Accounting Complexity and Misreporting: Manipulation or Mistake?

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Abstract

I explore the effect of accounting complexity on misreporting using a setting of revenue restatements. I measure revenue recognition complexity using a factor score based on the number of words and revenue recognition methods from the revenue recognition disclosure in the 10-K just prior to the restatement announcement. Results are consistent with revenue recognition complexity increasing the probability of revenue restatements, after controlling for other determinants of misreporting revenue. These results are significant both statistically and economically and are robust to a number of different specifications. I also test whether misreporting for complex revenue recognition firms is the result of mistakes or manipulation. My tests provide no evidence consistent with complex revenue recognition being associated with manipulating revenue. However, there is evidence that firms that restate revenue and have more complex revenue recognition are less likely to receive an AAER from the SEC and have less negative restatement announcement returns than firms with less complex revenue recognition, suggesting mistakes are more likely for more complex firms.

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1. Introduction

Regulators' recent concern about complexity in financial reporting is predicated on the belief that this complexity is costly to the financial markets. In regards to one particular cost, in December 2005 both Chairman Cox of the Securities and Exchange Commission (SEC) and Chairman Herz of the Financial Accounting Standards Board (FASB) suggested complex accounting and reporting was a major contributor to the increase in financial statement misreporting (Cox, 2005 and Herz, 2005). I investigate the effect of accounting complexity on financial statement misreporting, a question largely unexplored in the academic literature. I use revenue recognition as a setting to investigate this effect for three reasons. First, revenue recognition is a universal accounting issue that affects many, if not all, firms. In addition, prior research shows that revenue misreporting is a common type of restatement (Palmrose et al., 2004; GAO, 2002 and 2006), ensuring I can obtain a sufficiently large sample to test the effects of complexity on misreporting. Finally, anecdotal evidence suggests that revenue recognition can be complex for firms (Sondhi and Taub, 2006; Herz, 2007; Turner, 2001).

I define accounting complexity as the amount of uncertainty related to the mapping of transactions (or potential transactions) and standards into financial statements.[1] This definition incorporates complexity relevant to both preparers and users of financial statements. The uncertainty could result from unpredictable business environments, imperfect standards, or imperfect information about transactions. I conjecture that a description of the revenue recognition process captures aspects of this uncertainty. Therefore, I measure accounting complexity as it relates to revenue recognition using a factor score based on the number of words and number of revenue recognition methods from the firm's revenue recognition disclosure.

[1] Prior literature has not developed a formal definition of accounting complexity. While the SEC has been consistent in their discussion of complexity in SEC speeches and testimony, to my knowledge they have yet to formally define the concept.

There are two competing (although not exclusive) theories about how accounting complexity might affect financial misreporting. The 'mistake theory', adapted from Dechow and Dichev (2002), argues that complexity causes managers to make more mistakes or errors in judgment. When accounting is complex, managers are more likely to err when applying standards to transactions, increasing the likelihood of misreporting due to mistakes. The 'manipulation theory' argues that managers take advantage of complex accounting to manipulate the financial statements. For example, prior research suggests that investors do not fully understand information found in pension footnotes, and that managers manage earnings through complex pension accounting (Picconi, 2004; Bergstresser et al., 2006). Therefore, the manipulation theory suggests complex accounting provides managers an opportunity to manage the financial statements more easily.

Applying these theories to revenue, both theories suggest that revenue recognition complexity likely increases the propensity to misreport revenue. Assuming the probability of detection is similar across theories, I hypothesize that revenue recognition complexity increases the likelihood of revenue restatements. I then attempt to distinguish between the mistake theory and manipulation theory. The distinguishing feature between the two theories hinges on management's intent. I attempt to infer intent by testing certain attributes of the misreporting: (1) whether the misreporting caused the firm to meet a revenue benchmark, (2) whether the misreporting was an overstatement of revenue, and (3) whether the misreporting included multiple areas of the financial statements. To further test for intent, I examine the consequences of restating. Prior research provides evidence that misreporting costs are more severe if information related to the restatement calls into question the integrity of management (see Palmrose et al., 2004 and Hribar and Jenkins, 2004). Therefore, conditional on misreporting, the consequences of restatement should be more severe for intentional manipulation than for unintentional mistakes. An association between revenue recognition complexity and the consequences of misreporting provides an indication of intentional misreporting for more complex firms. I examine three consequences associated with the restatement: (1) the likelihood of an SEC Accounting and Auditing Enforcement Release (AAER), (2) the restatement announcement returns, and (3) CEO turnover following the restatement.

I test my hypotheses on a sample of 1,188 accounting restatements from 1997-2005 identified by the Government Accountability Office (GAO) in their 2002 and 2006 reports to Congress on accounting restatements. I compare firms restating revenue to firms that do not restate revenue, but restate other items. I use these other restatement firms for comparison principally because it provides an inherent control for determinants of restatement in general. I estimate a logistic regression model to test whether revenue recognition complexity increases the likelihood of a revenue restatement compared to other types of restatements, controlling for other determinants from prior literature. Logistic regression results provide evidence that firms with complex revenue recognition are more likely to restate revenue. A one standard deviation increase in revenue recognition complexity centered on the mean increases the probability of revenue misreporting by 8.8 percent. Relative to other determinants in the model, this marginal effect suggests complexity is one of the most important determinants of revenue restatements.

I then examine whether complex revenue recognition for firms that misreport revenue is associated with restatement attributes that suggest manipulation (missing benchmarks, overstatements, and restating multiple items). Results from these tests do not differentiate between the mistake and manipulation theories for complex revenue recognition firms. However, tests that examine the consequences of misreporting provide evidence more consistent with the mistake theory. Regression results show that, given a revenue restatement, firms with more complex revenue recognition are less likely to receive an AAER and have less negative restatement announcement returns. However, the results show that revenue recognition complexity is not associated with CEO turnover, suggesting that boards may not distinguish between mistakes and manipulation in determining CEO departure when restatements occur. In sum, my results provide evidence that accounting complexity increases the probability of restatement in the case of revenue. While there is no evidence consistent with the manipulation theory, I do provide some evidence consistent with the mistake theory.

In additional analysis, I also perform a number of robustness checks. These include using alternative measures of revenue recognition complexity, using alternative research designs, and controlling for changes in the revenue recognition disclosure environment. These additional tests provide results that are generally consistent with those presented in the main analysis.

This study contributes to the literature in several ways. First, I present evidence that complex accounting increases the occurrence of misreporting, and most importantly, show that the magnitude of that effect is significant. Second, prior research (e.g. Bergstresser et al., 2006) suggests that complexity is typically associated with earnings management or manipulation; however, I find no evidence of an association between accounting complexity and manipulation in this setting of revenue recognition. Third, I provide a definition of accounting complexity and an associated empirical measure that can be applied in future research. These results should be informative to both the SEC and FASB as they attempt to reduce complexity in financial reporting, including revising revenue recognition standards in the near future.[2] This research

[2] Both the SEC and FASB have taken steps to address complexity. On June 27, 2007, the SEC announced the establishment of an advisory committee with a goal of reducing unnecessary complexity in financial reporting and making information more useful and understandable for investors. The FASB is readdressing specific accounting standards that are overly complex and has initiated an effort to develop an integrated codification of all existing accounting literature that would be available electronically. In February, 2007 Congress voted unanimously to require the SEC, PCAOB and FASB to report yearly on their efforts to reduce complexity in financial reporting (H.R. 755).

should also be useful to investors, auditors, and firms to better understand the causes and consequences of revenue restatements.

The rest of the paper is outlined as follows. In the next section, I define accounting complexity and discuss the effect of complexity on misreporting. Section 3 discusses the empirical setting and develops my hypotheses. Section 4 discusses the sample, data, and empirical design. Results are presented in Section 5, with some additional analysis in Section 6. Section 7 concludes.

2. Accounting Complexity

2.1 Accounting Complexity Defined

To my knowledge, no formal definition of accounting complexity exists in the literature.[3] I define accounting complexity as the amount of uncertainty related to the mapping of transactions or potential transactions and standards into the financial statements.[4] This definition is intended to apply to both preparers and users of financial statements, and views accounting complexity as a scale or relation. I next discuss a few key points related to this definition to give some context.

Accounting is the confluence of transactions or potential transactions and standards. Preparers must take information about the firm's transactions and guidance from standards and map the two to determine the appropriate accounting. Users must also understand the mapping

[3] Prior research has examined firm or organization complexity (see Bushman et al. 2004), information complexity (see Plumlee, 2003), and information overload (see Schick et al., 1990 for a review), concepts not wholly unrelated to accounting complexity. I also recognize other definitions of accounting complexity likely exist; however, none has been explicitly stated.

