The Effect of Accounting Reporting Complexity on Financial Analysts

Abstract

We investigate the association between a new XBRL based measure of accounting reporting complexity (ARC) and analyst behavior. We find that analysts are less likely to cover firms with complex accounting. Further, higher ARC is associated with lower forecast accuracy, higher forecast dispersion, and lower informativeness of recommendation revisions and responsiveness to earnings announcements. This association is attenuated when analysts have longer tenure, greater firm-specific experience, and are focused on fewer industries. Investigating several complex accounts, we find that the complexity of derivatives, fair value, and pension accounts are each negatively associated with forecast accuracy, suggesting that understanding these complex accounts requires specialization. We propose a new measure of analysts' account-specific expertise and find that expertise with derivative and fair value accounts attenuates the negative effects of complexity in these accounts to a greater extent than general analyst experience. Overall, our findings suggest that analysts' expertise plays an important role in mitigating the adverse effects of ARC.

JEL Classification: G24, G29, M41

Keywords: XBRL, accounting complexity, financial analysts' performance, financial analysts' expertise

Data Availability: Data are publicly available from sources identified in the paper.

The Effect of Accounting Reporting Complexity on Financial Analysts

I. Introduction

Regulators and standard setters have long recognized that financial reporting has become overly complicated (SEC 2008; FRC 2009). As a result, the Securities and Exchange Commission (SEC) and the Financial Accounting Standards Board (FASB) undertook several initiatives to understand and simplify the financial reports (e.g. SEC 2008; FASB 2016). In this study, we examine how accounting reporting complexity (hereafter, ARC), measured as the count of accounting items disclosed in eXtensible Business Reporting Language (XBRL) 10-K filings, is associated with financial analysts' performance and coverage decisions. Since each accounting item is based on authoritative standards and regulations, understanding the financial reports of firms with higher ARC necessitates broader and more in-depth knowledge of accounting.

While Hoitash and Hoitash (2017) find that more accounting disclosure complicates the work of preparers and auditors, it is unclear how disclosure volume will be associated with the work of sophisticated market participants such as financial analysts. Greater volume of accounting disclosures can help analysts understand past performance and generate more accurate forecasts. Indeed, several studies find that more disaggregated disclosures can lead to better analyst performance (Lang and Lundholm 1996; Chen et al. 2015). In contrast, more disclosure requires greater knowledge of accounting rules and regulations on part of financial analysts and a need to collect, analyze, and incorporate more information into their predictions. As a result, ARC may hurt overall analyst performance or even discourage analysts from covering certain firms.[1]

[1] It is well established that financial analysts rely on the information that is disclosed in the financial reports. Ramnath, Rock and Shane (2008) list three primary sources that analysts use to form their recommendations (1) SEC filings (2) Industry and macroeconomic conditions and (3) Conference call and other management communications.

We rely on a report by the SEC's Advisory Committee on Improvements to Financial Reporting (ACIFR hereafter, SEC 2008) 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. We construct a measure of ARC using eXtensible Business Reporting Language (XBRL) filings with the SEC.[2,3] The XBRL taxonomy, maintained by FASB, contains a comprehensive list of nearly 16,000 tags that companies can use to report accounting information. Each tag depicts a GAAP concept such as inventory (e.g. the tag "InventoryGross" represents gross inventory) and refers to an authoritative accounting standard and regulation.[4] We compute ARC as the total number of tags used in Item 8 of the 10-K annual SEC filings. Therefore, as the number of tags increases, greater volume of accounting information is disclosed in SEC filings.[5] ARC is principally different from other firm-level proxies for complexity such as readability (Miller 2010; Lehavy et al. 2011) or disclosure fineness (Chen et al. 2015) because it focuses on all monetary accounting disclosures that are directly obtained from company filings.

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2 We recognize that ARC can be measured in different ways and recognize that using volume we capture only one, albeit important, dimension of accounting reporting complexity.

3 Under SEC rules (SEC 2009), firms must faithfully translate the financial statements and notes in Item 8 of their 10-K filings into XBRL. Therefore, the number of XBRL tags reported mimics the same information firms disclose in their HTML filings. Early research, questions the quality of company disclosures. Our research design, however, is primarily unaffected by this issue because we rely on the meta-data (tag names) instead of the actual disclosed values.

4 In cases where an appropriate tag is unavailable, companies can create their own tags (referred to as extensions because the new tags extend the taxonomy). We note that the use of extended tags is, at times, unwarranted. In fact, past research finds that firms may unnecessarily use extended tags (Debreceny et al. 2011). Nevertheless, an increased use of extensions reduces the use of tags that appear in the Taxonomy. Since ARC equals the overall number of tags, it is ambivalent to whether companies use extensions or not. In the sensitivity analysis section, we separate extensions and taxonomy tags and repeat our analyses.

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.

We hypothesize that it is more difficult for analysts to assess the current and future performance of firms with greater ARC for several reasons. First, past research suggests that more information contributes to task complexity (e.g., Steinmann 1976; Campbell 1988; Bonner 1994). In addition, firms that use a higher number of XBRL tags reference more accounting standards. Incorporating these accounting concepts into profitability calculations is difficult because it requires a broader and more diverse knowledge of accounting standards and regulations.[6] Finally, ARC can 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.

Our objective is to investigate three aspects of sell-side analysts' behavior. First, does ARC serve as a determinant of analysts' decision to cover a company? Second, is accounting complexity associated with analyst performance as measured by forecast accuracy, forecast dispersion, and the informativeness of their stock recommendation revisions? Third, can analyst experience, expertise, and industry focus moderate the effect of ARC? We examine these questions in a sample of 6,232 firm-year observations between 2011 and 2014.

At the outset, we examine the association between ARC and analysts' coverage. Evidence on the coverage of complex firms primarily shows that complex firms receive more coverage. Specifically, more complex firms in terms of intangibles, firm size, and financial statement

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[6] In many ways, accounting complexity 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, although we measure accounting reporting complexity, we also capture business complexity. Regardless, we are unaware of detailed measures of business complexity that exist for a large cross-section of firms. In the sensitivity analysis section, we perform analysis that disentangle *ARC* from observable measures of operating complexity.

readability have higher analyst following (Barth et al. 2001; Lehavy et al. 2011). In contrast, scant evidence documents that more complex firms are associated with lower coverage (Bhushan 1989). Different from most prior research, our results show that as ARC rises, analysts' coverage declines. These results are stronger for smaller brokerage houses, possibly because smaller brokers selectively cover firms and are therefore more likely to consider ARC in their cost-benefit considerations. Although the need for sophisticated intermediaries is greater as information becomes more complex (e.g., Palmon and Yezegel 2012), analysts are less likely to cover such firms, thus making it particularly hard to predict the performance of complex firms.

We predict that ARC will adversely affect analysts' performance in terms of forecast accuracy, forecast dispersion, the informativeness of stock recommendations, and their responsiveness to earnings announcements. However, since ARC measures the amount of reported accounting information, it is possible that it will be positively associated with analyst performance. Indeed, past research finds that more detailed disclosures can reduce mispricing (Fairfield et al. 1996) and increase the credibility of the financial reports because disaggregation is believed to reduce managers ability to manage earnings (D'Souza et al. 2010). Using a measure of overall disclosure quality, Lang and Lundholm (1996) find a positive association between increased disclosure and analyst performance. Surprisingly, few studies examine the association between disclosure volume and analysts performance.

In a recent study, Chen et al. (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.[7] Indeed, we find that the correlation between the two measures is negative, suggesting that they capture different constructs.[8] Consistent with ARC measuring complexity, we find that higher ARC (more disclosure) is associated with lower forecast accuracy, higher forecast dispersion, lower informativeness of stock recommendations revisions and less responsiveness to earnings announcements. These findings suggest that a greater volume of accounting disclosures that ARC measures is detrimental to the performance of financial analysts. We document that our results are not sensitive to several alternative methods to construct ARC. Further, we show that using the residuals from a model that regresses ARC on firm size, operating complexity, and industry and year fixed effects, produce similar results. This suggests that ARC captures complexity that is incremental to firm size and operating complexity.

We next examine how experience, industry focus, and expertise of financial analysts moderate the association between ARC and analyst performance. Prior research investigates the benefits of experience (Clement 1999; Mikhail et al. 1997) but to the best of our knowledge does not examine circumstances, such as complexity, under which the benefits of experience could vary. Using analyst-firm-year sample we find that general experience (tenure as analyst in years), firm-specific experience (number of years the analyst covered the firm), and industry focus (number of industries the analyst cover) attenuate the negative influence of ARC. These results suggest that experienced and focused analysts are better positioned to use more nuanced disclosures.

We further explore whether the complexity attributed to specific account categories that are inherently difficult-to-understand influences the performance of financial analysts and whether

[7] The objective of the Chen et al. (2015) study is different as they focus on the completeness of disclosure as a measure of disclosure fineness. They rely on about 145 Compustat items while our study considers several thousand items. We thank Chen, Miao, and Shevlin for graciously sharing with us their most recent data.
[8] When we include DQ in our models, our sample size declines by more than 60%, but our ARC results remain similar.

analysts' expertise in these specific accounts can mitigate this effect. Previous studies constructed novel measures to capture detailed account specific complexity (Picconi 2006; Magnan et al. 2015; Chang et al. 2016). Guided by these studies we construct ARC measures in three categories of particularly complex accounts: pensions, fair values, and derivatives. We construct these account-specific complexity measures by counting the reported XBRL tags in each account. Different from previous studies, our 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 is unattainable with measures of readability because it requires a precise measurement of the accounting context. We find that complexity in fair value, derivatives, and pension is associated with lower forecast accuracy.

