Financial Statement Complexity and Meeting Analysts' Expectations*

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1. Introduction

The benefits of meeting analysts' earnings expectations are well documented (Matsunaga and Park 2001; Bartov, Givoly, and Hayn 2002; Kasznik and McNichols 2002; Lopez and Rees 2002). Given these benefits, it is not surprising research suggests that managers use various mechanisms available to them to meet or beat analysts' forecasts (Degeorge, Patel, and Zeckhouser 1999; Payne and Robb 2000; Barton and Simko 2002; Bartov et al. 2002; Matsumoto 2002; Abarbanell and Lehavy 2003; Graham, Harvey, and Rajgopal 2005; Brown and Caylor 2005; Burgstahler and Eames 2006). Some research suggests that specific items in financial statements, like taxes and pensions, that are more complex may allow firms to be more likely to meet expectations (Dhaliwal, Gleason, and Mills 2004; Picconi 2006). However, the research on the effect of complexity on meeting expectations is both inconclusive and incomplete. We provide additional insight into this question by examining the effect of financial statement complexity on meeting expectations in a broad context using a new measure of complexity.

Complexity can be described as the state of being difficult to understand or apply; therefore, financial statement complexity represents the increased difficulty in understanding, interpreting, and forecasting financial statements. We develop a proxy for financial statement complexity using the abnormal length of accounting policy disclosures found in the notes to the financial statements. We rely upon accounting policy disclosures to proxy for financial statement complexity because these disclosures address the firm's significant economic transactions as well as their treatment in the financial statements. This proxy captures differences in transactions firms engage in (e.g., firms with and without derivatives), as well as the extent of the complexity of similar transactions across firms (e.g., point-of-sale versus multiple element revenue transactions).

We address two potential concerns with this proxy for financial statement complexity. First, our proxy is based on the length of disclosure and initially appears to contradict the general notion that additional disclosure captures higher quality information (Diamond 1985; Lang and Lundholm 1996; Botosan 1997; Hope 2003). However, recent studies suggest that more disclosure can proxy for complexity (Li 2008; Miller 2010; Lehavy, Li, and Merkley 2011; Peterson 2012). By examining the relationship between our proxy and audit

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fees, we validate that our proxy does capture financial statement complexity and not just the quality of disclosure across firms. If longer accounting policy disclosures just represent disclosure choices and not underlying financial statement complexity, we would not expect to find a significant increase in the fees auditors charge for auditing the financial statements of firms with longer disclosures. However, we find a significant positive relationship between our proxy and audit fees, even after controlling for 23 other factors that affect audit fees. A one standard deviation increase in financial statement complexity increases audit fees by $80,407 or 9.9 percent for the average firm.

The second concern is whether our proxy for financial statement complexity is distinct from other measures of firm-level complexity like size, organizational complexity (Bushman, Chen, Engel, and Smith 2004), and readability or complexity of the 10-K (Li 2008; You and Zhang 2009; Miller 2010; Lehavy et al. 2011). We argue our proxy captures the construct of financial statement complexity distinct from these other proxies. However, we recognize these other proxies could also capture elements of financial statement complexity. Therefore, we include these other proxies for complexity as controls in our analysis. Although including these controls potentially reduces the strength of our measure, doing so demonstrates that our results cannot be explained by other proxies for complexity.

We predict that firms with more complex financial statements are more likely to use three strategies to influence whether a firm beats an earnings forecast. First, managers of complex firms may have greater influence over analysts' forecasts because complexity makes forecasting more difficult for analysts (Plumlee 2003; Li 2008; Miller 2010; Lehavy et al. 2011). Managers may influence the forecasts of analysts to be walked down to beatable levels. Second, complex firms are more likely to have unfamiliar or unusual economic events and may be more likely to beat expectations by having analysts exclude these generally accepted accounting principle (GAAP) items from their non-GAAP actual earnings or "street earnings." This builds upon recent research suggesting that firms can beat expectations by having certain items excluded in their non-GAAP actual earnings number or "street earnings" (Christensen, Merkley, Tucker, and Venkataraman 2011; Doyle, Jennings, and Soliman 2013). Finally, firms with complex financial statements require more subjective estimation by managers, increasing their ability to manage accruals to beat expectations.

We conduct our tests on a large sample of firm-quarters with forecast errors within $0.02 around zero. Tests confirm that firms with complex financial statements are more likely to report small positive forecast errors than small negative errors, suggesting complexity gives managers an edge in meeting expectations at the margin. This differs from a test of the entire distribution of earnings forecasts, where we do not find that firms with complex financial statements have an increased propensity to meet expectations.

We then test each of the three underlying behaviors—managing expectations, excluding GAAP items, and managing accruals—to determine which strategies firms with complex financial statements use to meet expectations. We find evidence that complex firms use expectations management to beat analysts' estimates because they are more likely to have forecasts that were walked down to beatable levels than less complex firms. Firms with more complex financial statements are also significantly more likely to have income-increasing GAAP exclusions from analysts' determination of actual earnings. However, it does not appear that complex firms use these exclusions opportunistically to beat expectations. Contrary to our hypothesis, we find no evidence that complex firms use discretionary accruals manipulation to meet analyst expectations.

In additional analysis, we examine whether the propensity to meet or beat analysts' earnings expectations for complex firms also applies to alternative benchmarks: zero earnings and prior-period seasonal earnings per share (EPS). In contrast to our analyst results, we find a negative relation between financial complexity and beating these other benchmarks. These contrasting results suggest managers of complex firms focus more on meeting analyst benchmarks, perhaps since analyst benchmarks can be influenced while these other benchmarks cannot. We also provide corroborating evidence for our expectations management results that managers of complex firms have greater influence on analysts' expectations. We test whether complexity affects the relationship between management guidance and analysts' forecast revisions and find that analysts increase their reliance on management guidance of complex firms when revising their forecasts. We also examine the market reaction to beating expectations for complex firms. The investor response at the earnings announcement to just beating expectations is not statistically different for complex firms versus less complex firms, but investors have a more negative reaction to the walk-down of earnings during the quarter for firms with more complex financial statements, suggesting that perhaps investors are aware of the interaction between complex firms and analysts. However, there remains a net benefit to complex firms for walking down earnings and beating expectations. A complex firm with no forecast walk-down receives a 2.67 percent positive return for beating expectations, while a complex firm with an average walk-down of 7 percent still receives a net 2.24 percent positive return after considering the walk-down penalty.

Our research provides new evidence about the effect of complexity on analysts. A consensus finding in the literature is that analysts struggle with complexity or uncertainty that leads to more disagreement among analysts (Lehavy et al. 2011) and inaccurate (Duru and Reeb 2002; Plumlee 2003; Lehavy et al. 2011) or biased forecasts (Ackert and Athanassakos 1997; Duru and Reeb 2002; Zhang 2006). However, other studies suggest analysts have incentives to cover more complicated or complex firms (Barth, Kasznik, and McNichols 2001; Palmon and Yezegel 2011; Lehavy et al. 2011). We address how managers and analysts respond to complexity. Our results suggest that analysts do alter their behaviors for complex firms by walking down forecasts and relying more upon managers' forecasts so that their forecasting accuracy is not always negatively impacted. This evidence is important as it provides an additional, and ultimately a more complete, perspective regarding how managers' and analysts' decisions are affected by financial complexity.

We also contribute to literature that examines specific areas of complexity and provides suggestive evidence that managers manage earnings when accounting is complex (Dhaliwal et al. 2004; Picconi 2006; Peterson 2012). However, the evidence presented in those studies is not conclusive or complete regarding the use of complexity to meet expectations. Rather than explore a specific instance of complexity in the financial statements (e.g., pensions, taxes, revenue recognition), we examine how the overall complexity of the financial statements affects meeting or beating analysts' estimates. This approach reveals additional, unique insights not found in prior literature. In contrast to this prior research, we do not find evidence that managers of complex firms manage accruals upwards to meet analysts' estimates. Furthermore, prior research does not examine expectations management or the exclusion of GAAP items because their settings are not conducive to such tests.[1] Our analysis includes such tests and the results suggest firms with complex financial statements primarily use expectations management to meet analysts' estimates, and have more GAAP items excluded from actual earnings.

Finally, our research proposes a new measure of financial statement complexity distinct from other measures of complexity used in prior research. Regulators, standard-setters, and the press continue to express concern about financial complexity, but research on the types, causes, and consequences of complexity is extremely limited, which

1. Examining the effect of complexity on expectations management is difficult to do in a specific setting like pensions or taxes. Expectations management is difficult to test in these settings because analysts do not generally provide detailed income statement line-item estimates, just summary earnings estimates. Therefore, linking any expectations management to a specific accrual or line item is questionable.

potentially inhibits decision making.[2] Our research suggests some firms opportunistically take advantage of complexity, which provides some confirming evidence that the concern over complexity in financial reporting may be warranted. From an accounting research perspective, a specific measure of the underlying complexity stemming from the financial statements could be helpful to researchers trying to better understand the effects of financial reporting on users and preparers. The evidence in this paper suggests financial statement complexity influences audit fees and the interaction between managers and analysts. Future research could examine the effects of financial complexity on managers' other financial reporting decisions and on users of the financial statements.

In the next section, we develop the hypotheses. In section 3, we discuss the sample and validate our measure of financial statement complexity. We describe our tests in section 4, and conduct some additional analysis in section 5. We conclude in section 6.

2. Background and hypotheses

Since our hypotheses rely upon the construct of financial statement complexity, we start with a discussion of its underpinnings. We maintain that the primary source of financial statement complexity is the underlying complexity of the economic transactions or accounting standards relevant to the firm. Complex economic transactions could be due to particular transactions which are less familiar or more complicated or could result from firms engaging in a wide range of economic transactions, which when aggregated make it more difficult to identify how those economic events affect the firm. As examples of the first type, revenue contracts with multiple elements are considered more complex than point-of-sale transactions because the economic events are completed over multiple steps, while derivatives are generally considered complex transactions because they are less familiar to financial statement users. As an example of the second type, a restaurant business that has both owned and operated restaurants as well as franchised restaurants engages in a wider range of economic transactions than a business just engaging in one or the other.

Theoretically, transaction complexity is independent from the financial accounting system. Accounting standards could accurately represent the complexity of transactions or increase or decrease the level of complexity of transactions in financial statements. To make financial statements meaningful to users, the FASB recognizes the need for accounting standards to attempt to reflect economic events in financial statements on a timely basis. They are not interested in reducing representational faithfulness in favor of simplicity (FASB 2008, 18–19). If the FASB's claim is correct, then financial statement complexity is likely driven by underlying economic complexity. However, the purpose of our research is not to understand the factors underlying financial statement complexity but to understand its effect on analysts and meeting expectations. Peterson (2012) notes that it is not clear financial statement users care about the underlying causes of financial statement complexity. We think this is especially true in our setting of analysts forecasting earnings, where analysts must understand how transactions map into financial statements.

2. The report issued by the SEC's Advisory Committee on Improvements to Financial Reporting recommended that the FASB's mission statement should have a goal to minimize avoidable complexity (SEC 2008b). In addition, a recent article by PricewaterhouseCoopers suggests the FASB should have a specific advisory committee on reducing complexity in financial reporting (PWC 2011). Consistent with these recommendations, the FASB has recently expressed concern with financial reporting complexity (FASB 2008). More specific to our research question, the SEC also has cited concern over financial complexity and meeting analyst forecasts in their speeches (Turner 1998, 2000, 2001) and Accounting and Auditing Enforcement Releases (SEC 2002, 2004, 2008a). Finally, there is specific anecdotal discussion in the popular press that investors should be skeptical of firms beating analysts' expectations, especially for complex firms (Chanos 2006; Greenberg 2008; Ross and Syre 2008).