[4] I believe this definition is in line with Congress' and the SEC's recent characterization of complexity, which encompasses both complexity as it relates to disclosure (which affects users) and standards (which affects users and preparers). For example, H.R. 755 enacted by Congress in February 2007, identifies 5 major areas that the SEC, PCAOB, and FASB need to address, encompassing both disclosure and standards issues. These are (1) reassessing complex and outdated accounting standards; (2) improving the understandability, consistency, and overall usability of the existing accounting and auditing literature; (3) developing principles-based accounting standards; (4) encouraging the use and acceptance of interactive data; and (5) promoting disclosures in 'plain English'.

to interpret financial statements correctly. In many cases, this mapping is very straightforward, leading to a single, generally accepted and understood accounting choice. In other cases, there is uncertainty in the mapping, which can lead to potentially conflicting or erroneous accounting choices by preparers. Uncertainty also affects users since they must interpret how the mapping was performed based on limited disclosures. While some sources of uncertainty can be mutual for both preparers and users, uncertainty can also differ across preparers and users of financial statements. In some cases the mapping may be quite clear to preparers and auditors; however, uncertainty about the same transactions and standards can make accounting "appear" complex to users.[5] Increased transparency or disclosure can alleviate some uncertainty for users in terms of how the mapping *is* performed by preparers. However, increased transparency does not remove uncertainty regarding how the mapping *should be* performed by preparers.

Uncertainty in applying standards to transactions could come from many sources.[6] First, uncertainty could be the result of business environments that are not perfectly predictable. While accounting standards could require certainty of outcomes before recognition in the financial statements, most standards incorporate some aspect of this uncertainty, requiring managers to make estimates and judgments. Uncertainty could also result from flawed standards or deficient information about transactions. Unclear or ambiguous wording, inconsistencies across standards, or detailed rules-based standards can all cause uncertainty related to the standards.[7] Uncertainty could also stem from deficient information about transactions or contracts.

[5] While preparers and auditors are required to have some level of accounting expertise, there are no such requirements for investors. The FASB's SFAC 1 paragraph 36 acknowledges that users' understanding of financial information "may vary greatly", and that financial reporting should be accessible "to all—nonprofessionals as well as professionals—who are willing to learn to use it properly" (FASB, 1978).

[6] I provide a discussion on the potential sources of uncertainty to facilitate understanding, but my tests do not allow me to distinguish between the sources of uncertainty. However, understanding the precise causes of uncertainty may be important to regulators interested in eliminating avoidable sources of uncertainty.

[7] There is much discussion in the accounting literature on rules- v. principles-based accounting standards. While the intent of rules-based standards may be to remove uncertainty in the accounting, they can increase accounting complexity for users because of their inability to encompass all potential situations or their ability to obscure the original transaction's purpose beneath layers of rules.

Although the firm may have all available information related to contracts and transactions, uncertainty could still persist for preparers. Uncertainty about contracts and transactions can increase for firms with numerous, customer-specific contracts or agreements documented by multiple contracts. Lengthy contracts and technical or legal wording in contracts may also cause uncertainty. In multi-division firms, uncertainty may increase because detailed information about contracts and transactions may be decentralized, while accounting expertise may be centralized.

Uncertainty is the result of, or is amplified by, limits to human cognitive function. Research shows that individuals have limits to cognitive processing, especially under uncertainty, which leads to simplification, heuristics, or biases (see Payne, 1976; Iselin, 1988; Bettman et al., 1990). As argued by Tversky and Kahneman (1974), this simplification can occasionally lead to errors in estimation or judgment. If uncertainty limits the efficient processing of information for preparers and/or users, this suggests that complexity can be costly to financial markets. I discuss one of these costs, misreporting, in the next section.

2.2 Accounting Complexity and Misreporting

I present two theories regarding the causes and consequences of accounting complexity on misreporting. One theory of accounting complexity suggests that complexity from the preparer's perspective causes unavoidable mistakes in financial reporting. This idea is adapted from Dechow and Dichev (2002), who write that "estimation accuracy [of accruals] depends on firm characteristics like complexity of transactions and predictability of the firm's environment." Although Dechow and Dichev focus on accruals, the idea applies more generally to all accounting and reporting. Uncertainty in estimating accruals naturally leads to errors, which causes revision in future accruals and earnings. More generally, preparer uncertainty in mapping transactions and standards also leads to more errors and misreporting. However, unlike accruals, if the company makes errors when mapping transactions and standards (misinterpreting GAAP), the company must restate prior numbers. I term this the mistake theory of complexity.

Another theory of complexity suggests that managers opportunistically manage earnings when accounting is complex. In contrast to the mistake theory, which suggests that complexity affects the *preparer's* accuracy in financial reporting, the manipulation theory relies on complexity creating uncertainty for *investors* (and/or information intermediaries). For example, focusing on complex pension accounting, Picconi (2004) documents that investors and analysts do not understand the effect of changes in pension plan parameters on future earnings. He also shows that managers increase expected rates of return on pension assets to offset the effect of anticipated bad news in the future. Similarly, Bergstresser, Desai and Rauh (2006) show that managers increase rates of return assumptions on pension assets when the assumptions have a greater impact on earnings, or when managers are attempting to acquire other firms or exercise stock options. The findings on pensions suggest managers opportunistically alter financial reporting when accounting or reporting is complex. The manipulation theory argues that complexity increases uncertainty to outsiders, providing managers an opportunity to intentionally misreport more easily.[8]

3. Setting and Hypotheses

3.1 Revenue Recognition Setting

I study the effect of accounting complexity on misreporting with respect to revenue recognition for three reasons. First, revenue recognition is a universal accounting issue; therefore, my findings will apply to a broad set of firms. Second, revenue misreporting is one of

[8] Although this theory suggests managers take advantage of complex accounting by managing the financial statements, complexity is not a necessary condition for manipulation. Many fraudulent practices are implemented using simple accounting settings (e.g., fictitious sales, bill-and-hold transactions, and capitalizing expenses).

the most common types of restatement (see Palmrose et al., 2004; GAO, 2002 & 2006). This ensures that I can obtain a sufficiently large sample of revenue misreporting to test the effects of complexity on misreporting. Finally, anecdotal evidence suggests that revenue recognition can be complex for preparers and users of financial statements. I briefly discuss the evidence on the complexity of revenue recognition next.

Sondhi and Taub (2006) summarize the problems with revenue recognition when they write: "The lack of comprehensive guidance, in combination with the variety and complexity of revenue transactions, has resulted in a large number of financial reporting errors in the area of revenue recognition." Revenue recognition can be complex because of uncertainty about both standards and transactions. From 2001-2005, the FASB's advisory group named revenue recognition the top issue that should be addressed by the FASB (Schneider, 2005). The FASB states there are over 200 revenue recognition pronouncements by various standard setting bodies (Herz, 2007), and much of the authoritative guidance is industry- or transaction-specific. These issues can lead to inconsistencies across pronouncements or difficulties in applying multiple standards to a contract. In addition, complicated revenue transactions and contracts can increase uncertainty. Customer contracts can be lengthy, filled with legal wording, and include multiple clauses for customer acceptance, return policies, and payment terms. Companies with many customer-specific contracts can increase uncertainty and side agreements, whether written or oral, can also alter provisions in contracts leading to increased complexity (see Turner, 2001).

3.2 Measuring Revenue Recognition Complexity

I conjecture that a description of the revenue recognition practices captures uncertainty about recognizing revenue. Measuring complexity at the firm level is more appropriate than the standards level because standards apply to firms differently due to differences in transactions.

To measure the complexity of revenue recognition at the firm level, I examine the firm's revenue recognition disclosures found in the summary of significant accounting policies contained in the notes to the financial statements.[9] I measure revenue recognition complexity using a factor score (*RRC SCORE*) based on the number of words (*WORDS*) and a proxy for the number of methods (*METHODS*) obtained from the revenue recognition disclosure.[10] In untabulated results, *WORDS* and *METHODS* are highly correlated (0.87), suggesting that these variables capture similar variation in revenue recognition complexity. I use a factor score mainly for presentation purposes, but also to reduce noise relative to using each measure separately.[11] I discuss other measures of revenue recognition complexity in Section 6.

I believe the *RRC SCORE* is a sufficient measure of revenue recognition complexity. Relative to simple disclosures, longer disclosures and more methods capture the preparer's need to incorporate a diverse set of transactions and standards. In addition, longer disclosures are required for firms to explain more involved practices or methods. These characteristics are evidence of increased uncertainty. To illustrate this, Appendix 1 includes a few sample revenue recognition disclosures. For example, A.C. Moore Arts & Crafts recognizes revenue at the point of retail sale, which is likely an automated process with no uncertainty, suggesting low complexity. The number of words in their revenue recognition disclosure is 8 and the number of methods is 1. On the other hand, ARI Networks recognizes revenue for maintenance fees,

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[9] Prior to SAB 101, firms had a choice to disclose their revenue recognition policy depending on whether they thought it was a significant policy; however, SAB 101, which became effective in 2001, required firms to disclose their revenue recognition policies in the notes to the financial statements. I discuss the effect of this change in disclosure requirements on my results in Section 6.