Finally, we present a new approach for measuring analysts' expertise in specific accounts. We measure the degree of analyst expertise by counting the number of XBRL tags that analysts cover across their portfolio of firms. We conjecture that analysts who cover more account specific tags gain expertise in these accounts. This approach for measuring analyst account specific expertise is new and cannot be easily accomplished without XBRL data. We find that analyst expertise in fair value and derivatives attenuates the detrimental effect of complexity. Interestingly, this form of nuanced expertise weakens the negative effect of account specific complexity to a greater extent than general and firm specific analyst experience.

Our study contributes to the accounting literature in several ways. First, using a broad measure of accounting reporting complexity we demonstrate that complexity is inversely associated with analysts' coverage and performance. These results support efforts to simplify accounting disclosures and are inconsistent with the view that more disclosure is always beneficial to financial statement users. Second, we contribute to the analyst literature that uses different methods to measure complexity of specific accounts (Gu and Wang 2005; Chang et al. 2016) by offering a unified method that is based on the FASB XBRL taxonomy. This method is straightforward, objective, consistent across different accounts, can be extended to other accounts and is not limited to certain samples, periods, or events. Third, while past research shows that certain aspects of reporting complexity influence analyst performance, we are unaware of research that examines circumstances under which the negative effects are attenuated. We find that analysts' experience and industry focus can mitigate the adverse consequences detected. Finally, we propose a new approach to measure analysts' account specific expertise and demonstrate that this form of expertise is more beneficial than general experience 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 coverage and 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 and timely forecasts. Further, the difficulties associated with processing complex accounting information and the importance of experience, expertise, and industry focus should be considered in cost-benefit discussions and coverage decisions.

II. Background

Among users of financial statements, sell-side analysts are often viewed as experts in understanding and interpreting accounting disclosures. Accounting information is chiefly obtained from filings with the SEC and is one of the three primary sources that analysts use to prepare their reports (Ramnath et al. 2008). Regulators and standard setters voiced concerns about the increased complexity of the financial reports (SEC 2006) and initiated simplification efforts (SEC 2008; FASB 2016). The complexity of accounting disclosures in SEC filings significantly differs across firms and industries and can potentially influence analysts' coverage and performance. In our context, complex accounting disclosure can be viewed as the difficulty for financial statement users to understand and analyze detailed economic activities and firm performance from annual 10-K filings. Measuring this aspect of complexity is difficult and reliable broad accounting-based proxies are not widely available.

Accounting complexity and XBRL

We rely on a new approach that uses detailed information in the eXtensible Business Reporting Language (XBRL) to measure the accounting complexity in financial reports. Under SEC rules (SEC 2009), firms must faithfully translate the financial statements and notes in Item 8 of their 10-K filings into XBRL, which is a computer language used to communicate financial data electronically. In XBRL, each accounting concept is depicted with a distinct XBRL tag. Each tag refers to authoritative accounting standards and/or regulations.[9] Financial statements of firms that use a larger number of XBRL tags require reliance on more accounting standards and are therefore more complex to prepare. Consistently, using an accounting complexity measure that is based on the count of XBRL accounting items, Hoitash and Hoitash (2017) find that increased accounting

[9] For example, to represent net sales, companies can use the following XBRL tag: <us-gaap:SalesRevenueNet>. To represent pension and other post retirement defined benefits current liabilities, firms can use " < us-gaap:PensionAndOtherPostretirementDefinedBenefitPlansCurrentLiabilities>

complexity presents challenges for preparers, leading to financial reports that are more susceptible to errors and misapplications of GAAP.

Different from preparers, analysts do not produce financial reports. Instead, they use information disclosed within financial reports to formulate their predictions. Therefore, studies that examine the association between aspects of financial reporting complexity and analysts' performance focus on the difficulty in processing and interpreting the information in financial reports. Linguistic complexity is one feature that increases the difficulty in consuming the reports. The most commonly used measure of linguistic complexity is the Gunning (1952) Fog Index. This index measures the readability and the difficulty to consume the financial reports. Indeed, Lehavy et al. (2011) and Bozanic and Thevenot (2015) find that less readable reports are associated with poor analyst performance. While linguistic complexity is associated with inferior analyst performance, it is unclear whether it captures accounting complexity.

The Fog index focuses on the written narrative of the financial reports and cannot distinguish between accounting and non-accounting communications. In addition, unlike an accounting based measure of complexity, it is not possible to disaggregate the Fog index into topic-specific components. While it is possible that less readable reports are the result of accounting complexity, the XBRL based complexity measure is negatively correlated with the Fog index. This negative correlation is consistent with Li (2008), who finds that reports are less readable due to management incentives to obfuscate bad news, rather than the underlying information being complex. It is therefore likely that the Fog Index captures a different aspect of complexity.

Other studies show that overall operating complexity is detrimental to analyst performance (Duru and Reeb 2002). Few studies concentrate on specific accounts and demonstrate that increased complexity in these accounts can hinder analysts' performance (Plumlee 2003; Gu and

Wang 2005; Chang et al. 2016). The accounting complexity measure employed in this study is different from previous measures of linguistic and account-specific complexity because it captures the overall accounting complexity of the firm without focusing on a specific account.

III. Hypotheses Development

Analyst coverage

Analysts' decision to cover firms is important because the costs and benefits of coverage are rarely clear a priori. This decision principally depends on the cost and expected utility to the brokerage house and the analyst. Increased complexity introduces greater processing costs for investors. As a result, analysts may enjoy greater opportunities for profitable investment recommendations and higher trading commissions when complexity is high. Past research finds that firm size, trading volume, profitability outlook, earnings smoothness, presentations to analysts, voluntary disclosures, and stock beta are positively related to the number of analysts covering a firm (Bhushan 1989; Lang and Lundholm 1993; Previts et al. 1994; McNichols and O'Brien 1997; Francis and Soffer 1997; Healy and Wahlen 1999; Botosan and Harris 2000; Bradley et al. 2003). Concentrating on specific accounting features, Barth et al. (2001) find that analysts' coverage increases with intangible assets. They conclude that firms with more intangible assets have greater potential for mispricing and information asymmetry because the values of intangible assets are seldom disclosed in financial statements. As a result, analysts may be motivated to cover these firms, which are expected to produce greater brokerage income. Similarly, Lehavy et al. (2011) find that analysts are more inclined to cover firms with less readable 10-K filings. Together, these studies suggest that analysts are more likely to cover complex firms.

In contrast, the costs associated with processing complex information and the risk of issuing less accurate estimates for complex firms may discourage analysts from providing coverage. Supporting this, Bhushan (1989) finds a negative relationship between the number of business lines and analyst coverage. Based on these results, he argues that covering multiple industries introduces costs that exceed expected utility. This suggests that as complexity and the related cost of providing coverage increases, analysts are less likely to provide firms with coverage.

Overall, the literature provides conflicting results when examining the association between specific aspects of firm complexity and analyst coverage. Yet, prior research does not examine the association between a holistic measure of accounting reporting complexity and analyst coverage. Examining this issue is important because complexity is a multi-faceted construct and companies can be complex along certain aspects and simple along others. Therefore, focusing on a specific company characteristic or account may distort the results. Since previous studies yield contradicting results, we propose the following non-directional hypothesis:

H1: There is no association between analysts following and accounting complexity.

Analyst performance

Numerous studies examine components of analyst performance, such as forecast accuracy (Brown et al. 1987; Kross et al. 1990), forecast dispersion (Hope 2003a), the informativeness of stock recommendations (Palmon and Yezegel 2012) and the responsiveness of analysts to earnings announcements (Zhang 2008; Lehavy et al. 2011; Yezegel 2015). Many conclude that the accuracy and dispersion of analyst earnings forecasts depend on the difficulty of the forecasting task. Obtaining, analyzing, and interpreting more accounting information can complicate the task of generating accurate forecasts and recommendations because like most business actors, analysts face economic resource constraints and can only devote limited time, staff, and effort to each forecast. When complexity rises, more resources are needed to produce accurate forecasts. Further, even with adequate resources, complex information is harder to understand because it requires greater knowledge to assess current and future performance. Studies examining significant changes in the economics of companies suggest that complex activities reduce analysts' ability to produce accurate forecasts. For example, research finds that complexity as measured by merger activity (Haw et al. 1994) and international diversification (Duru and Reeb 2002) hinders analyst performance. Others focus on the complexity of certain accounts and conjecture that as complexity increases, analyst performance suffers. For example, using the Tax Reform Act of 1986, Plumlee (2003) shows that analysts' revisions of effective tax rate forecasts incorporate simple tax law changes but not complex ones. Similarly, Gu and Wang (2005) find that firms' intangible intensity is associated with lower forecast accuracy, and Chang et al. (2016) show that analysts' earnings forecasts for new derivative users are less accurate and more dispersed. Overall, several studies find that as complexity rises, analyst performance declines. This conclusion is consistent with a decline in judgment quality as task complexity increases (Payne 1976; Payne et al. 1988; Bonner 1994). Yet, research that directly links broad measures of accounting complexity to analysts' performance is scarce.

