measures along with their interactions. In addition to the account specific complexity measures, we sequentially include, experience, industry focus, and CFA variables in the models. The analyses also include all control variables, but for brevity of presentation we do not tabulate them. Column 1 of Panel A shows that *ARC-FAIR* is negative and significant (*p* < 0.01), suggesting that fair value complexity is inversely associated with analyst forecast accuracy. *EXPRT-FAIR* is positive and significant suggesting that expertise in this account improves analyst forecast accuracy (*p* < 0.01). While we find that *GEXP* is positive and significant, the interaction *ARC-FAIR X GEXP* is not, which lends no support to H2. In contrast, results in Columns 2, 3 and 4 show that the interaction of *ARC-FAIR* and *FEXP* (*p* < 0.01)*, INDFOCUS* (*p* < 0.01)*,* and *CFA* (*p* < 0.05)*,* respectively, are all positive and significant. These results support H2 and suggest that experience, expertise, and training help analysts cope with fair value complexity. Importantly, we find that the coefficient on the interaction variable, *ARC-FAIR X EXPRT-FAIR* is positive and significant across all columns (Col. 1-3: *p* < 0.01; Col. 4: *p* < 0.05). These results support H3 and suggest that analysts with fair-value expertise issue more accurate earnings estimates for companies that have complex fair-value reporting. We also test for differences in coefficient between *ARC-FAIR X EXPRT-FAIR* and the interactions of *ARC-FAIR* with the other expertise and experience measures (i.e. *GEPX, FEXP, INDFOCUS* and *CFA*) and find that *ARC-FAIR X EXPRT-FAIR* is significantly greater than the interactions of *ARC-FAIR* with *GEXP, FEXP,* and *CFA* (*p* < 0.01, *p* < 0.05, and *p* < 0.05, respectively), but not the interaction with *INDFOCUS*.

In Table 8, Panel B, we repeat our analysis in the previous panel (Panel A) using complexity and expertise in derivatives (*ARC-DERIV, EXPRT-DERIV*) as the main variables of interest. The results reported in Panel B concerning derivatives show that analysts with greater *FEXP* and *CFA* certification produce more accurate forecasts for companies with complex derivative accounting (*p* < 0.01 and *p* < 0.1, respectively) but those with greater *GEXP* and *INDFOCUS* do not. These results partially support H2. Further, we find that *ARC-DERIV X EXPRT-DERIV* is positive and significant across all models (*p* < 0.01, for all), supporting H3. We also test for differences in coefficients between *ARC-DERIV X EXPRT-DERIV* and the interactions of *ARC-DERIV* with the experience, industry focus, and certification measures (i.e. *GEXP, FEXP, INDFOCUS* and *CFA*) and find that *ARC-DERIV X EXPRT-DERIV* is significantly greater than the interactions of *ARC-DERIV* with *GEXP, INDFOCUS,* and *CFA* (*p* < 0.01, *p* < 0.05, *p* < 0.1), but not the interaction with *FEXP*.

Finally, in Panel C, we repeat our analysis for the pension category and find that only firm-specific experience (*FEXP*) and industry focus (*INDFOCUS*) are effective in helping analysts handle complexity in the pension accounts (*p* < 0.01, for both), which provide partial support for H2.[[33]](#footnote-33) Further, we find that *ARC-PENS X EXPRT-PENS* is positive and significant across all columns (*p* < 0.01, *p* < 0.05, *p* < 0.01, *p* < 0.01), supporting H3 andsuggesting that analyst with account specific expertise in pension produce more accurate forecasts for companies with complex pension accounting. We also test for differences in coefficient between *ARC-PENS X EXPRT-PENS* and the interactions of *ARC-PENS* with the other expertise and experience measures (i.e. *GEPX, FEXP, INDFOCUS* and *CFA*) and find that *ARC-PENS X EXPRT-PENS* is significantly greater than the interactions of *ARC-DERIV* with *GEXP,* and *CFA* (*p* < 0.01, *p* < 0.01), but not the interactions with *FEXP* and *INDFOCUS*. Results in Panel C partially indicate that analysts’ expertise in derivatives helps them to more accurately estimate earnings of companies with complex derivative accounting to a greater extent than analysts with other types of experience and expertise.

Overall, the results in Table 8 indicate that analysts with account specific expertise in fair value, derivatives, and pension produce more accurate estimates for companies wherein these accounts are more complex. Importantly, in most cases, for firm with greater account specific complexity, analyst with expertise in these accounts outperform analysts with other types of experience and expertise.

## Additional Analysis - Accounting complexity and the information environment

In our last set of analyses we examine whether the richness of the information environment surrounding complex firms can help mitigate the effect of accounting reporting complexity. Table 9 presents the estimation results of the regression of forecast accuracy on accounting reporting complexity (*ARC-NOTES*) and its interaction with a measure of analyst effort (*EFFORT*), volume of disclosure (*DVOLDISC*), and analyst following (*FOLL\_FOR*). In Column 1 of Table 9, we find that the coefficient on *EFFORT* is positive and significant, indicating that forecast accuracy is higher for firms where analysts invest more effort. However, we fail to find that the interaction of *ARC-NOTES X EFFORT* is statistically significant suggesting that accounting reporting complexity cannot be easily addressed by simply investing more effort as measured by the number of forecasts. In Column 2, we explore whether the negative effect of accounting reporting complexity (*ARC-NOTES*) is mitigated when managers disclose more information (*DVOLDISC*). We find that the coefficient on *DVOLDISC* is positive and significant (*p* < 0.01) suggesting that analysts forecast accuracy increases when managers voluntary disclose more information. However, the coefficient on the interaction variable (*ARC-NOTES X DVOLDISC*), is not significant, thereby attributing no incremental benefit to management voluntary disclosures in analysts’ earnings estimates of more complex firms. These results are interesting because while Guay et al. (2016) suggest that managers provide more guidance when the financial reports are complex, our results indicate that these disclosures do not alleviate the consequences of complexity related to analysts’ performance. Finally, in Column 3 we examine whether analyst following (*FOLL\_FOR*) moderates the relation between accounting reporting complexity and analysts’ accuracy. We find that *FOLL\_FOR* is positive and significant (*p* < 0.1), suggesting that greater analyst following improves overall forecast accuracy. Further, we find that the coefficient on the interaction variable, *ARC-NOTES X FOLL\_FOR* is positive and significant (*p* < 0.05). This suggests that analyst following moderates the negative relation between accounting complexity and accuracy. Overall, the results in Column 3 propose analyst following as an alternative mechanism to overcome the incremental challenges associated with covering more complex firms.

## Sensitivity analyses

*Components of ARC that are orthogonal to size and operating complexity*

*ARC* may encompass complexity that is due to operating complexity. Our results, therefore, may be driven by operating complexity rather than accounting reporting complexity. To partially alleviate this concern, we regress *ARC* on firm size, business segments, and foreign operations and industry controls. We estimate the model separately for each year. The model is well specified with an average adjusted R-square of 48.14%. Next, we use the residual from this model as a substitute for *ARC* and find similar results. This suggests that *ARC* captures complexity that goes beyond firm size and operating complexity.

*Other methodological choices*

We conduct a number of robustness checks, aimed at examining whether our results are sensitive to alternative methodological choices. First, we use *ARC* instead of *ARC-NOTES* and find similar results in tables 7 and 9. The one major difference in the Table 7 results is that the coefficient on *ARC X GEXP* (untabulated) is positive and significant (*p <* 0.1) whereas the coefficient on *ARC-NOTES X GEXP* (Table 7)is not. The results in Table 9 are the same with *ARC* or *ARC-NOTES*. Second, we repeat our analysis using the unique number of tags (recall that the *ARC* variable allows tags to repeat but not in the same financial statement or note table) and find similar results. Further, using the number of facts reported by companies (i.e., we do not remove any repeated fact) also yields similar results.

In a recent study, Chen, Miao, and Shevlin (2015) propose and test a measure of disclosure quality (DQ) based on the level of disaggregation of financial information in Compustat and find that DQ is associated with higher forecast accuracy and lower dispersion. An important distinction between DQ and ARC is that DQ is based on a particular set of Compustat items. Indeed, we find that the correlation between the two variables is negative (*ρ* = -0.1535; n = 2,830), suggesting that they measure different constructs. Using data on the DQ measure from the Chen et al. (2015) study, we re-estimate our analysis for the intersection of our samples.[[34]](#footnote-34) After controlling for DQ, we find that higher ARC is associated with lower forecast accuracy (*p* < 0.05), higher forecast dispersion (*p* < 0.01), and lower informativeness of stock recommendations revisions (*p* < 0.05).

Finally, we exclude data from the fiscal year 2011 because of the relatively low number of observations we have for that year as a result of the phased-in adoption. We reach identical inferences from all our analyses based on a sample of 2012-2014.