[10] I measure the number of methods (*METHODS*) the firm employs by counting the number of occurrences of the words "recogn" and "record" found in the disclosure. Counting the occurrences of "recogn" and "record" overestimates the actual number of revenue recognition methods the firm employs. To alleviate concerns of bias in this measure, I physically read the recognition disclosures and counted the number of methods for a sub-sample of firms. The correlation between the two measures is .77, suggesting my proxy for the number of methods is sufficient.

[11] I use the principal components method of factor analysis, although results are very similar when I use the common factor method. Only one retained factor is available when using two individual variables and the eigenvalue of my retained factor is 1.7.

services, subscriptions, and software. The fees may not be fixed and the customer acceptance terms can differ across contracts. For ARI, the number of words is 158 and the number of methods is 7. Thus, relative to A.C Moore, ARI Networks' revenue recognition is more complex and the *RRC SCORE* will capture that increased complexity. As with any measure based on firm disclosures, there is managerial discretion about how much to disclose with respect to revenue recognition. However, prior literature (Healy and Palepu, 2001) suggests that the risk of litigation (Skinner, 1994) and the presence of auditors (Leftwich, 1983) enhances credibility of reported financial statements and motivates managers to make accurate and timely disclosures. Therefore, the presence of auditors and risk of litigation should provide limiting boundaries on the disclosure choice with respect to revenue recognition, mitigating concern about discretion in the disclosure.

3.3 Research Questions and Hypothesis Development

Both the mistake and manipulation theory of complexity suggest that revenue recognition complexity increases the likelihood of misreporting revenue. Assuming that the probability of detecting the misreporting is similar across both theories, this leads me to the following hypothesis, stated in alternate form:

> *H1: Managers of firms with more complex revenue recognition are more likely to misreport revenue than managers of firms with less complex revenue recognition.*

I test this hypothesis because it is possible that the effect of complexity on revenue misreporting is quite small or that misreporting is solely driven by managerial incentives and governance, as hypothesized in prior literature (see Zhang, 2006; Callen et al., 2005). Beyond testing for the existence of a relation between accounting complexity and revenue misreporting, testing H1 allows me to quantify the economic significance of the effect of complexity on the likelihood of misstating revenue.

I next attempt to distinguish between the two theories of misreporting. The research question I investigate is: Is misreporting revenue in a complex revenue recognition environment the result of intentional manipulation or unavoidable mistakes? I do not provide specific hypotheses regarding this research question, but I develop tests to distinguish between the two competing theories. The distinguishing feature between manipulation and mistakes is managerial intent. Although inferring intent is difficult in an empirical setting, I conduct tests on both the *attributes* and *consequences* of misreporting to infer which theory best explains revenue misreporting. I discuss these tests in the next section after a brief discussion of the sample.

4. Sample Selection and Empirical Design

4.1 Data and Sample Selection

I use a sample of restatement firms collected by the GAO for their reports to Congress in 2002 and 2006 to identify firms that misreported their financial statements.[12] Included in the GAO database is the date of the restatement announcement, type of restatement, including whether the firm restated revenue, and who identified the misreporting (or source). The GAO study excludes certain types of restatements that are not due to "irregularities," including restatements from mergers and acquisitions, discontinued operations, and stock splits, among others. In the combined reports, the GAO identified 2,305 firms that restated their financial statements, covering the years 1997 to 2005. I exclude financial firms (SIC 6000-6999) as their revenue recognition is substantially different from other firms due to regulatory requirements. Firms may have multiple restatements over the sample period. For firms that have both a revenue restatement and a separate non-revenue restatement (meaning multiple restatements, rather than one restatement with multiple items), I keep the revenue restatement and remove any

[12] Restatement data from the GAO reports can be found at http://www.gao.gov/new.items/d03395r.pdf (2002 report) and http://www.gao.gov/special.pubs/gao-06-1079sp/toc.html (2006 report). Judson Caskey provides the data in one MS-Excel file here: http://personal.anderson.ucla.edu/judson.caskey/data.html.

non-revenue restatements. In addition, I only include the first restatement for firms that restated more than once within a one year period.[13] I recategorize 18 revenue restatements identified by the GAO because they are categorized incorrectly. For example, the GAO categorizes restatements relating to non-operating gains on sale and other non-operating income (such as interest income) as revenue restatements. I also exclude all revenue restatements in connection with SAB 101 or any EITF related to revenue issued during the sample period, as I consider these restatements as mandatory restatements caused by a change in accounting standard.[14] Missing variables from 10-K disclosures and COMPUSTAT and CRSP databases reduces the sample size to 1,188 restatements, 348 of which are revenue restatements. Table 1 contains more information about the attrition of the restatement sample.

I obtain stock returns from CRSP and analyst forecasts from I/B/E/S. CEO turnover is obtained from EXECUCOMP where available and hand collected from the proxy filings where not available. I collect revenue recognition disclosures contained in the firm's most recent 10-K prior to the restatement announcement using the Edgar Company Search on the SEC website.[15] Some restatements relate to quarterly filings only; however, revenue recognition disclosures are not found in 10-Q filings, so I also use the most recent 10-K filings for these firms. I use the

[13] The GAO sample may have firms with multiple restatements within a one year period for two reasons. First, although extremely rare, the firm may have separately identified multiple misreporting violations during that one-year period. More commonly, the firm has multiple restatements because the GAO incorrectly included separate restatement announcements that are just updates of previously announced restatements.
[14] During the sample period, the Emerging Issues Task Force issued EITFs 99-19, 00-10, 00-14, 00-22, 00-25 to clarify revenue recognition issues such as recognizing gross v. net, shipping and handling costs, sales incentives, and other consideration from a vendor to a reseller.
[15] I use the fiscal period prior to the restatement announcement to balance the need to have a disclosure that captures investors' perceptions of revenue recognition at the announcement and to have a disclosure that captures complexity during the misreporting. Almost all restatements include misreporting up to the restatement announcement suggesting that these disclosures capture the complexity during the misreporting.

Python programming language to obtain the revenue recognition disclosures where possible, personally checking for accuracy, and hand collecting the disclosures where Python fails.[16]

Table 2 displays the frequency of restatements by year for the type of restatement (Panel A), industry (Panel B), and source of the restatement (Panel C).[17] Panel A shows that revenue restatement firms are 29 percent of the total restatements in the sample and that 2000 and 2003 had especially high proportions of revenue restatements. Although not tabulated, the industry breakdown is similar to the composition of all firms in Merged CRSP/COMPUSTAT database over the sample period, except my sample is overweighted in Wholesale/Retail and Technology and underweighted in Other.[18] Panel C presents information about who identified the misreporting (or source) broken out by the type of restatement. More than half of the restatements are initiated by the company, although this potentially underestimates the effect of the auditor on discovering the misreporting since the auditor may identify the restatement but receive no credit in the restatement announcement.

4.3 Empirical Design

4.3.1 Control Firms

I test H1 by comparing the revenue recognition complexity of firms that restated revenue to firms that restated something other than revenue. I use non-revenue restatement firms as the control sample for three reasons. First, using restatement firms as the comparative group controls for incentives, governance effects, and other determinants of restatements, which are

[16] Python is an open-source, dynamic programming language useful for text and html processing. More information on Python can be found at www.python.org.
[17] Consistent with Palmrose et al. (2004), industries are defined by the following SIC codes: Mining & construction=0-1999, manufacturing=2000-3999 (except codes assigned to technology), technology=3570-3579 plus 7370-7379, transportation=4000-4799, communications=4800-4899, utilities=4900-4999, wholesale/retail=5000-5999, services=7000-8999 (except codes assigned to technology), and other=9000-9999.
[18] The overweighting in Wholesale/Retail is mostly explained by the large amount of lease-related restatements in 2005 for Wholesale/Retail firms.

difficult to control for because they are hard to measure (e.g., governance and incentives). Second, other research design approaches are problematic. Comparing revenue restating firms to a broad cross section of firms is prohibitive because revenue recognition complexity requires some hand collection. A matched sample approach is difficult to implement because it is not clear what attributes or what time period should be matched.[19] Third, by employing the same design as prior research (Zhang, 2006), which has hypothesized that unique incentives cause managers to manage revenue, I can compare my results with prior literature. One disadvantage of using other restatement firms for comparison is that results may not accurately reflect the full effect of complexity on misreporting in a large sample context if other restatement firms are not representative of the rest of the population of firms. Similarly, by comparing revenue restatement firms to other restatement firms, I only capture the incremental incentives to misreport revenue, which likely underestimates the effect of incentives relative to the population.

4.3.2 Revenue Restatement Model

The logistic model to test H1 is presented in equation (1). I organize control variables into three categories based on prior research and discuss them below.

$$P(\text{Revenue} \mid \text{Restate}) = f(\alpha + \beta\text{Complexity} + \sum \gamma \text{Value Relevance} + \sum \mu \text{Governance} + \sum \delta \text{ Other}) \quad (1)$$

where: Complexity $\in$ [*RRC SCORE*]
Value Relevance $\in$ [*BTM, LOSSPER, SALEFCST, GM, OM, R&D, EARNVOL*]
Governance $\in$ [*PRERETURN, CHSALES, BIGN, LOGMVE, AUDITOR*]
Other $\in$ [*AR ACCRUAL, INDUSTRY, YEAR*]

The proxy for complexity is discussed above. I discuss control variables next. Detailed variable definitions can also be found in Appendix 2.