Prior research has attempted to study or control for different aspects of firm-level complexity. A few studies have examined *organization* complexity specifically, and many studies, including those that examine analysts' forecasts, control for organization complexity using proxies such as size, operating segments, and geographic segments or sales (Barth et al. 2001; Bushman et al. 2004; Markarian and Parbonetti 2007; Coles, Daniel, and Naveen 2008; Li 2008; Lassila, Omer, Shelley, and Smith 2010; Bronson, Hogan, Johnson, and Ramesh 2011; Lehavy et al. 2011). Other recent studies have used the Gunning–Fox Index or 10-K length to proxy for *reporting* complexity (Li 2008; Miller 2010; Lehavy et al. 2011). These proxies for reporting complexity are related to financial statement complexity, but are fundamentally different. Some reporting issues and time-specific events may affect reporting complexity, but not necessarily financial statement complexity. For example, more sophisticated language (i.e., less readability), whether intentional or not, could make 10-K reports more difficult to read, but does not capture underlying financial statement complexity directly. Another important difference is reporting complexity proxies are also influenced by disclosures that do not capture financial statement complexity but capture uncertainty (e.g., lawsuit disclosures, research and development activities, new government regulations). We contend that both the theoretical construct of financial statement complexity and our proxy for it as discussed in section 3 captures a unique aspect of complexity relative to these proxies; however, this is ultimately an empirical question and therefore in our tests we control for these other aspects of complexity using proxies from prior research.

Hypotheses

Prior literature has identified four ways that firms can influence their likelihood of meeting analysts' estimates: (i) managing analysts' expectations, (ii) excluding specific items from analysts' actual or "street" earnings, (iii) managing accruals, and (iv) managing real activities. As we discuss in more detail below, we expect firms with more complex financial statements to be more likely or better able to engage in the first three behaviors to meet expectations relative to less complex firms.[3] If complex firms are more likely to engage in these behaviors, we expect complex firms should be more likely to meet or beat analyst expectations relative to less complex firms.[4] Burgstahler and Dichev (1997) and Degeorge et al. (1999) provide evidence that the benchmark discontinuities have a very tight window, suggesting that the strategies used to beat expectations are limited to those firms close to the benchmark. Therefore, we expect the effects of complexity will be especially prevalent at the margin (i.e., firms close to analysts' expectations), which leads us to our first prediction:

> Hypothesis 1. *Firms with more complex financial statements are more likely to meet or beat analysts' expectations at the margin than firms with less complex statements.*

Although we have an expectation about the effect of complexity being strongest at the margin, it is possible that complexity is influential enough to allow managers to beat expectations more generally. Therefore, for completeness we also examine whether the ability of complex firms to meet expectations applies more broadly to all earnings forecasts in our sample. Furthermore, we examine each of the explanations separately to better understand the behaviors complex firms engage in to meet expectations.

3. Given the nature of real activities manipulation described in Roychowdhury (2006) such as price discounts and overproduction, we expect real activities manipulation to be an equally viable tool for all firms, or perhaps more costly for financially complex firms due to an increase in coordination costs, and therefore not specifically used by complex firms. In untabulated analysis, we examined whether complex firms are more likely to engage in real earnings management to beat expectations and found no significant relationship in these tests as expected.
4. Throughout the paper we assume financial statement complexity is exogenous during the short window (3 months) of the quarterly earnings-forecast period.

We begin our discussion with the two approaches to beating expectations that require analyst participation, managing expectations and excluding items from analysts' street earnings. We conjecture that analysts will be more susceptible to firm influence in these areas when financial statements are more complex because analysts value more accurate forecasts (Mikhail, Walther, and Willis 1999; Hong and Kubik 2003; Groysberg, Healy, and Maber 2011) and analysts may want to curry favor with management (Francis and Philbrick 1993; Hong and Kubik 2003; Libby, Hunton, Tan, and Seybert 2008; Feng and McVay 2010). Prior literature indicates that complexity makes forecasting more difficult for analysts (Duru and Reeb 2002; Plumlee 2003; Picconi 2006; Lehavy et al. 2011; Peterson 2012). For example, Peterson (2012) finds evidence that revenue recognition complexity is positively associated with analysts' revenue forecast error and dispersion, while Lehavy et al. (2011) show that reporting complexity increases analysts' earnings-forecast dispersion and error. While this prior research finds an association between complexity and forecasting dispersion and error generally in data, none of these studies examine whether firms with complex financial statements use that complexity to help them beat analysts' earnings forecasts at the margin. In fact, these prior results suggest that firms with complex financial statements may be less likely to just beat analysts' forecasts. Given that analysts value accurate forecasts (Mikhail et al. 1999; Hong and Kubik 2003; Groysberg et al. 2011), when faced with increased uncertainty about future earnings and potential increased forecast errors an analyst should be more likely to be influenced by manager input. In fact, it is possible that the difficulty in forecasting induces analysts to seek management input and guidance to improve their accuracy. All else equal, this increased incidence of expectations management leads to a greater probability of beating expectations than missing expectations for firms with complex financial statements. Studies also suggest that analysts issue optimistic initial forecasts that get walked down to curry favor with managers in order to get additional access to management and attract future business (Libby et al. 2008; Francis and Philbrick 1993; Feng and McVay 2010). Given that complex firms are more difficult to forecast, it may be easier for analysts to justify the implied relationship building that occurs through the walk-down of forecasts.

Since it is difficult to examine all forms of expectations management directly, prior research has used the walk-down of earnings forecasts as evidence of expectations management (Bartov et al. 2002; Richardson, Teoh, and Wysocki 2004). We follow this prior research by examining whether complex firms are more likely to have expectation paths that suggest expectations were managed. Therefore, we predict:

HYPOTHESIS 2. *Firms with more complex financial statements are more likely to have walked down expectations that allow them to beat expectations than firms with less complex statements.*

Recent research provides evidence that firms can beat analysts' estimates by influencing which items analysts exclude from actual earnings. Christensen et al. (2011) find that management guidance can be used to influence analysts' exclusions from GAAP earnings to create "street earnings." Doyle et al. (2013) document that differences between GAAP earnings and "street earnings" for firms increases the likelihood that those firms will beat analysts' expectations. Although excluded items frequently include either nonrecurring or nonoperating items, these papers suggest there is not a consistent application of what does and does not get excluded.[5] We conjecture that complex firms are more likely to have

5. Both Christensen et al. (2011) and Doyle et al. (2013) provide discussions about the actual process by which GAAP items are excluded from analysts' actual earnings. The decision is ultimately made by a consensus of the analysts covering the firm but these studies suggest that managers can influence that decision. However, it is possible that analysts might insist on these exclusions irrespective of manager influence to ensure their forecasts are accurate.

events or transactions that could be excluded from street earnings, and managers of complex firms could influence the analysts' exclusion decision, resulting in an increased likelihood to meet or beat expectations (MBE). Analysts may be willing to comply with the exclusion for the same two reasons listed above, the concern about accurate forecasts and wanting to curry favor with managers. We hypothesize:

HYPOTHESIS 3. *Firms with more complex financial statements are more likely to meet expectations using GAAP exclusions than firms with less complex financial statements.*

The remaining option that managers of complex firms might use to beat estimates is accruals management. Firms with greater financial statement complexity should have more opportunities to manage earnings due to additional subjective accrual estimates. This idea is consistent with prior research. Picconi (2006) and Bergstresser, Desai, and Rauh (2006) find that investors and analysts do not understand the effect of changes in pension plan parameters on future earnings and that managers manipulate pension assumptions in certain settings. However, they do not provide specific evidence that managers manipulate pension assumptions to beat analysts' expectations. Dhaliwal et al. (2004) argue that both the complexity and especially the timing of estimating tax expense allows managers to manage earnings to beat analysts' forecasts and find evidence consistent with this conjecture. However, their results do not differentiate between these two explanations of complexity and timing.[6] Finally, although Peterson (2012) provides evidence that restatements can be a result of complexity, he does not examine whether managers of complex firms used complexity to beat analysts' forecasts.

We rely on the discretionary accruals literature to proxy for earnings management. We note two caveats about examining discretionary accruals. First, discretionary accruals are measured with error. McNichols (2003) argues that no single model can capture the heterogeneous discretion that managers have when deciding how to manage earnings. Second, the link between discretionary accruals and meeting analysts' expectations in prior literature is tenuous. Payne and Robb (2000) find that managers move earnings toward analysts' forecasts when earnings before discretionary accruals are below the consensus analyst forecasts. However, Matsumoto (2002) finds only limited support for the use of discretionary accruals to MBE. She finds that positive discretionary accruals are not able to explain whether or not a firm beats expectations when included with a full set of control variables. Phillips, Pincus, and Rego (2003) also struggle to find a link between traditional discretionary accruals measures and MBE. Burgstahler and Eames (2006) document a relationship between accruals and just beating versus just missing analysts' expectations using distributional analysis; however, their analysis does not contain multivariate tests. Athanasakou, Strong, and Walker (2009) find no evidence of the use of accruals management to MBE in a sample of UK firms. Despite the lack of strong evidence of a link from prior literature, our study may provide a more powerful setting than more general samples from prior research. A link between discretionary accruals and MBE is more likely to exist when the financial statements are more complex due to the enhanced ability to manage subjective accrual estimates. We hypothesize:

HYPOTHESIS 4. *Firms with more complex financial statements are more likely to meet expectations using accrual management than firms with less complex statements.*

6. Some research suggests that investors understand the effect of tax estimates (Givoly and Hayn 1992; Kumar and Visvanathan 2003; Dhaliwal, Kaplan, Laux, and Weisbrod 2013), suggesting the Dhaliwal et al. (2004) results may be driven by "last chance earnings management" and not the complexity of tax accounting.

3. Measurement and sample

Sample selection

Our sample contains firm-quarter observations from 1994 to 2008 with necessary data to run our tests. The sample begins in 1994 because our measurement of financial statement complexity requires us to obtain accounting policy disclosures from 10-K filings, which are available on EDGAR (the Electronic Data Gathering, Analysis, and Retrieval system) beginning in 1994. Once we obtain the 10-Ks from EDGAR, we perform a search of these 10-Ks using the Python programming language to obtain the accounting policies section of the notes to the financial statements. We discuss this process in more detail below. We obtain quarterly and annual financial data from COMPUSTAT Xpressfeed quarterly and annual files. We obtained segment data from the COMPUSTAT legacy files, institutional ownership, and management forecasts from Thomson Reuters, and analyst forecast data from I/B/E/S. The necessary data requirements result in a total sample of 85,266 firm-quarters, although the majority of our tests are conducted on a smaller sample of 34,616 firms with absolute forecast errors < 2 cents.

Measuring financial statement complexity

Accounting Principles Board (APB) Opinion No. 22 states the usefulness of financial statements "depends significantly on the user's understanding of the accounting policies followed by the entity" (APB 1972). Therefore, we proxy for financial statement complexity using a measure of abnormal length of a firm's accounting policies disclosure included in the notes to the financial statements.[7] Longer disclosures should reflect increased underlying financial statement complexity because additional words are needed to sufficiently explain more complicated transactions or a broader set of transactions. Specifically, $FS\_COMPLEX_{it}$ is the industry and year adjusted log number of words in the accounting policies disclosure found in the notes to the financial statements in the 10-K. Since the process to extract accounting policies has some error, we performed a number of checks and tests on our extracted accounting policy disclosures. We excluded observations where the accounting policy length was less than 200 words or greater than 80 percent of the 10-K length. In addition, we selected a random sample of 100 disclosures and manually verified their accuracy. The length of the disclosures from the verified random sample has a correlation of 0.94 with the length of the Python-extracted disclosures, suggesting that our measurement of these disclosures is relatively accurate. We winsorize the natural logarithm of the accounting policy disclosure length at 1 percent and 99 percent to reduce the effect of outliers. We then take each firm-year disclosure length and subtract the average accounting policy length for firms in the same two-digit SIC for that year. We expect our proxy to be increasing in financial statement complexity.

