Industry Accounting Complexity and Earnings Properties: Does Auditor Industry Expertise Matter?

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ABSTRACT

We test if auditor industry expertise affects the quality of audited earnings in those industries with greater accounting complexity, which is where differential auditor expertise is expected to matter the most. The research design in prior studies assumes auditor expertise affects earnings quality across-the-board in all industries. However, in industries with greater accounting complexity, the measurement of earnings is expected to be noisier with more measurement error, and auditor expertise is predicted to facilitate the reporting of less noisy (higher quality) earnings by firms in these industries. We develop a novel method to measure accounting complexity based on whether or not an industry has industry-specific accounting guidance to supplement GAAP accounting standards. This supplemental guidance is provided by the AICPA's *Audit and Accounting Practice Guides* and FASB's *Topic 900: Industry Series*, which results in 18 of 48 Fama-French industries being classified as complex. We validate this classification by examining earnings properties in the two industry groups. Consistent with the classification scheme, firms in complex industries have noisier earnings as evidenced by (1) larger within-industry yearly variation in earnings; (2) less earnings persistence over time; and (3) larger analysts' forecast errors. We then use the industry complexity classification framework to test if auditor industry expertise improves the quality of audited earnings in complex industries. As expected, in complex industries earnings quality improves (smaller accruals, less accrual estimation error, fewer restatements, and smaller analysts' forecast errors). However, auditor industry expertise is insignificant in non-complex industries. The study underscores the centrality of industry complexity in understanding earnings properties and illustrates how the incorporation of industry complexity can give a more nuanced understanding of accounting phenomena.

Keywords: Industry Complexity, Earnings Quality, Auditor Industry Expertise

JEL classification: L84, M41, M49

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1. Introduction

This paper investigates industry accounting complexity and the effect of auditor industry expertise on the quality of clients' audited earnings, conditional on industry complexity. We hypothesize that auditor industry expertise plays a greater role in improving earnings quality when the application of GAAP in the client's industry is inherently more complex. The reason is that industry-specific accounting complexity creates more opportunity for auditors to develop meaningful industry expertise and specialization, in contrast to simpler "plain vanilla" industries where there is less scope for auditors to develop deep expertise and to convincingly differentiate themselves from other auditors. While this distinction is intuitive, the research design in prior studies presumes that industry expertise is applicable across-the-board to all industries. In contrast to the prior literature, our evidence suggests this is not the case and that auditor industry expertise only matters in those industries with greater accounting complexity.

Our study is a response to the call in DeFond and Zhang (2014) to shift the focus of archival audit research beyond *whether* certain auditors provide differential audit quality, to the question of *why* this is the case. We believe inherent accounting complexity in an industry is fundamental to understanding why auditor industry expertise exists, why auditor differentiation occurs, and why it has the potential to affect the quality of audited earnings.[1] Accounting researchers have long recognized that industry affiliation can be an important consideration in research design choices. For example, it is common practice to incorporate industry affiliation into empirical models either with industry fixed effects or by estimating regression models by industry such as models of abnormal accruals. However, little attention has been paid to the fact that the difficulty

[1] DeFond and Zhang (2014) make this argument in the context of Big 4 differential audit quality (see p.8 therein), but the argument logically applies to other auditor characteristics such as industry expertise.

in implementing accounting standards varies across industries. Accordingly, our study investigates accounting complexity as a broad industry-wide phenomenon that affects all firms in the industry rather than as a firm-specific characteristic.

We develop a novel approach to measure industry accounting complexity based on industry-specific accounting guidance contained in either the Financial Accounting Standards Board's (FASB) *Topic 900: Industry Series* or the American Institute of Certified Public Accountants' (AICPA 2014) *Audit and Accounting Practice Guides*. Both sources provide authoritative guidance for handling complex accounting issues in industries to supplement GAAP accounting standards. We construct this measure by mapping each one of the 48 industries in Fama and French (1997) to the presence (a more complex industry) or absence (a less complex industry) of either an AIPCA guide or FASB guide.[2] The appeal of using these guides to measure industry-level accounting complexity is that they are based on either (1) the accounting profession's assessment of those industries with special accounting complexities in financial reporting (AICPA Guides); or (2) FASB's assessment of the need for special guidance in certain industries to supplement more generic GAAP accounting standards.

We begin the empirical analysis by providing some validation of the classification of industries into the complex and non-complex categories. By definition, the measurement of earnings is expected to be noisier in complex industries, even with supplemental guidance to GAAP standards. Our evidence confirms this. First, we predict and find supporting evidence that earnings of firms in complex industries have greater within-industry yearly variation suggesting greater heterogeneity, whereas the yearly variance in non-complex industries is smaller which indicates greater homogeneity. Second, earnings persistence is used because it is a common measure of earnings quality and because of its hypothesized relationship with decision usefulness

[2] The industry definitions are taken from Kenneth R. French's website:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html

(Dechow, Ge and Schrand 2010). If earnings are noisier earnings in complex industries, we expect to observe lower persistence over time, and this is confirmed in the analysis. Third, given the inherent noise in earnings, earnings are more difficult to forecast for firms in industries with complex accounting, and again, the tests confirm that this is the case. Together these three analyses provide confirmatory evidence on the validity the industry classifications.

We then use the industry classification framework to test if auditor industry specialization (expertise) affects the quality of audited earnings differently for firms in complex and non-complex industries. Consistent with a large body of prior research, audit quality is inferred by testing the association of auditor characteristics (industry expertise in our case) with statistical properties of earnings commonly used to assess earnings quality. We use three accrual-based proxies for earnings quality and two restatement-based properties. The accrual-based proxies are (1) performance-adjusted abnormal accruals (Jones 1991; Kothari et al. 2005)' (2) accrual estimation errors using the cross-sectional adaption of the model in Dechow and Dichev (2002) as implemented in Dechow et al. (2011); and (3) the absolute value of working capital accruals.[3] As Dechow et al. (1995) and Kothari et al. (2005) demonstrate, accruals metrics are a noisy and potentially biased measure of earnings quality, so we also use a more direct measure based on restatements. A restatement is prima facie evidence of low-quality accounting through the misapplication of GAAP when the financial statements were originally issued. The two restatement measures in the study are (1) an indicator variable coded one for any accounting-related restatement, and (2) an indicator variable coded one for those restatements that result in a downward restatement of earnings.

Drawing on prior research, audit industry experts or "specialists" are defined as city-specific industry leaders. These two terms are used interchangeably in the paper. City industry

[3] The analysis of firm fundamentals in Dechow and Dichev (2002) indicates that absolute working capital accruals is a good proxy for accruals/earnings quality.

leaders have been shown in prior studies to have higher fees, which is suggestive of higher quality differentiated audits, and the clients' of such auditors have higher earnings quality which is consistent with expert auditors improving their clients' application of GAAP (Ferguson et al. 2003; Reichelt and Wang 2010).[4] As expected, we find that firms in complex industries with specialist auditors have higher quality earnings, i.e., smaller abnormal and working capital accruals, smaller accrual estimation error, and fewer restatements. These results are robust to using a propensity score methodology and sample to control for potential endogeneity in the firm's auditor choice. In addition, we report evidence that analysts' forecasts for firms in complex industries are more accurate for firms whose auditor is an industry expert. In contrast, for firms in non-complex industries, an audit industry specialist has no significant association with earnings properties or analysts' forecasts. Together, these results are consistent with auditor industry expertise in complex industries reducing the noise in earnings measurement, leading to improved earnings quality and improved forecasts by analysts.

To summarize, this study develops and validates a novel measure of industry complexity based on industry guidance by the AICPA and FASB. We document the centrality of industry complexity in understanding basic properties of earnings and the usefulness of earnings for decision-making. Using this framework, we also contribute to the auditing literature by showing that auditor industry expertise has a narrower effect on earnings quality than previously documented. While reinforcing the importance of auditor industry expertise, our results also show that there is not an-across-the board effect as implied by prior studies. This finding may also explain some of the conflicting recent evidence in the literature regarding the association between

[4] We control for an audit firm's national industry leadership based on aggregate US market share, and the variable is not significant in any of the model estimations. In an alternative specification, national industry leadership is used as the test variable and is insignificant which is consistent with recent research documenting the primacy of audit office characteristics in understanding auditor differentiation.

industry specialization and earnings quality (e.g. Francis and Yu 2009; Choi et al. 2010; Reichelt and Wang 2010; Minutti-Meza 2013).

While our analysis examines the effect of auditor industry expertise on earnings quality, we believe the industry complexity framework has potential to sharpen research designs used in other areas of accounting research as well. We document that accruals are fundamentally different in complex industries, but other earnings properties such as comparability and conditional conservatism are also likely to be different in complex industries. For these reasons, in general we predict that accounting numbers will be less useful for debt contracting and executive compensation in complex industries relative to non-complex industries, and alternative monitoring and compensation mechanisms are more likely to be observed in complex industries. We would also expect corporate governance to be more challenging in complex industries because accounting numbers in these industries are inherently noisier and less useful for internal monitoring by boards of directors. Finally, with noisier earnings and less effective monitoring by boards, we would expect to observe greater managerial entrenchment, hubris, empire building and value-destroying behavior by firms in complex industries.

The study proceeds as follows. The next section develops the hypotheses. Section III describes the sample and reports evidence on earnings properties which validates the industry classification developed in the study. Sections IV and V report the effect of auditor industry expertise on earnings quality and analysts' forecast accuracy, conditional on industry-level accounting complexity. Section VI concludes the study.