[19] For example, matching on industry introduces a noisy sort on revenue recognition complexity, potentially controlling for the effect being tested. For the reasons stated above, I do not use a matched-sample design for the main analysis. However, in Section 6 I conduct an alternate test of H1 on a sub-sample of revenue restatements using a matched-sample approach.

Value-relevance of revenue

The two principal studies on revenue restatements, Zhang (2006) and Callen et al. (2005), have shown value relevance to be an important determinant of firms restating revenue. I use firm characteristics based on this prior research that suggest revenue has high value relevance and/or earnings has low value relevance. Ertimur et al. (2003) find the market reaction to revenue surprises to be greater for growth firms than value firms. Also, Ertimur and Stubben (2005) show that analysts are more likely to issue revenue forecasts for firms with higher growth prospects. Therefore, the existence of revenue forecasts should also increase the value relevance of revenue, since it provides the market a benchmark to evaluate revenue. Revenue may also be more important for firms with high gross margins and operating margins since Plummer and Mest (2001) find that firms with higher operating margins report higher sales surprises relative to analyst forecasts. Finally, Zhang (2006) includes R&D expenses based on Kama's (2004) evidence that the market reacts more to revenue surprises for firms with higher R&D expenditures, suggesting firms with higher R&D have revenue that is more value relevant.

Revenue may also be more important for valuation when net income is less value relevant. Hayn (1995), Collins et al. (1999) and others have shown that the returns-earnings relationship is weaker for loss firms than profit-making firms. Since loss firms have low value relevance of earnings, Callen et al. (2005) argue the market will substitute revenue for earnings in valuation. Zhang (2006) also argues that high earnings volatility is also likely to make earnings less value relevant, potentially increasing the value relevance of revenue.

In summary, growth prospects, analyst revenue forecasts, high gross and operating margins, losses, high R&D, and high earnings volatility all increase the value-relevance of revenue and the probability of revenue misreporting. Therefore, I include proxies in my model to control for these constructs. I use the book-to-market ratio of the firm at the fiscal year end just prior to the restatement (*BTM*) as a proxy for growth and an indicator equal to one if the firm has an analyst revenue forecast any time prior to the restatement announcement and zero otherwise (*SALEFCST*). I also include the 5-year average gross margin (*GM*) and 5-year average operating margin (*OM*) of the firm prior to the restatement. Finally, I include the proportion of loss years to total years the firm has earnings data on COMPUSTAT (*LOSSPER*), and the 5-year average R&D expenses scaled by sales (*R&D*) and earnings volatility (*EARNVOL*) of the firm prior to the restatement announcement.[20]

Governance

Prior research provides some evidence on the effect of auditing and governance on the occurrence of misreporting the financial statements in general (see Defond and Jiambalvo, 1991 and Palmrose et al., 2004), but provides little insight to whether managers will specifically misreport revenue. It is more likely that the previously mentioned variables on the value-relevance of revenue already capture an increasing monitoring effect on revenue reporting by auditors. In addition, Kinney and McDaniel (1989) find that firms correcting previously reported quarterly earnings are more likely to have negative stock returns leading up to the correction. They argue that poor recent performance causes auditors to scrutinize financial statements and accounting choices. I include the stock returns for the 12-month prior to the restatement announcement (*PRERETURN*) to control for this effect. Modifying this same idea specifically for revenue restatements, recent sales declines may cause auditors to reexamine the revenue recognition of prior sales, increasing the likelihood of restatement. I control for deteriorating sales by using the average change in sales for the two years prior to the restatement (*CHSALES*). I control for other potential monitoring effects by including the logged market value of equity of

[20] Zhang (2006) measures these variables relative to the initial period of misreporting. I measure the variables relative to the restatement announcement because I only have data on the misreporting period for a sub-sample of restatements. However, results are consistent with those presented in the paper when I measure these variables using Zhang's approach on the sub-sample.

the firm at the fiscal year end just prior to restatement (*LOGMVE*), an indicator equal to one if the firm is audited by a large accounting firm (*BIGN*), and an indicator equal to one if the restatement is attributed to the auditor (*AUDITOR*). However, I make no predictions regarding these effects.

Other determinants

Zhang (2006) also argues that large accounts receivable accruals allow managers more flexibility in managing revenue. Manipulating revenue when A/R accruals are already large decreases the likelihood of detection compared to small A/R accruals. I include the firm's 5-year average A/R Accrual prior to the restatement to control for high A/R accruals (*AR ACCRUAL*). Zhang makes a similar argument for unearned revenue accruals, but since data on unearned revenue accruals is only extensively available starting in 2002, I do not include unearned revenue accruals in the formal analysis.[21] Finally, I include industry and year indicators to control for industry and year effects that may affect the probability of restatements.

4.3.3 *Attributes of Misreporting Tests*

I examine three attributes of the revenue misreporting itself to provide some evidence on the intent of managers. For each misreporting attribute indicator described below, I perform univariate logistic regressions to test whether revenue recognition complexity (*RRC SCORE*) is associated with the particular attribute.

The first attribute I examine is meeting revenue benchmarks, including analyst forecasts and prior period revenue. Meeting revenue benchmarks can be beneficial to the firm and provides incentives to manage revenue (see Ertimur et al., 2003; Rees and Sivaramakrishnan, 2007; Stubben, 2006). If the restatement caused the firm to miss a benchmark that the firm

[21] As a robustness check, I include in the test an indicator equal to one if the firm has unearned A/R accruals as of 2002 and zero otherwise. The results remain consistent with those presented in the main analysis.

previously beat, this suggests the manager chose the recognition of revenue to manipulate revenue to beat the benchmark. Assuming the first period of misreporting was when the decision was made to recognize revenue in a particular way and the company maintained that policy in subsequent periods, the first period of misreporting is the period of interest. For each restatement I set *MISS GROWTH* to one if the firm had previously recorded positive sales growth in the first period of misreporting and the restatement caused the firm to have zero or negative sales growth for that period, and zero otherwise.[22] Similarly, for each restatement I set *MISS FCST* to one if the first period of the misreporting had an analyst revenue forecast and (1) the firm had previously beat the mean analyst revenue forecast for that period, and (2) the restatement caused the firm to miss the forecast for that period, and zero otherwise.

Second, if managers of firms with complex revenue recognition are manipulating revenue, there should be a greater likelihood that they overstate revenue compared to firms with less complex revenue recognition. In the extreme, one might suggest that evidence of mistakes should only exist if there are an equal number of over- and understatements. However, the probability of detection is not equal for over- and understatements because auditors and boards are more concerned with overstatements. In addition, this test attempts to determine if complex revenue recognition is more associated with unintentional mistakes, not solely driven by unintentional mistakes. I set an indicator equal to one if the sum of the restated revenue over the restating periods is less than the sum of the originally reported revenue over the restating period, and zero otherwise (*OVERSTATEMENT*).

Finally, the pervasiveness of the restatement may also give indication of intent. If the company restates another area of the financial statements in addition to revenue, it suggests the

[22] Since companies can restate annual results and/or quarterly results, I determine sales growth differently for annual and quarterly periods. For restated annual results, sales growth is calculated as the annual difference in sales. For restated quarterly results, sales growth is calculated as the lagged 4-quarter difference in sales.

misreporting is widespread and more likely intentional. In support of this, Palmrose et al. (2004) find that restatements involving multiple areas of the financial statements have more negative announcement returns, controlling for the magnitude of the restatement on net income. I set an indicator equal to one if the firm restated multiple areas of the financial statements, and zero otherwise (*MULTIPLE*).

4.3.4 Consequences of Misreporting Tests

In addition to the attributes of misreporting, I examine the negative consequences associated with the misreporting to partly infer whether stakeholders perceive there to be managerial intent associated with complexity. As Hribar and Jenkins (2004) argue, firms that announce restatements experience an increase in cost of capital partially because of uncertainty regarding managerial integrity. More generally, if managerial intent is important to stakeholders when they observe misreporting, then the theories suggest the consequences of misreporting will be more severe if managers are taking advantage of complexity and less severe if the complexity just results in more errors. I examine three reactions to misreporting that provide evidence of intent: SEC AAERs, restatement announcement returns, and CEO turnover following the restatement.[23]

First, I examine whether an SEC Enforcement Action (AAER) accompanies the revenue restatement.[24] While not all AAERs are accusations of fraud, the issuance of an AAER

[23] Using a different approach, Hennes, Leone, and Miller (2007) classify a restatement as intentional if the restatement disclosure discusses an irregularity, a board-initiated independent investigation, or an external regulatory inquiry. However, similar to my approach, they examine whether their classification is valid by examining the classification's association to announcement returns and class action lawsuits.