# Conclusions

The FASB (2017) recognizes that a complete simplification of the financial report is not possible and states (FASB 2010) that “[a]t times, even well-informed and diligent users may need to seek the aid of an *adviser to understand information about complex economic phenomena* [Emphasis added].” Indeed, given the difficulty to simplify the reports, developing the necessary skillset to analyze the financial reports may be necessary. In this study we examine the association between accounting complexity and analysts’ performance and how analysts’ qualifications moderates this association.

We rely on a measure of accounting reporting complexity that is based on the amount of accounting information in XBRL filings. Our tests reveal that accounting reporting complexity has an adverse effect on analysts’ performance. Specifically, we find that for companies with higher accounting reporting complexity, forecast accuracy is lower, dispersion is higher and informativeness of recommendations is significantly lower. We also examine whether the complexity of the recognized information on the face of the financial statements and in the notes, both contribute to the lower performance of analysts. We find that analysts are primarily impacted by the complexity in the notes to the financial statement, which are characterized by high volume and less structured disclosures. To aid analysts, regulators may consider imposing greater structure requirements on the disclosure in the notes.

We recognize that these adverse performance consequences are important to overcome and examine possible solutions to mitigate the negative association between accounting complexity and analyst performance. We find that analysts with greater firm-specific experience, industry focus, and CFA certification are able to alleviate some of the negative effects of accounting complexity. We further propose a new approach for measuring analysts’ expertise in specific account categories, including fair value, derivatives, and pensions. To the best of our knowledge, we are the first to do so. We find that account specific expertise is beneficial to forecast accuracy, especially among firms with greater complexity in these respective accounts. In most cases, we find that expertise in specific accounts appear to contribute more to forecast accuracy than other types of expertise.

Our research produces insights that are relevant to regulators and standard-setters concerned with developing a better understanding of, and solutions for the capital market consequences of accounting complexity. Further, the findings in this study may be of interest to investors and creditors who rely on analyst reports to make decisions.

**Appendix A- Description of account-specific complexity**

To identify tags in specific accounts we refer to the U.S. GAAP taxonomy which is available on the FASB’s website. In the taxonomy, tags are divided into categories of accounts. For instance, derivative and hedging tags appear under the heading "Disclosure - Derivative Instruments and Hedging Activities" and fair value tags appear under the heading “- Disclosure - Fair Value Measures and Disclosures”. We identify all tag names under each relevant heading and associate such tags with their specific account category. For example, to identify fair value tags, we refer to the “Calculation Tab” in the taxonomy file and identify 138 tags under the fair value heading. These tags are presented in Appendix B. We augment this list of tags with tags that appear under the Presentation Tab. We use this list of tags as the basis for identifying fair value tags.

Next, we identify tags that appear in multiple categories. Because we cannot uniquely attribute tags that appear in three or more account categories to any specific category we drop such tags from our list of fair value tags. For example, the tags “shareprice” appears under the fair value category but also in several other categories and therefore it is not classified as a fair value tag. Next, we supplement the classification of tags into account categories by using a list of keywords that we develop based tag names that appear in the taxonomy. This is especially important for extended tags because extended tags do not appear in the U.S. GAAP taxonomy. To develop this list we first look for keywords that frequently appear in the tag names. For example, the word “Fair” appears in 98 percent of fair value tags. Therefore, we search all extended tags and taxonomy tags that we did not classify based on the U.S. GAAP taxonomy and classify them as fair value tags if they include the word “Fair”. We follow a similar process to classify tags into the other two account categories.

**Appendix B- A sample of Fair value tags from the Calculation Link in the FASB XBRL Taxonomy**

|  |
| --- |
| **- Disclosure - Fair Value Measures and Disclosures** |
| **Tag Name** |
| EquityFairValueDisclosure |
| ContingentConsiderationClassifiedAsEquityFairValueDisclosure |
| EquityIssuedInBusinessCombinationFairValueDisclosure |
| WarrantsNotSettleableInCashFairValueDisclosure |
| FairValueMeasuredOnRecurringBasisGainLossIncludedInEarnings |
| FairValueAssetsAndLiabilitiesMeasuredOnRecurringBasisGainLossIncludedInEarnings |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisAssetGainLossIncludedInEarnings1 |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisLiabilityGainLossIncludedInEarnings |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisInstrumentsClassifiedInShareholdersEquityGainLossIncludedInEarnings |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisAssetPeriodIncreaseDecrease |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisAssetPurchasesSalesIssuancesSettlements |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisAssetPurchases |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisAssetSales |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisAssetIssues |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisAssetSettlements |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisAssetTransfersNet |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisAssetTransfersIntoLevel3 |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisAssetTransfersOutOfLevel3 |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisAssetGainLossIncludedInOtherComprehensiveIncomeLoss |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisAssetGainLossIncludedInEarnings1 |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisGainLossIncludedInOtherComprehensiveIncomeLoss |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisLiabilityGainLossIncludedInOtherComprehensiveIncome |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisAssetGainLossIncludedInOtherComprehensiveIncomeLoss |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisInstrumentsClassifiedInShareholdersEquityGainLossIncludedInOtherComprehensiveIncomeLoss |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisInstrumentsClassifiedInShareholdersEquityPeriodIncreaseDecrease |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisInstrumentsClassifiedInShareholdersEquityTransfersNet |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisInstrumentsClassifiedInShareholdersEquityTransfersIntoLevel3 |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisInstrumentsClassifiedInShareholdersEquityTransfersOutOfLevel3 |
| FairValueMeasurementWithUnobservableInputsReconciliationRecurringBasisInstrumentsClassifiedInShareholdersEquityPurchasesSalesIssuesSettlements |

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**TABLE 1**

*Variable definitions*

This table lists all the variables (in italics) used in the analyses and provides detailed descriptions on how we computed each variable. The table consists of three sections: dependent variables, variables of interest, and control variables. The data source(s) for each variable is reported in parentheses at the end of each definition.

|  |  |  |
| --- | --- | --- |
| Variable Name |  | Description |
| Dependent variables |
| *ACCURACY* | : | Absolute value of reported earnings minus the median earnings forecast for the fiscal year scaled by price and multiplied by -100 (I/B/ES and Compustat).  |
| *FORDISP* | : | The standard deviation of analysts’ annual earnings estimates divided by the end of fiscal year share price and multiplied by 100 (I/B/E/S and Compustat). |
| *RECVAL* | : | The mean three-day abnormal market reaction associated with recommendation revisions issued during the current fiscal year. We exclude the following: (1) revisions issued within two days after earnings announcements, (2) reiterations (i.e., recommendations that reiterate previous recommendation ratings), and (3) revisions issued on days when analysts issued conflicting recommendation revisions (e.g., one analyst issued an upgrade while another issued a downgrade). Finally, before calculating firm-year level values, we multiply the market reaction for downgrades with minus one to align the returns to downgrades with upgrades (I/B/E/S and CRSP). |
| Variables of interest |
| *ARC* | : | The natural logarithm of one plus the total number of monetary tags reported in Item 8 of 10-K filings, which includes the financial statements and notes (SEC filings). |
| *ARC-FS* | : | The natural logarithm of one plus the total number of monetary tags reported on the face of the financial statements (SEC filings). |
| *ARC-NOTES* | : | The natural logarithm of one plus the total number of monetary tags reported in the footnotes of the financial statements (SEC filings). |
| *ARC-FAIR* | : | The natural logarithm of one plus the total number of monetary tags related to fair value accounts reported in the financial statements and notes (SEC filings). |
| *ARC-DERIV* | : | The natural logarithm of one plus the total number of monetary tags related to derivative accounts reported in the financial statements and notes (SEC filings). |
| *ARC-PENS* | : | The natural logarithm of one plus the total number of monetary tags related to pension accounts reported in the financial statements and notes (SEC filings). |
| *GEXP* | : | The number of years since the analyst first appeared in the I/B/E/S database. We reset the variable to one when there is a period longer than two years when the analyst did not issue any earnings forecasts (I/B/E/S).  |
| *FEXP* | : | The number of years since the analyst began issuing forecasts for the company. We reset the variable to one when there is a period longer than two years when the analyst did not issue any earnings forecasts for the company (I/B/E/S). |
| *INDFOCUS* | : | One divided by the number of industries represented in the analyst’s portfolio of coverage. We use the industry definitions outlined in the 12-industry scheme in Fama and French (1997) (Compustat).  |
| *CFA* | : | The analyst holds a Chartered Financial Analyst© (CFA) credential (Factset). |
| *EXPRT-FAIR* | : | A binary variable equal to 1 if the total number of fair value related tags reported by the companies in the analyst’s portfolio of coverage (SEC filings and I/B/E/S) is greater than the sample median. |
| *EXPRT-DERIV* | : | A binary variable equal to 1 if the total number of derivative related tags reported by the companies in the analyst’s portfolio of coverage (SEC filings and I/B/E/S) is greater than the sample median. |
| *EXPRT-PENS* | : | A binary variable equal to 1 if the total number of pension related tags reported by the companies in the analyst’s portfolio of coverage (SEC filings and I/B/E/S) is greater than the sample median. |
| *EFFORT* | : | Natural logarithm of one plus the number of forecasts that the analyst issued for the current fiscal period (I/B/E/S). |
| *DVOLDISC* | : | An indicator variable that equals one for companies that issue at least one management forecast during the fiscal period (I/B/E/S). |
| *FOLL* | : | The natural logarithm of the one plus the number of analysts who issued earnings estimates (I/B/E/S). |
| Control variables |
| *LOGMV* | : | The natural logarithm of one plus the market value computed as of the end of the fiscal year (Compustat). |
| *IO* | : | Percentage of shares held by institutional investors (CRSP and Thomson Financial). |
| *B/M* | : | The ratio of the book and market values of equity as of the end of the fiscal year (Compustat). |
| *GROWTH* | : | The one-year change in sales (Compustat). |
| *NEWS10K* | : | The absolute value of the two-day market reaction associated with the company’s current 10-K filing (EDGAR Online and CRSP). |
| *LOGHORIZON* | : | The natural logarithm of median forecast horizon, where forecast horizon equals the earnings announcement date minus the forecast date (I/B/E/S). |
| *TURN* | : | The ratio of the number of shares traded during the fiscal year and the total number of shares outstanding (Compustat). |
| *ADV* | : | Advertising expenditure divided by total operating expense (Compustat). |
| *RND* | : | Research and development expenditure divided by total operating expense (Compustat). |
| *ROA* | : | Income before extraordinary items scaled by total assets (Compustat). |
| *FOROPS* | : | Equals one for companies that have non-missing foreign exchange income and zero otherwise (Compustat). |
| *LOGSGMT* | : | The natural logarithm of one plus the number of business segments (Compustat). |
| *EARNVOL* | : | The standard deviation of annual diluted earnings per share (excluding extraordinary items) figures reported during the last ten years. A minimum of three years of earnings per share data is required (Compustat). |
| *FOG10K* | : | The Fog Index value (Gunning (1952)) of the current fiscal year’s 10-K filing (EDGAR Online). |
| *STDRET* | : | The standard deviation of daily stock returns during the fiscal year (CRSP). |
| *LOSS* | : | A binary variable that equals one for companies that report negative income before extraordinary items (Compustat). |
| *FORAGE* | : | The natural logarithm of one plus the number of days that elapsed from the forecast issuance date until the earnings announcement date (I/B/E/S). |