We hypothesize that the inverse relation between forecast accuracy and complexity documented in prior research translates into a similar inverse relation between the value of stock recommendations and complexity. Analysts use models that rely heavily on earnings forecasts to value companies and base their recommendations on these valuations. Indeed prior research (Loh and Mian 2006), finds that analysts who issue more accurate earnings forecasts also issue more valuable stock recommendations. These results indicate that earnings forecasts serve as a critical input into analysts' valuation models. Consistently, we predict that to the extent that analysts' earnings estimates are less accurate for complex firms, their recommendations will be less informative.

Analysts' responsiveness to earnings announcement measures the timeliness of their forecasts and the effort they exert. Responsiveness, therefore, represents another dimension of analysts' performance. Investors frequently seek advice from analysts to make trading decisions, and because investors need help in interpreting new information, the demand for advice tends to increase following new public information arrivals (Yezegel 2015). One common type of event that often prompts investors to seek guidance from analysts is the earnings announcement. Prior research shows that when analysts are more responsive to earnings announcements, the post-earnings announcement drift tends to be smaller in magnitude, indicating higher market efficiency (Zhang 2008). However, when accounting complexity is higher, analysts will need to exert more effort and time before issuing their forecasts. Consistently, Lehavy et al. (2011) show that when financial reports are less readable it takes analysts more time for to issue forecasts. Similar evidence does not exist with respect to accounting complexity. Nevertheless, we predict that that when the accounting reporting is complex analysts will be less responsive following earnings announcements as they need to exert more effort and time to issue their forecasts.

The XBRL based measure captures accounting complexity under the premise that more accounting disclosures reference more accounting standards, which we posit generates task difficulty that may hinder analyst performance. However, it is also plausible that increased disclosure of accounting information, captured by the XBRL measure, can have a positive effect on analyst performance because additional disclosures more faithfully reflect underlying firm economics. This can potentially assist analysts in forming more accurate forecasts and releasing more impactful recommendation revisions. Indeed, past research finds that analysts' forecasts are more accurate when companies provide a greater level of disclosure about their accounting policies (Hope 2003a). Further, Lang and Lundholm (1996) find that firms with higher-quality disclosures have lower forecast dispersion and smaller forecast errors. Similarly, Lang et al. (2003) find that cross-listed foreign firms that disclose more information are associated with greater forecast accuracy.[10] Most related to our investigation, Chen et al. (2015) find that disclosure quality, measured based on the level of disaggregation of Compustat accounting line items in the financial reports, is associated with lower forecast dispersion and higher forecast accuracy. Overall, past research often suggests that the volume of disclosed accounting information is beneficial to financial analysts.

Although the XBRL based measure can capture the amount of accounting information disclosed by firms, Hoitash and Hoitash (2017) demonstrate that it is more consistent with accounting complexity. Since several studies show that certain aspects of financial report complexity hinder analysts' performance, we predict that a broad measure of accounting complexity will be associated with less accurate and more dispersed forecasts, less informative stock price recommendations, and lower analyst responsiveness. We formulate this prediction in the following hypothesis.

> **H2a:** There is a negative (positive) association between accounting complexity and analysts' forecast accuracy (dispersion).
>
> **H2b:** There is a negative association between accounting complexity and the value of analysts' recommendations.
>
> **H2c:** There is a negative association between accounting complexity and analysts' responsiveness to earnings announcements.

Analyst experience and industry focus

Prior research shows that 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

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10 It is also possible that forecast accuracy will increase and dispersion will decline if analysts of complex clients increase their mimicking behavior (Welch, 2000; Clement and Tse, 2005).

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. 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. The adverse effects of complexity on analysts' performance can potentially be attenuated as analysts' general and firm-specific experience increase.

In addition to general and firm specific knowledge, several studies find that analysts' industry knowledge is valuable (e.g. Piotroski and Roulstone 2004; Kadan et al. 2012).[11] Most recently, 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 higher when analysts cover fewer industries. In our context, it is possible that analysts with greater industry focus 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. This discussion leads to our third hypothesis:

> **H3:** The negative effect of accounting complexity on forecast accuracy is lower among analysts who possess greater general and firm-specific experience, and among analysts who focus on fewer industries.

Account specific analyst expertise

[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.

While prior research examines how general experience is associated with analyst performance, the extant literature lacks an empirical analysis of analyst expertise in specific accounts. Examining this issue is important because recent research shows that account specific complexity is negatively associated with analyst performance. For example, Picconi (2006) finds that analysts fail to fully incorporate and interpret information contained in pension disclosures. Similarly, 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. Finally, 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. Overall, extant research suggests that analysts struggle to fully incorporate information in these complex accounts.[12]

To date, past research has not examined channels through which analysts can alleviate the observed inferior performance. We propose that through their work on their portfolio of clients, analysts can develop high level of technical accounting expertise. Specifically, analysts who frequently encounter specific account categories are likely to rationalize the allocation of additional time to understand complex accounting topics, because the potential knowledge gains can be used across their clients' portfolios. This form of expertise is consistent with the learning by doing model proposed in a similar context by Mikhail et al. (1997). We predict that analysts who gain account specific expertise in pension, fair-value, and derivative accounts will perform

12 Pensions, fair value, and derivatives 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).

better in companies where these accounts are complex. We formulate this prediction in the following hypothesis.

> **H4:** There is a negative effect of account specific complexity on forecast accuracy and this effect is attenuated when analysts possess greater account specific expertise.

IV. 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] 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 from Calcbench, which is an XBRL data provider.[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 12,926 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.[15] Our final sample, after limiting the sample to observations with coverage in Compustat and imposing several other constraints, consists of 6,232 firm-year observations and 112,950 annual analyst earnings

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13 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 .

14 Calcbench is a provider of XBRL financial data, peer benchmarking, detailed analytics, and other XBRL based tools (www.calcbench.com). Calcbench is the primary provider of XBRL based financial data to the SEC. Since Calcbench extracts XBRL tags directly from SEC filings using a standard method, our measure is not based on subjective judgment and could be easily replicated.

15 The initial sample received from Calcbench includes 20,437 annual report filings.

estimates.[16] 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.[17]

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 disclosure needs beyond the taxonomy. XBRL's design enables companies to extend the taxonomy and create unique tags (extensions) that meet their needs.

The primary test variable is a measure of accounting reporting complexity (*ARC*). The construction of *ARC* follows Hoitash and Hoitash (2017) and begins with all reported monetary XBRL tags in Item 8 of the 10-K filings. Each tag refers to accounting standards and regulations. Therefore, more tags suggest greater accounting complexity because more accounting knowledge is required to understand the financial reports. However, since specific tags repeat within a particular disclosure (statement/note/table), we only count distinct tags in each disclosure. Tags that recur do not necessarily increase complexity because their underlying accounting is similar.

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16 We retain only the last annual estimates that analysts issue before the earnings announcement.

17 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.

This repetition typically happens in comparable financial statements that firms are required to report. For example, the tag "NetIncomeLoss" will repeat three times in the statement of cash flow 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.

Account Specific Complexity

One 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 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.[18] These files classify XBRL tags into various account categories. We rely on both 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).[19] We remove these tags because we cannot uniquely attribute them to a specific category.[20] The three new complexity variables are termed *ARC-FAIR*, *ARC-DERIV*, and *ARC-PENS* and capture the number of reported XBRL tags in each category.

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18 A detailed description of the process to construct account specific complexity and a sample of fair value tags appears in Appendices A and B, respectively.

19 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 files are available at: http://www.fasb.org/cs/ContentServer?c=Page&pagename=FASB%2FPage%2FSectionPage&cid=1176164649716 .

20 Companies also use extended tags, which are not part of the XBRL taxonomy. In our sample, 17.4 percent of tags are extensions. We search for common terms that the taxonomy uses to describe tags in specific categories and classify extended tags to those account categories. For example, the word "fair" exists in 98% of the fair value tags in the taxonomy. This process is described in more detail in appendices A and B.

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 analysis uses various 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 six dependent variables to test our hypotheses. The first two dependent variables are used to test H1, labeled *LOGFOLL_FOR* and *LOGFOLL_REC*, measure analyst coverage. As defined in Table 1, *LOGFOLL_FOR* equals the natural logarithm of one plus the number of analysts who issued annual earnings forecasts for the corresponding fiscal year and *LOGFOLL_REC* equals the number of analysts who issued stock recommendation revisions during the fiscal year. As additional analyses, we break down the analyst following measures based on brokerage size (i.e. large and small) and repeat our analyses. To capture analyst performance for testing H2 and H3, we use the accuracy of analysts' earnings forecasts (*ACCURACY*), dispersion of analysts' earnings forecasts (*FORDISP*), the informativeness of their stock recommendation revisions (*RECVAL*) and analysts' responsiveness to earnings announcements (*RESP*). 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] 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.