2. Industry complexity and hypotheses

2.1 Industry complexity

Prior studies have examined the relation between earnings and various aspects of a firm's complexity. For example, Bushman et al. (2004) show that proxies for organizational and operational complexity are associated with governance and earnings timeliness. Doyle et al. (2007) examine determinants of internal control weaknesses and find that firms disclosing material weaknesses have more complex business operations. In terms of firm-specific accounting complexity, Plumlee and Yohn (2010) find that complex accounting standards contribute to an increased incidence of restatements, while Petersen (2012) finds that revenue recognition complexity, measured through a 10-K content analysis, increases the probability of revenue restatements from both intentional and unintentional misreporting.[5]

Accounting complexity arises from the inherent difficulty in applying generally accepted accounting principles (GAAP), and mapping a firm's economic activity to accounting rules for the recognition and measurement of accounting elements (assets, liabilities, revenues, expenses, and owners' equity). The above-cited studies measure various aspects of complexity as a firm-specific characteristic. However, much of a firm's economic activity will share a commonality with other firms in the industry, such as a similar business model, so it is reasonable to think of accounting complexity as a broader industry-level construct.[6] That is, different industries have underlying characteristics that give rise to greater or lesser degree of accounting complexity (Danos et al. 1989; Simunic 1989; Solomon et al. 1999; Cahan et al. 2008; SEC 2014; Peterson 2012). In some industries, such as the service sector, the business model is often a near-cash operation that poses relatively little difficulty in applying GAAP. In contrast, firms in other industries such as software development, or industries with long operating cycles such as construction and government defense contractors have more complex business models which make the application of GAAP

[5] Two other studies examine the complexity of 10-K filings and investor activity and, while not directly linked to earnings quality, are nonetheless of note here. You and Zhang (2009) find that "sluggish" investor reaction to 10-K filings is stronger for firms with more complex 10-K reports while Miller (2010) reports that more complex filings are associated with lower overall trading. Both studies use the length of the 10-K as a measure of complexity (Miller also analyzes report readability) and attribute their findings to the increased costs to investors of processing complex reports.
[6] While there may also be idiosyncratic firm-specific complexities, our focus is on the general industry-wide characteristics that give rise to accounting complexity.

less straightforward, requiring more interpretation and judgment as well as creating more difficult recognition and measurement issues.

To illustrate industry-level accounting complexity, consider the computer and software industry. Firms in this sector typically bundle multiple products together, such as service agreements, free software updates, and installation or trouble-shooting help. As a result, revenue recognition for these firms often requires the application of “multiple deliverable” accounting rules. These rules can be quite complicated to implement, requiring the estimation of the selling price for each separate unit of accounting and a deep understanding of the industry’s products and services. This complexity, presumably, is what lead the AICPA to issue its guide “Auditing Revenue in Certain Industries” and the FASB to issue topic 985-20 “Costs of Software to Be Sold, Leased, or Marketed.”

Given inherent difficulty in applying GAAP and the greater likelihood of estimation error, earnings in complex industries are expected to be a noisier signal of firm performance, even in the presence of supplemental GAAP guidance. Because of this noise the earnings of firms in complex industries are predicted to have larger yearly cross-sectional variation, lower persistence over time, and larger analysts’ forecast errors compared to firms in less complex industries. These arguments lead our first hypothesis in alternative form:

H1: In complex industries, earnings of firms exhibit greater within-industry yearly variation, less persistence over time, and larger analysts’ forecast errors, compared to firms in non-complex industries.

While supplemental GAAP guidance may improve the implementation of GAAP in complex industries, H1 is still expected to hold because there is an upper bound on the effectiveness of such guidance in reducing the inherent noise in earnings for firms in complex industries.

2.2 Industry accounting complexity

Our measure of industry complexity is based on two sources of authoritative industry-specific guidance. The first is FASB's *Topic 900: Industry Series*. The *Industry Series* was created during the FASB's recent codification project. During this project, FASB reviewed US GAAP standards in order to simplify and standardize GAAP guidance. Any content that contained "***incremental*** industry-specific guidance [emphasis added]" (FASB 2014, p.13) was filtered and placed into one of the industry topics. Thus, the appeal of using this guidance to identify complex industries is that these are the industries which standard setters identify as requiring more specific guidance than provided by standard GAAP. All industry-specific topics are in the 900 section of the new codification.

The second source of authoritative guidance is the AICPA's *Audit and Accounting Practice Guides*, which address complex accounting issues and related reporting practices, and which provide authoritative "how-to" advice for administering the audit.[7] The industries and subject matter represented by the guides are selected by AICPA technical committees and industry experts, and chosen in part based on feedback from advice-seeking auditors and industry accountants (AICPA, 2014). Sixteen of the 28 guides focus on specific industries and these are the basis for determining industry complexity. The other 12 guides deal with either specific transactions or auditor testing procedures. The appeal of using the AICPA guides to measure industry complexity is that they are based on the auditing profession's self-assessment of those industries that give rise to challenging accounting implementation issues. Table 1 lists the industries addressed by the FASB's *Topic 900: Industry Series* and AICPA *Guides*. Note that the SEC (2014) also gives

[7] Auditing guidance provided in the *AICPA Guides* carries the same level of authority as auditing interpretations of Statements of Auditing Standards in accordance with Generally Accepted Auditing Standards, AU section 150 (AICPA 2014). Compared to other AICPA standards (e.g., Accounting Research Bulletins or Accounting Interpretations), a "relatively small portion of [AICPA Guides' content] was superseded by the Codification." An example of an AICPA Guide that was superseded is the guide for the Agriculture industry, which is now contained in FASB Topic 905. Thus, both sources of guidance still exist and both contain important authoritative guidance.

industry-specific 10-K disclosure guidance, though all industries in the SEC guides are already classified as complex in our framework.

[INSERT TABLE 1]

We define industries using the 48 industry groupings in Fama and French (1997). For each of the 48 industry codes (FF48) we determine the presence (a more complex industry) or absence (a less complex industry) of a FASB *Topic 900* or an AICPA *Audit and Accounting Practice Guide*. For most industries, the mapping process is straight forward as a majority of both the AICPA and FASB guides are explicitly industry-specific. For example, FASB *Topic 905: Agriculture* maps directly to FF48 industry code 1 (Agriculture). However, for a few industries the matching process is more nuanced. An example is the AICPA *Guide* entitled *Federal Government Contractors* which does not provide coverage for a specific industry as such, but there are certain industry sectors for which the guide is more applicable. For example, aerospace and defense firms, computer services companies, and engineering and construction firms receive a significant percentage of their revenues from government contracts.[8,9] Therefore we map the *Federal Government Contractors* AICPA guide to industries with the most defense, computer services, and engineering services firms (FF48 Codes 26 and 24). Table 1 Panel B lists all FF48 codes and the corresponding FASB *Topic 900* or AICPA *Guide*, if applicable. The last FF48 industry code in Table 1, "Almost Nothing", is a miscellaneous category for firms that did not fit well into other categories. Because it seems unlikely that auditors would be able to develop specialization in such an industry, we drop all firms in this industry from the analysis.

[8] For 2008, aerospace and defense firms, computer services firms, and engineering firms received 47.7 percent, 19.0 percent, and 11 percent of the dollars awarded to the 100 contractors with largest total government contracts. The top five government contractors in terms of dollars awarded were all defense-related firms. In 2008 these five firms received from 18 percent (The Boeing Co.) to 35 percent (Lockheed Martin Corp.) of their total revenues from government contracts (median of 26 percent). The top five contractors in the computer services and engineering services industries received a median 22 percent and 11 percent, respectively of their total revenue from government contracts for 2008. (source: http://washingtontechnology.com/toplists/top-100-lists/2009.aspx).

[9] Computer services companies are explicitly discussed as well by a second guide, *Auditing Revenue in Certain Industries*, which focuses heavily on revenue recognition in the computer hardware and software industry.

Next we create a dichotomous variable denoted *COMPLEX*, with a value of one for those industries with AICPA and/or FASB guidance, and zero otherwise. This is summarized in Panel C of Table 1, and results in 18 of 48 Fama-French industries being classified as complex. Based on these classifications, approximately 40 to 42 percent of the firm-year observations in the sample are in complex industries, depending on the sample requirements of the specific test.

Panel C also presents some initial univariate evidence to support the argument that earnings are nosier in complex industries. The variable *Persistence* is the coefficient from an industry-specific regression of operating earnings on lagged earnings (see equation 1b below). The mean of the coefficient estimates across the 18 complex industries is 0.527, compared to a mean of 0.663 in 30 non-complex industries. A t-test (n=47) indicates that this difference is statistically significant at $p<0.05$.

In addition, we calculate the average of yearly coefficients of variation for operating earnings in each industry. Each yearly coefficient of variation is the standard deviation of operating earnings (scaled by average assets), divided by the sample mean for that year. Because of noise and measurement error, we expect to observe more heterogeneity and greater within-industry yearly earnings variation in complex industries. In contrast, non-complex industries are expected to be more homogenous with less cross-sectional yearly variation. Because the coefficient of variation is only meaningful for variables with positive values, we only include firms with positive earnings in this calculation. As expected, the coefficient of variation for operating earnings is larger (more variation) in complex industries with a mean of 0.740 compared to 0.590 in non-complex industries, and the difference is statistically significant at $p<0.01$. We obtain similar results if we compare the standard deviation of operating ROA for firms in complex versus non-complex industries.

The analysis of industry-specific persistence and the coefficient of variation indicates robust classifications. For example, there no industries in which the average persistence and coefficient of variation metrics for complex industries are both above (below) the mean in non-complex industries for persistence (coefficient of variation). The opposite is also the case for non-complex industries, i.e., they do not look like complex industries for the two metrics together.