**TABLE 2**

*Sample Derivation and Composition*

This table reports the sample derivation (Panel A) and the number of observations in the final sample by year (Panel B).

Panel A: Sample derivation

|  |  |
| --- | --- |
| Steps | Obs. |
| Firm-year level sample |  |
| Sample of 2011-2014 fiscal year companies that meet the following conditions:* XBRL filings submitted within 150 days of the fiscal year end,
* At least ten taxonomy tags in each of the financial statements (i.e. income statement, balance sheet, and statement of cash-flows) and the notes.
 | 13,499 |
| Merge with the intersection of Compustat Annual File (comp.funda) based on CIK code. | 10,788 |
| Retain companies with positive sales (Compustat data item: *sale*), non-missing common shares outstanding (*csho*) and total assets (*at*) greater than $10 million. | 10,194 |
| Eliminate firms without the necessary accounting data and without analyst coverage (based on earnings forecasts). Specifically, we require that each firm-year has at least three earnings forecasts. Note: We require at a minimum three earnings forecasts to calculate forecast dispersion. | 8,361 |
|  |  |
| Analyst-firm-year level sample |  |
| Obtain annual earnings estimates issued by analysts covering the companies in the firm-year level sample. Retain the last estimate issued by each analyst who has a non-anonymous I/B/E/S analyst and brokerage code (i.e., *analys* and *estimator* variables unequal to “000000”).  | 113,073 |

Panel B: Observations per year

|  |  |  |
| --- | --- | --- |
| Year | Number of firms | Number of forecasts |
| 2011 | 1,050 | 18,397 |
| 2012 | 2,379 | 30,516 |
| 2013 | 2,425 | 32,107 |
| 2014 | 2,507 | 32,053 |
| Total | 8,361 | 113,073 |

**TABLE 3**

*Summary Statistics*

This table presents the descriptive statistics of the variables used in this study. Our sample spans from 2011 to 2014. The firm-year level sample consists of 8,361 observations for the forecast accuracy and dispersion analyses, and 6,417 firm-year observations for the stock recommendation analysis. The analyst-firm-year level sample consists of 113,073 observations. We obtain XBRL data from the SEC filings, earnings estimate and recommendation data from I/B/E/S, and accounting and market data from Compustat and CRSP, respectively. *ACCURACY* is defined as the absolute value of reported earnings minus the median earnings forecast for the fiscal year scaled by price and multiplied by -100. *FORDISP* equals the standard deviation of analysts’ annual earnings estimates divided by the end of fiscal year share price and multiplied by 100 (I/B/E/S and Compustat). *RECVAL* is calculated as the mean three-day abnormal market reaction associated with recommendation revisions issued during the fiscal year. *ARC*\* is the total number of monetary tags reported in Item 8 of 10-K filings, which includes the financial statements and notes. *ARC-FS*\*, and *ARC-NOTES*\* equal the total number of monetary tags reported in the face of the financial statements and notes, respectively. *ARC-FAIR*\*, *ARC-DERIV*\*, and *ARC-PENS*\* are the total number of monetary tags related to fair-value, derivative, and pensions accounts, respectively. All continuous variables, with the exception of the log-transformed ones, are winsorized at the bottom and top one-percentile. For ease of interpretation, we report descriptive statistics on the raw values of the starred (\*) variables but use their log-transformations in the regression analysis.

Panel A: Firm-year level sample

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |
|  | Mean | Median | Std. Dev. | 1st Quartile | 3rd Quartile |
| Dependent variables: |  |  |  |  |  |
| *ACCURACY* | -0.716 | -0.178 | 1.899 | -0.515 | -0.059 |
| *FORDISP* | 1.239 | 0.337 | 2.914 | 0.125 | 0.994 |
| *RECVAL* | 3.198 | 1.963 | 5.357 | 0.501 | 4.407 |
|  |  |  |  |  |  |
| Variables of interest: |  |  |  |  |  |
| *ARC\** | 386.977 | 362.000 | 148.790 | 279.000 | 467.000 |
| *ARC-FS\** | 113.025 | 109.000 | 25.282 | 96.000 | 125.000 |
| *ARC-NOTES\** | 273.952 | 250.000 | 131.497 | 178.000 | 344.000 |
| *ARC-FAIR\** | 18.242 | 12.000 | 21.150 | 6.000 | 21.000 |
| *ARC-DERIV\** | 17.437 | 13.000 | 15.676 | 5.000 | 25.000 |
| *ARC-PENS\** | 26.729 | 6.000 | 32.104 | 2.000 | 53.000 |
|  |  |  |  |  |  |
| Control variables: |  |  |  |  |  |
| *MV\** | 7744.880 | 1590.822 | 25932.442 | 551.067 | 4656.045 |
| *IO* | 66.021 | 70.619 | 22.390 | 53.494 | 82.389 |
| *B/M* | 0.508 | 0.434 | 0.392 | 0.243 | 0.710 |
| *GROWTH* | 0.128 | 0.064 | 0.375 | -0.008 | 0.166 |
| *NEWS10K* | 0.025 | 0.013 | 0.032 | 0.006 | 0.030 |
| *TURN* | 223.553 | 178.073 | 170.376 | 112.913 | 279.096 |

Panel A: Firm-year level sample **–** *Continued*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |
|  | Mean | Median | Std. Dev. | 1st Quartile | 3rd Quartile |
| Control variables: |  |  |  |  |  |
| *ADV* | 0.014 | 0.000 | 0.033 | 0.000 | 0.013 |
| *RND* | 0.066 | 0.000 | 0.143 | 0.000 | 0.055 |
| *ROA* | 0.009 | 0.032 | 0.146 | 0.005 | 0.070 |
| *FOROPS* | 0.382 | 0.000 | 0.486 | 0.000 | 1.000 |
| *EARNVOL* | 2.588 | 0.846 | 7.718 | 0.431 | 1.721 |
| *SEGMENT\** | 2.639 | 2.000 | 1.973 | 1.000 | 4.000 |
| *FOG10K* | 23.332 | 23.200 | 1.330 | 22.400 | 24.000 |
| *WORDS* | 59589.703 | 50898.000 | 34638.242 | 39870.000 | 68027.000 |
| *STDRET* | 2.231 | 1.999 | 1.027 | 1.465 | 2.739 |
| *LOSS* | 0.221 | 0.000 | 0.415 | 0.000 | 0.000 |
| *FOLL\_FOR\** | 13.833 | 11.000 | 10.007 | 6.000 | 19.000 |
| *HORIZON* | 99.391 | 98.000 | 38.358 | 90.000 | 112.000 |
|  |  |  |  |  |  |