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[21] Share price is measured as of the end of the fiscal period and adjusted for stock splits and stock dividends.

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] 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] We multiply the market reaction for downgrades by minus one to align the returns to upgrades and downgrades.[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] Finally, we measure *RESP* by calculating the percentage of analysts who issued earnings forecasts for the next fiscal quarter within two-days (0, +1) of the current earnings announcement. To the extent that analysts find it more difficult to analyze information disclosed by companies with greater accounting complexity, we expect an inverse relation between ARC and the proportion of analysts issuing forecasts within two-days after earnings announcements.

Firm-year Level Sample: Control variables

We control for a number of factors that prior research shows to be associated with analyst coverage and performance. Prior studies find attributes of information environment to be strongly associated with analyst coverage and their performance (Bhushan 1989; O'Brien and Bhushan 1990; Lang and Lundholm 1996; Barth et al. 2001; Frankel et al. 2006; Lehavy et al. 2011). Firm size (*LOGMV*), institutional ownership (*IO*), growth potential (*B/M* and *GROWTH*), disclosure

[22] We eliminate revisions after earnings announcements to ensure that confounding events do not affect our measure.
[23] We eliminate revisions issued on days with conflicting recommendation revisions because it is unclear which revision share prices are reacting to (or ignoring).
[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.
[25] We assume that markets are at a minimum semi-strong efficient.

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 firm complexity and information uncertainty by including a host of variables (*FOROPS*, *LOGSGMT*, *EARNVOL*, *FOG10K*, *STDRET*, and *LOSS*). Table 1 defines in detail the control variables that are used in the regression analyses.

Analyst-firm-year Level Sample

In the analyst-firm-year level sample, we focus on forecast accuracy as our performance measure. We do not examine forecast dispersion and proportion of responsive analysts because these measures can only be calculated at the firm-year level. Further, estimates of the informativeness of recommendations are unreliable at the analyst level because analysts issue only a few recommendations for each firm per year. 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, and industry focus (*INDFOCUS*), which is the inverse of the numbers of industries the analyst covers. We also examine whether forecast accuracy, controlling for the firm-specific variables discussed before, is associated with a number of account-specific complexity (*ARC-FAIR*, *ARC-DERIV*, and *ARC-PENS*) and expertise (*EXPRT-FAIR*, *EXPRT-DERIV*, and *EXPRT-PENS*) measures.

Descriptive Statistics

Table 3 Panel A reports descriptive statistics for the final sample. The first section in Table 3 lists the five dependent variables used in the analyses. For ease of interpretation, we report statistics based on untransformed values for all variables. The mean (median) values of analysts following based on earnings estimates (*FOLL_FOR*) and recommendation revisions (*FOLL_REC*) are 16.393 (14) and 7.191 (6), respectively. The mean (median) *ACCURACY* is -0.606 (-0.144). The interquartile range is between -0.403 and -0.052.[26] The mean and median *ACCURACY* values indicate a left skewed distribution. This is primarily because, as in prior research (Lang and Lundholm 1996; Mikhail et al. 1999; Duru and Reeb 2002; Hope 2003b; 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 1.034 (0.275). Similar to *ACCURACY*, *FORDISP* exhibits a skewed distribution (right-skewed). The mean (median) three-day (-1, +1) abnormal market reaction associated with revisions (*RECVAL*) is 3.041 (1.89) percent. Finally, the mean (median) *RESP* is 50.3 (53) percent which suggest that approximately 50% of analyst issue an earnings forecast within two-days after the earnings announcement.

The next section in Table 3 presents descriptive statistics on the four variables that we use to measure accounting reporting complexity. The mean (median) *ARC*, which is the overall tag

[26] 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 minus one so that higher values indicate higher forecast accuracy.

count, equals 407.567 (379).[27] The following three variables represent the tag counts based on account categories: pensions (*ARC-PENS*), fair values (*ARC-FAIR*), and derivatives (*ARC-DERIV*). The mean (median) tag counts for the three categories are 24.866 (5), 12.649 (8), and 8.252 (5), respectively. There is significant variation within the account specific complexity measures. For instance, the first and third quartile values for *ARC-PENS* equal 1 and 48.

The final section in Table 3 Panel A, reports statistics on the control variables used in our analyses. The mean and median market values of firms in our sample are $9.9B and $2.2B and have an average institutional ownership level of 69.2 percent. These statistics indicate that the final sample generally consists of large companies that have a strong institutional presence. Since our focus is on understanding the relation between accounting complexity and analysts' behavior, we require data on analysts' outputs and therefore our sample, by design, consists of larger companies. 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 4.6 years of firm-specific experience and covers an average of 1.72 industries.[28] 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 (0.580).[29] Further, the raw values of our fair value, derivatives and pensions expertise measures equal 211.226, 171.775, and 381.197, respectively. These values represent the mean number of tags reported by companies in analysts' portfolio of coverage in each of these three accounts.[30] Finally, the average (median) forecast age for our sample is 108.948 (97) days.

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[27]Although the natural logarithm of some variables is used in our models, we discuss statistics based on their raw values.
[28] *INDFOCUS* equals one divided by the number of industries covered. Since the mean value for *INDFOCUS* is 0.579 we infer that the average analyst covers 1/0.58 = 1.72 industries.
[29] This transformation reverses the variable's order so that higher (lower) values indicate greater (lower) industry focus.
[30] For example, if an analyst covers four firms, we sum all the fair-value tags covered by that analyst across all four firms. The mean values are the averages in our sample.

Table 4 Panel A presents the Pearson correlations among the accounting reporting complexity measures and the dependent variables. As expected, the estimated correlation between our two analyst coverage variables based on forecasts (*LOGFOLL_FOR*) and recommendation revisions (*LOGFOLL_REC*) is high (0.86) and statistically significant. The strong correlation is consistent with prior research and indicates that most analysts who issue recommendations also provide earnings forecasts for the same company. Other correlation estimates between the dependent variables, with the exception of *FORDISP* and *ACCURACY* (-0.63), are smaller than 0.25 in magnitude. The estimated correlation between *FORDISP* and *ACCURACY* indicates that there is generally greater disagreement among analysts when earnings estimates are less accurate. The two variables, however, do not overlap entirely. Therefore, we study both variables with the aim of providing a comprehensive analysis of the relation between complexity and forecast performance.

The correlation estimates between accounting reporting complexity measures (e.g., *ARC*) and analyst following (*LOGFOLL_FOR*, *LOGFOLL_REC*) reported in Table 4 are all positive and statistically significant. In contrast, the estimated correlations between accounting reporting complexity and measures of forecast accuracy (*ACCURACY*) and forecast dispersion (*FORDISP*) are weaker. We also observe a negative correlation between the value of recommendation revisions and accounting reporting complexity measures suggesting that when complexity rises the value of recommendations declines. Finally, we observe a negative correlation between analysts' responsiveness and complexity. This suggests that as accounting complexity increases analysts find it harder to promptly issue forecasts after earnings announcements. However, we note that the correlation estimates in Table 4 do not control for factors that may influence analyst following and performance. We therefore base our inferences on the regression analyses, which control for confounding factors.

Examining the correlation estimates between the four accounting reporting complexity variables reported in Table 4, we observe that the correlations between overall *ARC* and the other three complexity variables (e.g., *ARC-PENS*, *ARC-FAIR*) are generally high. The high correlations, however, are by design. *ARC* represents an aggregation of the other complexity variables. Finally, the correlations between the complexity measures based on the three account categories (i.e. pensions, fair-values, and derivatives) are lower and range between 0.26 and 0.52. The relatively low correlations indicate that while the account-specific complexity variables are associated with overall *ARC*, they measure more refined and less correlated aspects of accounting complexity.

Table 4 Panel B presents the correlation matrix for the variables in the analyst-firm-year sample that are incremental to the ones in the firm-year sample. We find that the general and firm-specific experience measures correlate positively with our expertise measures. The positive associations imply that analysts with more experience tend to develop greater expertise in areas that are considered to be more complex. Finally, the correlation coefficients among the two experience measures and the three expertise measures are generally high.[31] We, therefore, avoid including these variables simultaneously in the regression models. In addition, we mean center the experience, industry focus, and expertise measures to avoid multicollinearity from biasing the estimation results.

V. Empirical Results

[31] The two experience measures are *GEXP* and *FEXP*. The three expertise measures are *EXPRT-FAIR*, *EXPRT-DERIV*, and *EXPRT-PENS*. *INDFOCUS* measures industry focus. The correlation between *INDFOCUS* and other variables is not high.

Accounting complexity and analyst coverage

Table 5 presents the results of our analysis examining the relation between accounting complexity and analyst coverage. The first model in Table 5 reports the results based on *LOGFOLL_FOR*. The coefficient on *ARC* is estimated to be -0.128 ($p<0.01$) and indicates that a ten percent increase in accounting complexity is associated with an approximately 1.3 percent reduction in analyst coverage. In the following two models, we separately re-estimate the analyst following model for large and small brokerage houses. The *ARC* coefficient estimates are -0.084 ($p<0.05$) and -0.174 ($p<0.01$) for large and small brokerage houses, respectively. The coefficient on *ARC*, estimated based on a sample of large brokerage houses, is significantly smaller than the coefficient on *ARC* based on a sample of small brokerage houses ($p<0.05$). These results suggest that *ARC* serves as a stronger deterrent for small brokerage houses than it does for larger ones. The last three columns in Table 5 show consistent results when we measure analyst following based on recommendations.