Table 1 shows the time trend and variation both across and within industries for our sample's accounting policy length to help explain why we adjust for industry and year effects. First, as shown in panel A, we find that accounting policy length has increased substantially throughout time, from an average of 887 words to 4,154 words, so it is important to control for this time effect. Second, because analysts should generally be familiar with average levels of complexity in an industry, we believe that what is abnormal

7. The notion that additional disclosure is better appears at odds with our proxy (Diamond 1985; Lang and Lundholm 1996; Botosan 1997). However, we contend that variation in the accounting policy disclosure length does not capture high-quality or low-quality information, but principally captures differences in the complexity of the underlying economics or accounting of the firm. In contrast, Hope (2003) uses a measure of the extent of accounting policy disclosures in an international setting and finds that the existence of policy disclosures helps analysts in their forecasting. This "existence" measure is appropriate in Hope (2003), and likely captures information quality, as he studies the effect of policy disclosures in a cross-country setting, where disclosure regulations differ significantly during his sample period.

TABLE 1
Accounting policy length by year and industry

Panel A: Average accounting policy length by year

Fiscal year	Average accounting policy length
1994	887
1995	1,056
1996	1,171
1997	1,319
1998	1,453
1999	1,451
2000	1,705
2001	2,179
2002	2,841
2003	3,037
2004	3,270
2005	3,506
2006	3,730
2007	3,919
2008	4,154

Panel B: Accounting policy length by industry

	N	Mean	SD
Consumer nondurables	4,516	2,183	1,317
Consumer durables	2,049	2,097	1,386
Manufacturing	8,750	2,162	1,375
Oil, gas, and coal extraction and products	4,129	2,733	1,401
Chemicals and allied products	1,957	2,271	1,306
Business equipment	19,848	2,879	1,547
Telephone and television transmission	2,166	3,145	1,717
Utilities	1,529	3,668	1,955
Wholesale, retail, and some services	9,799	2,331	1,427
Healthcare, medical equipment, and drugs	10,027	2,551	1,497
Finance	9,324	3,469	1,777
Other—Mines, Constr, Trans, Bus Serv, Entertainment, etc.	11,172	2,536	1,527
Total	85,266	2,668	1,577
Standard deviation of industry means		525	

Notes:

This table presents data about the composition of accounting policy length for firms in the sample. Panel A presents the the average word count in the accounting policy section by year and panel B displays accounting policy length for the sample by industry. Statistics presented by industry include the number of observations (*N*), mean, and SD. Accounting policy length is winsorized at 1 percent and 99 percent by year. For brevity, industry classification is based on Fama-French 12-industry classification.

to the analyst will have the greatest impact on a firm's ability to meet or beat analysts' expectations, consistent with prior literature (Gu and Wang 2005). Panel B of Table 1 documents the variation in policy disclosure length both across industries and within industries. We find substantial variation across industries with large differences in consumer products and manufacturing firms compared to financial and utility firms. In addition, panel B demonstrates there is also substantial variation within each industry, suggesting these policy disclosures are not boilerplate within industry.

While we exclude the effects across years and across industries in our measure of financial statement complexity, one could argue that firms have increased in complexity over time and that differences across industries represent significant aspects of complexity. Notwithstanding this argument, which does have merit, removing industry and year variation in the disclosures provides for more powerful tests because it excludes alternative explanations for our results. For example, during the sample period the FASB and SEC have both encouraged and mandated firms to be more forthcoming in their disclosures. Therefore, the dramatic increase in accounting policy disclosure length over time could be a result of more informative disclosure and not necessarily increased complexity.

Analysts' forecasts

Most of our dependent variables are calculated using quarterly analyst EPS forecast error (*FCSTERR*), which is calculated as:

$$FCSTERR_{it} = Actual\ IBES\ EPS_{it} - Mean\ EPS\ Forecast_{it} \tag{1}$$

We obtain analysts' estimates from the I/B/E/S Summary unadjusted file and actual EPS numbers from the I/B/E/S Actuals unadjusted file. Since forecast error is a per share number and the actual and forecasts are at different points in time, we use the unadjusted files and adjust for stock splits with the approach suggested by Robinson and Glushkov (2006), which utilizes the CRSP cumulative adjustment split factors from the daily file. For most of our tests, we use the last consensus EPS forecast for the quarter before the earnings announcement date. In a few tests, we use the first consensus EPS forecast for the quarter, which is the first consensus forecast following the prior quarter's earnings announcement.

Descriptive statistics and FS_COMPLEX validation

Table 2 presents univariate statistics for many of the variables included in our analysis. We note that the distribution of *JUSTBEAT* in our sample is consistent with patterns described in Burgstahler and Dichev (1997) since there is a disproportionate number of observations "just beating" versus "just missing." By construction, the mean of *FS_COMPLEX* is zero because it is simply the deviations from mean values within industry and year. Also, the mean of *FCSTERR* is 0.03, which is consistent with the average firm beating expectations. Turning to control variables, we see that the Fog Index, *10KFOG* (calculated as 0.4 × [words per sentence + 100 × percent of complex words]), has a mean of 19.34, which is comparable to the sample from Lehavy et al. (2011). The average (median) firm has beat expectations for 3.8 (2.0) consecutive quarters. We winsorize continuous variables at 1 and 99 percentiles to reduce the effect of outliers, consistent with prior research.[8]

Sample correlations are found in Table 3. We note that *FS_COMPLEX* is positively correlated with constructs used in prior literature to measure complexity. *FS_COMPLEX* is positively correlated with size (*LOGMVE*), the number of operating

8. The results presented in the paper are consistent if we do not winsorize the continuous variables. The only exception is the coefficient on the interaction between complexity and earnings walk-down in Table 10. We measure the earnings walk-down as a percentage walk-down in these tests. One issue with using a percentage walk-down is the presence of extreme values due to some firms having very small EPS forecasts in the denominator. If we scale the walk-down by price instead and do not winsorize, we find similar results to those presented in Table 10.

TABLE 2
Univariate statistics

Variable	*N*	Mean	SD	p25	p50	p75
JUSTBEAT	34,616	0.79	0.41	1.00	1.00	1.00
BEAT	85,266	0.69	0.46	0.00	1.00	1.00
FS_COMPLEX	85,266	0.00	0.42	−0.21	0.04	0.27
FCSTERR	85,266	0.03	4.04	−0.01	0.01	0.03
10KFOG	85,266	19.34	1.89	18.37	19.22	20.06
STREAK	85,266	3.80	5.46	0.00	2.00	5.00
INSTPERC	85,266	0.62	0.26	0.42	0.64	0.82
RD	85,266	0.01	0.03	0.00	0.00	0.02
LABOR	85,266	0.69	0.26	0.52	0.76	0.91
NEGEARN	85,266	0.91	1.39	0.00	0.00	1.00
BTM	85,266	0.50	0.40	0.25	0.42	0.64
LOGMVE	85,266	6.60	1.59	5.48	6.48	7.60
CHGEARN	85,266	0.05	4.02	−0.36	0.14	0.63
CV	85,266	0.19	0.39	0.03	0.07	0.17
LEVERAGE	85,266	0.38	0.22	0.20	0.37	0.53
LOG_OP_SEG	85,266	0.48	0.67	0.00	0.00	1.10
LOG_GEO_SEG	85,266	0.73	0.67	0.00	0.69	1.10
CFVOL	85,266	0.05	0.05	0.02	0.04	0.06
LOGSHARES	85,266	3.68	1.17	2.87	3.54	4.34
TENURE	85,266	5.13	3.68	2.00	4.00	7.00
SCFO	85,266	0.03	0.10	0.00	0.04	0.08
NOA	85,266	4.28	6.92	1.29	2.32	4.16
NUMEST	85,266	7.20	5.53	3.00	5.00	10.00
BIGN	85,266	0.92	0.27	1.00	1.00	1.00

Notes:

This table reports univariate statistics for key variables used in our analysis. Statistics presented include the number of observations (*N*), mean, standard deviation, and key points in the distribution. Forecast error (*FCSTERR*) is defined as (Adjusted Actual I/B/E/S EPS − Mean Consensus EPS estimate). *JUSTBEAT* is an indicator equal to one if $0 \leq FCSTERR \leq 0.02$ and zero if $-0.02 \leq FCSTERR < 0$. *BEAT* is an indicator equal to one if $0 \leq FCSTERR$ and zero if $FCSTERR < 0$. *FS_COMPLEX* is the industry-year mean adjusted accounting policy length, winsorized at 1 percent and 99 percent by year. All other variables are described in detail in the Appendix.

segments (*LOG_OP_SEG*), the number of geographic segments (*LOG_GEO_SEG*), and whether the firm is audited by a large accounting firm (*BIGN*), all variables that have been suggested by prior researchers to proxy for firm-level operating complexity. We explicitly control for these proxies of operating complexity in the tests of our hypotheses.[9] Our analysis also controls for *reporting complexity* using the Gunning–Fog Index of the whole 10-K filing (*10KFOG*).[10] The correlations between *FS_COMPLEX* and

9. An alternative approach would be to include these controls in a first-stage regression and obtain the residuals as a proxy for financial statement complexity. Untabulated results using this approach provide results that are similar to those presented in the paper, as expected.

10. Loughran and McDonald (2014) make a case that the Fog Index is measured with error for financial texts like 10-K filings. In untabulated analysis, we use the number of words in the 10-K (less the words in the accounting policy footnote) instead of the Fog Index and find very similar results for our coefficients on *FS_COMPLEX* relative to those presented in the tables.

TABLE 3
Sample correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)	*FS_COMPLEX*	1.000	0.019	0.007	0.138	0.015	0.125	0.062	0.099	0.120	0.020	0.041	0.059
			(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(2)	*JUSTBEAT*	0.020	1.000	1.000	0.003	−0.085	0.075	0.013	0.029	0.084	0.044	−0.342	−0.170
		(0.00)			(0.60)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(3)	*BEAT*	0.005	1.000	1.000	−0.017	−0.142	0.142	0.024	0.058	0.128	0.061	−0.254	−0.238
		(0.11)			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(4)	*10KFOG*	0.066	−0.003	−0.023	1.000	0.040	0.124	0.065	−0.098	0.118	−0.075	0.069	0.048
		(0.00)	(0.58)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(5)	*BTM*	0.015	−0.075	−0.140	0.055	1.000	−0.293	0.077	−0.084	−0.180	−0.046	0.121	0.164
		(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(6)	*LOGMVE*	0.087	0.075	0.141	0.085	−0.312	1.000	0.239	0.155	0.682	0.193	0.008	−0.236
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
(7)	*LOG_OP_SEG*	0.052	0.014	0.024	0.047	0.036	0.252	1.000	0.261	0.083	0.075	0.051	−0.038
		(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(8)	*LOG_GEO_SEG*	0.091	0.027	0.056	−0.085	−0.084	0.170	0.254	1.000	0.118	0.110	−0.038	−0.023
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)
(9)	*NUMEST*	0.090	0.074	0.116	0.059	−0.155	0.678	0.077	0.135	1.000	0.153	−0.065	−0.112
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
(10)	*BIGN*	0.026	0.044	0.061	−0.085	−0.047	0.183	0.074	0.101	0.138	1.000	0.000	−0.048
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.99)	(0.00)
(11)	*ABS_FCSTERR*	0.032	−0.323	−0.172	0.081	0.166	0.012	0.033	−0.036	−0.030	−0.004	1.000	0.264
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.26)		(0.00)
(12)	*CV*	0.028	−0.100	−0.172	0.022	0.143	−0.171	−0.035	−0.011	−0.093	−0.035	0.172	1.000
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Notes:

This table reports pairwise correlation coefficients and p-values for select variables from Table 2. *FS_COMPLEX* is the industry-year mean adjusted accounting policy length, winsorized at 1 percent and 99 percent by year. All variables in the table are described in detail in the Appendix. Spearman (Pearson) rank correlations are above (below) the diagonal.