Panel B: Analyst-firm-year level sample

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |
|  | Mean | Median | Std. Dev. | 1st Quartile | 3rd Quartile |
| *GEXP\** | 9.356 | 8.000 | 6.482 | 4.000 | 13.000 |
| *FEXP\** | 4.477 | 3.000 | 3.722 | 2.000 | 6.000 |
| *INDFOCUS\** | 0.570 | 0.500 | 0.326 | 0.333 | 1.000 |
| *CFA* | 0.330 | 0.000 | 0.470 | 0.000 | 1.000 |
| *EXPRT-FAIR* | 0.619 | 1.000 | 0.486 | 0.000 | 1.000 |
| *EXPRT-DERIV* | 0.624 | 1.000 | 0.484 | 0.000 | 1.000 |
| *EXPRT-PENS* | 0.588 | 1.000 | 0.492 | 0.000 | 1.000 |
| *FORAGE\** | 109.661 | 97.000 | 84.313 | 50.000 | 118.000 |

**TABLE 4**

*Accounting complexity and forecast accuracy & dispersion and value of recommendation revisions*

This table reports the OLS estimation results of three specifications of the following equation, which involves the regression of measures of analysts’ performance on accounting reporting complexity, control variables and industry and year fixed effects.

DVit = α + β1ARC + ∑γControls + ∑δIndustry + ∑θYear + εit

The three dependent variables (*DV*s) are forecast accuracy (*ACCURACY*), forecast dispersion (*FORDISP*), and the value of recommendation revisions (*RECVAL*). *ACCURACY* is defined as the absolute value of reported earnings minus the median earnings forecast for the fiscal year scaled by price and multiplied by -100. *FORDISP* equals the standard deviation of analysts’ annual earnings estimates divided by the end of fiscal year share price and multiplied by 100 (I/B/E/S and Compustat). *RECVAL* is calculated as the mean three-day abnormal market reaction associated with recommendation revisions issued during the fiscal year. *ARC* is the natural logarithm of one plus the total number of monetary tags reported in Item 8 of 10-K filings, which includes the financial statements and notes. The *t-*statistics are in parenthesis, next to the coefficient estimates, and are computed based on standard errors clustered by firm. The symbols \*, \*\*, and \*\*\* indicate statistical significance at the ten, five, and one percent levels, respectively. Industry and year fixed-effects are included in all models. The number of observations and goodness of fit statistics are reported at the bottom of the table.

|  |  |  |  |
| --- | --- | --- | --- |
| Dependent Variable = | *ACCURACY* | *FORDISP* | *RECVAL* |
|  | (1) | (2) | (3) |
| Intercept | 4.073\*\*\* | (4.62) | -6.182\*\*\* | (-4.71) | 5.468\*\*\* | (2.84) |
|  |  |  |  |  |  |  |
| Accounting complexity: |  |  |  |  |  |  |
| *ARC* | -0.323\*\*\* | (-3.15) | 0.479\*\*\* | (3.24) | -0.899\*\*\* | (-3.38) |
|  |  |  |  |  |  |  |
| Information environment: |  |  |  |  |  |  |
| *LOGMV* | 0.033 | (0.81) | -0.107\* | (-1.78) | -0.145\* | (-1.79) |
| *IO* | 0.006\*\*\* | (4.31) | -0.014\*\*\* | (-6.80) | -0.002 | (-0.41) |
| *B/M* | -0.517\*\*\* | (-4.00) | 1.062\*\*\* | (5.58) | 0.573\*\* | (2.51) |
| *GROWTH* | 0.066 | (0.80) | -0.052 | (-0.36) | -0.826\*\* | (-2.44) |
| *NEWS10K* | -3.887\*\*\* | (-3.82) | 3.672\*\* | (2.47) | -3.375 | (-1.29) |
| *LOGFOLL\_FOR* | 0.210\*\*\* | (2.74) | 0.066 | (0.57) | -0.539\*\*\* | (-3.00) |
| *LOGHORIZON* | -0.170\*\*\* | (-3.52) | 0.318\*\*\* | (4.47) | -0.289\*\* | (-2.31) |
|  |  |  |  |  |  |  |
| Incentive to cover: |  |  |  |  |  |  |
| *TURN* | -0.000 | (-1.51) | 0.001\*\* | (2.39) | -0.002\*\*\* | (-2.82) |
| *ADV* | -0.971 | (-1.24) | 0.228 | (0.23) | 7.338\*\*\* | (3.39) |
| *RND* | 1.099\*\*\* | (3.84) | -1.716\*\*\* | (-3.33) | -0.516 | (-0.51) |
| *ROA* | 0.625\* | (1.68) | -2.610\*\*\* | (-3.99) | -2.238\*\* | (-2.06) |

**TABLE 4 –** *Continued*

*Accounting complexity and forecast accuracy & dispersion and value of recommendation revisions*

|  |  |  |  |
| --- | --- | --- | --- |
| Dependent Variable = | *ACCURACY* | *FORDISP* | *RECVAL* |
|  | (1) | (2) | (3) |
| Complexity: |  |  |  |  |  |  |
| *FOROPS* | 0.099\*\* | (2.20) | -0.117\* | (-1.66) | -0.111 | (-0.83) |
| *LOGSGMT* | -0.042 | (-1.13) | 0.083 | (1.53) | -0.084 | (-0.99) |
| *EARNVOL* | 0.005 | (1.10) | 0.033\*\*\* | (4.05) | -0.001 | (-0.13) |
| *FOG10K* | -0.014 | (-0.72) | 0.046 | (1.52) | -0.018 | (-0.36) |
| *LOGWORDS* | -0.157\* | (-1.92) | 0.113 | (0.86) | 0.394\*\* | (2.13) |
|  |  |  |  |  |  |  |
| Uncertainty: |  |  |  |  |  |  |
| *STDRET* | -0.242\*\*\* | (-4.19) | 0.596\*\*\* | (6.53) | 1.906\*\*\* | (10.58) |
| *LOSS* | -0.867\*\*\* | (-8.79) | 1.203\*\*\* | (8.45) | 0.137 | (0.50) |
|  |  |  |  |  |  |  |
| Industry & Year Dummies  | Yes |  | Yes |  | Yes |  |
| *N* | 8,361 |  | 8,361 |  | 6,417 |  |
| R-square | 0.185 |  | 0.318 |  | 0.225 |  |
| Adj. R-square | 0.182 |  | 0.315 |  | 0.221 |  |

**TABLE 5**

*Accounting complexity based on financial statements and notes and forecast accuracy & dispersion and value of recommendation revisions: firm-year level sample*

This table reports the OLS estimation results of three specifications of the following equation, which involves the regression of measures of analysts’ performance on accounting reporting complexity, control variables and industry and year fixed effects.

DVit = α + β1ARC-FS + β2ARC-NOTES + ∑γControls + ∑δIndustry + ∑θYear + εit

The three dependent variables (*DV*s) are forecast accuracy (*ACCURACY*), forecast dispersion (*FORDISP*), and the value of recommendation revisions (*RECVAL*). *ACCURACY* is defined as the absolute value of reported earnings minus the median earnings forecast for the fiscal year scaled by price and multiplied by -100. *FORDISP* equals the standard deviation of analysts’ annual earnings estimates divided by the end of fiscal year share price and multiplied by 100. *RECVAL* is calculated as the mean three-day abnormal market reaction associated with recommendation revisions issued during the fiscal year. *ARC-FS* is the natural log of one plus the total number of tags reported in the financial statements (Item 8 of 10-K filings), and *ARC-NOTES* is the natural log of one plus the total number of tags reported in the notes section. The *t-*statistics are in brackets, next to the coefficient estimates, and are computed based on standard errors clustered by firm. The symbols \*, \*\*, and \*\*\* indicate statistical significance at the ten, five, and one percent levels, respectively. Industry and year fixed-effects are included in all models. The number of observations and goodness of fit statistics are reported at the bottom of the table.