2.3 Auditor industry expertise

The relation between auditor industry expertise and earnings quality has been extensively researched. Initial studies measured expertise based on an auditor's aggregate share of industry audit fees for all listed companies in a country (Francis et al. 1995). More recent evidence documents that an auditor's "national" industry market share is driven by a subset of individual engagement offices in which the offices are city-specific industry leaders (Ferguson 2003; Reichelt and Wang 2010). This is consistent with Choi et al. (2012) who document that the audit office which administers the audit engagement is located within 60 miles of the client's corporate headquarters for 83 percent of SEC registrants, and is in the same Metropolitan Statistical Area (MSA), for 80 percent of clients.[10] Audit markets are thus predominantly city-specific markets. Reichelt and Wang (2010) report that the city-level industry leader has an average market share of 73 percent of city-level industry audit fees compared to only 23 percent for the second largest auditor, which points to substantially greater office-level industry experience for the city leader compared to all other auditors in the same locale. In contrast, "national" industry market shares tend to be more evenly distributed among the large accounting firms. Based on national-level industry market share data, Reichelt and Wang (2010) report the top-ranked auditor averages only 42 percent of fees, compared to 26 percent and 17 percent for the second- and third-ranked

[10] The lead engagement office on an audit is identified from the audit report filed in the client's10-K in which the report is issued on office-specific letterhead. Francis et al. (2005) note that other offices may participate in the audit if it is a large multi-location client, but the critical elements of the audit such as engagement planning and the final audit report decision are made by the audit team in the lead engagement office.

auditors. Based on this stream of research our primary measure of industry expertise is the industry leader in city-specific audit markets which is recalculated each year in the sample period. For completeness we also control for auditor expertise based on aggregate national industry-level fee leadership. Similar to the measure of industry complexity, the calculation of auditor industry expertise (both city and national) is based on FF48 industry codes.

With rare exceptions such as Cahan et al. (2008), prior research assumes the effect of auditor industry expertise is, on average, applicable across-the-board to all industries. In contrast, we believe an auditor's capacity to develop industry expertise is more likely to exist and be important in complex industries. Complex industries present a more complicated task in terms of assessing a client's audit risk, assessing the client's interpretation and implementation of GAAP, and more generally the judgments required in issuing an audit report. For these reasons, there is a learning curve in complex industries, and the auditor's accumulated experience through the audits of multiple clients is an important factor in developing credible industry expertise and achieving auditor differentiation in these industries. However, for less complex industries there is less of a learning curve, and experience with clients in the industry less important since the financial reporting issues and audit judgments are more straightforward and there is relatively little learning or incremental expertise to be gained from an auditor's repeat experience with multiple clients in the industry. These arguments lead to the following hypothesis in alternative form:

H2: Earnings are of higher quality (lower abnormal accruals, lower absolute working capital accruals, smaller accrual estimation errors, fewer restatements) for firms in complex industries that use audit industry specialists, compared to firms with audit industry specialists in non-complex industries, where audit specialists are defined as city-level industry leaders.

H2 predicts that reported earnings by firms in complex industries with audit specialists have less noise and are, by implication are of higher quality. If true, this should also result in greater accuracy by analysts in predicting future earnings which leads to the following hypothesis in alternative form:[11]

H3: Analysts' forecasts are more accurate for firms in complex industries that use audit industry specialists, but auditor industry expertise has less or no effect in non-complex industries.

3. Tests of earnings persistence and analysts' earnings forecast errors

3.1 Sample

We focus on the post-SOX era and the sample period is 2003-2013. In addition, because very few non-Big 4 auditors are industry experts, we only include firms audited by Big 4 auditors in the sample. When using restatements as the dependent variable, we stop the sample in 2012 because prior research indicates restatements typically occur one to two years after the original issuance of the financial statements (Francis and Michas 2013). Data in the study come from three sources: Compustat, Audit Analytics, and IBES. Sample sizes vary in different tests, depending on which variables are required and from which particular database. The Appendix contains detailed definitions and the source of all variables. For example, when we test the persistence of earnings, we require relatively few variables from Compustat, so this test has the largest sample: 14,062 (13,404) firm-year observations and 2,481 (2,146) unique firms in complex (non-complex) industries. When we test analysts' forecast errors in the full multivariate model, the data from IBES along with additional control variables reduce the sample to 8,337 firm-year observations (3,590 and 4,747 in complex and non-complex industries, respectively). When we test earnings quality in Tables 3-5, the sample size changes again because we require data from Compustat and Audit Analytics (but not IBES), and require several additional control variables so that we are left with 7,799 (9,760) firm-year observations in complex (non-complex) industries. The earnings quality prior literature typically excludes firms in the financial sector because accruals are

[11] Behn et al. (2007) find that analysts' forecast errors are smaller for firms with Big 4 auditors, but they find no evidence of an association with Big 4 audit industry specialists.

fundamentally different form other industries, and we follow this practice by excluding financial firms ($44 \leq FF48 \leq 47$) from any test that uses an accrual-based measure as the dependent variable.

3.2 Test of H1: validation of the industry complexity classification

3.2.1 Earnings persistence and cross-section earnings variation

Following Sloan (1996), we test persistence by regressing current period earnings on prior-period earnings, as well a separate regression using the accrual and operating cash flow components of prior-period earnings:

$$Earnings_t = \alpha + \beta_1\, Earnings_{t-1} + \varepsilon \tag{1a}$$

$$Earnings_t = \alpha + \beta_1\, Accruals_{t-1} + \beta_2\, OCF_{t-1} + \varepsilon \tag{1b}$$

where *Earnings* equals operating earnings (OIADP) divided by average total assets, *Accruals* equals the difference between operating earnings and operating cash flow divided by average total assets, and *OCF* equals operating cash flows divided by average total assets.[12] Hypothesis H1 predicts that earnings of firms in complex industries have lower persistence than firms in less complex industries. Accordingly we estimate equations (1a) and (1b) separately for firms in complex industries and for firms in non-complex industries and do a two-sample test of differences in the persistence coefficients. Results are presented in Panel A of Table 2.

[INSERT TABLE 2 HERE]

The first two columns in Table 2 report the estimates of equations (1a) and (1b) for the pooled sample as in Sloan (1996). In all of our reported results, robust standard errors are clustered for each unique firm in the sample. The coefficient of lagged earnings, β_1 is 0.715 with a t-statistic of 52.753 ($p<0.001$). Similar to prior studies, the second column shows that the accruals

[12] Consistent with Sloan (1996), we test persistence using operating income. Results are similar if we use either income before extraordinary items or bottom line net income. Because we use operating income in these tests, we also modify the definition of accruals here to be based on operating earnings. In the earnings quality tests described below, we define accruals as the difference between earnings before extraordinary items (IB) and operating cash flows, consistent with most studies in the accruals literature.

component of earnings is significantly less persistent than the cash flow component (0.617 compared to 0.745).

The next set of columns in Table 2 report the estimations of equations (1a) and (1b) separately for firms in complex and non-complex industries. Consistent with our prediction, earnings are less persistent in more complex industries, with a much lower coefficient for $OPINCOME_{t-1}$ of 0.544 in complex industries compared to 0.798 in non-complex industries. A Chow-test confirms that this difference across the two regressions is statistically different from zero (p-value < 0.001).

In addition, we find a much larger difference in the persistence of operating cash flows than accruals in complex industries compared to non-complex industries. In complex (non-complex) industries, the coefficients for $Accruals_{t-1}$ and OCF_{t-1} are 0.513 (0.668) and 0.546 (0.843), respectively. A Chow-test confirms that the difference in coefficients between complex and non-complex industries is statistically different from zero for both lagged accruals and lagged cash flows at the p<0.001 level.

3.2.2 Analysts' earnings forecasts

Given the results of Section 3.2.1, the lower earnings persistence of firms in complex industries, as well as lower persistence of operating cash flows, could make it harder for analysts to forecast earnings and make it more likely that analysts disagree in the earnings forecasts. To this end, we expect to see larger analysts' forecast errors and greater analysts' forecast dispersion (less consensus) for firms in complex industries.

To calculate absolute analysts' forecast errors (*AFE*) we subtract the median consensus estimate of annual earnings as reported in the IBES Summary File. We use only the most recent consensus estimate provided by IBES for each firm-year and require the consensus estimate to be no earlier than 30 days before the earnings announcement date to avoid stale forecasts. As we are most interested in the size of forecast errors rather than direction, we use the absolute value of analysts' forecast error in the analysis. To measure analyst forecast dispersion (*STDFCST*), we use the standard deviation of individual analyst forecasts included in the consensus estimate.

The forecast results are partitioned by industry complexity and reported in Panel B of Table 2. We report both the univariate differences between complex and non-complex industries, as well as a multivariate model that includes the number of analyst forecasts included in the consensus estimate (*LNNUMEST*), and all firm-level control variables used later in the tests of auditor industry expertise. STDFCST (AFE) is 0.019 (0.047) higher (i.e., just over one (four) cent per share) in complex industries than in non-complex industries, consistent with earnings in these industries being harder to forecast. Including the additional control variables reduces the coefficient for COMPLEX for both STDFCST and AFE to 0.010 and 0.016, respectively, but in all cases the coefficient for COMPLEX is statistically significant at $p<0.01$.

To summarize, the tests reported in this section support our industry classification and the prediction in H1. All three tests are consistent with earnings being noisier for firms in complex industries.

4. Test of H2: auditor industry expertise and earnings quality

We now use the framework to investigate if auditor industry expertise is associated with the quality of audited earnings for firms in complex and non-complex industries. A large body of research examines the association of auditor characteristics with statistical properties of audited earnings in order to draw inference about the quality of both earnings and auditing. DeFond and Zhang (2014) provide a recent review of research using this approach and note that different measures of earnings quality can triangulate and reinforce each other. To that end, we use three accrual-based measures of client earnings quality and two measures of client restatements.