Collectively, the estimation results reveal a negative association between analyst coverage and accounting complexity. These results are consistent with financial analysts being less inclined to cover companies with higher accounting complexity. The inverse effect appears to be more pronounced for smaller brokerage houses, which presumably have limited resources to deal with accounting reporting complexity and are more likely to selectively cover firms. Finally, similar to Lehavy et al.'s (2011) findings, our results show that *FOG10K* is associated with greater analyst coverage.

Accounting complexity and analysts' performance

Table 6 presents the regression analysis results for testing H2 using four dependent variables: *ACCURACY, FORDISP, RECVAL,* and *RESP*. In the column labeled "*ACCURACY*", we find that the coefficient on *ARC* is estimated to be -0.438 (p<0.01). *ARC*'s coefficient indicates that a single standard deviation increase in *ARC* is associated with a 0.16 decline in analysts' forecast accuracy (*ACCURACY*). Placing this association in perspective, note that the interquartile range of *ACCURACY* is 0.351. In other words, a single standard-deviation change in *ARC* is associated with nearly half an interquartile range difference in *ACCURACY*. In short, the estimation results point to an economically meaningful and statistically significant inverse relation between accounting complexity and analysts' performance. These results are consistent with accounting complexity representing a significant challenge for financial analysts.

Next, we study the relation between *ARC* and dispersion in analysts' earnings forecasts. In the second column of Table 6, labeled "*FORDISP*", the estimated coefficient on *ARC* equals 0.514 (p<0.01) and indicates a 0.189 increase in forecast dispersion per one standard deviation increase in *ARC*. This increase corresponds to more than a quarter of the interquartile range for forecast dispersion (*FORDISP*). Similar to our inferences from the first model, we find that as accounting complexity increases, analysts' earnings estimates are adversely affected. The two models together provide support for H2a and indicate that analysts' forecasts are less accurate and more dispersed for firms with higher *ARC*. Higher dispersion along with lower accuracy undoubtedly makes it more challenging for investors to use analysts' research in their investment decisions.

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. In Table 6, the column labeled "*RECVAL*" reports the estimation results of our empirical model with the value of stock recommendation revisions serving as the dependent variable. The coefficient on *ARC* in this model represents the association between accounting complexity and the informativeness of analysts' revisions. We find a negative and significant association between *ARC* and *RECVAL* (p< 0.01). The -0.829 *ARC* coefficient suggests a 31 basis point decrease in the market reaction to revisions, per one standard deviation increase in *ARC*. Given that the mean *RECVAL* is 3.04 percent, this corresponds to nearly a ten-percent decrease in the value of revisions per standard deviation increase in *ARC*. This result supports H2b and suggests that analysts have difficulty producing informative research for companies with greater *ARC*. A priori, *ARC* presents a challenge for ordinary investors which may yield a comparative advantage to financial analysts in identifying mispriced securities. However, in contradiction to this notion, we find that *ARC* adversely affects the value of analysts' recommendation revisions.

Finally, we study the relation between *ARC* and analysts' responsiveness to earnings announcement. In the last column of Table 6, labeled "*RESP*", the coefficient on *ARC* is estimated to be -0.09 (p<0.01) and indicates a 3.31 percentage point decrease in analysts' responsiveness per one standard deviation increase in *ARC*. Given that the average analyst responsiveness is 50.3 percent, a 3.31 percentage point change corresponds to nearly a 6.6 percent decrease in analyst responsiveness which is economically meaningful. This result provides support for H2c. Overall, the results in Table 6 suggest an inverse relation between *ARC* and forecast accuracy, the informativeness of recommendations, and responsiveness and a positive relation between *ARC* and forecast dispersion.

Analyst experience and industry focus

The findings reported in Table 6 show that *ARC* is inversely associated with analysts' performance, which is consistent with the conclusion that complexity adversely affects analysts' performance. We next explore whether analyst experience and industry focus mitigate some of the adverse effects of 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 three models that include general experience (*GEXP*), firm-specific experience (*FEXP*), and industry focus (*INDFOCUS*) measures and their interactions with *ARC*. In line with our findings from the firm-year level analysis, we find that *ARC* is inversely associated with forecast accuracy. The coefficient on *GEXP* is positive, suggesting that forecast accuracy increases with general experience. More importantly, we find that the coefficient on the interaction variable, *ARC X GEXP*, is positive and statistically significant (p< 0.01). The positive coefficient on the interaction variable implies that experience helps attenuate the negative effect of complexity. In Model 2, we find that the firm-specific experience (*FEXP*) measure is not statistically significant. Similar to Model 1, however, the coefficient on the interaction variable *ARC X FEXP* is positive and statistically significant (p< 0.01). Overall, experience appears to be helpful to analysts as they deal with accounting reporting complexity. Finally, in Model 3, we examine the relation between analysts' industry focus and their forecast accuracy. We find that the coefficient on the interaction variable, *ARC X INDFOCUS,* is positive and statistically significant (p< 0.01); this implies that analysts who concentrate on fewer industries (i.e. covering fewer industries) perform better, in particular, for firms with more accounting reporting complexity. Overall these results provide support for H3.

Account specific analyst expertise

We next examine whether expertise in certain topics (i.e., fair value, derivatives, and pensions) helps analysts forecast earnings for companies that are more complex in those respects. The first three models in Panel A of Table 8 present the estimation results of the analysis with account-specific complexity and expertise measures along with their interactions. In model 1, we find that the coefficient on *ARC-FAIR* is negative and statistically significant (p<0.01). Our fair-value expertise measure (*EXPRT-FAIR*) is also estimated to be statistically significant (p<0.01) and suggests that analysts who have greater expertise in covering companies that report more fair-value XBRL tags perform better overall in forecasting earnings. Most importantly, we find that the coefficient on the interaction variable, *ARC-FAIR X EXPRT-FAIR* is positive and statistically significant ($p<0.01$). The positive *ARC-FAIR X EXPRT-FAIR* suggests that analysts with fair-value expertise issue earnings estimates that are more accurate, particularly for companies that have complex fair-value reporting. The results reported in Model 2 concerning derivatives echo our findings from Model 1 for fair value. Overall, we find that expertise in derivatives helps analysts estimate earnings of companies that have more complex derivative reporting. In Model 3, we fail to find a statistically significant negative association between pension-specific complexity and forecast accuracy. However, the coefficient on *EXPRT-PENS* implies that analysts with expertise in pensions issue more accurate earnings estimates overall. We do not find an interaction effect that implies a more pronounced positive effect of analysts' pension expertise for firms that are complex in the pensions reporting area.

To ensure that our finding that account-specific expertise attenuates adverse performance consequences is not a manifestation of omitted measures of experience, in Panel B of Table 8 we include the general experience (*GEXP*) measure in the fair value, derivatives, and pension expertise models. This comparison is important because while research finds that *GEXP* is associated with analyst performance, it is infeasible to disaggregate this general experience into specific account categories. We find that the coefficients on our primary variables of interest (*EXPRT-FAIR*, *EXPRT-DERIV*, and *EXPRT-PENS*) and their interactions with account-specific complexity measures (*ARC-FAIR*, *ARC-DERIV*, and *ARC-PENS*) remain unchanged. Further, we find that the coefficients on general experience (*GEXP*), in models 4-6, are positively associated with forecast accuracy. However, the coefficients on the interaction of *GEXP* with account-specific measures are not statistically significant in any of the models. These results suggest that while general experience has an overall positive effect on forecast accuracy, experience does not appear to be associated with an incremental benefit for firms that are complex in their fair-value, derivatives, or pensions reporting. Overall, results in this section provide support for H4.

Sensitivity analyses

Component of ARC that is orthogonal to size and operating complexity

ARC may encompass complexity that is due to operating and linguistic complexity. Therefore, our results 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 include industry and year controls. The model is well specified with an adjusted R-square of 42%. Next, we substitute the residual from this model for *ARC* and find similar results. This suggests that *ARC* captures complexity that goes beyond firm size and operating complexity.

Alternative measurement of ARC

We conduct a number of robustness checks, aimed at examining whether our results are sensitive to alternative methodological choices. First, we split *ARC* into two categories: one based on taxonomy tags and another based on extensions (custom-made tags by companies). We find that our H1 results for analyst coverage are largely driven by the taxonomy counts, whereas in the H2 performance analyses we find a more balanced effect. Responsiveness is negatively associated with *ARC* based on both taxonomy and extension counts. Forecast accuracy is inversely associated with the extension based complexity measure while forecast dispersion and value of recommendations are associated with the taxonomy based complexity measure. 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 reported fact) also yields similar results. Third, we adopt a different approach for classifying XBRL tags into account-specific categories. We search for a list of keywords and their stems that we identify from the taxonomy. For example, to search for derivatives, we use keywords such as derivative, hedge, hedging, and instrument. The advantage of this approach is that it allows us to categorize more tags. We manually verify this classification and noticed that although it is correct, it is subject to cross-membership in multiple accounts. Specifically, some tags are counted twice or more, for example, a particular tag can be classified as fair value, derivatives, and pension tag. We combine this classification with our initial, more conservative, classification that we used in our tables. Although this approach increases the tag counts in each category, results remain unchanged.