[24] I use the term 'accompanies' because the timing of restatements and AAERs can vary across firms. SEC investigations into misreporting, whether formal or informal, typically closely accompany restatement announcements. However, the complete resolution of restatements and AAERs can take years.

represents a greater likelihood of intentional actions.[25] For example, Karpoff et al. (2007), find that 622 of the 788 enforcement actions (79 percent) in their sample from 1978-2006 include charges of fraud. In addition, a 2007 Deloitte study finds that of revenue recognition AAERs, roughly half of the AAERs are issued for recording fictitious revenue, revenue swaps or round-tripping, or "bill and hold" transactions, which are all intentional manipulations (Deloitte Forensic Center, 2007). Data on firms subject to SEC AAERs is a sub-sample of AAERs that Dechow et al. (2007) use in their study. Using AAERs, Dechow et al. (2007) identify financial statement variables that predict financial manipulations and develop a Fraud Score based on their prediction model. Their sample contains AAERs from 1982 through 2004 and identifies if the AAER relates to revenue or receivables issues. Since my sample of restatements runs through 2005, I determine whether later restatements resulted in AAERs by searching the listings of AAERs on the SEC website through August 2007.

I use estimates from a logistic regression to test whether revenue recognition complexity affects the likelihood of receiving an AAER for revenue restatement firms. The dependent variable is one if the firm has an AAER associated with revenue or receivables within three years of the restatement announcement and zero otherwise. Equation (2) presents the model with a discussion of the variables following.

$$\begin{aligned} P(\text{AAER} \mid \text{Rev Restate}) = f(&\alpha + \gamma_1 RRC\,SCORE + \gamma_2 MULTIPLE + \gamma_3 AUDITOR \\ &+ \gamma_4 CAR + \gamma_5 MISS\,FCST + \gamma_6 RESTLEN + \gamma_7 CHREV \\ &+ \gamma_8 CHNI + \gamma_9 LOGMVE + \gamma_9 BIGN + \gamma_{10-18} INDUSTRY) \end{aligned} \tag{2}$$

Generally, studies on AAERs (Dechow et al., 1996; Beniesh, 1999; Dechow et al., 2007) have compared AAER firms to either a large sample of public firms or to small matched-

[25] Erickson, Hanlon and Maydew (2006) and Feroz et al. (1991) correctly argue that the SEC can issue administrative actions that do not imply charges of fraud or gross negligence. Generally, these administrative actions end with a settlement and an AAER, where the firm admits to no wrong-doing but agrees to avoid future securities violations.

samples. These studies examine firm characteristics like governance, incentives, and financial statement characteristics to predict AAERs. In contrast, this test focuses on the likelihood of an AAER for a specific type of misreporting event; therefore, restatement characteristics are likely more important in determining if an AAER will be issued. I conjecture that the SEC is more likely to issue an AAER if managers had intent to manipulate revenue, if the misstatements are large, and if the SEC gets greater exposure from issuing the AAER. I include four variables to identify intent: (1) whether the firm restated more than just revenue (*MULTIPLE*); (2) whether the restatement is credited to the firm's auditor (*AUDITOR*); (3) the 5-day cumulative restatement announcement return for the market's assessment of intent (*CAR*); and (4) a dummy equal to one if the restatement caused the firm to miss the sales forecast for the first period of the restatement and zero otherwise (*MISS FCST*).[26] I include three measures of the magnitude of the restatement: (1) the number of periods the company is restating in quarters (*RESTLEN*); (2) the percentage change in revenue over all periods of the misreporting due to the restatement (*CHREV*); and (3) the percentage change in net income over all periods of the misreporting due to the restatement (*CHNI*).[27] Finally, the SEC may target large firms and firms audited by large accounting firms because it benefits from enforcement of those firms relative to smaller firms. To control for these effects, I include in the model both the log of the market value of equity for the fiscal year end prior to the restatement (*LOGMVE*) and whether the firm was audited by a large accounting firm (*BIGN*).

Recognizing that AAERs probably do not constitute a complete set of intentional misreporting violations, I examine two other events associated with the restatement,

[26] Although the purpose of the test is to infer intent using the association between revenue recognition complexity and AAERs, I control for other obvious indications of intent since the SEC likely uses this other information in conjunction with complexity to determine if the company was intentionally misreporting revenue.

[27] The last two measures of magnitude, *CHREV* and *CHNI* will not capture restatements that are solely timing issues, since there is no "change" in revenue or net income. However, few restatements can be categorized as solely revenue recognition timing problems because at the time of restatement the timing has not been fully resolved.

announcement returns and CEO turnover. If investors are sensitive to management integrity and are capable (through disclosures or inference) of identifying managerial intent when a restatement is announced, then examining the effect of complexity on returns provides the market's indication of intent. If complex revenue recognition firms have lower (higher) market returns it would suggest the market interprets revenue restatements for complex firms as more (less) intentional.

I test whether the market reaction to revenue restatement announcements differs based on revenue recognition complexity using OLS regression estimates of 5-day cumulative abnormal returns (*CAR*) centered on the announcement date regressed on complexity variables and other control variables. I measure the cumulative abnormal return using market adjusted returns, where the daily market returns are subtracted from the firm's raw returns and compounded over the period. The model is presented in equation (3), followed by a discussion of control variables.

$$\begin{aligned}\mathrm{CAR} = {} & \alpha + \gamma_1 RRC\ SCORE + \gamma_2 MULTIPLE + \gamma_3 AUDITOR + \gamma_4 AAER + \gamma_5 CHREV \\ & + \gamma_6 CHNI + \gamma_7 LOGMVE + \gamma_8 PRERETURN + \gamma_9 BTM + \gamma_{10-18} INDUSTRY + \varepsilon\end{aligned} \tag{3}$$

Palmrose et al. (2004) identify a number of restatement and firm characteristics that affect restatement announcement returns. They show that restatement announcement returns are negatively associated with restatements involving fraud, affecting multiple accounts, decreasing net income, and attributed to auditors or management. I control for these findings using *MULTIPLE* and *AUDITOR* as previously defined. In addition, I include an indicator for whether the restatement is eventually associated with an AAER (*AAER*) to identify fraud. Since AAERs are not usually announced concurrently with accounting restatements, I include this variable to account for information the market infers or receives about fraud or SEC investigations from the announcement. I control for the magnitude of the restatement by including both *CHREV* and *CHNI* as previously defined. The model includes *LOGMVE* to control for size since adverse news is likely to be magnified for small firms, which typically have weak information environments (Collins et al., 1987 and Freeman, 1987). Since announcement returns are partially due to investors' revisions of future growth expectations, the returns are likely related to the book-to-market ratio of the firm just prior to the announcement (*BTM*) and recent stock performance (*PRERETURN*) as previously defined.

Finally, I examine evidence from CEO turnovers to infer intent. If corporate boards are more likely to dismiss CEOs that manipulate revenue, then an association between revenue recognition complexity and CEO turnover provides an indication of intent. However, it is possible that boards do not distinguish between manipulation, an indication of CEO integrity, and mistakes, an indication of CEO competence, when making turnover decisions. Therefore, I expect this test to be less powerful than the other consequences tests. Consistent with Desai, Hogan, and Wilkins (DHW, 2006), I test a logistic regression model where the dependent variable is one if the CEO resigned or was dismissed from the firm within two years following the restatement announcement and zero otherwise. The model, presented in Equation (4), includes a number of control variables that I discuss below.

$$\begin{aligned} P(\text{CEOTurn} \mid \text{Rev Restate}) = f(&\alpha + \gamma_1 RRC\,SCORE + \gamma_2 AAER + \gamma_3 MULTIPLE \\ &+ \gamma_4 LOGMVE + \gamma_5 CHREV + \gamma_6 CHNI + \gamma_7 PRERETURN \\ &+ \gamma_8 POSTRETURN + \gamma_9 ROA + \gamma_{10} CAR + \gamma_{11-19} INDUSTRY) \end{aligned} \quad (4)$$

Desai, Hogan, and Wilkins (2006) identify a number of variables that are associated with CEO turnover following restatements, many of which I include as control variables in my model. I include *MULTIPLE* and *AAER* as previously defined as partial controls for managerial culpability. I control for firm size by including *LOGMVE* as previously defined. I also include both *CHREV* and *CHNI* to capture the magnitude of the restatement. Prior stock return and operating performance are directly linked with CEO turnover decisions (see Warner et al., 1988 and Engel et al., 2003). Following DHW, I include both the stock returns for the year prior to (*PRERETURN*) and the year following (*POSTRETURN*) the restatement announcement to control for market-based performance. Consistent with DHW, I also include the return-on-equity (*ROA*) for the fiscal year prior to the restatement announcement to control for operating-based performance. Finally, I include the restatement announcement return (*CAR*) to capture the market's assessment of the restatement. DHW also provide some evidence that CEO age, tenure, stock ownership and occupying the Chairman position all contribute to the turnover. However, since over half of my sample firms are not covered by EXECUCOMP, I exclude these variables from the model. I discuss the effect of this research design choice on my results in the next section.