4.1 Accrual-based measures

The first accrual-based measure of earnings quality is abnormal accruals, derived from the estimation of "expected accruals" in equation (2). The residual error term is denoted abnormal or unexpected accruals, (Jones 1991; DeFond and Jiambalvo 1994; Dechow et al. 1995). Unlike studies such as Jones (1991) we are not using abnormal accruals to test for earnings management behavior. Rather, we expect there will be a larger deviation around "expected" accruals in complex industries, which reflects the noise and measurement error in applying GAAP in these industries. We estimate abnormal accruals with a performance-adjusted Jones model (Kothari et al. 2005). The model is estimated for all available firm-year observations from Compustat, by year and industry (Fama-French 48 industry codes), and requires a minimum of ten observations for each industry-year.

$$TA = \alpha + \beta_1\, \Delta REV + \beta_2\, PPE + \beta_3\, ROA + \varepsilon \qquad (2)$$

where:

TA = total accruals (net income from continuing operations minus operating cash flows, divided by average total assets),

ΔREV = change in revenue from prior year, scaled by average total assets,

PPE = gross property, plant, and equipment divided by average total assets,

ROA = income from continuing operations, divided by beginning of year total assets.

Because we are only interested in the magnitude of the deviation around expected accruals, not the directional sign, we use the absolute value of abnormal accruals in the multivariate tests (Warfield et al. 1995).

The second accrual-based measure of earnings quality is based on the accrual estimation error model of Dechow and Dichev (2002), estimated cross-sectionally as in Dechow, Ge, Larson and Sloan (2011), as follows:

$$WCACCR_t = \alpha + \beta_1 OCF_{t-1} + \beta_2 OCF_t + \beta_3 OCF_{t+1} + \varepsilon \qquad (3)$$

where:

$WCACCR$ = working capital accruals, divided by average total assets

OCF = operating cash flows, divided by average total assets

Equation (3) is estimated separately by year for each industry (FF48). The measure of accrual estimation errors (ABSDD) is the mean-adjusted absolute value of the residual from equation (3), calculated by subtracting the mean absolute value of the residual for each industry-year from the absolute value of each firm's residual.

The third accrual-based measure of earnings quality is the absolute value of working capital accruals (ABSWC). Dechow and Dichev (2002) note a positive correlation between the level of accruals and the magnitude of accrual estimation errors, and suggest that accruals will be at their largest levels when operating cash flows have the most timing and mismatching problems. They also suggest absolute working capital accruals are a good proxy for accruals and earnings quality.

Auditor industry expertise is predicted to reduce noise in the estimation of earnings for firms in complex industries, resulting in smaller unexpected accruals in equation (2), smaller accrual estimation errors in equation (3), and smaller absolute values of working capital accruals.

4.2 Restatement-based measures of earnings quality

We use two measures of restatements as an alternative to accrual-based measures of earnings quality. The first measure, accounting restatements (*ACC_RES)*, is an indicator variable equal to one whenever the audited financial statements are subsequently restated due to a GAAP application failure. The second restatement measure, adverse restatements (ADV_RES), is an indicator variable equal to one whenever the audited financial statements are subsequently restated and the restatement reduces the previously reported net income. Prior research indicates that auditors suffer greater litigation risk and reputation risk from upward earnings management, which suggests that an industry audit expert will be especially concerned with detecting and preventing overstated earnings by clients (Abbott, Parker and Peters 2006). Both of the restatement measures are coded by Audit Analytics. A higher rate of restatements is expected in complex industries due to greater noise and inherent measurement difficulty in these industries. As with accruals, audit industry expertise is predicted to mitigate these effects in complex industries.

4.3 Empirical models

Hypothesis H2 predicts that auditor industry expertise will have a greater effect on earnings quality in complex industries. To test H2, the following model is estimated separately for firms in complex industries and for firms in non-complex industries:

$$Earning\ Quality = \alpha + \beta_1\ INDUSTRYEXPERT\ + \beta_2\text{-}\beta_{14}\ CONTROLS + FE\text{'}s + \varepsilon \qquad (4)$$

where:

Earnings Quality	=	one of five measure of earnings quality: *ABSDA*, *ABSDD, ABSWC*, *ACC_RES*, or *ADV_RES*
INDUSTRYEXPERT	=	one if an auditor is the local level industry leader in FF48 industry code, and zero otherwise,
CONTROLS	=	a vector of control variables (described below),
FE	=	industry (FF48) and year fixed effects.

A comprehensive set of control variables is included in the empirical model, and by estimating the model separately for firms in complex and non-complex industries we have an additional control by allowing the coefficients on the controls to differ between the two industry groups. In addition to the above variables, the systematic effects of time and industry are controlled with year and industry (FF48) fixed effects. To reduce the effects of serial dependence in the error term from multiple observations of the same firm over the sample period, robust standard errors are clustered by each unique firm (Petersen 2009).

The Appendix provides detailed descriptions, calculations, and data sources for all variables. We include three auditor-related control variables: (1) an indicator variable, *NATINDLEAD*, to control for an audit firm's industry leadership based on aggregate market share at the national level, to assure the results on city-specific industry leadership are driven by local office expertise, as opposed to the audit firm's aggregate national-level market share and leadership; (2) audit office size (*LNOFFICE*, which is the natural log of total audit fees in the auditor's office) as prior research finds that office size is correlated with earnings quality (Choi et al. 2010; Francis et al. 2013); and (3) auditor tenure (*TENURE*) as a control for the effects of tenure on earnings quality. Minutti-Meza (2013) provides evidence that measures of auditor industry expertise may be confounded with several client characteristics, and so we include the same set of firm-level control variables used in his study: client size (*LNMVE*), leverage (*LEVERAGE*), return on assets (*ROA*), lagged return on assets (*LAGROA*), operating losses (*LOSS*), operating cash flows (*OCF*), the book to market ratio (*BTM*), lagged absolute value of accruals (*LAGABSACCRUALS*), revenue growth (*REVGWTH*), Altman's z-score (*ZSCORE*), and the standard deviation of earnings (*STDEARN*).

4.4 Descriptive statistics

Table 3 reports summary statistics for the model variables in equation (3). Panel A reports statistics for the 7,799 observations in complex industries and Panel B for the 9,760 observations in non-complex industries.[13] All continuous variables are winsorized at the 1st and 99th percentiles. Firms in complex industries are larger, more highly leveraged, have lower book-to-market ratios, and smaller z-scores (indicating greater bankruptcy risk) than firms in non-complex industries. Firms in complex industries also exhibit better performance during the sample period, as *ROA*, *LAGROA*, and *OCF* are all larger in complex industries, and *LOSS* is smaller, although non-complex firms have higher revenue growth (*REVGRTH*). Consistent with the persistence results from Table 2, firms in complex industries also have a higher standard deviation of earnings.

[13] There are fewer observations with non-missing values for *ABSDD* because the construction of this variable requires lead cash flows and three consecutive years of data.

Separate estimations for firms in complex versus non-complex industries would appear prudent given the numerous differences in the control variables.

[INSERT TABLE 3]

We do not draw any conclusions on the dependent variables from univariate statistics because there is no control for other variables. However, *ABSDA* and *ABSWC* are slightly smaller in complex industries, which indicates less deviation around the industry norm (rather than more as expected), but it is also consistent with firms in these industries being larger, as noted above. In contrast the dependent variables *ABSDD*, *ACC_RES*, and *ADV_RES* are similar across the two industry groups.

4.5 Results

Table 4 reports the results of estimating equation (4) to test H2. The models in Table 4 are all significant at $p < .01$. All t-tests are reported conservatively as two-tail p-values, and controls are generally in the direction predicted from prior research (Francis and Yu 2009; Choi et al. 2010; Reichelt and Wang 2010). For parsimony, we only report t-statistics for the test variables, and indicate statistical significance for control variables using asterisks. For completeness, we first estimate the model using the full sample. Then, to test hypothesis H2, the models are estimated on the separate subsamples of firms in complex and non-complex industries.

[INSERT TABLE 4]

Table 4 Panel A reports the results using the three accrual-based measures of earnings quality. For the full sample of firms (first set of columns) the coefficient for *INDUSTRYEXPERT* is statistically significant only for *ABSDA* ($p<0.05$) and is not significant for *ABSDD* or *ABSWC*. However, the weak results in the full sample mask important differences between the two industry groups. In complex industries, the coefficient for *INDUSTRYEXPERT* is negative and significant for *ABSDA* at $p<0.01$ and for *ABSDD* and *ABSWC* at $p<0.05$, indicating smaller accruals and smaller estimation errors for firms with industry audit experts. The results are economically significant as well. The coefficient of -0.005 (-0.003) when *ABSDA* (*ABSDD* and *ABSWC*) is the dependent variable indicates that clients of industry experts report abnormal accruals (accrual estimation errors and working capital accruals) that are lower by 0.5 percent (0.3 percent) of total assets, all else equal. In contrast, in non-complex industries, *INDUSTRYEXPERT* is not statistically significant at conventional levels for any of the accrual-based measure of earnings quality.

We find similar results in Panel B of Table 4 using the two restatement measures. In the full sample (first set of columns), we find a negative and marginally significant relationship between *INDUSTRYEXPERT* and restatements, -0.146 ($p<0.05$) and -0.148 ($p<0.10$) for *ACC_RES* (*ADV_RES*). Again, the full sample results mask differences between the two industry groups. In complex industries the coefficient for *INDUSTRYEXPERT* is -0.243 ($p<0.05$) for accounting restatements, and the coefficient is -0.277 ($p<0.05$) for adverse earnings restatements. As in Panel A, for firms in non-complex industries *INDUSTRYEXPERT* is not statistically significant at the 0.10 level for either restatement variable.