10KFOG are positive and significant (0.066 and 0.138), suggesting these two variables are related, but could not necessarily be used as substitute proxies since a substantial portion of the variation in *FS_COMPLEX* is still unexplained by *10KFOG*. *FS_COMPLEX* is also positively correlated with analysts' absolute forecast error (*ABS_FCSTERR*) and variation in those forecasts (*CV*) in the broader sample. These last two correlations provide evidence consistent with prior literature (Lehavy et al. 2011; Peterson 2012) that proxies for complexity are positively correlated with forecast error and variation in the forecasts.[11] Finally, we note the correlation between *FS_COMPLEX* and *JUSTBEAT* is also positive and significant, consistent with our first hypothesis.

We validate our measure of financial statement complexity by testing whether *FS_COMPLEX* is associated with audit fees for a subset of our sample. A positive effect on audit fees would suggest that longer abnormal accounting policies proxy for real financial statement complexity and not just disclosure differences. In addition, because these tests include *10KFOG*, we document that *FS_COMPLEX* is distinct from reporting complexity. We collect audit fee data from proxy statements for a subsample of firms from 2001 to 2005. We begin in 2001 because firms were required by the SEC to disclose audit fees beginning in 2001. We test the following model, where *FEES* is the natural logarithm of audit fees:

$$FEES_{it} = \beta_1 + \beta_2 FS\_COMPLEX_{it} + \beta_3 10KFOG_{it} + \sum \beta_{4\text{-}25} Controls + \varepsilon_{it}. \quad (2)$$

We pattern our model after Francis and Simon (1987) and Whisenant, Sankaraguruswamy, and Raghunandan (2003), where control variables used in the model are described in the Appendix.[12] The results of these tests are found in Table 4. *p*-values are listed to the right of coefficient estimates using heteroscedasticity-robust standard errors clustered by firm. In addition, year and industry effects are also included (using Fama-French 30-industry classification). The coefficient on *FS_COMPLEX* is positive and significant (*p*-value = 0.000), even after controlling for the Fog Index which also has a positive coefficient. Coefficient estimates for control variables are similar to the estimates from the previously mentioned studies. The effect of *FS_COMPLEX* is also economically significant. A one-standard deviation in *FS_COMPLEX* increases audit fees by 9.9 percent, which for the average firm is $80,407. This validation test suggests that *FS_COMPLEX* is a reasonable proxy for financial statement complexity.

11. These positive correlations with forecast error and forecast variation in the broader sample do not contradict our prediction that financial statement complexity could influence a firm's ability to meet or beat earnings close to zero. While the general effect of financial statement complexity may cause analysts to be less accurate in their forecasting, the effect of that complexity on firm and analyst decisions when the firm is close to a threshold may be different.
12. Control variables include whether the firm had a restatement in the current year (*RESTATE*), firm size (*LOGASSETS*), number of operating segments (*LOG_OP_SEG*), number of employees (*EMPLOY*), debt-to-assets (*DA*), liquidity (*LIQ*), the size of inventory and receivables to total assets (*INVREC*), return on assets (*ROA*), institutional ownership (*INSTPERC*), the presence of an initial audit engagement (*INITIAL*), large auditor (*BIGN*), the existence of foreign operations (*FOROPS*), whether the firm has a loss (*LOSS*), recent growth in sales (*GRSALES*), volatility of abnormal returns (*VOL*), audit opinion (*OPINION*), whether the firm has a pension or postretirement plan (*EMPPLAN*), book-to-market (*BMKT*), discontinued operations or extraordinary items (*XDOPS*), the change in Altman's *Z*-Score (*ZSCORE*), recent stock returns (*RETURN*), and the earnings announcement lag time (*LAG*).

TABLE 4
Audit fee regression estimates

Variable	Audit fees
FS_COMPLEX	0.2240 (0.000)
10KFOG	0.0413 (0.007)
RESTATE	0.1717 (0.001)
LOGASSETS	0.4462 (0.000)
LOG_OP_SEG	0.0761 (0.001)
EMPLOY	0.0422 (0.001)
DA	−0.0363 (0.688)
LIQ	−0.0290 (0.000)
INVREC	0.6344 (0.000)
ROA	−0.2579 (0.032)
INSTPERC	0.0269 (0.719)
INITIAL	−0.0834 (0.031)
BIGN	0.1189 (0.115)
FOROPS	0.2050 (0.000)
LOSS	0.0710 (0.037)
GRSALES	−0.0277 (0.195)
VOL	51.3429 (0.003)
OPINION	0.0699 (0.020)
EMPPLAN	0.1784 (0.000)
BTM	−0.1188 (0.020)
XDOPS	0.0658 (0.033)
ZSCORE	0.0029 (0.056)
RETURN	0.0201 (0.000)
LAG	0.0068 (0.000)
CONSTANT	1.6757 (0.000)
Year & Industry FE	Yes
N	2,590
Adjusted R^2	0.77

Notes:

This table reports OLS regression estimates of the natural logarithm of audit fees on *FS_COMPLEX* and control variables. *FS_COMPLEX* is the industry-year mean adjusted accounting policy length, winsorized at 1 percent and 99 percent by year. Two tailed *p*-values (to the right of coefficient estimates) are calculated using heteroscedasticity-robust standard errors clustered by firm. Industry effects are included using the Fama-French 30-industry classification. See the Appendix for a description of control variables.

4. Tests and results

Meeting or beating expectations tests

Our first test examines whether firms with complex financial statements are more likely to meet analyst expectations. Specifically, we estimate a logistic model where the dependent variable (*JUSTBEAT*) is one if $0 \leq FCSTERR_{it} \leq 0.02$ and zero if $-0.02 \leq FCSTERR_{it} < 0$. The classification of just meeting or beating based on forecast error is not measured consistently in prior literature. Some studies (McAnally, Srivastava, and Weaver 2008; Prawitt, Smith, and Wood 2009) use price-scaled forecast errors, while others use unscaled forecast errors (i.e., cents) (Frankel, Johnson, and Nelson 2002; Cheng and Warfield 2005; Yu 2008; Athanasakou et al. 2009). We tabulate results using a 2 cent interval, but our results are robust to using alternative intervals.[13] Our test of Hypothesis 1 uses the following logistic regression:

$$P(JUSTBEAT_{it}) = f\left(\beta_1 + \beta_2 FS\_COMPLEX_{it} + \sum \beta_{3\text{-}22} Controls + \varepsilon_{it}\right). \quad (3)$$

In addition, we estimate the following regression to explore whether this effect is persistent more generally across the entire distribution of forecast error. The dependent variable (*BEAT*) for that regression is one if $0 \leq FCSTERR_{it}$ and zero otherwise:

$$P(BEAT_{it}) = f\left(\beta_1 + \beta_2 FS\_COMPLEX_{it} + \sum \beta_{3\text{-}22} Controls + \varepsilon_{it}\right). \quad (4)$$

JUSTBEAT, *BEAT*, and *FS_COMPLEX* were described above. Since we use quarterly observations and *FS_COMPLEX* is an annual measure, we assume that the accounting policies reported in the 10-Ks are in effect for the entire year. Our controls include $10KFOG_{it}$ to proxy for *reporting* complexity as discussed above. We also include other control variables that have been shown in prior literature to be correlated with meeting or beating analyst expectations. The intuition for variables included in the models is briefly discussed here, but detailed variable definitions can be found in the Appendix.

We control for different incentives managers have to MBE. The number of consecutive prior quarters the firm met or beat analyst expectations (*STREAK*) controls for additional motivation for MBE (Barton and Simko 2002; Kross, Ro, and Suk 2011). Matsumoto (2002) documents that institutional ownership (*INSTPERC*), implicit claims with stakeholders (*RD* and *LABOR*), and the strength of the relationship between earnings and stock prices (*NEGEARN*) incentivize managers to MBE. Growth prospects may also impact investors' response to earnings information, so we include the book-to-market ratio (*BTM*) as well (McAnally et al. 2008). Prior research has also shown that the ability of managers to MBE may be constrained by a number of factors. Barton and Simko (2002) show that higher levels of net assets serves as a constraint to MBE. In addition, firms with larger numbers of shares may have more difficulty to MBE because a larger amount of earnings must be managed per penny of EPS (Barton and Simko 2002). Therefore, we include *NOA* and *LOGSHARES* as controls. We include leverage (*LEVERAGE*) to proxy for the firm's proximity to debt default, which may serve as an incentive or a constraint to MBE (McAnally et al. 2008). We include proxies for audit quality (*TENURE* and *BIGN*) because audit quality may constrain managers' ability to MBE (Frankel et al. 2002; Davis, Soo, and Trompeter 2009).[14] The level of operating cash flows (*SCFO*) for a firm may also serve as a constraint (Frankel et al. 2002). Analyst following (*NUMEST*), the seasonal change in earnings (*CHGEARN*), the coefficient of variation in analysts' earnings forecasts (*CV*), and cash flow volatility (*CFVOL*) are all included to control for difficulty in the forecasting environment (Davis et al. 2009; Matsumoto 2002; Cheng and Warfield 2005; Prawitt et al. 2009). Finally, we control for other aspects of operating complexity by including firm size (*LOGMVE*), the number of operating segments (*LOG_OP_SEG*), and

13. In studies that use cents, the interval for establishing "just beat" versus "just miss" has not been consistently measured. Athanasakou et al. (2009) use the interval $-£0.02 \leq FCSTERR < £0.02$. Cheng and Warfield (2005) and Frankel et al. (2002) define "just beat" as beating by 0–1 cent. Yu (2008) utilizes an interval of $-0.08 \leq FCSTERR \leq 0.04$. Prawitt et al. (2009) choose to test the sensitivity of their primary scaled measure with an unscaled interval of $-0.02 \leq FCSTERR \leq 0.02$. We obtain similar results defining "just beating" by 1 cent using the interval $-0.02 \leq FCSTERR \leq 0.01$. Scaling forecast error by beginning of the period stock price, which is common in the literature, with just beating/missing at 0.001, also obtains similar results to those presented.

14. It is possible the effect of auditing firms on financial statement complexity is more specific than the *BIGN* variable captures. In untabulated analysis, we include separate indicators for each large accounting firm as an alternative control to the more general *BIGN* control and find similar results.

TABLE 5
Tests of meeting or beating expectations on financial statement complexity

Variable	(1) *JUSTBEAT*	(2) *BEAT*
FS_COMPLEX	0.1029 (0.007)	0.0235 (0.338)
10KFOG	0.0156 (0.092)	0.0049 (0.327)
STREAK	0.0532 (0.000)	0.0917 (0.000)
INSTPERC	0.2064 (0.005)	0.1133 (0.017)
RD	−0.5516 (0.351)	−0.5303 (0.131)
LABOR	0.4846 (0.000)	0.5717 (0.000)
NEGEARN	−0.0077 (0.599)	0.0263 (0.005)
BTM	−0.1985 (0.000)	−0.2025 (0.000)
LOGMVE	0.0793 (0.007)	0.1507 (0.000)
CHGEARN	0.0312 (0.000)	0.0947 (0.000)
CV	−0.4192 (0.000)	−0.5410 (0.000)
LEVERAGE	0.1305 (0.098)	−0.0720 (0.157)
LOG_OP_SEG	0.0102 (0.690)	−0.0062 (0.713)
LOG_GEO_SEG	−0.0078 (0.762)	0.0158 (0.368)
CFVOL	0.1135 (0.739)	0.8712 (0.000)
LOGSHARES	−0.1010 (0.002)	−0.1034 (0.000)
TENURE	−0.0116 (0.024)	−0.0055 (0.083)
SCFO	0.6928 (0.000)	1.3911 (0.000)
NOA	−0.0040 (0.111)	−0.0066 (0.000)
NUMEST	0.0140 (0.001)	0.0092 (0.001)
BIGN	0.0777 (0.153)	0.1216 (0.001)
CONSTANT	−0.1217 (0.636)	−0.7409 (0.000)
Year & Industry FE	Yes	Yes
N	34,616	85,266
Chi-squared	1,447.58	7,038.04
Pseudo R^2	0.05	0.10

Notes:

This table presents coefficient estimates from logit regressions of *JUSTBEAT* and *BEAT* on *FS_COMPLEX*. *JUSTBEAT* is an indicator equal to one if $0 \leq FCSTERR \leq 0.02$ and zero if $-0.02 \leq FCSTERR < 0$. *BEAT* is an indicator equal to one if $0 \leq FCSTERR$ and zero if $FCSTERR < 0$. *FS_COMPLEX* is the industry-year mean adjusted accounting policy length, winsorized at 1 percent and 99 percent by year. Two tailed *p*-values (to the right of coefficient estimates) are calculated using heteroscedasticity-robust standard errors clustered by firm. Industry effects are included using the Fama-French 30-industry classification. See the Appendix for a description of control variables.

the number of geographic segments (*LOG_GEO_SEG*), as well as *BIGN* previously mentioned.