|  |  |  |  |
| --- | --- | --- | --- |
| Dependent Variable = | *ACCURACY* | *FORDISP* | *RECVAL* |
|  | (1) | (2) | (3) |
| Intercept | 3.172\*\*\* | (3.35) | -5.697\*\*\* | (-4.00) | 6.410\*\*\* | (2.84) |
|  |  |  |  |  |  |  |
| Accounting complexity: |  |  |  |  |  |  |
| *ARC-FS* | 0.142 | (0.80) | 0.086 | (0.35) | -0.793\* | (-1.66) |
| *ARC-NOTES* | -0.285\*\*\* | (-3.11) | 0.344\*\*\* | (2.69) | -0.470\*\* | (-2.03) |
|  |  |  |  |  |  |  |
| Information environment: |  |  |  |  |  |  |
| *LOGMV* | 0.033 | (0.83) | -0.106\* | (-1.77) | -0.154\* | (-1.89) |
| *IO* | 0.006\*\*\* | (4.39) | -0.014\*\*\* | (-6.83) | -0.002 | (-0.46) |
| *B/M* | -0.514\*\*\* | (-3.97) | 1.063\*\*\* | (5.57) | 0.565\*\* | (2.48) |
| *GROWTH* | 0.066 | (0.79) | -0.052 | (-0.36) | -0.823\*\* | (-2.43) |
| *NEWS10K* | -3.871\*\*\* | (-3.81) | 3.660\*\* | (2.46) | -3.415 | (-1.31) |
| *LOGFOLL\_FOR* | 0.213\*\*\* | (2.78) | 0.065 | (0.56) | -0.537\*\*\* | (-2.99) |
| *LOGHORIZON* | -0.172\*\*\* | (-3.58) | 0.319\*\*\* | (4.48) | -0.287\*\* | (-2.29) |
|  |  |  |  |  |  |  |
| Incentive to cover: |  |  |  |  |  |  |
| *TURN* | -0.000 | (-1.53) | 0.001\*\* | (2.39) | -0.002\*\*\* | (-2.82) |
| *ADV* | -0.966 | (-1.23) | 0.222 | (0.22) | 7.384\*\*\* | (3.42) |
| *RND* | 1.104\*\*\* | (3.86) | -1.715\*\*\* | (-3.33) | -0.516 | (-0.51) |
| *ROA* | 0.633\* | (1.71) | -2.620\*\*\* | (-4.01) | -2.209\*\* | (-2.03) |

**TABLE 5 –** *Continued*

*Accounting complexity based on financial statements and notes and forecast accuracy & dispersion and value of recommendation revisions: firm-year level sample*

|  |  |  |  |
| --- | --- | --- | --- |
| Dependent Variable = | *ACCURACY* | *FORDISP* | *RECVAL* |
|  | (1) | (2) | (3) |
| Complexity: |  |  |  |  |  |  |
| *FOROPS* | 0.095\*\* | (2.11) | -0.117\* | (-1.66) | -0.096 | (-0.72) |
| *LOGSGMT* | -0.040 | (-1.07) | 0.083 | (1.51) | -0.089 | (-1.05) |
| *EARNVOL* | 0.005 | (1.10) | 0.033\*\*\* | (4.06) | -0.002 | (-0.15) |
| *FOG10K* | -0.015 | (-0.72) | 0.045 | (1.51) | -0.019 | (-0.39) |
| *LOGWORDS* | -0.166\*\* | (-2.02) | 0.117 | (0.89) | 0.410\*\* | (2.22) |
|  |  |  |  |  |  |  |
| Uncertainty: |  |  |  |  |  |  |
| *STDRET* | -0.241\*\*\* | (-4.19) | 0.596\*\*\* | (6.54) | 1.904\*\*\* | (10.56) |
| *LOSS* | -0.867\*\*\* | (-8.79) | 1.202\*\*\* | (8.45) | 0.137 | (0.50) |
|  |  |  |  |  |  |  |
| Industry & Year Dummies  | Yes |  | Yes |  | Yes |  |
| *N* | 8,361 |  | 8,361 |  | 6,417 |  |
| R-square | 0.185 |  | 0.318 |  | 0.225 |  |
| Adj. R-square | 0.182 |  | 0.315 |  | 0.221 |  |

**TABLE 6**

*Accounting complexity based on financial statements and notes and forecast accuracy: analyst-firm-year level sample*

This table presents the estimation results of the following equation where the dependent variable is the absolute value of forecast errors.

-1 × |Forecast Error| = α + β1ARC + β2ARC-FS + β3ARC-NOTES + ∑γControls + ∑δIndustry + ∑θYear + εit.

|*Forecast Error*| is calculated as the absolute value of actual minus forecasted earnings scaled by price and multiplied by 100. *ARC* equals the natural logarithm of one plus the total number of monetary tags reported in Item 8 of 10-K filings, which includes the financial statements and notes. *ARC-FS* is the natural logarithm of one plus the total number of tags reported in the financial statements (Item 8 of 10-K filings), and *ARC-NOTES* is the natural logarithm of one plus the total number of tags reported in the notes section. The *t*-statistics are in brackets, next to the coefficient estimates, and are computed based on standard errors clustered by analyst and firm. The symbols \*, \*\*, and \*\*\* indicate statistical significance at the ten, five, and one percent levels, respectively. Industry and year fixed-effects are included in all models. The number of observations and goodness of fit statistics are reported at the bottom of the table.

|  |  |
| --- | --- |
| Dependent Variable = | -1 × |Forecast Error| |
|  | (1) |  | (2) |  | (3) |  | (4) |  |
| Accounting complexity: |  |  |  |  |  |  |  |  |
| *ARC* | -0.247\*\* | (-2.19) |  |  |  |  |  |  |
| *ARC-FS* |  |  | -0.141 | (-0.90) |  |  | 0.068 | (0.41) |
| *ARC-NOTES* |  |  |  |  | -0.195\*\* | (-2.30) | -0.211\*\* | (-2.35) |
|  |  |  |  |  |  |  |  |  |
| Information environment: |  |  |  |  |  |  |  |  |
| *LOGMV* | 0.097\*\*\* | (5.20) | 0.082\*\*\* | (4.65) | 0.098\*\*\* | (5.27) | 0.098\*\*\* | (5.34) |
| *IO* | 0.012\*\*\* | (7.86) | 0.012\*\*\* | (7.79) | 0.012\*\*\* | (7.90) | 0.012\*\*\* | (7.89) |
| *B/M* | -0.726\*\*\* | (-6.12) | -0.766\*\*\* | (-6.63) | -0.725\*\*\* | (-6.14) | -0.724\*\*\* | (-6.15) |
| *GROWTH* | 0.160 | (1.50) | 0.183\* | (1.68) | 0.159 | (1.49) | 0.159 | (1.48) |
| *NEWS10K* | -4.234\*\*\* | (-3.87) | -4.210\*\*\* | (-3.84) | -4.226\*\*\* | (-3.86) | -4.221\*\*\* | (-3.86) |
|  |  |  |  |  |  |  |  |  |
| Incentive to cover: |  |  |  |  |  |  |  |  |
| *TURN* | -0.000 | (-1.30) | -0.000 | (-1.40) | -0.000 | (-1.28) | -0.000 | (-1.28) |
| *ADV* | -0.372 | (-0.73) | -0.281 | (-0.55) | -0.375 | (-0.74) | -0.377 | (-0.74) |
| *RND* | 0.901\*\*\* | (2.95) | 1.011\*\*\* | (3.35) | 0.897\*\*\* | (2.94) | 0.898\*\*\* | (2.95) |
| *ROA* | 1.483\*\*\* | (3.40) | 1.560\*\*\* | (3.64) | 1.484\*\*\* | (3.40) | 1.484\*\*\* | (3.40) |

**TABLE 6** **–** *Continued*

*Accounting complexity based on financial statements and notes and forecast accuracy: analyst-firm-year level sample*

|  |  |
| --- | --- |
| Dependent Variable = | -1 × |Forecast Error| |
|  | (1) |  | (2) |  | (3) |  | (4) |  |
| Complexity: |  |  |  |  |  |  |  |  |
| *FOROPS* | 0.098\*\* | (2.33) | 0.083\* | (1.91) | 0.099\*\* | (2.34) | 0.098\*\* | (2.30) |
| *LOGSGMT* | -0.015 | (-0.44) | -0.016 | (-0.48) | -0.014 | (-0.42) | -0.014 | (-0.40) |
| *EARNVOL* | -0.028\*\*\* | (-4.02) | -0.028\*\*\* | (-4.08) | -0.028\*\*\* | (-4.02) | -0.028\*\*\* | (-4.02) |
| *FOG10K* | -0.014 | (-0.72) | -0.014 | (-0.74) | -0.013 | (-0.70) | -0.013 | (-0.69) |
| *LOGWORDS* | -0.076 | (-0.77) | -0.122 | (-1.29) | -0.078 | (-0.81) | -0.082 | (-0.83) |
|  |  |  |  |  |  |  |  |  |
| Uncertainty: |  |  |  |  |  |  |  |  |
| *STDRET* | -0.356\*\*\* | (-6.28) | -0.350\*\*\* | (-6.26) | -0.357\*\*\* | (-6.28) | -0.357\*\*\* | (-6.29) |
| *LOSS* | -0.928\*\*\* | (-8.66) | -0.927\*\*\* | (-8.67) | -0.927\*\*\* | (-8.65) | -0.927\*\*\* | (-8.65) |
|  |  |  |  |  |  |  |  |  |
| Forecast attribute: |  |  |  |  |  |  |  |  |
| *FORAGE* | -0.183\*\*\* | (-14.84) | -0.182\*\*\* | (-14.78) | -0.183\*\*\* | (-14.84) | -0.183\*\*\* | (-14.79) |
| Industry & Year Dummies  | Yes |  | Yes |  | Yes |  | Yes |  |
| *N* | 113,073 |  | 113,073 |  | 113,073 |  | 113,073 |  |
| R-square | 0.247 |  | 0.246 |  | 0.247 |  | 0.247 |  |
| Adj. R-square | 0.247 |  | 0.246 |  | 0.247 |  | 0.247 |  |

**TABLE 7**

*Accounting complexity based on financial statements and notes and forecast accuracy: analyst-firm-year level sample*

The table below presents the results of the regression analysis (OLS) of analysts’ forecast accuracy at the estimate level.