5. Results

Table 3 contains summary statistics for revenue restatement firms and non-revenue restatement firms, with t-tests for the difference in means. The univariate results are consistent with Hypothesis 1. I present individual statistics for both *WORDS* and *METHODS* in this table, but use only *RRC SCORE* in the subsequent analysis. On average, revenue restatement firms have more *WORDS* (268 vs. 187, t-stat 5.26), *METHODS* (5.9 vs. 4.0, t-stat 6.82), and higher *RRC SCORE* (0.45 vs. -0.18, t-stat 7.92) than non-revenue restatement firms. The differences in means also show that revenue restatement firms have lower book-to-market (*BTM*), incur more losses (*LOSSPER*), are more likely to have an analyst sales forecast (*SALE FCST*), and have larger A/R accruals (*AR ACCRUAL*) prior to the restatement. Contrary to prediction, revenue restatement firms have higher increases in revenue for the two years prior to the restatement (*CHSALES*) compared to other restatement firms (.212 vs. .175), although the difference is not significant (t-stat 1.18). Finally, revenue restatement firms are younger (*AGE*) than and the same size (*LOGMVE*) as the non-revenue restatement firms.

Table 4 presents correlations for many of the variables listed in Table 3. Note that *RRC SCORE* is positively correlated with *REVENUE* (.219 and .236), consistent with the results in Table 3, suggesting that revenue recognition complexity is positively associated with revenue restatements. Revenue recognition complexity is also positively correlated with some of the variables that suggest revenue is more value relevant (e.g., *LOSSPER* (.152), *SALEFCST* (.193), and *AR ACCRUAL* (.234)).

Table 5 presents results from the logistic estimation of equation (1). I calculate Z-statistics using robust standard errors with firm-level clustering to account for multiple observations for the same firm (93 cases). The first observation from Table 5 is that *RRC SCORE* has a positive, statistically significant coefficient (.357, z-stat 4.86) indicating that revenue recognition complexity increases the likelihood that a firm will restate revenue relative to other restatement firms. This provides support for H1. In addition, the results indicate that firms with lower *BTM* and with an analyst sales forecast (*SALESFCST*) are more likely to restate revenue. Multivariate results also suggest that revenue restatement firms are experiencing a decline in sales (*CHSALES*) and have poor stock return performance (*PRERETURN*) prior to the restatement. Governance characteristics suggest that revenue restatement firms are less likely to be audited by a large accounting firm, which may suggest a lack of oversight of revenue restating firms' auditors (i.e., the non-Big N auditors are less likely to uncover revenue restatement problems). Finally, revenue restating firms also have much larger A/R accruals prior to the restatement (5.147, z-stat 3.2).

I examine the economic significance of complexity relative to other determinants of revenue restatements by computing marginal effects. To allow for comparison across variables, marginal effects are calculated for each continuous variable as the change in the predicted probability as the variable moves one standard deviation centered at the mean, holding all other variables constant at their mean values. Marginal effects for indicator variables are similarly calculated, but with the change in the predicted probability calculated as the indicator moves from zero to one. A one standard deviation change in *RRC SCORE* (from -0.65 to 0.65) increases the probability of revenue restatement by 8.8 percent. The effect of revenue recognition complexity on the probability of restatement is higher than any other continuous variable, and roughly equal to or greater than all indicator variables. This provides further evidence that revenue recognition complexity is an important determinant in firms misreporting revenue. Generally, the results in Table 5 suggest the effect of revenue recognition complexity on revenue misreporting is significant, both statistically and economically.

5.1 Attributes of Misreporting Results

The results of the attributes of misreporting tests are found in Table 6. The table presents univariate logistic regression estimates of each misreporting attribute on *RRC SCORE*. Statistical significance is calculated using 2-tailed tests. Although the coefficients on *RRC SCORE* are positive for each model, none are statistically significant at conventional levels. Therefore, these results do not provide convincing evidence that managers of complex revenue recognition firms make more mistakes or are intentionally manipulating revenue. However, the lack of results for these tests may indicate weaknesses in my proxies for intentional manipulation. While these tests appear to be the most apparent attributes related to intentional manipulation, other more subtle and less observable characteristics could provide indications of manipulation. I present the consequences of misreporting results next.

5.2 Consequences of Misreporting Results

Table 7 contains descriptive statistics for the sample of 348 revenue restatement firms (Panel A) and consequence variables broken down by high and low revenue recognition complexity (Panel B). Panel A shows that 20 percent of all revenue restatements result in SEC AAERs and 31 percent of revenue restatement firms have CEO turnover in the two years following the restatement. The mean (median) announcement *CAR* is -10 percent (-5.4 percent), consistent with the findings in Palmrose et al. (2004). The mean stock return for the year prior to the restatement is -19.1 percent and the mean return for the year following the restatement is -21.3 percent. Restatement attributes show the mean number of quarters restated (*RESTLEN*) is 8.2, with a mean decrease in revenue (*CHREV*) of 5.7 percent and a mean decrease in earnings (*CHNI*) of 13.4 percent. In Panel B, the sample of revenue restatements are divided into high and low revenue recognition complexity based on *RRC SCORE* relative to the mean of *RRC SCORE* for the sample. The results in Panel B show that high complex revenue recognition firms are less likely to receive an AAER (0.16 vs. 0.24, t-test -1.82) and have less negative announcement returns (-0.08 vs. -0.119, t-test 1.78) than low complexity firms. The t-tests show no significant difference for CEO turnover.

Table 8 contains regression estimates for consequences of misreporting tests. The results on AAERs show *RRC SCORE* is negatively associated with AAERs (-0.361, z-stat -2.85), suggesting restatements involving complex revenue recognition are less likely intentional. The results also show the SEC targets firms with larger market values. *CHREV* has a negative coefficient (-3.65, significant at less than 1%), which is expected if the SEC is more concerned with revenue overstatements. More surprising is the coefficient on *CHNI* is 0.178 (significant at 10%). However, this does not indicate that earnings increases are most associated with AAERs, but suggests that, given the change in revenue, an increase in earnings is more associated with AAERs. Therefore, these coefficients must be interpreted collectively.

The results for announcement returns in Table 8 also show that firms with complex revenue recognition have less negative announcement returns (0.023, t-stat 2.61). The economic effect on returns is also significant. Although not tabulated, a one standard deviation increase in *RRC SCORE* (1.22) increases announcement returns by 2.8 percent. With an average market capitalization of $1.9 billion prior to the restatement, the mean change in announcement return dollars is $52 million. The CAR results in Table 8 also show that understatements of revenue (*CHREV*) have higher announcement returns, and firms that eventually receive AAERs have much lower restatement announcement returns (-12.6 percent). As predicted, the coefficient on *PRERETURN* is negative (-0.036, t-stat -3.96), suggesting the market must lower expectations of future growth to a greater degree for firms with good recent stock performance.

Contrary to the evidence for AAERs and CARs, the results from Table 8 on CEO turnover do not support the mistake hypothesis. While the coefficient for *RRC SCORE* is negative, it is insignificant at conventional levels. This may be resulting from one of two different effects. First, the model may not be fully specified due to missing data on CEO characteristics like age, tenure and occupying the Chairman position as mentioned in Section 4.3.4; however, it seems unlikely that these variables are correlated with revenue recognition complexity, suggesting that the lack of specification may not influence the complexity coefficient. Second, as expected, it may be that complexity is not associated with CEO turnover decisions because boards may not distinguish between mistakes and manipulation in determining CEO departure. The regression results do indicate that CEO turnover is higher if the firm receives an AAER, has poor operating performance prior to the restatement (*ROA*) and poor stock returns following the restatement (*POSTRETURN*). Overall, the results in Table 8 provide evidence that revenue restatements resulting from complex revenue recognition have less severe consequences.

6. Additional Analysis

6.1 Other Measures of Revenue Recognition Complexity

To test the robustness of my proxy for revenue recognition complexity, I conduct all the previous tests using alternative proxies. First, to control for the effect of multi-division firms on revenue recognition disclosures, I scale *RRC SCORE* by the number of operating segments obtained from the COMPUSTAT Segments Database. Firms with missing segment information are assumed to have a single business line. Results using this scaled complexity score are consistent with those presented in the main analysis. Also, I conduct the tests using the individual variables *WORDS* and *METHODS* and results are substantively similar. In addition, I develop a measure to capture the subjectivity of the revenue recognition methods employed by using key-word searches for the following practices: the percentage of completion method, providing multiple deliverables, vendor-specific objective evidence, barter or non-monetary exchange revenue, or fair valuing aspects of the contract. While using this measure provides support for H1, it is insignificant in any of the tests to determine intent (attributes or consequences). Finally, I conduct the analysis using a factor score obtained from *WORDS*, *METHODS*, and the subjectivity measure. Again, the results remain substantially unchanged from those presented in the main analysis.