Controlling for financial reporting quality and for sample bias

ARC is associated with poor financial reporting quality (Hoitash and Hoitash 2017). It is, therefore, possible that analyst performance suffers from poor financial reporting quality rather than accounting complexity. To alleviate this concern, we control for financial reporting quality measures including misstatements, material weakness, discretionary accruals, and audit delay and find similar results.[32] 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.

VI. Conclusions

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[32] As an alternative sensitivity analysis, we exclude observations in which the company reported a material weakness *or* restatement. Our findings based on this sub-sample are identical to those derived from the full sample.

Accounting reporting complexity leads to greater costs for preparers, requires more time to audit, and complicates regulatory efforts (SEC 2008). In addition, accounting complexity often increases the amount of time and effort that users of financial information need to invest to understand the company's financial position and performance (SEC 2008). Consistently, the FASB (2010) states that "At 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]." This raises the question of whether advisers (e.g., financial analysts) can decipher accounting disclosures, interpret information, and provide informative guidance in cases where there is higher accounting reporting complexity. In order to shed light on how accounting reporting complexity influences the activities of advisers, this study examines variation in analysts' coverage decisions and performance in relation to accounting reporting complexity.

We measure accounting reporting complexity based on the amount of accounting information in XBRL filings. First, we find that analysts shy away from coverage of companies with higher accounting reporting complexity and that this association is stronger among smaller brokerage firms. The inverse relation is at odds with the notion that analysts choose to cover complex firms to enjoy greater opportunities for profitable investment recommendations and higher trading commissions. Second, we find that accounting reporting complexity has an adverse effect on analysts' performance. Specifically, we find that for companies with higher accounting reporting complexity, analysts are less responsive following earnings announcements, and that the accuracy and informativeness of their forecasts and recommendations are significantly lower. In addition, we find greater dispersion among analysts when accounting complexity is high. The increased disagreement among analysts presumably makes it more challenging for investors to rely on analysts' advice.

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 general experience, firm-specific experience, industry focus, and account-specific expertise are able to alleviate the negative effects of accounting complexity. These solutions are relevant to both analysts and those who rely on and monitor analysts. 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 associated 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, because this list of tags applies only to taxonomy tags and not to extended tags, we follow the following process to identify extended tags. To do so, 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 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		
LOGFOLL_FOR	:	The natural logarithm of one plus the number of analysts who issued earnings forecasts for the current fiscal year (I/B/E/S).
LOGFOLL_REC	:	The natural logarithm of one plus the number of analysts who issued stock recommendation revisions during the current fiscal year (I/B/E/S).
ACCURACY	:	Absolute value of reported earnings minus the median earnings forecast for the fiscal year scaled by price and multiplied by minus one (I/B/ES and Compustat).
FORDISP	:	The standard deviation of analysts' annual earnings estimates divided by the end of fiscal year share price (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).
RESP		The percentage of analysts who issued earnings forecasts for the next fiscal quarter within two-days (0, +1) of the current earnings announcement date.
Variables of interest		
ARC	:	The natural logarithm of one plus the total number of numeric tags reported in Item 8 of 10-K filings, which includes the financial statements and notes (Calcbench).
ARC-FS	:	The natural logarithm of one plus the total number of numeric tags reported in the face of the financial statements (Calcbench).
ARC-NOTES	:	The natural logarithm of one plus the total number of numeric tags reported in the footnotes of the financial statements (Calcbench).
ARC-FAIR	:	The natural logarithm of one plus the total number of numeric tags related to fair value accounts reported in the financial statements and notes (Calcbench).
ARC-DERIV	:	The natural logarithm of one plus the total number of numeric tags related to derivative accounts reported in the financial statements and notes (Calcbench).

ARC-PENS	:	The natural logarithm of one plus the total number of numeric tags related to pension accounts reported in the financial statements and notes (Calcbench).
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 where 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 where 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).
EXPRT-FAIR	:	The total number of fair value related tags reported by the companies in the analyst's portfolio of coverage (Calcbench and I/B/E/S).
EXPRT-DERIV	:	The total number of derivative related tags reported by the companies in the analyst's portfolio of coverage (Calcbench and I/B/E/S).
EXPRT-PENS	:	The total number of pension related tags reported by the companies in the analyst's portfolio of coverage (Calcbench and I/B/E/S).
<u>Control variables</u>		
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	:	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.
<u>Firm-year level sample</u>	
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.	12,926
Merge with the Compustat Annual File (comp.funda) based on CIK code.	12,063
Retain companies with positive sales (Compustat data item: *sale*), non-missing common shares outstanding (*csho*) and total assets (*at*) greater than $10 million.	12,062
Require a minimum of two consecutive years of XBRL filings. Note: We implement this filter because firms must tag the financial statement notes only in the second XBRL filing.	11,377
Eliminate firms without the necessary accounting data and without analyst coverage (based on both earnings forecasts and stock recommendations). Specifically, we require that each firm-year has at least three earnings forecasts and one stock recommendation revision (excluding recommendation revisions issued immediately after earnings announcements). Note: We require at a minimum three earnings forecasts to calculate forecast dispersion.	6,232
<u>Analyst-firm-year level sample</u>	
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 not equal to “000000”).	112,950

Panel B: Observations per year

Year	Number of firms	Number of forecasts
2011	900	19,576
2012	1,732	29,735
2013	1,839	32,601
2014	1,761	31,038
Total	6,232	112,950

Table 3 - Descriptive Statistics

The table below reports the descriptive statistics of the variables used in this study. The sample consists of 6,247 observations that represent the fiscal years 2011-2014. Table 1 defines all variables. 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. All variables presented in Panel B, with the exception of *FORAGE,* are mean centered before being included in the regression analysis.

Panel A: Firm-year level sample

	Mean	Median	Std. Dev.	1st Quartile	3rd Quartile
Dependent variables:					
*FOLL_FOR**	16.393	14.000	10.597	8.000	23.000
*FOLL_REC**	7.199	6.000	5.092	3.000	10.000
ACCURACY	-0.606	-0.144	1.886	-0.403	-0.052
FORDISP	1.034	0.275	2.603	0.109	0.777
RECVAL	3.041	1.888	5.067	0.494	4.162
RESP	0.503	0.529	0.223	0.347	0.667
Variables of interest:					
*ARC**	407.567	379.000	159.148	296.000	487.000
*ARC-PENS**	24.866	5.000	28.407	1.000	48.000
*ARC-FAIR**	12.649	8.000	16.055	4.000	15.000
*ARC-DERIV**	8.252	5.000	10.420	1.000	12.000
Control variables:					
*MV**	9941.328	2220.636	29510.629	756.904	6889.813
IO	69.186	72.753	20.118	59.025	83.337
B/M	0.501	0.423	0.423	0.241	0.685
GROWTH	0.105	0.060	0.306	-0.008	0.150
NEWS10K	0.024	0.013	0.032	0.006	0.028
HORIZON	94.856	97.000	35.480	88.000	111.000
TURN	242.658	196.959	170.704	129.198	303.357
ADV	0.015	0.000	0.033	0.000	0.015
RND	0.061	0.000	0.131	0.000	0.051
ROA	0.022	0.039	0.136	0.008	0.078
FOROPS	0.392	0.000	0.488	0.000	1.000
*SEGMENT**	2.741	2.000	1.992	1.000	4.000
EARNVOL	2.633	0.880	8.928	0.463	1.747
FOG10K	19.238	19.208	1.053	18.519	19.939
STDRET	2.184	1.968	0.993	1.470	2.658
LOSS	0.189	0.000	0.392	0.000	0.000
N	6,232				

Panel B: Analyst-firm-year level sample

	Mean	Median	Std. Dev.	1st Quartile	3rd Quartile
*GEXP**	9.402	8.000	6.512	4.000	13.000
*FEXP**	4.606	3.000	3.777	2.000	6.000
INDFOCUS	0.580	0.500	0.326	0.333	1.000
*EXPRT-FAIR**	211.226	120.000	284.100	72.000	202.000
*EXPRT-DERIV**	171.775	108.000	184.770	59.000	204.000
*EXPRT-PENS**	381.197	262.000	389.044	97.000	540.000
*FORAGE**	108.948	97.000	84.888	48.000	118.000
N	112,950				

Table 4 - Correlation Table

The table below reports the estimates of Pearson correlations among the dependent variables and accounting reporting complexity measures. The symbols * and ** indicate statistical significance at the five and one percent levels, respectively.