The results in Table 4 support the prediction of H2 that industry audit expertise is associated with higher quality audited earnings and that expertise matters more in complex industries than non-complex industries. In fact the evidence indicates that expertise only matters in complex industries. This finding stands in contrast to prior research which use research designs that logically imply auditor expertise is relevant for all industries, without considering why this should necessarily be the case. The results are also consistent with experimental work which finds auditor experience affects the quality of audit judgments more in industries with special characteristics compared to simpler more straightforward industries (e.g., Solomon et al. 1999).

4.6 Propensity score matching

Minutti-Meza (2013) argues that multivariate regressions do not sufficiently disentangle auditor characteristics from endogenous client characteristics and suggests propensity score matching (PSM) as a possible solution. To investigate the sensitivity of our results in PSM samples, we calculate a propensity score for each observation by regressing *INDUSTRYEXPERT* on all of the client characteristics included as control variables in equation (4). The propensity score equation is estimated separately for firms in the complex and non-complex industry subsamples.[14] We then match each observation with an industry audit expert (city-specific industry leader) to non-industry experts within the complex and non-complex subsamples, respectively. We use a caliper of 0.03, match with replacement, and allow up to three non-industry expert observations to be matched to each industry expert observation.[15] As in Table 4 robust standard errors clustered for each unique firm in the sample are used to calculate the coefficient p-values.

Results using the propensity score matched sample are presented in Table 5 and are similar to those in Table 4. In the full sample, *INDUSTRYEXPERT* is negative and marginally significant only for *ABSDA* ($p<0.10$) and *ADV_RES* ($p<0.10$). However, in complex industries, the coefficient for *INDUSTRYEXPERT* is negative and statistically significant at $p<.05$ for all five measures of earnings quality. As in Table 4, auditor expertise is never statistically significant in non-complex industries. The PSM estimations give confidence that the primary results for auditor

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[14] When estimated for complex (non-complex) industries, the propensity score model had a pseudo-R2 of 0.045 (0.060) and the area under the ROC curve was 0.641 (0.658).

[15] DeFond, Erkens, and Zhang (2014) argue that matching with replacement reduces bias in the treatment effect, because each treatment can be matched to the closest control firm, even if the control firm has already been matched to another treatment firm. They also note that allowing multiple control firms to match to each treatment firm can potentially increase bias, but reduces variance by allowing a larger sample size. If we allow only one or two neighbors, inferences remain the same. In fact, statistical significance slightly increases for both restatement measures when we allow two matches, but slightly decreases for the accrual-based measures, highlighting the increase in variance that can arise in PSM samples (DeFond et al. 2014). When we allow only one match, statistical significance decreases, but remains significantly different from zero at conventional levels ($p < 0.10$, two-tailed) for all five measures. In non-complex industries, *INDUSTRYEXPERT* is never significant, regardless of the caliper or number of matches allowed. Since our results to not appear overly sensitive to the number of control firms matched to each treatment firm, we report the largest sample size.

industry expertise in Table 4 are not due to endogeneity with respect to observable client characteristics.

[INSERT TABLE 5]

Together the results in Tables 4 and 5 provide robust evidence that the quality of audited earnings improves both statistically and economically for firms in complex industries that hire an audit specialist. Given this evidence it is surprising we find no evidence (untabled results) of a corresponding improvement in earnings persistence for such firms. One possible explanation is that the persistence differences between the two industry groups are driven the low persistence of operating cash in complex industries which has approximately twice the effect of accruals in Table 2. Audit quality is unlikely to affect this aspect of low persistence. However, even we analyze those firms with greater accruals intensity (as in the analysts' tests below) there is still no observable effect on persistence. This is a puzzling result because Xie (2001) shows that abnormal accruals are less persistent than "expected' accruals, and the tests reported in Tables 4 and 5 show that firms in complex industries audited by industry specialists have smaller abnormal accruals of a reasonable economic magnitude. We have no explanation for why there is not an observable effect on persistence of using an industry audit specialist in complex industries, though possibly the effect is too small to detected with our research design.

5. Test of H3: industry auditor expertise and analysts' forecasts

The analysis in section 4 and test of H2 finds that audit industry leaders in complex industries are associated with higher quality client earnings, which suggests it may be easier for analysts to forecast earnings if the underlying earnings measurement process has less noise and measurement error. However, recall in Section 2 (and above) that complex industries have significantly lower earnings persistence, mostly due to the operating cash flow component of earnings. If analyst forecast errors are higher in complex industries because of the lack of cash flow persistence (rather than low accruals quality), then it is not obvious that the earnings quality improvements from having an industry audit expert will flow through to better analysts' forecasts. For this reason in the regression model in equation (5) we further separate firms into subgroups where we expect the accrual portion of earnings will be relatively more important in assessing earnings quality:

$$AFE = \alpha + \beta_1\ INDUSTRYEXPERT + \beta_2\ X + \beta_3\ INDUSTRYEXPERT{*}ACCINTENS + \beta_4\text{-}\beta_{19}\ CONTROLS + FE's + \varepsilon \tag{5}$$

where:

AFE	=	the absolute value of analyst forecast errors, calculated as in Section 3
INDUSTRYEXPERT	=	one if an auditor is the local level industry leader in FF48 industry code, and zero otherwise,
ACCINTENS	=	One if the firm is in the top quartile of working capital accruals intensity, as measured by the absolute value of working capital accruals, scaled by total assets (ABSWC).
CONTROLS	=	the same vector of control variables included in the tests of forecast accuracy reported in Table 2
FE	=	industry (FF48) and year fixed effects.

As with Tables 4 and 5 the coefficient p-values are based on robust standard errors clustered for each unique firm, and all p-values are two-tailed.

The model in equation 5 uses the same sample as the results reported in Table 2, except we estimate separately for complex and non-complex industries and include *INDUSTRYEXPERT* which is also interacted with an indicator variable for accruals intensity (*ACCINTENS*). As discussed above, Dechow and Dichev (2002) note that working capital accruals will be larger when the firm's operating cash flows have the most timing and matching problems. Thus, we expect accruals quality to play a relatively more important role in analysts' forecast accuracy for these firms.

Table 6 presents the results from estimating equation (5). We begin by estimating the effect of auditor industry expertise for full sample, before estimating separately for firms in complex and non-complex industries. We also report results both with and without partitioning of firms by *ACCINTENS*. In models without the interaction between *INDUSTRYEXPERT* and *ACCINTENS*, *INDUSTRYEXPERT* is not significant in the full sample nor for either industry group. Next we estimate the models with firms partitioned based on their accruals intensity. Here, *INDUSTRYEXPERT* by itself captures the effect of auditor industry expertise for firms with low accruals intensity (i.e., when we expect accruals to be less important to predicting the firm's next-period earnings). The interaction term represents the incremental effect of auditor industry expertise for firms with high accruals intensity. *INDUSTRYEXPERT* by itself is not statistically significant in any of the regressions. However, in complex industries, the interaction term *INDUSTRYEXPERT*ACCINTENS* is negative and statistically significant at p<.05. The evidence suggests analysts are better able to predict a firm's future earnings in complex industries when the firm is audited by an industry expert auditor, but only for the subset of firms where accrual quality is likely to be relatively more important in assessing the quality of past earnings and forecasting a firm's future earnings.

[INSERT TABLE 6]

7. Conclusion

Our starting point in the study is the question of when (if at all) does auditor industry expertise improve the quality of audited earnings, and why? The research designs in prior studies implicitly assume it always matter for any and all industries. We do not find this to be intuitive and our conjecture is that auditor expertise is most likely to matter when accounting and GAAP implementation in an industry is inherently more complex. In such settings, auditors have a longer learning curve and are more likely to develop deep expertise through repeated audits of multiple clients in the industry. We expect this expertise to reduce the inherent noise in earnings and lead to better earnings estimation and therefore higher-quality earnings. In other industries, by contrast, there is a shorter learning curve, less potential for an auditor to develop meaningful expertise and differentiation from other auditors, and less of an effect on the quality of audited earnings.

Given these conjectures we need to identify those industries with greater accounting complexity and, by implication, inherently noisier earnings due to GAAP implementation difficulties in accounting recognition and measurement. We use a novel approach to classify complex industries based on those industries identified by the FASB and/or the AICPA as requiring industry-specific guidance to supplement standard GAAP. This results in 18 of 48 Fama-French industries being classed as "complex" and approximately 40 percent of firm-year observations in the study over the sample period 2003-2103. We provide validation of the industry classification framework with three tests. Earnings of firms in complex industries have greater cross-sectional yearly variation compared to firms in non-complex industries, consistent with greater noise in applying GAAP in complex industries. Earnings of firms in complex industries also have less persistence over time which is also consistent with noisier earnings. Finally, we document that analysts have greater difficulty in forecasting earnings in complex industries and exhibit less consensus.

Having validated the industry classification framework we then test if audit experts (city-level industry leaders) improve the quality of audited earnings. The answer is yes: firms in complex industries have smaller abnormal accruals, smaller absolute working capital accruals, and smaller accrual estimation errors. They are also less likely to have a subsequent restatement. In contrast, for firms in non-complex industries, audit specialists have no observable effect on the quality of audited earnings. We also document that analysts' earnings forecasts are more accurate in complex industries for firms with audit specialists, but only for those firms where accruals are relatively large and more important to assessing overall earnings quality. Unlike prior audit studies that report an "average" across-the-board association between earnings quality and auditor industry expertise, our analysis suggests this relation is important but that it only holds for the subset of firms in industries with complex accounting where there is a more credible basis for differential auditor expertise and the potential for audit specialists to improve earnings quality.