-1 × |Forecast Error| = α + β1ARC-NOTES + λ1AQLF +η1ARC-NOTES×AQLF

+ ∑γControls + ∑δIndustry + ∑θYear + εit.

|*Forecast Error*| is calculated as the absolute value of actual minus forecasted earnings scaled by price and multiplied by 100. *ARC-NOTES* is the natural logarithm of one plus the total number of monetary tags reported in the notes section. *AQLF* measures analysts’ qualifications using four different variables: *GEXP*, *FEXP*, *INDFOCUS*, and *CFA*. *GEXP* equals the number of years since the analyst first appeared in the I/B/E/S database and *FEXP* equals the number of years since the analyst began issuing forecasts for the company. *INDFOCUS* equals one divided by the number of industries (FF - 12) represented in the analyst’s portfolio of coverage. *CFA* is an indicator variable that equals one for analysts who hold a Chartered Financial Analyst credential. With the exception of CFA, we mean center all variables that are interacted. For each variable, the two rows report estimated coefficients, and t-statistics (in brackets) computed based on standard errors clustered by analyst and firm. The symbols \*, \*\*, and \*\*\* indicate statistical significance at the ten, five, and one percent levels, respectively. Industry and year fixed-effects are included in all models. The number of observations and goodness of fit statistics are reported at the bottom of the table.

|  |  |
| --- | --- |
| Dependent Variable = | -1 × |Forecast Error| |
|  | (1) | (2) | (3) | (4) |
| Accounting complexity: |  |  |  |  |
| *ARC-NOTES* | -0.199\*\* | -0.193\*\* | -0.209\*\* | -0.226\*\* |
|  | (-2.35) | (-2.29) | (-2.51) | (-2.55) |
| *GEXP* | 0.087\*\*\* |  |  |  |
|  | (6.06) |  |  |  |
| *ARC-NOTES X GEXP* | 0.038 |  |  |  |
|  | (1.24) |  |  |  |
| *FEXP* |  | -0.000 |  |  |
|  |  | (-0.02) |  |  |
| *ARC-NOTES X FEXP* |  | 0.183\*\*\* |  |  |
|  |  | (4.77) |  |  |
| *INDFOCUS* |  |  | 0.009 |  |
|  |  |  | (0.17) |  |
| *ARC-NOTES X INDFOCUS* |  |  | 0.376\*\*\* |  |
|  |  |  | (3.24) |  |
| *CFA* |  |  |  | 0.068\*\*\* |
|  |  |  |  | (2.96) |
| *ARC-NOTES X CFA* |  |  |  | 0.083\* |
|  |  |  |  | (1.88) |

**TABLE 7** **–** *Continued*

*Accounting complexity based on financial statements and notes and forecast accuracy: analyst-firm-year level sample*

|  |  |
| --- | --- |
| Dependent Variable = | -1 × |Forecast Error| |
|  | (1) | (2) | (3) | (4) |
| Information environment: |  |  |  |  |
| *LOGMV* | 0.096\*\*\* | 0.096\*\*\* | 0.097\*\*\* | 0.096\*\*\* |
|  | (5.21) | (5.16) | (5.27) | (5.17) |
| *IO* | 0.012\*\*\* | 0.012\*\*\* | 0.012\*\*\* | 0.011\*\*\* |
|  | (7.86) | (7.97) | (7.95) | (7.22) |
| *B/M* | -0.726\*\*\* | -0.725\*\*\* | -0.746\*\*\* | -0.690\*\*\* |
|  | (-6.15) | (-6.14) | (-6.30) | (-5.90) |
| *GROWTH* | 0.164 | 0.154 | 0.167 | 0.219\*\* |
|  | (1.54) | (1.45) | (1.56) | (2.09) |
| *NEWS10K* | -4.207\*\*\* | -4.218\*\*\* | -4.222\*\*\* | -3.877\*\*\* |
|  |  |  |  |  |
| Incentive to cover: |  |  |  |  |
| *TURN* | -0.000 | -0.000 | -0.000 | -0.000 |
|  | (-1.25) | (-1.26) | (-1.15) | (-1.03) |
| *ADV* | -0.395 | -0.360 | -0.441 | -0.589 |
|  | (-0.78) | (-0.71) | (-0.88) | (-1.12) |
| *RND* | 0.894\*\*\* | 0.893\*\*\* | 0.943\*\*\* | 0.878\*\*\* |
|  | (2.93) | (2.94) | (3.04) | (2.89) |
| *ROA* | 1.493\*\*\* | 1.518\*\*\* | 1.455\*\*\* | 1.576\*\*\* |
|  | (3.43) | (3.49) | (3.34) | (3.57) |
| Complexity: |  |  |  |  |
| *FOROPS* | 0.100\*\* | 0.100\*\* | 0.098\*\* | 0.094\*\* |
|  | (2.37) | (2.38) | (2.33) | (2.23) |
| *LOGSGMT* | -0.013 | -0.012 | -0.008 | -0.018 |
|  | (-0.39) | (-0.35) | (-0.23) | (-0.54) |
| *EARNVOL* | -0.028\*\*\* | -0.028\*\*\* | -0.028\*\*\* | -0.027\*\*\* |
|  | (-4.01) | (-4.00) | (-4.04) | (-3.92) |
| *FOG10K* | -0.013 | -0.012 | -0.011 | -0.013 |
|  | (-0.68) | (-0.64) | (-0.59) | (-0.74) |
| *LOGWORDS* | -0.078 | -0.084 | -0.082 | -0.070 |
|  | (-0.81) | (-0.87) | (-0.85) | (-0.79) |
| Uncertainty: |  |  |  |  |
| *STDRET* | -0.356\*\*\* | -0.361\*\*\* | -0.363\*\*\* | -0.363\*\*\* |
|  | (-6.28) | (-6.35) | (-6.40) | (-6.06) |
| *LOSS* | -0.924\*\*\* | -0.924\*\*\* | -0.918\*\*\* | -0.885\*\*\* |
|  | (-8.64) | (-8.64) | (-8.60) | (-8.03) |
| Forecast attribute: |  |  |  |  |
| *FORAGE* | -0.184\*\*\* | -0.183\*\*\* | -0.182\*\*\* | -0.166\*\*\* |
|  | (-14.93) | (-14.83) | (-14.88) | (-12.32) |
| Industry & Year Dummies  | Yes | Yes | Yes | Yes |
| N | 113,073 | 113,073 | 113,073 | 89,700 |
| R-square | 0.248 | 0.247 | 0.247 | 0.243 |
| Adj. R-square | 0.247 | 0.247 | 0.247 | 0.243 |

**TABLE 8**

*Account-specific complexity and expertise*

The table below presents the results of the regression analysis (OLS) of analysts’ forecast accuracy at the estimate level.

-1 × |Forecast Error| = α + β1ARC-X + λ1AQLF + η1ARC-X×AQLF + π1EXPRT-X

+ ρ1ARC-X×EXPRT-X + ∑γControls + ∑δIndustry + ∑θYear + εit.

|*Forecast Error*| is calculated as the absolute value of actual minus forecasted earnings scaled by price and multiplied by 100. *ARC-X* represents the three account-specific complexity variables. *ARC-FAIR*, *ARC-DERIV*, and *ARC-PENS* are the natural logarithms of one plus the total number of reported tags related to fair values, derivatives, and pensions, respectively. *AQLF* sequentially equals four different aspects of analysts’ qualifications: *GEXP*, *FEXP*, *INDFOCUS*, and *CFA*. *GEXP* equals the number of years since the analyst first appeared in the I/B/E/S database and *FEXP* equals the number of years since the analyst began issuing forecasts for the company. *INDFOCUS* is equal to one divided by the number of industries (FF - 12) represented in the analyst’s portfolio of coverage. *CFA* is an indicator variable that equals one for analysts who hold a Chartered Financial Analyst credential. *EXPRT-X* represents the expertise measure for each of the three account-specific complexity categories. Specifically, *EXPRT-FAIR*, *EXPRT-DERIV*, and *EXPRT-PENS* are indicator variables that equal one for analysts whose portfolio of coverage are in the top 50 percentile in terms of the sum of the number of tags related to fair values, derivatives, and pensions, respectively. With the exception of the CFA and expertise variables, we mean center all variables that appear as part of an interaction. For each variable, the two rows report estimated coefficients, and t-statistics (in brackets) computed based on standard errors clustered by analyst and firm. The symbols \*, \*\*, and \*\*\* indicate statistical significance at the ten, five, and one percent levels, respectively. Industry and year fixed-effects are included in all models. The number of observations and goodness of fit statistics are reported at the bottom of the table. The coefficient estimates of the control variables are omitted to conserve space.