Panel A: Firm-year level sample

		1	2	3	4	5	6	7	8	9	10
LOGFOLL_FOR	1	1.00									
LOGFOLL_REC	2	0.86^{**}	1.00								
ACCURACY	3	0.16^{**}	0.10^{**}	1.00							
FORDISP	4	-0.14^{**}	-0.08^{**}	-0.63^{**}	1.00						
RECVAL	5	-0.24^{**}	-0.18^{**}	-0.12^{**}	0.18^{**}	1.00					
RESP	6	0.08^{**}	0.04^{**}	0.14^{**}	-0.17^{**}	0.09^{**}	1.00				
ARC	7	0.20^{**}	0.17^{**}	0.01	-0.03^{*}	-0.22^{**}	-0.18^{**}	1.00			
ARC-PENS	8	0.15^{**}	0.11^{**}	0.10^{**}	-0.13^{**}	-0.22^{**}	-0.12^{**}	0.59^{**}	1.00		
ARC-FAIR	9	0.16^{**}	0.13^{**}	0.03^{*}	-0.02	-0.11^{**}	-0.10^{**}	0.66^{**}	0.26^{**}	1.00	
ARC-DERIV	10	0.28^{**}	0.25^{**}	0.04^{**}	-0.06^{**}	-0.21^{**}	-0.16^{**}	0.67^{**}	0.44^{**}	0.52^{**}	1.00

Panel B: Analyst-firm-year level sample

		1	2	3	4	5	6	7
GEXP	1	1.00						
FEXP	2	0.60	1.00					
INDFOCUS	3	-0.06	-0.02	1.00				
EXPRT-FAIR	4	0.24	0.15	0.12	1.00			
EXPRT-DERIV	5	0.21	0.14	-0.02	0.85	1.00		
EXPRT-PENS	6	0.23	0.19	-0.18	0.61	0.71	1.00	
FORAGE	7	0.02	0.02	-0.07	-0.07	-0.10	-0.08	1.00

Table 5 - Accounting complexity and analyst coverage (H1)

The table below presents the results of the regression analysis (OLS) of analyst coverage based on forecasts and recommendation revisions. Table 1 defines all the variables used below. 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 both models. The number of observations and goodness of fit statistics are reported at the bottom of the table.

	Analyst following based on forecasts (*LOGFOLL_FOR*)						Analyst following based on recommendations (*LOGFOLL_REC*)					
	All brokerage houses		Large brokerage houses		Small brokerage houses		All brokerage houses		Large brokerage houses		Small brokerage houses	
Accounting complexity:												
ARC	-0.128***	(-4.45)	-0.084**	(-2.30)	-0.174***	(-4.99)	-0.111***	(-4.09)	-0.078**	(-2.51)	-0.139***	(-4.03)
Information environment:												
LOGMV	0.293***	(47.84)	0.343***	(41.78)	0.200***	(25.77)	0.253***	(41.82)	0.279***	(38.47)	0.169***	(21.84)
IO	0.001**	(2.14)	0.002***	(3.73)	-0.000	(-0.84)	-0.000	(-0.77)	0.001**	(2.34)	-0.002***	(-3.97)
B/M	0.089***	(4.43)	0.085***	(3.36)	0.116***	(4.69)	0.071***	(3.57)	0.069***	(3.13)	0.082***	(3.33)
GROWTH	-0.049**	(-2.49)	-0.098***	(-3.86)	0.015	(0.67)	-0.028	(-1.53)	-0.061***	(-2.84)	-0.003	(-0.12)
NEWS10K	-0.028	(-0.16)	-0.204	(-0.85)	0.071	(0.33)	-0.023	(-0.12)	-0.076	(-0.31)	-0.078	(-0.33)
Incentive to cover:												
TURN	0.001***	(20.21)	0.001***	(14.94)	0.001***	(16.94)	0.001***	(21.95)	0.001***	(16.94)	0.001***	(16.48)
ADV	0.512**	(2.49)	0.683**	(2.33)	0.256	(0.97)	0.391*	(1.88)	0.373	(1.48)	0.263	(0.90)
RND	-0.044	(-0.58)	-0.212**	(-2.17)	0.185*	(1.93)	-0.057	(-0.74)	-0.238***	(-2.74)	0.163	(1.59)
ROA	-0.409***	(-6.40)	-0.448***	(-4.85)	-0.260***	(-3.20)	-0.167**	(-2.48)	-0.270***	(-3.25)	-0.021	(-0.26)
Complexity:												
FOROPS	-0.014	(-0.95)	-0.049**	(-2.55)	0.038**	(1.97)	0.014	(0.87)	-0.016	(-0.90)	0.044**	(2.19)
LOGSGMT	-0.038***	(-3.13)	-0.038**	(-2.50)	-0.046***	(-2.99)	-0.035***	(-2.89)	-0.023	(-1.63)	-0.048***	(-3.12)
EARNVOL	-0.002***	(-3.28)	-0.003***	(-3.29)	-0.001	(-0.59)	-0.001	(-1.49)	-0.002**	(-2.37)	-0.000	(-0.08)
FOG10K	0.018***	(2.70)	0.017*	(1.94)	0.015*	(1.75)	0.018***	(2.70)	0.022***	(2.97)	0.006	(0.76)
Uncertainty:												
STDRET	-0.049***	(-4.32)	-0.053***	(-3.30)	-0.047***	(-3.60)	0.002	(0.19)	-0.001	(-0.04)	0.005	(0.38)
LOSS	0.048**	(2.32)	0.059**	(2.18)	0.032	(1.29)	0.052**	(2.50)	0.041	(1.64)	0.040	(1.50)
Intercept	0.409**	(1.98)	-0.760***	(-2.92)	0.692***	(2.80)	-0.159	(-0.78)	-1.194***	(-5.26)	0.350	(1.40)
Ind. & Yr. Dummies	Yes		Yes		Yes		Yes		Yes		Yes	
N	6,232		6,232		6,232		6,232		6,232		6,232	
R-square	0.691		0.651		0.451		0.588		0.541		0.333	
Adj. R-square	0.690		0.649		0.448		0.586		0.539		0.330	

Table 6 - Accounting complexity and forecast accuracy & dispersion and value of recommendation revisions (H2)

The table below presents the results of the regression analysis (OLS) of analysts' performance using forecast accuracy (ACCURACY), forecast dispersion (FORDISP), the value of recommendation revisions (RECVAL) and responsiveness (RESP). Table 1 defines all the variables used below. 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, with probability levels one-tailed for hypothesized directional expectations. Industry and year fixed-effects are included in both models. The number of observations and goodness of fit statistics are reported at the bottom of the table.

	ACCURACY		FORDISP		RECVAL		RESP	
Accounting complexity:								
ARC	-0.438***	(-3.43)	0.514***	(3.36)	-0.829***	(-3.94)	-0.090***	(-6.94)
Information environment:								
LOGMV	0.035	(1.12)	-0.120***	(-2.78)	-0.158**	(-2.03)	0.005	(1.25)
IO	0.005***	(3.07)	-0.012***	(-5.79)	0.001	(0.14)	0.002***	(8.55)
B/M	-0.222	(-1.40)	0.874***	(4.15)	0.032	(0.15)	-0.040***	(-4.25)
GROWTH	0.172	(1.22)	-0.247	(-1.27)	-1.044***	(-3.09)	-0.032***	(-3.24)
NEWS10K	-4.285***	(-3.08)	4.579**	(2.56)	-4.074	(-1.63)	-0.178*	(-1.67)
LOGFOLL_FOR	0.102	(1.38)	0.280***	(2.92)	-0.556***	(-3.25)	-0.005	(-0.49)
LOGHORIZON	-0.115**	(-2.20)	0.172***	(2.59)	0.016	(0.14)	-0.020***	(-2.73)
Incentive to cover:								
TURN	-0.000	(-0.76)	0.001	(1.46)	-0.002***	(-2.60)	0.000	(1.41)
ADV	-1.147	(-1.26)	0.883	(0.89)	7.740***	(3.69)	0.635***	(5.91)
RND	1.666***	(4.93)	-1.548***	(-3.37)	1.669**	(2.04)	0.245***	(7.58)
ROA	1.512***	(2.88)	-3.159***	(-3.91)	-1.369	(-1.27)	0.212***	(6.21)
Complexity:								
FOROPS	0.092*	(1.84)	-0.067	(-1.04)	-0.056	(-0.44)	0.035***	(4.37)
LOGSGMT	-0.025	(-0.69)	0.056	(1.24)	0.005	(0.06)	-0.012**	(-2.00)
EARNVOL	0.003	(0.95)	0.013**	(2.33)	0.001	(0.13)	-0.001**	(-2.37)
FOG10K	-0.014	(-0.73)	-0.020	(-0.75)	0.102**	(2.07)	-0.001	(-0.19)
Uncertainty:								
STDRET	-0.393***	(-4.84)	0.742***	(7.35)	1.791***	(10.09)	0.001	(0.11)
LOSS	-0.720***	(-5.76)	0.951***	(6.00)	0.241	(0.86)	0.018	(1.63)
Intercept	3.051***	(2.94)	-3.790***	(-3.07)	5.479***	(3.34)	0.965***	(9.08)
Ind. & Yr. Dummies	Yes		Yes		Yes		Yes	
N	6,232		6,232		6,232		6,232	
R-square	0.193		0.353		0.219		0.132	
Adj. R-square	0.190		0.351		0.216		0.129	

Table 7 - Analysts' performance and the interaction between accounting complexity, experience and industry focus (H3)

The table below presents the results of the regression analysis (OLS) of analysts' forecast accuracy at the forecast level. Table 1 defines all the variables used below. All variables used in the interaction analysis are mean centered. The *t*-statistics are in parentheses, 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, with probability levels one-tailed for hypothesized directional expectations. Industry and year fixed-effects are included in both models. The number of observations and goodness of fit statistics are reported at the bottom of the table.