Table 5 presents the coefficient estimates of the logistic regressions from (3) and (4). For Table 5 and the following tables, *p*-values are listed to the right of coefficient estimates using heteroscedasticity-robust standard errors clustered by firm. In addition, year and industry effects are also included (using Fama-French 30-industry classification).[15]

15. It is not entirely clear what the true nature of the correlation structure is for the standard errors for our regressions. We use fixed effects for industry and time while clustering by firm because we have a relatively short time series and to be consistent with prior research (Lehavy et al. 2011). However, we find similar results if we use two-way clustering on firm and quarter or do not cluster and just include industry and time fixed effects.

For *JUSTBEAT*, the coefficient on *FS_COMPLEX* is positive (0.1029) and significant (p-value = 0.007). This result is consistent with Hypothesis 1 in that firms with greater financial statement complexity have a higher propensity to just beat than to just miss analyst expectations. The second specification where *BEAT* is the dependent variable has a positive but insignificant coefficient on *FS_COMPLEX*. Together these results suggest firms with complex financial statements are more likely to beat expectations at the margin, but are not more likely to beat expectations generally. Most control variables included are statistically significant, which underscores their importance in explaining the other incentives and characteristics that cause or allow firms to meet or beat analysts' expectations. Consistent with prior research we find positive coefficients on *STREAK*, *INSTPERC*, *LOGMVE*, *CHGEARN*, and *NUMEST* indicating their positive influence on just meeting or beating expectations over just missing expectations. We find that *10KFOG* is positive and marginally significant (p-value = 0.092) in the *JUSTBEAT* regression. This suggests that reporting complexity, in addition to financial statement complexity, may be somewhat influential in a firm's ability to just beat versus just miss analyst expectations.

We also calculate marginal effects to address the economic importance of the results. We find that for a one standard deviation change in *FS_COMPLEX* (at the mean), there is a 4.3 percent increase in the odds of just meeting or beating analysts' earnings forecasts versus just missing. In terms of words, a one standard deviation in *FS_COMPLEX* around the mean firm represents an 857 word increase in the accounting policy disclosure. Compared to other variables in the model, *FS_COMPLEX* has a marginal effect similar to that of *TENURE*, *INSTPERC*, *LEVERAGE*, *BTM*, and *SCFO*.

Expectation management tests

We perform two tests to determine whether financial statement complexity is associated with expectations management (test of Hypothesis 2). First, we rerun the logistic regression in (3) where *JUSTBEAT* is the dependent variable, but separate the effect of *FS_COMPLEX* on *JUSTBEAT* for firms that were going to meet or beat using the first consensus forecast of the quarter (*BEG_BEAT* = 1) versus firms that were going to miss using the first forecast (*BEG_BEAT* = 0). If the effect of complexity on meeting expectations is due to expectations management we would expect to see a higher coefficient on *FS_COMPLEX* for firms that were missing expectations at the beginning of the period. The control variables are exactly the same as in (3).

Our second test also requires estimating a logistic regression. Our dependent variable is measured only for those firms that just met or beat the analysts' most recent forecast. The dependent variable is one if the firm would have missed the forecast using the first forecast of the quarter and zero otherwise (*EXPMGMT*).[16] A dependent variable of one is consistent with expectations management. Using this dependent variable, we estimate the following regression:

$$P(EXPMGMT_{it}) = f\left(\beta_1 + \beta_2 FS\_COMPLEX_{it} + \sum \beta_{3\text{-}22} Controls + \varepsilon_{it}\right). \tag{5}$$

A positive coefficient on *FS_COMPLEX* would be evidence consistent with Hypothesis 2. We include the same control variables from the previous models.

Table 6 presents the results to test for expectations management for complex firms. The results in specification (1) document the positive and statistically significant effect of financial statement complexity on beating analysts' estimates only exists for complex firms that were missing expectations at the beginning of the period (coeff. 0.2064, p-

16. As an alternative to the beginning of the period forecast, which may also be influenced by managers, in untabulated tests we use Matsumoto (2002) expected forecast model as modified by Koh, Matsumoto, and Rajgopal (2008) as a benchmark in our expectations management test and find similar results.

TABLE 6
Tests for expectations management

Variable	(1) *JUSTBEAT*	(2) *EXPMGMT*
FS_COMPLEX		0.1342 (0.003)
FS_COMPLEX (*BEG_BEAT* = 0)	0.2064 (0.000)	
FS_COMPLEX (*BEG_BEAT* = 1)	0.0444 (0.640)	
BEG_BEAT	3.5542 (0.000)	
10KFOG	0.0147 (0.179)	−0.0043 (0.719)
STREAK	0.0203 (0.000)	−0.0436 (0.000)
INSTPERC	0.4284 (0.000)	0.3383 (0.000)
RD	−0.0909 (0.910)	0.9567 (0.239)
LABOR	0.1889 (0.096)	−0.6740 (0.000)
NEGEARN	−0.0538 (0.002)	−0.0780 (0.000)
BTM	0.0860 (0.159)	0.5681 (0.000)
LOGMVE	−0.0126 (0.722)	−0.1181 (0.002)
CHGEARN	−0.0091 (0.058)	−0.0651 (0.000)
CV	−0.1988 (0.000)	0.4285 (0.000)
LEVERAGE	0.1819 (0.058)	0.1500 (0.136)
LOG_OP_SEG	0.0479 (0.127)	0.0787 (0.011)
LOG_GEO_SEG	−0.0001 (0.997)	0.0313 (0.351)
CFVOL	−0.1407 (0.745)	−0.0891 (0.854)
LOGSHARES	−0.0253 (0.524)	0.0895 (0.030)
TENURE	−0.0041 (0.514)	0.0142 (0.038)
SCFO	0.5261 (0.031)	−0.4874 (0.036)
NOA	−0.0018 (0.583)	0.0040 (0.268)
NUMEST	0.0241 (0.000)	0.0146 (0.003)
BIGN	0.0181 (0.795)	−0.0573 (0.481)
CONSTANT	−1.2811 (0.000)	−0.7538 (0.026)
Year & Industry FE	Yes	Yes
N	34,616	27,390
Chi-squared	6,673.48	1,300.62
Pseudo R^2	0.37	0.06

Notes:

This table presents coefficient estimates from logit regressions of various dependent variables on *FS_COMPLEX*. *JUSTBEAT* is an indicator equal to one if $0 \leq FCSTERR \leq 0.02$ and zero if $-0.02 \leq FCSTERR < 0$. *BEG_BEAT* is equal to one if the firm was beating based on the first consensus forecast of the period, zero otherwise. *EXPMGMT* is an indicator equal to one if the firm would have missed analyst expectations using the first consensus forecast of the period, but meets or beats analyst expectations using the last consensus forecast of the period, and zero otherwise. *FS_COMPLEX* is the industry-year mean adjusted accounting policy length, winsorized at 1 percent and 99 percent by year. Two tailed *p*-values (to the right of coefficient estimates) are calculated using heteroscedasticity-robust standard errors clustered by firm. Industry effects are included using the Fama-French 30-industry classification. See the Appendix for a description of control variables. Model (2) has fewer observations relative to model (1) because it only includes observations where firms met expectations using the last consensus analyst forecasts of EPS for the quarter.

value < 0.001), but not for complex firms that were already beating expectations (coeff. 0.0444, *p*-value = 0.640). These coefficients are statistically different from each other using a one-tailed test (*p*-value = 0.064). This effect exists even while controlling for the direct effect of a firm's increased likelihood that they beat expectations if they were beating those expectations at the beginning of the period (*BEG_BEAT*).

Specification (2) in Table 6 reports coefficients from estimating (5) using *EXPMGMT*. Consistent with Hypothesis 2 we find a positive coefficient (coeff. 0.1342, p-value = 0.003) on *FS_COMPLEX* in this test. This positive coefficient means for firms that just beat expectations, those with complex financial statements are more likely to have had a walk-down of expectations relative to firms with less complex financial statements. Overall, these results provide evidence consistent with Hypothesis 2 that expectations management is at least partially responsible for firms with more complex financial statements to be more likely to just meet or beat analysts' expectations.[17]

Excluding GAAP items tests

Next, we test whether complex firms are more likely to beat analyst estimates by influencing the exclusions from GAAP earnings when analysts determine "actual" EPS. Although we are interested in whether GAAP exclusions help firms beat analysts' estimates, we first test whether firms with complex financial statements are more likely to have GAAP exclusions:

$$P(EXCL\_USE_{it}) = f\left(\beta_1 + \beta_2 FS\_COMPLEX_{it} + \sum \beta_{3\text{-}22} Controls + \varepsilon_{it}\right). \tag{6}$$

We define *EXCL_USE* consistent with Doyle et al. (2013) as equal to one if $I/B/E/S$ Actual EPS exceeds the GAAP EPS number before extraordinary items and discontinued operations, and zero otherwise. In (6) we expect a positive coefficient on β_2. We then test whether firms with complex financial statements are more likely to use GAAP exclusions to beat expectations using the following two logistic models:

$$P(EXCL\_MGMT_{it}) = f\left(\beta_1 + \beta_2 FS\_COMPLEX_{it} + \sum \beta_{3\text{-}22} Controls + \varepsilon_{it}\right), \tag{7}$$

$$\begin{aligned} P(JUSTBEAT_{it}) = \; & f(\beta_1 + \beta_2 FS\_COMPLEX_{it} + \beta_3 EXCL\_USE_{it} \\ & + \beta_4 FS\_COMPLEX_{it} \times EXCL\_USE_{it} \\ & + \sum \beta_{5\text{-}24} Controls + \varepsilon_{it}). \end{aligned} \tag{8}$$

We define *EXCL_MGMT* in (7) only for firms with positive forecast errors within \$0.02. It is equal to one if the firm would have missed expectations without the use of the exclusions and zero otherwise. In (8) we test whether the use of exclusions for complex firms is significantly different for firms that beat expectations versus those that missed expectations. We expect the coefficient β_2 in (7) to be positive and the coefficients $\beta_2 - \beta_4$ in (8) to be positive. We include the same controls as the prior tables, which are more extensive than the controls used in Doyle et al. (2013).

The results of estimating (6), (7), and (8) are found in Table 7. The results in specification (1) show that for firms with forecast errors close to zero, the firms with more complex financial statements are more likely to have income-increasing GAAP exclusions (coeff. 0.5168, p-value < 0.001). When we turn to estimating (7) in specification (2), we find a positive and significant coefficient on *FS_COMPLEX* (coeff. 0.5024, p-value < 0.001), suggesting that among those who beat expectations, complex firms were more likely to do so

17. In untabulated tests, we reestimate specifications (1) and (2), but limit the sample to firms where the forecast error based on the beginning forecast was also within \$0.02 of zero. We rerun these tests using this more restricted sample to ensure that the expectations management we observe is not driven by severely inaccurate beginning forecasts that would be more susceptible to expectations management. These untabulated results are consistent with those presented in Table 6 suggesting that the expectations management we document is not solely driven by "wild" initial forecasts.