A limitation of the study is that the tests are associational in nature, like much of the extant accounting literature. The results are consistent with audit specialists causing earnings quality to improve for firms in complex industries, and even though the results are robust to a propensity scoring sample to control for the potential endogeneity of auditor choice, we cannot entirely rule out the confounding effect of endogeneity.

Appendix – Variable Descriptions*

Variable	Description	Source

Dependent variables in Table 2 and 6:

OPINCOME	Operating income (OIADP) scaled by lagged total assets (AT).	Compustat
FCST_STD	The standard deviation of analyst forecast errors	IBES
FCST_ERR	The absolute value of the difference between the IBES consensus forecast and actual earnings per share.	IBES

Dependent variables in Tables 4 and 5:

ABSDA	The absolute value of the residual from the Jones (1991) model with a control for performance (Kothari et al. 2005). See equation (2).	Compustat
ABSDD	The absolute value of the residual from the cross-sectional adaptation in Dechow et a. (2011) of the Dechow and Dichev (2002) model of accrual estimation errors, less the mean absolute value of the residual for all observations in the same industry-year. See equation (3).	Compustat
ABSWC	The absolute value of working capital accruals, defined as $(ACT_t - ACT_{t-1})$ - $(CHE_t - CHE_{t-1})$ – $(LCT_t - LCT_{t-1})$ + $(TXP_t - TXP_{t-1})$ + $(DLC_t - DLC_{t-1})$	Compustat
ACC_RES	An indicator variable equal to one if the financial statements were subsequently restated due to a failure to properly apply GAAP.	Audit Analytics
ADV_RES	An indicator variable equal to one if the financial statements were eventually restated and the restatement adversely affected net income.	Audit Analytics

Independent Variables:

COMPLEX	A dichotomous variable equal to one if the firm belongs to an industry identified as "complex" in Table 1.	Manually coded.
INDUSTRYEXPERT	An indicator variable equal to one if the auditor is the city-level market leader, measured by audit fees in the client's industry using Fama-French 48 industry codes.	Audit Analytics
NATINDLEAD	An indicator variable equal to one if the auditor is the national-level market leader, measured by audit fees in the client's industry (Fama-French 48 industry codes).	Audit Analytics
LNOFFICE	The natural logarithm of total audit office fees, calculated for all firm-years Audit Analytics before data restrictions.	Audit Analytics

LNMVE	The natural log of total market value (PRCC_F*CSHO).	Compustat
LEVERAGE	Total liabilities (LT), scaled by average total assets (AT).	Compustat
ROA	Net income (NI) scaled by average total assets.	Compustat
LAGROA	ROA for period t-1.	Compustat
LOSS	A dichotomous variable equal to 1 if the company reported negative income (NI) before extraordinary items and zero otherwise.	Compustat
OCF	Operating cash flows, scaled by average total assets.	Compustat
BTM	The ratio of the book value of equity (CEQ) to the market value of equity (PRCC_F*CSHO).	Compustat
LAGABSACCRUALS	The absolute value of total accruals for period t-1, where total accruals are defined as income before extraordinary items (IB) less operating cash flows (OANCF), divided by average total assets.	Compustat
REVGWTH	The yearly percentage change in sales over prior year.	Compustat
ZSCORE	Altman's zscore = $3.107*(OIADP_t/AT_{t-1}) + .717*((ACT_t-LCT_t)/AT_{t-1}) + .998*(SALE_t/AT_{t-1}) + .42*(CEQ_t/LT_{t-1}) + .847*(RE_t/AT_{t-1})$.	Compustat
STDEARN	The rolling 3-year standard deviation of income before extraordinary items (IB).	Compustat
TENURE	A dichotomous variable equal to 1 if audit tenure is equal to three years or less and zero otherwise.	Audit Analytics
LNNUMEST	The natural logarithm of the total number of unique analysts that issued annual EPS forecasts for the firm during the year.	IBES
ACCINTENS	A dichotomous variable equal to one if the firm is in the top quartile of accruals intensity, as measured by the absolute value of working capital accruals, scaled by total assets (ABSWC).	Compustat
**Compustat mnemonics provided in parenthesis, where applicable.*		

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Table 1
Mapping AICPA Audit Guides and FASB 900 Guidance to Industry Codes

Panel A: AICPA Industry Audit Guides

Industry-Specific Guides

1) Airlines
2) Auditing Revenue in Certain Industries
3) Brokers and Dealers in Securities
4) Construction Contractors
5) Depository and Lending Institutions: Banks and Savings Institutions, Credit Unions, Finance Companies, and Mortgage Companies
6) Employee Benefit Plans
7) Entities with Oil and Gas Producing Activities
8) Gaming
9) Government Auditing Standards and Circular A-133 Audits
10) Health Care Entities
11) Investment Companies
12) Life and Health Insurance Companies
13) Not-for-Profit Entities
14) Property and Liability Insurance Entities
15) State and Local Governments
16) Wiki - Common Interest Realty Associations

Specific Transactions

17) Assets Acquired to Be Used in Research and Development Activities
18) Special Considerations in Auditing Financial Instruments
19) Testing Goodwill for Impairment
20) Valuation of Privately-Held Company Equity Securities Issued as Compensation

Audit Procedures and Other Issues

21) Reporting on Controls at a Service Organization Relevant to Security, Availability, Processing Integrity, Confidentiality, or Privacy (SOC 2)
22) Analytical Procedures
23) Assessing and Responding to Audit Risk in a Financial Statement Audit
24) Audit Sampling
25) Compilation and Review Engagements
26) Prospective Financial Information
27) Service Organizations: Reporting on Controls at a Service Organization Relevant to User Entities' Internal Control Over Financial Reporting Guide

Table 1 (cont.)

Panel B: FASB 900 Series Industry Guidance

FASB 900 Code	Industry
905	Agriculture
908	Airlines
910	Contractors-Construction
912	Contractors-Federal Government
915	Development stage entities
920	Entertainment-Broadcasters
922	Entertainment-Cable Television
924	Entertainment-Casinos
926	Entertainment-Films
928	Entertainment-Music
930	Extractive Industries - Mining
932	Extractive Industries - Oil and Gas
940	Financial services
952	Franchisors
954	Health care entities
958	Not-for-profit entities
960	Plan accounting
970	Real estate
980	Regulated operations
985	Software
985-20	Costs of software to be sold
995	U.S. steamship entities

Table 1 (continued)

Panel C: Map of Industry-specific guidance and univariate statistics

Complex Industries

Industry	Industry Description	AICPA	FASB 900	N	Persistence	Coeff. Variation
1	Agriculture		905	45	0.937	0.733
7	Entertainment	8	924,926,928	331	0.479	0.619
11	Healthcare	10	954	462	0.578	0.548
18	Construction	4	910	348	0.701	0.695
26	Defense		912	12	0.681	0.524
27	Precious Metals		930	24	0.746	0.603
28	Non-metallic and Industrial Metal Mining		930	53	0.273	0.756
29	Coal		930	119	0.770	0.945
30	Petroleum and Natural Gas	7	932	1085	0.352	0.688
31	Utilities		980	961	0.223	0.370
32	Communication		920,922	779	0.542	0.668
34	Business Services	2	912,985-20	3276	0.622	0.744
35	Computers	2	985,985-20	1017	0.647	0.632
40	Transportation	1	908	689	0.431	0.702
44	Banking	3,5,11	940	2204	0.307	1.273
45	Insurance	12,14	940	1170	0.465	0.869
46	Real Estate		940	227	0.283	0.771
47	Trading		940,970	1967	0.452	1.176
				Mean	0.527	0.740

Non-Complex Industries

Industry	Industry Description	AICPA	FASB 900	N	Persistence	Coeff. Variation
2	Food Products			420	0.432	0.579
3	Candy & Soda			50	0.987	0.476
4	Beer & Liquor			78	0.831	0.592
6	Recreation			120	0.646	0.533

8	Printing and Publishing	196	0.336	0.572
9	Consumer Goods	411	0.605	0.690
10	Apparel	362	0.686	0.580
12	Medical Equipment	885	0.836	0.566
13	Pharmaceutical Products	1639	0.783	0.634
14	Chemicals	588	0.780	0.623
15	Rubber and Plastic Products	51	0.664	0.410
16	Textiles	70	0.869	0.566
17	Construction Materials	395	0.712	0.609
19	Steel works, etc.	304	0.419	0.603
20	Fabricated Products	45	0.786	0.533
21	Machinery	920	0.545	0.562
22	Electrical Equipment	379	0.970	0.508
23	Automobiles and Trucks	360	0.690	0.700
24	Aircraft	150	0.187	0.421
25	Shipbuilding, Railroad Equipment	45	0.534	0.721
33	Personal Services	316	0.803	0.868
36	Electronic Equipment	1695	0.720	0.753
37	Measuring and Control Equipment	585	0.731	0.587
38	Business Supplies	322	0.292	0.672
39	Shipping Containers	97	0.773	0.296
41	Wholesale	863	0.567	0.577
42	Retail	1625	0.669	0.644
43	Restaurants, Hotels, Motels	467	0.709	0.644
		Mean	0.663	0.590
		H_0: $\text{Mean}_{[Complex=1]} = \text{Mean}_{[Complex=0]}$	2.30**	3.07***

Panels A and B provide a list of the industry-specific guidance provided by the AICPA Accounting and Auditing Guides and the FASB 900 Topics Series, respectively. Panel C provides the map of the industry specific guidance to each of the unique Fama-French 48 industry codes. The variable *Persistence* in Panel C is the coefficient estimate from an industry-specific regression of operating earnings on lagged operating earnings. The coefficient of variation is the standard deviation of operating earnings, scaled by mean operating earnings. The coefficient of variation is only calculated for firm-year observations with positive earnings. N refers to the number of firm-year observations with non-missing operating earnings and lagged operating earnings. The t-stats from a test of equality of means between complex and non-complex industries is also reported, with ** and *** indicating two-tailed statistical significance at the p<0.05 and p<0.01 levels.