**Panel A:** Accounting complexity based on fair value tags.

|  |  |
| --- | --- |
| Dependent Variable = | -1 × |Forecast Error| |
|  | (1) | (2) | (3) | (4) |
| Accounting complexity: |  |  |  |  |
| *ARC-FAIR* | -0.192\*\*\* | -0.187\*\*\* | -0.194\*\*\* | -0.194\*\*\* |
|  | (-4.88) | (-4.73) | (-4.94) | (-4.80) |
| *GEXP* | 0.074\*\*\* |  |  |  |
|  | (5.38) |  |  |  |
| *ARC-FAIR X GEXP* | -0.000 |  |  |  |
|  | (-0.00) |  |  |  |
| *FEXP* |  | -0.008 |  |  |
|  |  | (-0.49) |  |  |
| *ARC-FAIR X FEXP* |  | 0.065\*\*\* |  |  |
|  |  | (3.73) |  |  |
| *INDFOCUS* |  |  | 0.027 |  |
|  |  |  | (0.49) |  |
| *ARC-FAIR X INDFOCUS* |  |  | 0.158\*\*\* |  |
|  |  |  | (2.91) |  |
| *CFA* |  |  |  | 0.069\*\*\* |
|  |  |  |  | (3.01) |
| *ARC-FAIR X CFA* |  |  |  | 0.044\*\* |
|  |  |  |  | (1.97) |
| *EXPRT-FAIR* | 0.095\*\*\* | 0.123\*\*\* | 0.121\*\*\* | 0.079\*\* |
|  | (3.30) | (4.25) | (4.12) | (2.56) |
| *ARC-FAIR X EXPRT-FAIR* | 0.162\*\*\* | 0.153\*\*\* | 0.158\*\*\* | 0.140\*\*\* |
|  | (4.81) | (4.62) | (4.89) | (3.99) |
| Industry & Year Dummies  | Yes | Yes | Yes | Yes |
| N | 113,073 | 113,073 | 113,073 | 89,700 |
| Control Variables | Yes | Yes | Yes | Yes |
| R-square | 0.248 | 0.248 | 0.248 | 0.243 |
| Adj. R-square | 0.248 | 0.248 | 0.248 | 0.243 |
| Equality of the two interactions | 17.286 | 5.385 | 0.000 | 5.353 |
| p-value | 0.000 | 0.020 | 0.998 | 0.021 |

**Panel B:** Accounting reporting complexity based on derivatives.

|  |  |
| --- | --- |
| Dependent Variable = | -1 × |Forecast Error| |
|  | (1) | (2) | (3) | (4) |
| Accounting complexity: |  |  |  |  |
| *ARC-DERIV* | -0.239\*\*\* | -0.237\*\*\* | -0.245\*\*\* | -0.234\*\*\* |
|  | (-5.94) | (-5.80) | (-6.07) | (-5.59) |
| *GEXP* | 0.075\*\*\* |  |  |  |
|  | (5.56) |  |  |  |
| *ARC-DERIV X GEXP* | 0.003 |  |  |  |
|  | (0.17) |  |  |  |
| *FEXP* |  | -0.007 |  |  |
|  |  | (-0.44) |  |  |
| *ARC-DERIV X FEXP* |  | 0.091\*\*\* |  |  |
|  |  | (5.18) |  |  |
| *INDFOCUS* |  |  | 0.022 |  |
|  |  |  | (0.40) |  |
| *ARC-DERIV X INDFOCUS* |  |  | -0.003 |  |
|  |  |  | (-0.06) |  |
| *CFA* |  |  |  | 0.069\*\*\* |
|  |  |  |  | (3.06) |
| *ARC-DERIV X CFA* |  |  |  | 0.033\* |
|  |  |  |  | (1.65) |
| *EXPRT-DERIV* | 0.060\*\* | 0.083\*\*\* | 0.087\*\*\* | 0.041 |
|  | (2.14) | (2.95) | (3.06) | (1.36) |
| *ARC-DERIV X EXPRT-DERIV* | 0.115\*\*\* | 0.106\*\*\* | 0.120\*\*\* | 0.093\*\*\* |
|  | (3.77) | (3.45) | (3.96) | (3.04) |
| Industry & Year Dummies | Yes | Yes | Yes | Yes |
| N | 113,073 | 113,073 | 113,073 | 89,700 |
| Control Variables | Yes | Yes | Yes | Yes |
| R-square | 0.251 | 0.251 | 0.250 | 0.246 |
| Adj. R-square | 0.250 | 0.250 | 0.250 | 0.245 |
| Equality of the two interactions | 9.585 | 0.143 | 4.241 | 3.296 |
| p-value | 0.002 | 0.705 | 0.040 | 0.070 |

**Panel C:** Accounting reporting complexity based on pensions.

|  |  |
| --- | --- |
| Dependent variable: | -1 × |Forecast Error| |
|  | (1) | (2) | (3) | (4) |
| Accounting complexity: |  |  |  |  |
| *ARC-PENS* | -0.075\*\*\* | -0.070\*\* | -0.079\*\*\* | -0.068\*\* |
|  | (-2.70) | (-2.54) | (-2.92) | (-2.42) |
| *GEXP* | 0.079\*\*\* |  |  |  |
|  | (5.61) |  |  |  |
| *ARC-PENS X GEXP* | -0.019\*\* |  |  |  |
|  | (-2.00) |  |  |  |
| *FEXP* |  | -0.009 |  |  |
|  |  | (-0.53) |  |  |
| *ARC-PENS X FEXP* |  | 0.030\*\*\* |  |  |
|  |  | (2.68) |  |  |
| *INDFOCUS* |  |  | 0.027 |  |
|  |  |  | (0.48) |  |
| *ARC-PENS X INDFOCUS* |  |  | 0.090\*\*\* |  |
|  |  |  | (2.63) |  |
| *CFA* |  |  |  | 0.069\*\*\* |
|  |  |  |  | (3.01) |
| *ARC-PENS X CFA* |  |  |  | -0.002 |
|  |  |  |  | (-0.12) |
| *EXPRT-PENS* | 0.087\*\* | 0.111\*\*\* | 0.113\*\*\* | 0.072\*\* |
|  | (2.54) | (3.22) | (3.27) | (2.08) |
| *ARC-PENS X EXPRT-PENS* | 0.070\*\*\* | 0.059\*\* | 0.075\*\*\* | 0.067\*\*\* |
|  | (2.97) | (2.55) | (3.27) | (2.89) |
| Industry & Year Dummies | Yes | Yes | Yes | Yes |
| N | 113,073 | 113,073 | 113,073 | 89,700 |
| Control Variables | Yes | Yes | Yes | Yes |
| R-square | 0.247 | 0.247 | 0.247 | 0.243 |
| Adj. R-square | 0.247 | 0.247 | 0.247 | 0.242 |
| Equality of the two interactions | 11.096 | 1.217 | 0.121 | 6.814 |
| p-value | 0.001 | 0.270 | 0.728 | 0.009 |

**TABLE 9**

*Accounting complexity and the information environment*

The table below presents the results of the regression analysis (OLS) of analysts’ forecast accuracy at the estimate level.