TABLE 7
Test for the use of GAAP exclusions to MBE

Variable	(1) *EXCL_USE*	(2) *EXCL_MGMT*	(3) *JUSTBEAT*
FS_COMPLEX	0.5168 (0.000)	0.5024 (0.000)	0.1153 (0.008)
EXCL_USE			0.0625 (0.059)
FS_COMPLEX × *EXCL_USE*			−0.0652 (0.386)
10KFOG	0.0030 (0.803)	0.0046 (0.730)	0.0157 (0.090)
STREAK	−0.0062 (0.106)	−0.0080 (0.054)	0.0532 (0.000)
INSTPERC	0.8620 (0.000)	0.8984 (0.000)	0.1982 (0.007)
RD	5.2426 (0.000)	7.0273 (0.000)	−0.5250 (0.375)
LABOR	0.9056 (0.000)	0.8949 (0.000)	0.4754 (0.000)
NEGEARN	0.2067 (0.000)	0.2324 (0.000)	−0.0098 (0.504)
BTM	0.6611 (0.000)	0.6657 (0.000)	−0.2045 (0.000)
LOGMVE	0.0713 (0.081)	0.1162 (0.010)	0.0795 (0.007)
CHGEARN	−0.1747 (0.000)	−0.2021 (0.000)	0.0326 (0.000)
CV	−0.0537 (0.283)	−0.1331 (0.030)	−0.4191 (0.000)
LEVERAGE	0.9425 (0.000)	0.9149 (0.000)	0.1197 (0.128)
LOG_OP_SEG	0.0605 (0.102)	0.0965 (0.016)	0.0093 (0.716)
LOG_GEO_SEG	0.2322 (0.000)	0.2268 (0.000)	−0.0117 (0.650)
CFVOL	−2.5290 (0.000)	−3.2710 (0.000)	0.1268 (0.710)
LOGSHARES	0.1431 (0.003)	0.0828 (0.109)	−0.1033 (0.002)
TENURE	−0.0050 (0.519)	−0.0022 (0.791)	−0.0116 (0.023)
SCFO	1.4852 (0.000)	1.3058 (0.000)	0.6724 (0.001)
NOA	0.0025 (0.526)	0.0030 (0.511)	−0.0041 (0.106)
NUMEST	0.0132 (0.019)	0.0133 (0.025)	0.0139 (0.001)
BIGN	0.0682 (0.478)	0.0212 (0.840)	0.0768 (0.158)
CONSTANT	−5.0397 (0.000)	−5.1858 (0.000)	−0.1030 (0.689)
Year & Industry FE	Yes	Yes	Yes
N	34,607	27,390	34,607
Chi-squared	1,958.84	1,619.63	1,453.65
Pseudo R^2	0.15	0.16	0.05

Notes:

This table presents coefficient estimates from regressions testing for the use of GAAP exclusions to MBE. GAAP exclusions are defined as the difference between actual EPS in I/B/E/S and COMPUSTAT. *EXCL_USE* is an indicator variable equal to one if GAAP exclusions are greater than zero, zero otherwise. *EXCL_MGMT* is restricted to firm-quarters where *JUSTBEA*T is equal to one, and is defined as one if the firm would have missed expectations without the use of exclusions and zero otherwise. *JUSTBEAT* is 1 if $0 \leq FCSTERR \leq 0.02$ and 0 if $-0.02 \leq FCSTERR < 0$. Two tailed *p*-values (to the right of coefficient estimates) are calculated using heteroscedasticity-robust standard errors clustered by firm. Industry effects are included using the Fama-French 30-industry classification. See the Appendix for a description of control variables.

because of GAAP exclusions. However, the results in specification (3) suggest a slightly different explanation. Although the coefficients for *FS_COMPLEX* and *EXCL_USE* are positive and significant, the interaction term is negative, although insignificant (*p*-value = 0.386). This suggests that complex firms are more likely to have GAAP exclusions for both firms that beat and missed expectations. These results highlight that although complex firms are more likely to have GAAP exclusions, they are not more likely to use GAAP exclusions to help them beat expectations at the margin.

Accruals management tests

Our tests of Hypothesis 4 examine whether complex firms utilize abnormal accruals as a form of earnings management to meet or beat analysts' expectations at the margin. We define abnormal discretionary accruals as the residuals from estimating a performance controlled Jones (1991) regression as outlined in Kothari, Leone, and Wasley (2005) estimated each year by two-digit SIC using quarterly observations.[18]

We implement our test of Hypothesis 4 using two specifications. The first specification tests a logistic regression similar in nature to our expectations management test. The dependent variable, *ACCMGMT*, is defined only for firms that just meet or beat expectations. *ACCMGMT* is equal to one if the firm beat expectations, but would have missed expectations if discretionary accruals were removed from earnings and zero otherwise.[19] We estimate the following model:

$$P(ACCMGMT_{it}) = f\Big(\beta_1 + \beta_2 FS\_COMPLEX_{it} + \sum \beta_{3\text{-}22} Controls + \varepsilon_{it}\Big). \tag{9}$$

All variables have been previously defined. We predict β_2 to be positive in that firms with more complex financial statements are more likely to use accrual management to beat expectations. This first specification relies on a precise estimate of discretionary accruals to determine whether firms managed accruals to meet expectations. Since discretionary accruals are measured with error, we conduct a more general interaction test to determine whether firms with more complex accounting and higher discretionary accruals are more likely to meet or beat analysts' earnings expectations. We estimate the following logistic regression:

$$\begin{aligned} P(JUSTBEAT_{it}) = f(&\beta_1 + \beta_2 FS\_COMPLEX_{it} + \beta_3 ACCRUALS_{it} \\ &+ \beta_4 FS\_COMPLEX_{it} \times ACCRUALS_{it} \\ &+ \sum \beta_{5\text{-}24} Controls + \varepsilon_{it}). \end{aligned} \tag{10}$$

Since *FS_COMPLEX* and our discretionary accruals estimates have both positive and negative values, we cannot interact both raw measures. To alleviate this problem, we use either an indicator or decile rank measure of discretionary accruals. The first measure of discretionary accruals (*ACCRUALS*) is an indicator set to one if abnormal discretionary accruals is positive (income increasing) and zero if negative (income decreasing). The second measure of *ACCRUALS* takes the estimated discretionary accruals and sorts firms into accrual deciles. In untabulated analysis, we find our results are similar if we use the continuous measure of discretionary accruals instead of these discrete measures and transform the *FS_COMPLEX* variable instead. A positive β_4 would be consistent with H4 in that the marginal effect of complexity on just meeting or beating expectations is increased for firms with higher discretionary accruals.

Table 8, panel A presents the results of the first test for the use of accruals management to beat expectations. The results in the table are inconsistent with our hypothesis that firms with greater financial statement complexity are more likely to manage accruals to beat expectations. The coefficient on *FS_COMPLEX* is negative, although insignificant

18. Using the residuals from this regression assumes "normal" discretionary accruals are zero for a particular firm, which may not be accurate if the accrual model does not fit well for some firms. In a sensitivity test, we compare the discretionary accrual residuals to the prior period's discretionary accruals as the benchmark and find similar results to those presented in the paper.
19. Specifically, the estimate of discretionary accruals is multiplied by lagged total assets, and then scaled by shares outstanding. This amount is subtracted from the *Actual IBES* EPS_{it} to arrive at an "unmanaged" level of earnings. *ACCMGMT* is set equal to one if this unmanaged level of earnings is less than the mean consensus *EPS* $forecast_{it}$.

TABLE 8
Tests for accruals management

Panel A: Test for accruals management for complex firms

Variable	*ACCMGMT*
FS_COMPLEX	−0.0214 (0.594)
10KFOG	0.0076 (0.444)
STREAK	0.0003 (0.905)
INSTPERC	0.1831 (0.029)
RD	−8.7980 (0.000)
LABOR	−0.4543 (0.000)
NEGEARN	−0.1448 (0.000)
BTM	−0.0870 (0.184)
LOGMVE	−0.0454 (0.194)
CHGEARN	0.0460 (0.000)
CV	0.1893 (0.000)
LEVERAGE	−0.1996 (0.047)
LOG_OP_SEG	−0.0087 (0.760)
LOG_GEO_SEG	−0.0191 (0.517)
CFVOL	−0.9655 (0.027)
LOGSHARES	0.0001 (0.999)
TENURE	0.0008 (0.898)
SCFO	−14.7992 (0.000)
NOA	−0.0090 (0.041)
NUMEST	0.0020 (0.651)
BIGN	−0.1331 (0.043)
CONSTANT	0.9784 (0.001)
Year & Industry FE	Yes
N	27,377
Chi-squared	1,535.52
Pseudo R^2	0.15

Panel B: Alternative accruals management tests

Variable	(1) *JUSTBEAT*	(2) *JUSTBEAT*
FS_COMPLEX	0.1298 (0.013)	0.1670 (0.040)
HIGH_ACCRUAL	−0.0893 (0.004)	
FS_COMPLEX × *HIGH_ACCRUAL*	−0.0703 (0.292)	
ACCRUAL_DECILE		−0.0181 (0.002)
FS_COMPLEX × *ACCRUAL_DECILE*		−0.0128 (0.304)
10KFOG	0.0207 (0.038)	0.0206 (0.038)
STREAK	0.0538 (0.000)	0.0538 (0.000)
INSTPERC	0.2108 (0.005)	0.2095 (0.005)
RD	−0.6460 (0.287)	−0.7140 (0.241)
LABOR	0.4680 (0.000)	0.4633 (0.000)
NEGEARN	−0.0091 (0.545)	−0.0105 (0.488)
BTM	−0.2056 (0.000)	−0.2066 (0.000)
LOGMVE	0.0722 (0.019)	0.0727 (0.018)
CHGEARN	0.0317 (0.000)	0.0323 (0.000)
CV	−0.4097 (0.000)	−0.4083 (0.000)

(The table is continued on the next page.)

TABLE 8 (continued)

Panel B: Alternative accruals management tests

Variable	(1) *JUSTBEAT*	(2) *JUSTBEAT*
LEVERAGE	0.1400 (0.089)	0.1382 (0.093)
LOG_OP_SEG	0.0133 (0.617)	0.0133 (0.618)
LOG_GEO_SEG	−0.0054 (0.837)	−0.0050 (0.849)
CFVOL	−0.0375 (0.914)	−0.0496 (0.886)
LOGSHARES	−0.0980 (0.004)	−0.0984 (0.004)
TENURE	−0.0092 (0.084)	−0.0093 (0.082)
SCFO	0.4287 (0.046)	0.3307 (0.144)
NOA	−0.0037 (0.186)	−0.0037 (0.186)
NUMEST	0.0139 (0.001)	0.0139 (0.001)
BIGN	0.0774 (0.168)	0.0783 (0.163)
CONSTANT	−0.1613 (0.552)	−0.0981 (0.719)
Year & Industry FE	Yes	Yes
N	32,273	32,273
Chi-squared	1,367.20	1,371.04
Pseudo R^2	0.05	0.05

Notes:

This table presents coefficient estimates from two separate accruals management tests. Panel A tests a logit regression of *ACCMGMT* on *FS_COMPLEX* and control variables. *ACCMGMT* is defined for firms that just meet or beat expectations. *ACCMGMT* is equal to one if the firm beat expectations, but would have missed expectations if abnormal discretionary accruals are removed from earnings and zero otherwise. Panel B presents an alternative accruals maangement test where *JUSTBEAT* is 1 if $0 \leq FCSTERR \leq 0.02$ and 0 if $-0.02 \leq FCSTERR < 0$. *HIGH_ACCRUAL* is measured as an indicator variable equal to one if 0 < Abnormal_Accruals and zero otherwise. *ACCRUAL_DECILE* is simply Abnormal_Accruals sorted into deciles. Abnormal_Accruals is the residuals from a performance controlled Jones (1991) style regression as outlined in Kothari et al. (2005). *FS_COMPLEX* is the industry-year mean adjusted accounting policy length, winsorized at 1 percent and 99 percent by year. Two tailed *p*-values (to the right of coefficient estimates) are calculated using heteroscedasticity-robust standard errors clustered by firm. Industry effects are included using the Fama-French 30-industry classification. See the Appendix for a description of control variables.

at conventional levels. However, this test is particularly vulnerable to measurement error in discretionary accruals.