6.2 Alternative specifications to test H1

6.2.1 Matched sample design

In the main analysis I use a research design to test H1 that compares revenue restatement firms to other restatement firms. While this research design has many advantages, which I discuss in Section 4.3.1, it may underestimate the effects of incentives and complexity on misreporting. I conduct an alternative design specification to test H1 using a matched sample design that allows me capture the full effect of incentives and complexity on misreporting.[28] Before obtaining the matched sample for revenue restatements, I reduce the restatement sample to 124 firms that have data on both COMPUSTAT and EXECUCOMP in order to calculate necessary control variables using this alternative specification. One of the difficulties in executing a matched sample design in this setting is identifying what characteristics to match. I choose to match on fiscal year, assets, and the book-to-market ratio. Because my sample of revenue restatement firms are generally smaller firms, this helps match firms that are of similar size and have similar growth prospects. I first identify all firms without any restatement during the sample period that have both data on COMPUSTAT and EXECUCOMP. Firms with assets between 70% and 130% of the assets of the sample firm in the same fiscal year are chosen as potential matches. From this set of firms, I choose the matched firm with the book-to-market ratio closest to that of the sample firm.

I estimate a logistic regression model for revenue restatements with control variables obtained from Burns and Kedia (2006). Using a sample of S&P 500 firms, Burns and Kedia (2006) find evidence that the sensitivity of CEO option portfolios to stock price is higher for restatement firms than non-restatement firms, suggesting that compensation incentives matter to misreporting. I include control variables from their study for growth (earnings-to-price ratio), external financing (equity and debt financing), firms close to violating debt covenants (leverage), operating accruals, and CEO equity incentives (the pay-for-performance sensitivity of CEO stock options). Untabulated results from estimating this specification also provide strong evidence that

[28] As stated in section 4.3.1, although this alternative research design *allows* me to capture the full effect of incentives and governance on misreporting, there still may be difficulty correctly identifying or measuring governance and incentives associated with misreporting.

revenue recognition complexity increases the probability of revenue restatement, controlling for other incentives and governance characteristics.

6.2.2 Exclusion of lease-related restatements

In addition to this matched-sample design, I conduct the test for H1 using a more restrictive sample. Due to the large number of lease-related restatements in 2005 that some may consider a change in accounting policy, I estimate the logistic regression to test H1 excluding these restatements. I proxy for these lease restatements by excluding all restatements identified as "cost or expense" restatements in 2005 (198 cases). Results are consistent with those presented in the main analysis.

6.3 Regulations affecting revenue recognition disclosure

Effective in 2001, SAB 101 required disclosure of the firm's revenue recognition policies and gave more substantive guidance related to the content of those disclosures. Since my proxy for revenue recognition complexity relies upon these disclosures, a positive association between complexity and misreporting may be due to a disclosure change and not a change in revenue recognition complexity. I conduct all the tests splitting the sample into pre- and post-SAB 101 restatements. All results are consistent with the results presented in the paper except results for *RRC SCORE* coefficients are insignificant for the AAER and CAR regressions in the pre-SAB 101 period. Results remain consistent in the post-SAB 101 period: higher revenue recognition complexity is associated with fewer AAERs and less negative CARs. The difference in results pre- and post-SAB 101 may suggest that lack of guidance in pre-SAB 101 period caused firm disclosures to be less reliable measures of the firm's real revenue recognition polices, increasing noise in the measure of revenue recognition complexity in the pre-period.

7. Conclusion

I investigate the effect of accounting complexity on misreporting using a setting of revenue recognition complexity and revenue restatements. I find that revenue recognition complexity significantly increases the probability of a revenue restatement relative to other types of restatements. Because complexity can lead to more mistakes and/or create opportunities for manipulation, I conduct two sets of tests to determine whether the increase in misreporting from complexity is likely the result of more mistakes or opportunistic behavior. These tests examine both the attributes of the misreporting and the consequences of misreporting. Tests on the attributes of misreporting do not provide clear evidence that managers of complex revenue firms are more likely to manipulate or make mistakes. However, results are consistent with the consequences of misreporting being less severe - firms with complex revenue recognition have less negative announcement returns and are less likely to receive AAERs. Finally, my analysis shows revenue recognition complexity is not associated with CEO turnover, suggesting that boards may not distinguish between mistakes and manipulation in determining CEO departure when restatements occur.

Collectively, the results suggest that in the case of revenue recognition, complexity is a major factor in the occurrence of misreporting. This provides evidence consistent with accounting complexity being costly to financial markets, which lends support to regulators' concerns about accounting complexity. While there appears to be no strong evidence of manipulation by firms with more complex revenue recognition, accounting complexity appears to be more associated with mistakes. More research is needed to determine if accounting complexity increases misreporting in other areas besides revenue and to understand other effects of accounting complexity besides misreporting.

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Appendix 1

Example Revenue Recognition Disclosures

A.C. Moore Arts & Crafts, 2005 10-K
Revenue is recognized at point of retail sale.

UStel, Inc., 1997 10-K
Revenue is recognized upon completion of the telephone call.

Brooks Automation, 2002 10-K
Revenue from product sales are recorded upon transfer of title and risk of loss to the customer provided there is evidence of an arrangement, fees are fixed or determinable, no significant obligations remain, collection of the related receivable is reasonably assured and customer acceptance criteria have been successfully demonstrated. Revenue from software licenses is recorded provided there is evidence of an arrangement, fees are fixed or determinable, no significant obligations remain, collection of the related receivable is reasonably assured and customer acceptance criteria have been successfully demonstrated. Costs incurred for shipping and handling are included in cost of sales. A provision for product warranty costs is recorded to estimate costs associated with such warranty liabilities. In the event significant post-shipment obligations or uncertainties remain, revenue is deferred and recognized when such obligations are fulfilled by the Company or the uncertainties are resolved.

Revenue from services is recognized as the services are rendered. Revenue from fixed fee application consulting contracts and long-term contracts are recognized using the percentage-of-completion method of contract accounting based on the ratio that costs incurred to date bear to estimated total costs at completion. Revisions in revenue and cost estimates are recorded in the periods in which the facts that require such revisions become known. Losses, if any, are provided for in the period in which such losses are first identified by management. Generally, the terms of long-term contracts provide for progress billing based on completion of certain phases of work. For maintenance contracts, service revenue is recognized ratably over the term of the maintenance contract.

In transactions that include multiple products and/or services, the Company allocates the sales value among each of the deliverables based on their relative fair values.

ARI Network Services, Inc., 2001 10-K
Revenue for use of the network and for information services is recognized in the period such services are utilized. Revenue from annual or periodic maintenance fees is recognized over the period the maintenance is provided. Revenue from catalog subscriptions is recognized over the subscription term.

The Company recognizes the revenue allocable to software licenses and specified upgrades upon delivery of the software product or upgrade to the end user, unless the fee is not fixed or determinable or collectibility is not probable. The Company considers all arrangements with payment terms extending beyond 12 months and other arrangements with payment terms longer than normal not to be fixed or determinable. If the fee is not fixed or determinable, revenue is recognized as payments become due from the customer. Arrangements that include acceptance terms beyond the Company's standard terms are not recognized until acceptance has occurred. If collectibility is not considered probable, revenue is recognized when the fee is collected.

Appendix 2
Variable Definitions

Variable Name	**Data Source**	**Variable Definition**
WORDS	Hand Collected	The number of words in the revenue recognition footnote disclosure in the most recent 10-K filing before the restatement announcement.
METHODS	Hand Collected	The number of times "recogn" or "record" is used in the revenue recognition footnote disclosure in the most recent 10-K filing before the restatement announcement.
RRC SCORE	Hand Collected	A factor score of *WORDS* and *METHODS* using the principal components method.
NODISC	Hand Collected	An indicator set to one if the firm does not have a revenue recognition disclosure in the most recent 10-K filing before the restatement announcement and zero otherwise.
LOSSPER	Compustat	The percentage of years that earnings before extraordinary items (data18) was negative since the company began coverage on COMPUSTAT through the restatement announcement.
CHSALES	Compustat	The average change in net sales of the firm (data12) for the two years prior to the restatement ((Sales – lag_2(Sales))/lag_2(Sales)).
BIGN	Compustat	An indicator variable equal to one if the firm was audited by a large accounting firm (data149) and zero otherwise.
SALESFCST	I/B/E/S	An indicator set to one if the firm has an analyst forecast of sales any time prior to the restatement announcement and zero otherwise.
BTM	Compustat	The firm's book-to-market ratio (data60 / [data25 * data199]) at the end of fiscal year just prior to the restatement announcement.
OM	Compustat	The 5-year average operating margin (operating income before depreciation/sales - data13/data12) prior to the restatement announcement.
GM	Compustat	The 5-year average gross margin (gross profit/sales - [1-data41/data12]) prior to the restatement announcement.
AR ACCRUAL	Compustat	The 5-year average A/R accrual scaled by sales (-data302 /data12) prior to the restatement announcement.
R&D	Compustat	The 5-year average R&D expense scaled by sales (data46/data12) prior to the restatement announcement.
EARNVOL	Compustat	The standard deviation of earnings (NIBEI, data18) scaled by the absolute mean value of earnings using the 5 fiscal years prior to the restatement announcement.
AGE	Compustat	The number of years the firm has data on COMPUSTAT up to the restatement announcement.
PRERETURN	CRSP	The 12-month stock returns for the firm prior to the restatement announcement, including delisting returns.
LOGMVE	Compustat	The logged MVE (data25*data199) at the end of fiscal year just prior to the restatement announcement.
OVERSTATEMENT	Hand collected	An indicator equal to one if the sum of the restated revenue over the restating periods is less than the sum of the originally reported revenue over the restating period, and zero otherwise
MULTIPLE	GAO Database	An indicator equal to one if the firm's restatement included additional areas of restatement besides revenue, and zero otherwise.