Table 2
Earnings Persistence and Analysts' Forecast Errors in Complex and Non-complex industries
Panel A: Persistence

	Full Sample		*Complex = 1*		*Complex = 0*		*Chow-test*
$OPINCOME_{t-1}$	0.715		0.544		0.798		80.55
	(52.753)***		(21.904)***		(58.705)***		(<0.0001)
$ACCRUALS_{t-1}$		0.617		0.513		0.668	18.13
		(34.362)***		(19.736)***		(26.268)***	(<0.0001)
OCF_{t-1}		0.745		0.546		0.843	92.52
		(48.221)***		(20.468)***		(54.332)***	(<0.0001)
Constant	0.018	0.014	0.030	0.029	0.012	0.007	
	(15.246)***	(9.996)***	(15.917)***	(13.560)***	(8.415)***	(4.183)***	
N	27466	27466	14062	14062	13404	13404	
Adjusted R^2	0.586	0.583	0.410	0.411	0.674	0.672	
Model F	2782.906	1233.002	479.791	235.992	3446.299	1518.612	

Panel B: Analyst Forecast Dispersion and Forecast Errors

	DV=FCST_STD		DV=FCST_ERR	
COMPLEX	**0.019*****	**0.010*****	**0.047*****	**0.016*****
	(6.739)	**(4.417)**	**(6.377)**	**(2.708)**
LNNUMEST		-0.017***		-0.071***
LNMVE		0.005***		0.007*
LEVERAGE		0.041***		0.091***
ROA		-0.054***		-0.196***
LAGROA		0.015		0.107***
LOSS		0.021***		0.070***
OCF		-0.033*		0.050
BTM		0.010***		0.007
LAGABSACCRUAL		0.036**		0.036
REVGWTH		0.019***		0.036***
ZSCORE		0.002**		0.005**
STDEARN		0.000***		0.000***
TENURE		-0.006		-0.033**
Constant	0.042***	-0.017*	0.094***	0.075**
N	9430	7660	10424	8337
Adjusted R^2	0.012	0.134	0.007	0.096
Model F	45.410	15.167	40.671	12.681

Panel A presents the results of regressing operating income on lagged operating income or lagged accruals and lagged operating cash flow for complex and non-complex industries. The chi-squared and p-value from a Chow-test that the coefficients are equal across complex and non-complex industries is presented in the last column. Panel B presents the results of regressing analyst forecast dispersion (FCST_STD) and the absolute value of analyst forecast errors (FCST_ERR) on an indicator variable for COMPLEX and control variables. In both panels, *, **, and *** indicates two-tailed statistical significance calculated using robust standard errors clustered for each unique firm in the sample. In Panel A, t-statistics are presented in parentheses below the coefficient estimates, except for the Chow-test where p-values are presented in parentheses below the Chi-squared statistic. In Panel B, for conciseness, t-statistics are only presented below the coefficient estimates for the test variable, COMPLEX, for conciseness.

Table 3
Descriptive Statistics

	Panel A: Complex Industries				Panel B: Non-Complex Industries			
Variable	N	Mean	Median	S.D	N	Mean	Median	S.D.
ABSDA	7799	0.064	0.044	0.071	9760	0.077	0.054	0.081
ABSDD	7265	-0.028	-0.032	0.049	9178	-0.027	-0.029	0.056
ABSWC	7780	0.035	0.020	0.053	9752	0.044	0.027	0.057
ACC_RESTATE	7799	0.115	0.000	0.319	9760	0.115	0.000	0.319
ADV_RESTATE	7799	0.105	0.000	0.306	9760	0.101	0.000	0.302
INDUSTRYEXPERT	7799	0.347	0.000	0.476	9760	0.445	0.000	0.497
NATINDLEADER	7799	0.150	0.000	0.357	9760	0.112	0.000	0.316
LNOFFICE	7799	17.918	18.045	1.124	9760	18.041	18.153	1.125
LNMVE	7799	6.818	6.773	1.787	9760	6.566	6.496	1.777
LEVERAGE	7799	0.548	0.538	0.271	9760	0.492	0.471	0.278
ROA	7799	0.012	0.035	0.151	9760	-0.018	0.041	0.213
LAGROA	7799	0.000	0.033	0.182	9760	-0.024	0.038	0.221
LOSS	7799	0.276	0.000	0.447	9760	0.324	0.000	0.468
OCF	7799	0.095	0.094	0.117	9760	0.047	0.082	0.179
BTM	7799	0.467	0.436	0.662	9760	0.498	0.421	0.635
LAGABSACCRUALS	7799	0.101	0.071	0.113	9760	0.091	0.061	0.111
REVGWTH	7799	0.149	0.097	0.330	9760	0.158	0.085	0.438
ZSCORE	7799	1.715	1.660	2.500	9760	2.147	2.446	2.922
STDEARN	7799	135.412	25.187	298.971	9760	98.395	22.443	228.012
TENURE	7799	0.906	1.000	0.292	9760	0.917	1.000	0.275

Table 4
Earnings Quality of Firms with Industry Audit Experts in Complex and Non-Complex Industries

Panel A: Accrual-Based Measures

	Full Sample			COMPLEX=1			COMPLEX=0		
D.V.=	ABSDA	ABSDD	ABSWC	ABSDA	ABSDD	ABSWC	ABSDA	ABSDD	ABSWC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
INDUSTRYEXPERT	**-0.003****	**-0.000**	**-0.000**	**-0.005*****	**-0.003****	**-0.003****	**-0.002**	**0.001**	**0.002**
	(-2.072)	**(-0.515)**	**(-0.285)**	**(-2.594)**	**(-2.044)**	**(-2.098)**	**(-0.940)**	**(0.700)**	**(1.155)**
NATINDLEAD	0.001	-0.001	0.000	-0.001	-0.001	0.001	0.003	-0.000	-0.000
LNOFFICE	0.000	-0.000	-0.001	-0.001	-0.000	-0.001	0.000	0.000	-0.001
LNMVE	-0.004***	-0.005***	-0.007***	-0.003***	-0.004***	-0.006***	-0.004***	-0.005***	-0.007***
LEVERAGE	-0.003	0.002	0.008***	-0.014**	0.000	0.007	0.006	0.003	0.009**
ROA	-0.185***	-0.017**	-0.019*	-0.172***	-0.024**	-0.041**	-0.200***	-0.017*	-0.008
LAGROA	-0.000	0.007	0.007	0.006	0.010*	0.015**	-0.001	0.004	0.002
LOSS	-0.019***	-0.001	-0.002	-0.013**	-0.002	-0.006**	-0.024***	-0.001	0.000
OCF	0.176***	-0.004	-0.022**	0.150***	-0.017	-0.030*	0.184***	-0.000	-0.024*
BTM	-0.006***	-0.003***	-0.004*	-0.006***	-0.003**	-0.004	-0.006***	-0.004***	-0.003**
LAGABSACCRUALS	0.047***	0.043***	0.044***	0.079***	0.046***	0.048***	0.025**	0.040***	0.041***
REVGWTH	0.016***	0.007***	0.009***	0.015***	0.007***	0.003	0.017***	0.007***	0.011***
ZSCORE	-0.002***	-0.001**	-0.001	-0.003***	-0.001***	-0.001	-0.001	-0.000	-0.000
STDEARN	0.000***	0.000***	0.000***	0.000**	0.000	0.000**	0.000***	0.000***	0.000*
TENURE	-0.001	-0.000	0.001	-0.002	0.002	0.001	0.001	-0.003	0.000
Industry & year FE's	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	16985	15916	16934	7225	6738	7182	9760	9178	9752
Adjusted R^2	0.235	0.170	0.120	0.190	0.192	0.140	0.258	0.169	0.109
Model F	18.285	25.479	24.330	14.836	20.155	10.422	10.072	12.414	16.617
Model P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 4 (continued)

Panel B: Restatement-Based Measures

	Full Sample		COMPLEX=1		COMPLEX=0	
D.V.=	ACC_RES	ADV_RES	ACC_RES	ADV_RES	ACC_RES	ADV_RES
	(1)	(2)	(3)	(4)	(5)	(6)
INDUSTRYEXPERT	**-0.146****	**-0.148***	**-0.243****	**-0.277****	**-0.049**	**-0.020**
	(-1.961)	**(-1.880)**	**(-2.070)**	**(-2.257)**	**(-0.510)**	**(-0.198)**
NATINDLEAD	0.152	0.234**	0.124	0.251	0.180	0.227
LNOFFICE	0.023	0.002	0.080	0.053	-0.020	-0.035
LNMVE	0.050*	0.051*	0.114***	0.117***	-0.001	-0.004
LEVERAGE	0.419***	0.448***	0.688***	0.688***	0.203	0.243
ROA	0.156	0.264	0.175	0.342	0.035	0.101
LAGROA	-0.071	-0.011	-0.058	0.152	-0.118	-0.214
LOSS	0.121	0.092	0.125	0.165	0.110	0.025
OCF	0.320	0.384	0.220	0.465	0.397	0.355
BTM	0.297***	0.317***	0.449***	0.464***	0.188**	0.210**
LAGABSACCRUALS	0.243	0.038	0.276	0.355	0.154	-0.339
REVGWTH	-0.075	-0.134	-0.107	-0.121	-0.051	-0.147
ZSCORE	-0.012	-0.013	-0.042*	-0.048**	0.017	0.022
STDEARN	-0.000	-0.000	-0.001**	-0.001**	0.000	0.000
TENURE	0.018	-0.010	0.141	0.111	-0.095	-0.131
Industry & year FE's	Yes	Yes	Yes	Yes	Yes	Yes
N	17169	17169	7691	7691	9478	9478
Psuedo R^2	0.055	0.062	0.045	0.050	0.070	0.080
Model Chi^2	404.807	415.809	172.483	166.669	269.584	288.042
Model P-value	0.000	0.000	0.000	0.000	0.000	0.000

Table 4 (continued)

Panel A presents results using the three accrual-based measures of earnings quality: absolute discretionary accruals (ABSDA), accrual estimation errors (ABSDD), and absolute working capital accruals (ABSWC). Columns 1-3 present the full sample results, Columns 4-6 present results for complex industries only, and Columns 7-8 for non-complex industries only. Panel B presents the same information using the two restatement-based measures of earnings quality, ACC_RES and ADV_RES. Industry and year fixed effects are included in all models but are not reported for brevity. *, **, and *** indicate two-tailed statistical significance at the $p<0.10$, $p<0.05$, and $p<0.01$ levels, respectively. Statistical significance is calculated using robust standard errors clustered for each unique firm in the sample.