Table 8, panel B presents the alternative more general association test for accruals management for complex firms. The first specification uses an indicator for whether the firm has positive or negative discretionary accruals while the second specification uses decile rankings of discretionary accruals. Inconsistent with our prediction, we again find negative coefficients on the *FS_COMPLEX* and *ACCRUALS* interaction terms in both specifications, although insignificant at conventional levels. This suggests firms with greater financial statement complexity and positive discretionary accruals are not more likely to just meet expectations versus just miss expectations. However, we continue to find that complexity increases the likelihood of just meeting expectations for firms with negative discretionary accruals. In untabulated sensitivity tests, we examined whether timing issues related to accruals management affect our results. For example, accruals management may become more attractive in later quarters as annual results firm up. To examine this, we estimated the regressions from Table 8 by quarter. These tests also do not provide evidence of accrual management for complex firms. Overall, these results do not support the hypothesis that complex firms use discretionary accruals to meet expectations. One potential explanation for the lack of earnings management results stems from our results that financial statement complexity is positively associated with audit fees. Higher audit fees may be the result of increased audit effort for complex firms, which may curtail accrual-based earnings management. We also reiterate that the lack of results on accrual management by complex firms could be driven by misestimated discretionary accruals.[20]

5. Additional tests

Alternative benchmarks

Analysts provide one benchmark with which to evaluate earnings, but prior literature suggests that other benchmarks, like zero earnings and last period's earnings, may also be important to firms (Burgstahler and Dichev 1997; Degeorge et al. 1999; Brown and Caylor 2005). We examine whether managers of firms with complex financial statements are more likely to also beat these alternative benchmarks. We reestimate (3), but redefined *JUSTBEAT* to be one when EPS beats seasonally adjusted prior quarter's EPS by less than \$0.02 and zero if EPS misses by less than \$0.02. We also reestimated (3) with *JUSTBEAT* being defined as EPS within \$0.02 of \$0.00 EPS. We excluded the controls from the model specifically related to analysts. In untabulated results, we find a significant negative relation between *FS_COMPLEX* and *JUSTBEAT* using these alternative benchmarks suggesting that firms with complex financial statements are not more likely to beat these alternative benchmarks. This result provides further evidence that our results are primarily driven by the analyst and manager interaction. Complex firms may focus their attention on beating analyst expectations and may not care about or be able to beat these alternative benchmarks. This is consistent with the benchmark hierarchy proposed in Brown and Caylor (2005) and the findings in Herrmann, Hope, Payne, and Thomas (2011) that these alternative benchmarks are not as important to investors. Part of this focus on analyst benchmarks may also stem from the fact that firms with complex financial statements have more volatile operating performance, making it more difficult to beat static benchmarks like last period's earnings, and instead focus on analyst benchmarks that can be more easily influenced.

Pseudo target tests

As additional validation of our main results, we conduct pseudo target tests similar to tests found in Ayers, Jiang, and Yeung (2006). The purpose of these tests is to determine whether the effect we document around beating or missing analysts' forecasts is specific to this part of the analyst forecast distribution. Similar to Ayers et al. (2006), we created 19 pseudo targets in 0.02 cent intervals from -0.20 to 0.20 as the beat group. For example, one pseudo target uses $[-0.20, -0.18]$ as the beat group compared to $[-0.22, -0.20]$ as the miss group. We have 19 pseudo targets because we exclude the actual target intervals in the main tests from this pseudo analysis. When we replicate our main results using these 19 pseudo windows, we find that only 2 of the 19 targets have positive and significant coefficients on financial statement complexity, which is very similar to what we would expect to occur by chance. Assuming a 10 percent likelihood of drawing a significant relationship by chance, a binomial test finds a 58 percent probability of observing two or more significant coefficients. We conclude from these pseudo tests that the significant positive relationship we document between financial statement complexity

20. Brown and Pinello (2007) argue that interim quarterly periods are more likely to contain upwards earnings management than annual periods due to the interim reporting requirements and lack of a formal audit. Since our tests are performed in quarterly periods, the power of our tests should be increased relative to annual tests.

and beating analyst expectations is specifically related to the meet or just beat part of the distribution.

Analyst skill explanation

Ke and Yu (2006) find that proxies for analysts' skill or ability are positively related to analysts issuing optimistic initial forecasts and walking them down. It is also possible, given the difficulty in forecasting complex firms that more skilled analysts are more likely to follow and forecast earnings for complex firms. In untabulated analysis, we find *FS_COMPLEX* is positively correlated with the average size of the brokerage house for analysts following the firm and the percentage of All-Star analysts following the firm as determined by *Institutional Investors*, but is negatively correlated with average analyst experience. This provides some justification that more skilled analysts follow complex firms. However, if we include these proxies for analyst skill into our test for expectations management (Equation 5), we find similar results to those presented suggesting that we are not just picking up the effect of skilled analysts documented in Ke and Yu (2006).

Management guidance reliance tests

Our main results suggest that expectations management is the primary mechanism that firms with complex financial statements use to beat analyst expectations. To corroborate the evidence from these main tests, we examine whether analysts place greater reliance on the management guidance of complex firms when revising their own forecasts. Although management guidance is just one mechanism that managers can use to influence analysts, we expect these tests to provide more direct evidence of this influence. Our test is similar to the main test in Feng and McVay (2010). They find that analysts' forecast revisions overweight management guidance for firms that are planning to issue equity in an effort to curry favor with those managers. We test the following model for the subset of our sample firms with management guidance and other necessary data:

$$\begin{aligned} REVISE_{it} = \beta_0 &+ \beta_1 MGUIDE_{it} + \beta_2 HIGH\_COMPLEX_{it} \\ &+ \beta_3 MGUIDE_{it} \times HIGH\_COMPLEX_{it} + \alpha Controls \\ &+ \theta MGUIDE_{it} \times Controls + \varepsilon_{it} \end{aligned} \tag{11}$$

The *MGUIDE* and *REVISE* variables measure the magnitude of management guidance and the subsequent analysts' revision, with β_1 measuring the analysts' reliance on management guidance as reflected in their forecast revision. *MGUIDE* is the difference between the management earnings forecast and the preexisting median consensus analyst forecast scaled by stock price. The preexisting consensus analyst forecast is the most recent consensus before the management guidance. *REVISE* is the difference between the revised consensus analyst forecast and the preexisting consensus analyst forecast scaled by stock price, where the revised consensus forecast must be issued within 15 days of the management guidance. We include controls and their interactions with *MGUIDE* consistent with Feng and McVay (2010) which control for the usefulness and credibility of the management guidance. Consistent with Feng and McVay (2010), we use the last forecast of the quarter if there is more than one management forecast in the quarter. To simplify interpretation of the coefficient on the interaction between complexity and *MGUIDE*, we measure *HIGH_COMPLEX* as an indicator equal to one if *FS_COMPLEX* is greater than the mean and zero otherwise.

The results of the test are presented in Table 9. We estimate the model first without control variables. We find a positive coefficient on *MGUIDE*, consistent with prior literature that analysts incorporate management guidance into their forecasts. The coefficient on the interaction between management guidance and complexity is positive and

TABLE 9
Analysts' reliance on management guidance tests

Variable	(1) *REVISE*	(2) *REVISE*
MGUIDE	0.1880 (0.000)	0.7348 (0.000)
MGUIDE × *HIGH_COMPLEX*	0.0814 (0.013)	0.0865 (0.009)
HIGH_COMPLEX	0.0001 (0.203)	0.0001 (0.324)
MGUIDE × *SEO*		0.0168 (0.820)
MGUIDE × *DOWN*		0.1064 (0.010)
MGUIDE × *REPUTATION*		0.0713 (0.003)
MGUIDE × *AGREE*		0.0888 (0.004)
MGUIDE × *HORIZON*		−0.1444 (0.000)
MGUIDE × *RANGE*		2.6097 (0.325)
MGUIDE × *ANALYSTS*		−0.0875 (0.003)
CONSTANT	−0.0002 (0.000)	0.0002 (0.371)
Main effects included	No	Yes
N	4,535	4,535
Adjusted R^2	0.20	0.31

Notes:

This table presents coefficient estimates from an OLS regression of *REVISE* on *MGUIDE*, including interactions with *HIGH_COMPLEX* and control variables. Variables in the model are generally measured consistent with Feng and McVay (2010). *MGUIDE* is the difference between the management earnings forecast and the preexisting median consensus analyst forecast scaled by stock price. The preexisting consensus analyst forecast is the most recent consensus before the management guidance. *REVISE* is the difference between the revised consensus analyst forecast and the preexisting consensus forecast scaled by stock price, where the revised consensus forecast must be issued within 15 days of the management guidance. *HIGH_COMPLEX* is an indicator equal to one if *FS_COMPLEX* is greater than the mean and zero otherwise. *SEO* is equal to one if COMPUSTAT variable sstk scaled by total assets is in the top decile of all firms. *DOWN* is equal to one if the management guidance is below the preexisting consensus analyst forecast and zero otherwise. *REPUTATION* is the average accuracy of the management guidance issued in the prior three years, where accuracy is equal to 1, 0 and −1, respectively, if the absolute value of the preexisting analyst forecast error is greater than, equal to, or less than the absolute value of the management forecast error. *AGREE* is equal to one if the three-day abnormal return around the management guidance has the same sign as the management revision, and zero otherwise. *HORIZION* is the log number of days between the management guidance date and the earnings announcement. *RANGE* is the range of the management guidance scaled by price and equal to zero for a point forecast. *ANALYSTS* is the log number of analysts following the firm. Main effects for control variables are included in the model but not tabulated. Two-tailed *p*-values (to the right of coefficient estimates) are calculated using heteroscedasticity-robust standard errors clustered by firm.

significant (0.0814, *p*-value = 0.013), consistent with our expectation that analysts rely on management guidance more for firms with more complex financial statements. We find similar results when we include control variables for the credibility and usefulness of management guidance. The coefficient on the interaction between *HIGH_COMPLEX* and *MGUIDE* remains positive and significant (0.0865, *p*-value = 0.009). In economic terms, analysts incorporate into their forecasts 8.7 percent more of the management guidance for high complex financial statement firms relative to firms with low financial statement complexity. These results provide more direct evidence confirming that complex firms have a greater influence on the expectations of analysts, resulting in complex firms being more likely to beat expectations.

Returns tests

Finally, we conduct tests to determine the effect of financial statement complexity on the stock price response to meeting or beating analysts' estimates. Prior literature has documented a market reward to beating analyst expectations (Kasznik and McNichols 2002; Bartov et al. 2002; Lopez and Rees 2002; Koh et al. 2008; Bhojraj, Hribar, Picconi, and Mcinnis 2009). Bartov et al. (2002) find the reward to meeting expectations is not significantly diminished for firms that use expectations management or accrual management. However, two recent studies, Koh et al. (2008) and Keung, Lin, and Shih (2010), identify circumstances where investors appear to be skeptical of firms that just beat expectations.