-1 × |Forecast Error| = α + β1ARC-NOTES + λ1IE + η1ARC-NOTES×IE + ∑γControls

+ ∑δIndustry + ∑θYear + εit.

|*Forecast Error*| is calculated as the absolute value of actual minus forecasted earnings scaled by price and multiplied by 100. *ARC-NOTES* equals the natural logarithm of one plus the total number of monetary tags reported in the footnotes of the financial statements. *IE* represents the three measures of the information environment: *EFFORT*, *DVOLDISC*, and *FOLL\_FOR*. *EFFORT* equals the natural logarithm of one plus the number of forecasts that the analyst issued during the fiscal period. *DVOLDISC* is an indicator variable that equals one for companies that issued at least one management forecast during the fiscal period. *FOLL\_FOR* is the natural logarithm of one plus the number of analysts who issued earnings estimates. *EFFORT*, *DVOLDISC*, and *FOLL\_FOR* are mean centered. For each variable, the two rows report estimated coefficients, and t-statistics (in brackets) computed based on standard errors clustered by analyst and firm. The symbols \*, \*\*, and \*\*\* indicate statistical significance at the ten, five, and one percent levels, respectively. Industry and year fixed-effects are included in all models. The number of observations and goodness of fit statistics are reported at the bottom of the table.

|  |  |
| --- | --- |
| Dependent Variable = | -1 × |Forecast Error| |
|  | (1) | (2) | (3) |
|  |  |  |  |
| Accounting complexity: |  |  |  |
| *ARC-NOTES* | -0.229\* | -0.213\*\* | -0.183\*\* |
|  | (-1.95) | (-2.52) | (-2.17) |
| *EFFORT* | 0.191\*\*\* |  |  |
|  | (7.78) |  |  |
| *ARC-NOTES X EFFORT* | 0.019 |  |  |
|  | (0.33) |  |  |
| *DVOLDISC* |  | 0.189\*\*\* |  |
|  |  | (2.94) |  |
| *ARC-NOTES X DVOLDISC* |  | -0.154 |  |
|  |  | (-1.32) |  |
| *FOLL\_FOR* |  |  | 0.106\* |
|  |  |  | (1.71) |
| *ARC-NOTES X FOLL\_FOR* |  |  | 0.175\*\* |
|  |  |  | (2.24) |
| Industry & Year Dummies | Yes | Yes | Yes |
| *N* | 113,073 | 113,073 | 113,073 |
| Control variables | Yes | Yes | Yes |
| R-square | 0.248 | 0.248 | 0.248 |
| Adj. R-square | 0.248 | 0.247 | 0.247 |

1. Each accounting concept in XBRL is assigned a tag to give it a machine-readable meaning. For example, the net sale accounting concept is assigned the following tag <us-gaap:SalesRevenueNet>. [↑](#footnote-ref-1)
2. In many ways, ARC is a result of complex economic activities. By construction, the objective of the financial reports is to “communicate the economic substance of a transaction or event and the overall financial position and results of a company” (SEC 2008). Therefore, ARC captures complexity that is due to operational decisions as well as accounting reporting choices, our study is not aimed at disentangling the two. Regardless, we are unaware of other granular, accounting-based, measures of business complexity (beyond a simple count of segments or existence of foreign operations) that are available for a large cross-section of firms. In the sensitivity analysis section, we report results of analysis that disentangles ARC from observable measures of operating complexity. [↑](#footnote-ref-2)
3. ARC can also influence financial analysts’ cost-benefit considerations. Specifically, the amount of time and resources that analysts need to commit to extract, incorporate, analyze, and interpret accounting data increases with the supply of accounting information. As a result, analysts may fail to invest sufficient time to understand and fully incorporate the disclosures of complex firms into their analyses. [↑](#footnote-ref-3)
4. ARC is based on eXtensible Business Reporting Language (XBRL) filings with the SEC. Since ARC is built on XBRL it is only available from 2011. [↑](#footnote-ref-4)
5. Whether or not analysts actually rely on XBRL disclosures, on HTML filings, or on information from data aggregators does not influence our investigation. In fact, it is assumed that analysts do not directly use XBRL (Harris and Morsfield 2012). Our approach only relies on XBRL disclosures to measure firms’ accounting reporting complexity. [↑](#footnote-ref-5)
6. In robustness tests, we demonstrate that our results are not sensitive to several alternative methods to construct ARC. [↑](#footnote-ref-6)
7. Using other data sources such as Compustat it is not trivial to distinguish between items that appears in the face of the financials versus items that appear in the notes. [↑](#footnote-ref-7)
8. We manually collect the CFA credential information from Factset for each analyst in our sample. We were able to identify this information for roughly 80 percent of our sample. [↑](#footnote-ref-8)
9. This is similar to the approach in Ma, Markov and Wu (2016). They suggest that analyst can gain nuanced expertise, in their case global expertise, from similar firms in their portfolio. [↑](#footnote-ref-9)
10. For example, Compustat includes about 10 fair value variables. In contrast, the FASB U.S. GAAP XBRL taxonomy includes more than 400 monetary fair value tags. [↑](#footnote-ref-10)
11. In a related paper, Bradshaw et al. (2009) find that atypical accounting methods impede analysts’ performance, suggesting that analysts specialize in covering specific methods within industries and deviation from common industry methods can be detrimental to their work. [↑](#footnote-ref-11)
12. Fair value, derivatives and pensions have also received significant attention from standard setters. The FASB included several of these accounts in the simplification initiative, suggesting that these are complex accounts (FASB Simplification Project 2016). [↑](#footnote-ref-12)
13. Chen, Wang, and Zhou 2017 provide an excellent discussion of the legislative events that led to the enactment of the rule on XBRL and their analysis shows that the legislation had an overall positive market reaction, in particular for firms with weaker information environments. More information on the XBRL taxonomy, tags and extensions is available at the following link: <https://xbrl.us/wp-content/uploads/2015/03/PreparersGuide.pdf> . [↑](#footnote-ref-13)
14. Since we extract XBRL tags directly from SEC filings using a standard method, our measure is not based on subjective judgment and could be easily replicated. [↑](#footnote-ref-14)
15. We retain only the last annual estimates that analysts issue before the earnings announcement. [↑](#footnote-ref-15)
16. Specifically, smaller filers were not required to file XBRL reports that include the financial statement notes until 2012. As we describe later, removing 2011 from our sample does not alter our results. [↑](#footnote-ref-16)
17. We included a detailed description of the process to construct account specific complexity and a sample of fair value tags in Appendices A and B, respectively. [↑](#footnote-ref-17)
18. To identify account categories we rely on “Disclosure” headings in the taxonomy files. Some tags appear in multiple financial statements and/or notes. We remove tags that repeat in more than three disclosures because we cannot uniquely associate them with a specific account category. The FASB taxonomy files are available at: <http://www.fasb.org/cs/ContentServer?c=Page&pagename=FASB%2FPage%2FSectionPage&cid=1176164649716>. [↑](#footnote-ref-18)
19. This is required for extended tags, which are not part of the XBRL taxonomy and adds to classification accuracy of tags that are part of the taxonomy. This process is described in more detail in appendices A and B. [↑](#footnote-ref-19)
20. For example, if an analyst covers four firms, we sum all fair-value tags across all four firms. [↑](#footnote-ref-20)
21. We measure share price as of the end of the fiscal period and adjust it for stock splits and stock dividends. [↑](#footnote-ref-21)
22. We eliminate revisions after earnings announcements to ensure that confounding events do not affect our measure. [↑](#footnote-ref-22)
23. We eliminate revisions issued on days with conflicting recommendation revisions because it is unclear which revision share prices are reacting to (or ignoring). [↑](#footnote-ref-23)
24. The expected market reaction to an upgrade is positive whereas it is negative for a downgrade. Hence, while a more positive reaction to an upgrade indicates greater informativeness, it indicates less informativeness for a downgrade. Multiplying the returns associated with downgrades allows us to interpret the results for both upgrades and downgrades in the same way. [↑](#footnote-ref-24)
25. We assume that markets are at a minimum semi-strong efficient. [↑](#footnote-ref-25)
26. The Fog index algorithm classifies each word with three or more syllables as complex. For example, the words significant, corporation, management and telecommunications will all be classified as complex. Yet, it is clear that these words should not pose a challenge to financial statement users, especially to financial analysts. [↑](#footnote-ref-26)
27. We exclude forecast dispersion (*FORDISP*) because it can only be calculated at the firm-year level. We also exclude the value of recommendations (*RECVAL*) since estimates of the informativeness of recommendations are unreliable at the analyst level because analysts issue only a few recommendations for each firm per year. [↑](#footnote-ref-27)
28. Note that the sign of the *ACCURACY* variable does not indicate the direction of the forecast error. We first compute the absolute value of forecast errors and then multiply by -100 so that higher values indicate higher forecast accuracy. [↑](#footnote-ref-28)
29. Although we use the natural logarithm for the complexity variables, for ease of interpretation, we report statistics based on untransformed values. [↑](#footnote-ref-29)
30. *INDFOCUS* equals one divided by the number of industries covered. Since the mean value for *INDFOCUS* is 0.57 we infer that the average analyst covers 1/0.57 = 1.75 industries. [↑](#footnote-ref-30)
31. This transformation reverses the variable’s order so that higher (lower) values indicate greater (lower) industry focus. [↑](#footnote-ref-31)
32. To avoid multicollinearity, we mean-center the experience, industry focus, and expertise measures. [↑](#footnote-ref-32)
33. Analyst with CFA certification do not perform better when pension accounting is complex but they do perform better when fair value and derivatives are. This is consistent with the topics covered in the CFA certification that includes fair value and derivatives. [↑](#footnote-ref-33)
34. We thank Chen, Miao, and Shevlin for graciously sharing with us their data. [↑](#footnote-ref-34)