Table 5
PSM Samples: Earnings Quality of Firms with Industry Audit Experts in Complex and Non-Complex Industries

Panel A: Accrual-Based Measures

	Full Sample			COMPLEX=1			COMPLEX=0		
D.V.=	ABSDA	ABSDD	ABSWC	ABSDA	ABSDD	ABSWC	ABSDA	ABSDD	ABSWC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
INDUSTRYEXPERT	**-0.002***	**-0.001**	**-0.000**	**-0.005****	**-0.003****	**-0.003****	**-0.002**	**0.001**	**0.001**
	(-1.776)	**(-0.614)**	**(-0.245)**	**(-2.557)**	**(-2.066)**	**(-2.338)**	**(-0.803)**	**(0.719)**	**(0.951)**
NATINDLEAD	-0.000	-0.001	-0.001	-0.003	-0.000	0.001	0.003	-0.001	-0.001
LNOFFICE	0.000	-0.000	-0.001	-0.000	-0.000	-0.000	0.000	0.000	-0.001
LNMVE	-0.004***	-0.004***	-0.006***	-0.003***	-0.004***	-0.005***	-0.004***	-0.005***	-0.007***
LEVERAGE	-0.000	0.002	0.009***	-0.009	0.003	0.010*	0.007	0.002	0.008**
ROA	-0.194***	-0.018**	-0.019*	-0.193***	-0.029**	-0.043**	-0.203***	-0.019*	-0.011
LAGROA	-0.001	0.008	0.007	-0.003	0.003	0.014	0.000	0.006	0.004
LOSS	-0.019***	-0.001	-0.001	-0.016**	-0.002	-0.006*	-0.026***	-0.000	-0.000
OCF	0.185***	-0.001	-0.016	0.179***	-0.004	-0.026	0.194***	0.002	-0.023
BTM	-0.006***	-0.003***	-0.002**	-0.005**	-0.003**	0.000	-0.006***	-0.005***	-0.005***
LAGABSACCRUALS	0.041***	0.043***	0.042***	0.070***	0.038***	0.056***	0.025*	0.043***	0.044***
REVGWTH	0.017***	0.008***	0.010***	0.018***	0.009***	0.005**	0.017***	0.008***	0.012***
ZSCORE	-0.002**	-0.001**	-0.001	-0.003***	-0.001***	-0.001	-0.001	-0.000	-0.000
STDEARN	0.000***	0.000***	0.000***	0.000*	0.000	0.000**	0.000***	0.000***	0.000*
TENURE	-0.003	-0.002	0.000	-0.004	0.003	-0.001	0.001	-0.004	0.000
Industry & year FE's	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	14572	13674	14557	5748	5373	5744	8762	8242	8752
Adjusted R^2	0.246	0.174	0.119	0.200	0.204	0.140	0.269	0.173	0.108
Model F	15.454	21.758	22.573	11.255	16.577	9.170	9.567	11.801	15.699
Model P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Panel B: Restatement-Based Measures

	Full Sample		COMPLEX=1		COMPLEX=0	
D.V.=	ACC_RES	ADV_RES	ACC_RES	ADV_RES	ACC_RES	ADV_RES
	(1)	(2)	(3)	(4)	(5)	(6)
INDUSTRYEXPERT	**-0.120**	**-0.141***	**-0.241****	**-0.278****	**-0.089**	**-0.057**
	(-1.558)	**(-1.756)**	**(-2.020)**	**(-2.225)**	**(-0.913)**	**(-0.551)**
NATINDLEAD	0.104	0.190*	0.100	0.171	0.140	0.213
LNOFFICE	0.032	0.002	0.072	0.055	-0.018	-0.036
LNMVE	0.041	0.039	0.089*	0.092*	-0.018	-0.016
LEVERAGE	0.364**	0.378**	0.654***	0.565**	0.263	0.356
ROA	0.189	0.234	0.131	0.168	0.028	-0.011
LAGROA	-0.206	-0.071	-0.255	0.016	-0.041	-0.107
LOSS	0.114	0.088	0.125	0.154	0.071	-0.009
OCF	0.421	0.458	0.531	0.719	0.343	0.342
BTM	0.296***	0.324***	0.453***	0.466***	0.206***	0.233***
LAGABSACCRUALS	-0.028	-0.282	-0.068	-0.066	0.109	-0.241
REVGWTH	-0.051	-0.119	-0.085	-0.124	-0.044	-0.130
ZSCORE	-0.016	-0.016	-0.032	-0.037	0.024	0.028
STDEARN	-0.000	-0.000	-0.001**	-0.000*	0.000	0.000
TENURE	0.011	-0.005	0.229	0.211	-0.072	-0.113
Industry & year FE's	Yes	Yes	Yes	Yes	Yes	Yes
N	14742	14742	6152	6152	8510	8510
Adjusted/Psuedo R^2	0.055	0.064	0.043	0.046	0.070	0.081
Model F/Chi^2	359.625	380.414	133.102	121.109	250.826	274.448
Model P-value	0.000	0.000	0.000	0.000	0.000	0.000

This table presents the same information as in Table 4, but using propensity score matched samples. Panel A presents results using the three accrual-based measures of earnings quality: absolute discretionary accruals (ABSDA), accrual estimation errors (ABSDD), and absolute working capital accruals (ABSWC). Columns 1-3 present the full sample results, Columns 4-6 present results for complex industries only, and Columns 7-9 for non-complex industries only. Panel B presents the same information using the two restatement-based measures of earnings quality, ACC_RES and ADV_RES. Industry and year fixed effects are included in all models but are not reported for brevity. *, **, and *** indicate two-tailed statistical significance at the p<0.10, p<0.05, and p<0.01 levels, respectively. Statistical significance is calculated using robust standard errors clustered for each unique firm in the sample.

Table 6: Industry Audit Experts and Analysts' Forecast Errors

	FULL SAMPLE		COMPLEX=1		COMPLEX=0	
INDUSTRYEXPERT	**0.004**	**0.007**	**0.006**	**0.012**	**0.003**	**0.003**
	(0.945)	**(1.513)**	**(0.849)**	**(1.566)**	**(0.564)**	**(0.583)**
ACCINTENS		**0.019*** **		**0.019***		**0.015***
		(2.864)		**(1.827)**		**(1.744)**
INDUSTRYEXPERT*ACCINTENS		**-0.013**		**-0.036****		**-0.001**
		(-1.344)		**(-2.028)**		**(-0.069)**
NATINDLEAD	-0.006	-0.006	0.006	0.007	-0.014**	-0.014**
LNOFFICE	0.000	0.000	0.002	0.002	-0.000	-0.000
LNNUMEST	-0.028***	-0.028***	-0.035***	-0.036***	-0.022***	-0.022***
LNMVE	-0.003	-0.002	-0.002	-0.002	-0.002	-0.002
LEVERAGE	0.049***	0.047***	0.034**	0.033*	0.056***	0.055***
ROA	-0.035	-0.036	-0.205**	-0.205**	0.084*	0.081*
LAGROA	0.022	0.020	0.027	0.023	0.012	0.010
LOSS	0.026***	0.026***	0.018	0.018	0.030***	0.030***
OCF	-0.023	-0.018	0.132*	0.134*	-0.135***	-0.128**
BTM	0.000	0.001	-0.015	-0.014	0.013	0.014
LAGABSACCRUALS	0.023	0.018	0.036	0.031	-0.005	-0.010
REVGWTH	0.015	0.014	-0.004	-0.005	0.018	0.016
ZSCORE	0.002	0.002	0.000	0.001	0.002*	0.002*
STDEARN	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
TENURE	0.008	0.008	0.007	0.007	0.005	0.005
Industry & Year FE's	Yes	Yes	Yes	Yes	Yes	Yes
N	8604	8604	3655	3655	4949	4949
Adjusted R^2	0.068	0.070	0.088	0.089	0.066	0.068
Model F	8.142	7.571	4.088	3.816	5.653	5.243
Model p-value	0.000	0.000	0.000	0.000	0.000	0.000

The dependent variable in all regressions is FCST_ERR. The first two columns present results for the full sample, followed by complex industries only, and non-complex industries only. The second four columns present results for non-complex industries. Standard errors are presented below the coefficient estimates for test variables, but are not reported on control variables for brevity. *, **, and *** indicate two-tailed statistical significance at the p<0.10, p<0.05, and p<0.01 levels, respectively. Standard errors are clustered for each unique firm in the sample.