TABLE 10
Market reaction tests

	(1) CAR (Earnings announcement)	(2) CAR (Rest of the quarter)	(3) CAR (Full quarter)
SURPRISE	0.0041 (0.807)	0.7314 (0.000)	0.7355 (0.000)
WALKDOWN	−0.0005 (0.875)	−0.0293 (0.044)	−0.0298 (0.047)
JUSTBEAT	0.0194 (0.000)	0.0043 (0.428)	0.0237 (0.000)
HIGH_COMPLEX	−0.0024 (0.268)	−0.0049 (0.485)	−0.0073 (0.315)
JUSTBEAT × *HIGH_COMPLEX*	0.0007 (0.758)	0.0023 (0.773)	0.0030 (0.713)
SURPRISE × *HIGH_COMPLEX*	−0.0138 (0.590)	−0.0719 (0.484)	−0.0857 (0.410)
WALKDOWN × *HIGH_COMPLEX*	0.0001 (0.987)	−0.0335 (0.068)	−0.0334 (0.076)
BTM	0.0155 (0.000)	−0.0653 (0.000)	−0.0498 (0.000)
LOGMVE	0.0001 (0.805)	0.0004 (0.665)	0.0005 (0.615)
MOMENTUM	−0.0252 (0.000)	−0.4105 (0.000)	−0.4357 (0.000)
CONSTANT	−0.0252 (0.000)	0.0437 (0.000)	0.0185 (0.049)
N	33,944	33,944	33,944
Adjusted R^2	0.026	0.227	0.234

Notes:

This table presents coefficient estimates from an OLS regression to examine whether the market reaction to quarterly earnings is different for complex firms. CAR is the cumulative abnormal market returns calculated using a market model over the prior 60 days before the start of the quarter. In column (1), CAR is measured during the three days surrounding the earnings announcement. In column (2), CAR is measured from two days following the prior quarter's earnings announcement to two days before the earnings announcement. (3) combines the CAR from (1) and (2). *SURPRISE* is equal to the forecast error using the beginning of the period forecast. *WALKDOWN* is equal to the magnitude of the walk-down of the mean analyst forecast during the quarter scaled by the absolute value of the beginning of the period forecast. *HIGH_COMPLEX* is an indicator equal to one if *FS_COMPLEX* is greater than the mean and zero otherwise. *MOMENTUM* is the abnormal returns for the firm measured during the six months prior to the start of the quarter. All other variables are defined in the Appendix. Two-tailed *p*-values (to the right of coefficient estimates) are calculated using heteroscedasticity-robust standard errors clustered by firm.

We examine the market response to complex firms beating expectations in Table 10. We measure the cumulative abnormal return using a market model over three different windows: (i) the three days centered on the earnings announcement, (ii) the period from two days following the prior earnings announcement to two days prior to the current earnings announcement, and (iii) the full quarter. We regress the abnormal return on the forecast error based on the beginning consensus analyst forecast (*SURPRISE*), the magnitude of the walk-down during the quarter (*WALKDOWN*), and whether the firm just beat analyst expectations (*JUSTBEAT*). We test whether there is a different market reaction for complex firms to these events by interacting all three variables with *HIGH_COMPLEX*. We also control for BTM, size, and momentum for factors that could affect returns. At the earnings announcement (column 1), investors react positively to firms that just beat expectations versus just miss, but that response is not different for firms with more complex financial statements. During the rest of the quarter (column 2), we see the market responds positively to larger earnings surprises and negatively to analysts' earnings walk-downs. The interaction between *WALKDOWN* and *HIGH_COMPLEX* is also negative and significant suggesting investors respond more negatively when analysts walk down earnings for firms with more financial complexity. The negative reaction over the quarter to a walk-down in earnings for complex firms is twice the reaction for less complex firms (from −0.20 percent to −0.43 percent for an average walk-down of approximately 7 percent). When we examine the full quarter returns we find results consistent with the first two columns. For complex firms, there appears to be an additional penalty for the walking down of earnings during the quarter. These results suggest that investors are aware of the effects of complexity on influencing analysts' forecasts and react with a more negative response. However, examining the other coefficients suggests there is still a net benefit to a complex firm because the premium to beating expectations at the earnings announcement is greater than the negative reaction during the walk-down. For example, a complex firm with no walk-down in earnings will receive a 2.67 percent positive return for beating expectations at the margin. However, a complex firm with a walk-down of 7 percent (the average walk-down in the sample) that allows them to just beat expectations will have a negative 0.43 percent return during the quarter. This results in a net benefit of 2.24 percent return to the complex firm.

6. Conclusion

We examine the effects of financial statement complexity on the propensity of firms to meet or beat analysts' earnings expectations. We find that firms with more complex financial statements have a higher propensity to just meet or beat analysts' expectations than to just miss analysts' expectations. Of the four mechanisms, complex firms could use to meet expectations—managing expectations, excluding GAAP items from "actual" earnings, managing accruals, and real earnings management—we find complex firms primarily use expectations management. Analysts do rely on the management guidance more for complex firms, corroborating the expectation management result. Although we do find firms with complex financial statements are more likely to have GAAP exclusions, they are not an important determinant in complex firms meeting expectations. Our results examining the market reaction to meeting or beating estimates suggest that while the reward to meeting or beating expectations is not diminished at the time of the earnings announcement, investors react more unfavorably to walk-down behavior during the quarter for complex firms. We document that financial statement complexity affects audit fees and the ability of firms to meet or beat analysts' forecasts. Future research could examine other effects of financial statement complexity such as its influence on investor reaction to earnings news or the compensation of managers.

There are some caveats and limitations to our research. First, our lack of evidence that complex firms do not use earnings management could be the result of an imprecise estimate of earnings management using discretionary accrual proxies. Second, our analyst reliance tests suggest that managers of firms with complex financial statements can initiate a walk-down by issuing forecasts since analysts are more likely to respond to those forecasts for complex firms. However, without observing all the manager/analyst interactions, we cannot rule out that analysts may encourage managers of complex firms to issue forecasts. Finally, some studies interpret the behaviors we examine as opportunistic (Jones 1991; Matsumoto 2002; Richardson et al. 2004; Cohen and Zarowin 2010; Roychowdhury 2006) while others view them as informative (Holthausen 1990; Subramanyam 1996; Gunny 2010). If we interpret our main results and returns tests similar to prior research, we would conclude that managers and analysts of complex firms engage in opportunistic behavior to beat expectations. However, in our context financial statement complexity may induce managers to use these behaviors to better inform analysts, making it difficult to definitively conclude that these behaviors are opportunistic in nature since we cannot observe the underlying motivations of managers.

Appendix

Variable name	Calculation
10KFOG	Fog Index of current year 10-K. 0.4 × (words per sentence + 100 × percent of complex words), where complex words are words with three or more syllables. Winsorized
ABS_FCSTERR	abs(*FCSTERR*). Winsorized
ACCMGMT	Accrual management indicator equal to one if firm beat expectations, but would have missed if accruals are removed from earnings, zero otherwise. Only defined for cases where *JUSTBEAT* equals one
ACCRUAL_DECILE	Decile rank of estimated abnormal discretionary accruals
BEAT	Indicator equal to one if *FCSTERR* ≥ 0, zero otherwise
BEG_BEAT	Indicator equal to one if *beginning* of the period forecast error is greater than zero, zero otherwise
BIGN	Indicator variable equal to one if a firm is audited by a "Big 5" audit firm
BTM	Book-to-market ratio (ceqq/(prccq × cshoq)). Winsorized
CFVOL	The standard deviation of the companies' cash flow from operations (oancf) for the previous five years scaled by quarterly total assets (atq). Winsorized
CHGEARN	Earnings (ibq) less earnings from the same quarter of the prior year, all scaled by same quarter prior-year earnings. Winsorized
CV	The standard deviation of the consensus forecast used to calculate *FCSTERR* scaled by the absolute value of the mean *FCSTERR*. Winsorized
DA	Debt-to-assets ratio (lt/at). Winsorized
EMPLOY	Square root of the number of employees $\sqrt{(\text{emp})}$. Winsorized
EMPPLAN	Indicator equal to one if the company has a pension or postretirement plan (either ppic, pplao, or ppsc > 0)
EXCL_USE	Use of GAAP exclusions indicator equal to one if *I/B/E/S* Actual EPS exceeds COMPUSTAT EPS (either epspxq or epsfxq depending on the I/B/E/S primary or diluted indicator), zero otherwise

(The appendix is continued on the next page.)

Appendix (continued)

Variable name	Calculation
EXCLMGMT	Exclusions management indicator equal to one if a firm beat expectations, but would have missed if exclusions are removed from earnings, zero otherwise. Only defined for cases where *JUSTBEAT* equals 1
EXPMGMT	Expectations management indicator equal to one if a firm beat expectations, but would have missed if using the beginning of the period consensus forecast, zero otherwise. Only defined for cases where *JUSTBEAT* equals one
FCSTERR	Forecast error. Actual I/B/E/S EPS less mean EPS forecast as of the end of the quarter. Winsorized
FEES	Natural log of audit fees collected from proxy statements from 2001 to 2006. Winsorized
FOROPS	Indicator equal to one if the firm has foreign currency adjustments as identified by a nonmissing value of fca
FS_COMPLEX	Financial statement complexity. The natural logarithm of industry and year adjusted accounting policy length. Winsorized
GRSALES	Growth in sales ((sale−lagged sale)/lagged sale). Winsorized
HIGH_ACCRUAL	Indicator equal to one if estimated abnormal discretionary accruals are positive, zero otherwise
INITIAL	Indicator equal to one if the audit engagement is in its initial two years
INSTPERC	Percentage of institutional ownership SUM(shares)/(mean (shrout1) × 1,000,000). Where shares are institutional shares held at the end of the quarter, shrout1 are total shares outstanding, both taken from the tfn.s34 data set
INVREC	Inventory and receivables divided by total assets (invt + rect)/at. Winsorized
JUSTBEAT	Indicator equal to one if $0 \leq FCSTERR \leq 0.02$, zero if $-0.02 \leq FCSTERR < 0$
LABOR	Labor intensity (1 − ppegtq)/(atq + dpactq) as in Matsumoto (2002). We replace missing values with 1 − (ppentq/atq) to increase our sample size
LAG	Number of days between fiscal end date and earnings announcement date (rdq-datadate). Winsorized
LEVERAGE	Financial leverage SUM(dlttq,lctq)/atq. Winsorized
LIQ	Current assets divided by current liabilities (act/lct). Winsorized
LOG_GEO_SEG	ln(number of geographic segments), obtained from the COMPUSTAT Legacy dataset
LOG_OP_SEG	ln(number of operating segments), obtained from the COMPUSTAT Legacy dataset
LOGASSETS	ln(at). Winsorized
LOGMVE	ln(prccq × cshoq). Winsorized
LOGSHARES	Log of shares outstanding ln(cshoq)
LOSS	Indicator equal to one if there is a loss in the current period (ni < 0)
NEGEARN	The number of prior 4 quarters with negative earnings (ibq)
NOA	Scaled beginning of the period net operating assets SUM(ceqq,−cheq,dlcq,dlttq)/saleq. Winsorized
NUMEST	The number of analysts following the firm making up the consensus forecast used to calculate *FCSTERR*
OPINION	Indicator equal to one if there was a recent modified audit opinion (auop or lag(auop) > 1)

(The appendix is continued on the next page.)

Appendix (continued)

Variable name	Calculation
RD	Research and development expense scaled by total assets (xrdq/atq), we assume if xrdq is missing then RD = 0
RESTATE	Indicator equal to one if a restatement was announced during the fiscal year. Restatement data were obtained from the GAO (2002, 2006) reports
RETURN	Stock return over the year (prcc_f + dvc − l1prcc_f)/l1prcc_f. Winsorized
ROA	Return on assets (oiadp/at). Winsorized
SCFO	Operating cash flow (oancfy) scaled by total assets (atq). Winsorized
STREAK	The number of consecutive prior quarters the firm as met or beat analyst expectations
TENURE	The total number of years the firm has been audited by the current audit firm from COMPUSTAT
VOL	The variance of the residual from the market model calculated over the current fiscal year. Winsorized
XDOPS	Indicator equal to one if extraordinary items or discontinued operations (xido) is not equal to zero
ZSCORE	Change in Altman's *Z*-Score ($ZScore_t - ZScore_{t-1}$), where *Z*-Score is: ((act + lct)/at) × 1.2 + (re/at) × 1.4 + (ebit/at) × 3.3 + (revt/at) × 0.99 + ((prcc_f × csho)/lt) × 0.6. Winsorized

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