	Model 1		Model 2		Model 3	
<u>Accounting complexity:</u>						
ARC	-0.262***	(-2.74)	-0.260***	(-2.71)	-0.276***	(-2.93)
GEXP	0.083***	(6.04)				
ARC X GEXP	0.064**	(1.79)				
FEXP			0.017	(1.14)		
ARC X FEXP			0.182***	(4.23)		
INDFOCUS					-0.022	(-0.42)
ARC X INDFOCUS					0.482***	(3.38)
<u>Information environment:</u>						
LOGMV	0.039*	(1.70)	0.038*	(1.65)	0.039*	(1.72)
IO	0.010***	(6.19)	0.010***	(6.26)	0.010***	(6.22)
B/M	-0.637***	(-4.91)	-0.636***	(-4.90)	-0.655***	(-5.03)
GROWTH	0.151	(1.23)	0.146	(1.19)	0.155	(1.27)
NEWS10K	-4.644***	(-3.75)	-4.660***	(-3.76)	-4.662***	(-3.77)
LOGFOLL_FOR	0.115**	(2.53)	0.117**	(2.55)	0.116**	(2.56)
<u>Incentive to cover:</u>						
TURN	-0.000*	(-1.67)	-0.000*	(-1.69)	-0.000	(-1.55)
ADV	-0.342	(-0.66)	-0.316	(-0.62)	-0.421	(-0.84)
RND	0.785***	(2.61)	0.785***	(2.61)	0.853***	(2.77)
ROA	1.779***	(3.94)	1.792***	(3.97)	1.738***	(3.85)
<u>Complexity:</u>						
FOROPS	0.117***	(2.79)	0.118***	(2.80)	0.117***	(2.79)
LOGSGMT	-0.013	(-0.43)	-0.012	(-0.40)	-0.007	(-0.24)
EARNVOL	-0.031***	(-4.02)	-0.031***	(-4.01)	-0.032***	(-4.07)
FOG10K	0.013	(0.72)	0.012	(0.70)	0.012	(0.68)
<u>Uncertainty:</u>						
STDRET	-0.395***	(-6.54)	-0.398***	(-6.58)	-0.403***	(-6.69)
LOSS	-0.911***	(-8.19)	-0.912***	(-8.19)	-0.906***	(-8.17)
<u>Forecast attribute:</u>						
FORAGE	-0.178***	(-14.80)	-0.178***	(-14.74)	-0.178***	(-14.81)
Intercept	-0.043	(-0.11)	-0.042	(-0.10)	-0.035	(-0.09)
Industry & Year Dummies	Yes		Yes		Yes	
N	112,950		112,950		112,950	
R-square	0.255		0.254		0.255	
Adj. R-square	0.255		0.254		0.254	

Table 8 – Analyst performance, account-specific accounting complexity and analysts' account-specific expertise (H4)

The table below presents the estimation results of the regression (using OLS) of accuracy at the forecast level on, account-specific complexity and expertise measures, general experience, and control variables. Table 1 defines all the variables used below. All variables used in the interaction analysis are mean centered. The *t*-statistics are in parentheses, 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, with probability levels one-tailed for hypothesized directional expectations. Industry and year fixed-effects are included in both models. The number of observations and goodness of fit statistics are reported at the bottom of the table.

Panel A

	Model 1		Model 2		Model 3	
Accounting Complexity:						
ARC-FAIR	-0.078**	(-2.56)				
EXPRT-FAIR	0.096***	(5.35)				
ARC-FAIR X EXPRT-FAIR	0.071***	(4.74)				
ARC-DERIV			-0.121***	(-4.42)		
EXPRT-DERIV			0.051***	(3.00)		
ARC-DERIV X EXPRT-DERIV			0.044***	(3.25)		
ARC-PENS					-0.022	(-1.18)
EXPRT-PENS					0.056***	(3.43)
ARC-PENS X EXPRT-PENS					0.011	(1.10)
Information environment:						
LOGMV	0.018	(0.86)	0.037*	(1.70)	0.013	(0.57)
IO	0.010***	(6.24)	0.010***	(6.16)	0.010***	(6.15)
B/M	-0.715***	(-5.55)	-0.655***	(-5.24)	-0.700***	(-5.62)
GROWTH	0.182	(1.46)	0.163	(1.30)	0.183	(1.47)
NEWS10K	-4.612***	(-3.72)	-4.643***	(-3.73)	-4.625***	(-3.71)
LOGFOLL_FOR	0.107**	(2.36)	0.119***	(2.59)	0.120***	(2.61)
Incentive to cover:						
TURN	-0.000*	(-1.69)	-0.000*	(-1.83)	-0.000*	(-1.87)
ADV	-0.134	(-0.26)	-0.381	(-0.75)	-0.121	(-0.23)
RND	1.010***	(3.38)	0.830***	(2.77)	1.003***	(3.31)
ROA	1.981***	(4.50)	1.848***	(4.09)	1.967***	(4.45)
Complexity:						
FOROPS	0.104**	(2.48)	0.114***	(2.73)	0.098**	(2.32)
LOGSGMT	0.007	(0.21)	-0.012	(-0.40)	-0.012	(-0.40)
EARNVOL	-0.033***	(-4.22)	-0.031***	(-4.02)	-0.033***	(-4.20)
FOG10K	0.010	(0.58)	0.011	(0.64)	0.013	(0.73)
Uncertainty:						
STDRET	-0.395***	(-6.66)	-0.399***	(-6.67)	-0.385***	(-6.36)
LOSS	-0.890***	(-8.02)	-0.909***	(-8.12)	-0.906***	(-8.16)
Forecast attribute:						
FORAGE	-0.174***	(-14.41)	-0.177***	(-14.61)	-0.175***	(-14.31)
Intercept	0.196	(0.48)	0.041	(0.10)	0.133	(0.32)
Industry & Year Dummies	Yes		Yes		Yes	
N	112,950		112,950		112,950	
R-square	0.255		0.255		0.254	
Adj. R-square	0.255		0.255		0.253	

Table 8 – Panel B

	Model 4		Model 5		Model 6	
Accounting Complexity:						
ARC-FAIR	-0.075**	(-2.47)				
EXPRT-FAIR	0.082***	(4.31)				
ARC-FAIR X EXPRT-FAIR	0.070***	(4.44)				
ARC-DERIV			-0.116***	(-4.27)		
EXPRT-DERIV			0.035*	(1.91)		
ARC-DERIV X EXPRT-DERIV			0.042***	(2.91)		
ARC-PENS					-0.020	(-1.06)
EXPRT-PENS					0.045***	(2.69)
ARC-PENS X EXPRT-PENS					0.012	(1.13)
GEXP	0.053***	(3.66)	0.070***	(4.59)	0.065***	(4.44)
ARC-FAIR X GEXP	0.001	(0.10)				
ARC-DERIV X GEXP			0.004	(0.29)		
ARC-PENS X GEXP					-0.016	(-1.76)
Information environment:						
LOGMV	0.018	(0.83)	0.037*	(1.67)	0.013	(0.56)
IO	0.010***	(6.20)	0.010***	(6.11)	0.010***	(6.11)
B/M	-0.714***	(-5.54)	-0.655***	(-5.25)	-0.700***	(-5.61)
GROWTH	0.185	(1.48)	0.168	(1.34)	0.185	(1.48)
NEWS10K	-4.609***	(-3.72)	-4.634***	(-3.72)	-4.617***	(-3.70)
LOGFOLL_FOR	0.108**	(2.38)	0.119***	(2.60)	0.120***	(2.62)
Incentive to cover:						
TURN	-0.000*	(-1.67)	-0.000*	(-1.80)	-0.000*	(-1.86)
ADV	-0.154	(-0.30)	-0.413	(-0.81)	-0.169	(-0.32)
RND	1.007***	(3.37)	0.822***	(2.74)	0.983***	(3.24)
ROA	1.980***	(4.50)	1.849***	(4.09)	1.968***	(4.45)
Complexity:						
FOROPS	0.104**	(2.48)	0.113***	(2.71)	0.098**	(2.31)
LOGSGMT	0.006	(0.18)	-0.013	(-0.42)	-0.011	(-0.36)
EARNVOL	-0.033***	(-4.20)	-0.031***	(-4.00)	-0.033***	(-4.19)
FOG10K	0.010	(0.59)	0.011	(0.65)	0.013	(0.71)
Uncertainty:						
STDRET	-0.396***	(-6.66)	-0.399***	(-6.68)	-0.386***	(-6.37)
LOSS	-0.889***	(-8.02)	-0.908***	(-8.12)	-0.906***	(-8.17)
Forecast attribute:						
FORAGE	-0.175***	(-14.47)	-0.178***	(-14.67)	-0.176***	(-14.35)
Intercept	0.195	(0.48)	0.053	(0.13)	0.157	(0.38)
Industry & Year Dummies	Yes		Yes		Yes	
N	112,950		112,950		112,950	
R-square	0.256		0.256		0.254	
Adj. R-square	0.255		0.256		0.254	