Variable Name	Data Source	Variable Definition
MISS GROWTH	Compustat and Hand Collected	An indicator equal to one if first restating period had positive sales growth prior to the restatement and zero or negative sales growth after the restatement, and zero otherwise.
MISS FCST	I/B/E/S and Hand Collected	An indicator equal to one if for the first restating period (1) the firm had an analyst revenue forecast, (2) the firm had previously beat the analyst revenue forecast for that period, and (3) the restatement caused the firm to miss for that period, and zero otherwise.
AAER	Dechow et al. (2007)	AAER is an indicator set to one if the firm has an SEC AAER related to revenue or receivables within 2 years of the restatement announcement.
CAR	CRSP	The 5-day cumulative abnormal return centered on the restatement announcement date. Abnormal returns are market adjusted returns and calculated as the raw return for the firm less the market return for each day.
CEO LEFT	Execucomp & Hand Collected	An indicator set to one if the CEO resigns or is terminated within two years of the restatement announcement, but excludes CEO resignation where the former CEO retains a Chair or a Director position.
RESTLEN	Hand Collected	The number of quarters the firm restated.
CHREV	Hand Collected	The percentage change in revenue over all periods of the restatement due to the restatement.
CHNI	Hand Collected	The percentage change in income over all periods of the restatement due to the restatement.
ROA	Compustat	The return on assets (NIBEI/Assets – data18/data6) for the fiscal year just prior to the restatement announcement
POSTRETURN	CRSP	The 12-month stock returns for the firm following the restatement announcement, including delisting returns.
SUBJECTIVE	Hand Collected	A count variable equal to the number of subjective revenue recognition methods identified in the revenue recognition disclosure. I search for the following key words: “percentage of completion” or “percentage-of-completion”, “multiple deliverables”, “vendor-specific objective evidence” or “VSOE”, “barter” or “non-monetary”, and “fair value” or “fair-value.”

TABLE 1
Sample selection

	Revenue	Non-Revenue	Total
Total GAO Restatement Firms (1997 - 2005)	738	1,567	2,305
Missing Compustat/CRSP Data	(150)	(249)	(399)
Multiple restatements/year	(33)	(48)	(81)
Financial Firms	(53)	(221)	(274)
No filings available	(11)	(86)	(97)
Not Revenue restaters	(39)	19	(20)
SAB101 and EITF firms	(104)		
In Revenue sample	-	(142)	(142)
Sample Firms	348	840	1,188

This table presents the attrition of the restatement sample. The sample of restatements is obtained from the 2002 and 2006 GAO restatement reports and contains restatements during the years 1997-2005. Firms with missing Compustat/CRSP data necessary to run tests are also removed. I keep only the first restatement for firms that have more than one restatement within a calendar year. Also, for firms with both a revenue restatement and another non-revenue restatement, I keep only the revenue restatement. Financial firms are removed from the sample (one-digit SIC=6) as these firms have revenue recognition that is substantially different from other firms. Firms with missing 10-K filings on the SEC Edgar website prior to the restatement announcement are removed from the sample. Finally, I delete/change 18 revenue restatement firms identified by the GAO because they are not restatements or categorized incorrectly.

TABLE 2
Restatement frequency

Panel A: Restatements by year and restatement type

	Year									
Restatement Type	1997	1998	1999	2000	2001	2002	2003	2004	2005	Total
Revenue	15	23	30	53	28	45	51	53	50	348
Non-Revenue	33	38	67	50	55	110	87	138	262	840
Total Restatements	48	61	97	103	83	155	138	191	312	1188

Panel B: Restatements by year and industry

	Year									
Industry[a]	1997	1998	1999	2000	2001	2002	2003	2004	2005	Total
Mining & construction	1	3	1	2	4	13	11	14	11	60
Technology	11	16	23	27	14	27	19	29	29	195
Manufacturing	21	23	33	34	32	50	53	60	89	395
Transportation	0	1	1	2	1	7	3	9	5	29
Communications	4	0	0	3	2	6	8	15	14	52
Utilities	2	0	6	1	2	13	10	11	11	56
Wholesale & retail	3	6	13	6	10	20	17	17	94	186
Services	4	5	6	11	7	13	13	27	35	121
Other	2	7	14	17	11	6	4	9	24	94
Total	48	61	97	103	83	155	138	191	312	1188

Panel C: Restatements by source

	Source				
Restatement Type	Company[b]	Auditor	SEC	Other/Unknown	Total
Revenue	211	47	20	70	348
Non-Revenue	444	87	99	210	840
Total Restatements	655	134	119	280	1188

This table presents the frequency of restatements for each year in the sample by revenue restatements and non-revenue restatements (Panel A) and by industry (Panel B). Panel C presents the frequency of restatement type by source of the restatement according to the press release for the restatement. The sample of restatements is obtained from the 2002 and 2006 GAO restatement reports and contains restatements during the years 1997-2005. Financial firms are removed from the sample (one-digit SIC=6) as these firms have revenue recognition that is substantially different from other firms.

[a] Industries are defined by the following SIC codes: Mining & construction=0-1999, manufacturing=2000-3999 (except codes assigned to technology), technology=3570-3579 plus 7370-7379, transportation=4000-4799, communications=4800-4899, utilities=4900-4999, wholesale/retail=5000-5999, services=7000-8999 (except codes assigned to technology), and other=9000-9999.

[b] 72 observations have both company and another source for the restatement and are excluded as being identified by the company.

TABLE 3
Restatement sample descriptive statistics

	Revenue Restatements						Non-Revenue Restatements							
Variable	N	Mean	Std. dev.	25th pctl.	Median	75th pctl.	N	Mean	Std. dev.	25th pctl.	Median	75th pctl.	Diff.	t-test
WORDS	348	267.8	248.8	91.0	188.0	346.0	840	186.7	224.6	50.0	104.0	235.0	81.10	5.26
METHODS	348	5.9	4.4	2.0	5.0	8.0	840	4.0	3.9	1.0	3.0	5.0	1.853	6.82
RRC SCORE	348	0.445	1.225	-0.373	0.316	1.138	840	-0.184	1.297	-0.847	-0.286	0.453	0.629	7.92
BTM	348	0.496	0.534	0.165	0.395	0.712	840	0.613	0.606	0.258	0.500	0.814	-0.117	-3.30
LOSSPER	348	0.408	0.337	0.125	0.333	0.667	840	0.321	0.319	0.043	0.222	0.500	0.087	4.11
SALEFCST	348	0.753	0.432	1.0	1.0	1.0	840	0.665	0.472	0.0	1.0	1.0	0.087	3.09
OM	348	-0.608	3.319	-0.060	0.059	0.141	840	-0.688	3.801	0.035	0.097	0.159	0.080	0.36
GM	348	0.105	2.073	0.247	0.389	0.543	840	-0.052	2.388	0.213	0.324	0.449	0.157	1.14
R&D	348	0.279	1.109	0.000	0.055	0.210	840	0.283	1.355	0.000	0.000	0.046	-0.004	-0.06
EARNVOL	348	5.751	13.643	0.963	1.715	3.914	840	5.106	12.234	0.904	1.482	3.737	0.645	0.76
CHSALES	348	0.212	0.481	0.012	0.123	0.318	840	0.175	0.496	-0.020	0.085	0.233	0.037	1.18
PRERETURN	348	-0.191	0.954	-0.704	-0.352	0.032	840	0.004	0.964	-0.436	-0.134	0.214	-0.194	-3.19
BIGN	348	0.876	0.330	1.0	1.0	1.0	840	0.880	0.325	1.0	1.0	1.0	-0.003	-0.16
LOGMVE	348	5.659	1.822	4.368	5.458	6.734	840	5.668	2.069	4.191	5.621	7.047	-0.009	-0.08
AR ACCRUAL	348	0.054	0.069	0.011	0.035	0.072	840	0.024	0.051	0.001	0.009	0.032	0.029	7.09
AGE	348	13.825	12.537	6.0	9.0	16.0	840	17.549	14.253	7.0	12.0	23.0	-3.724	-4.47

This table contains descriptive statistics for revenue and non-revenue restatements. The sample of restatements is obtained from the 2002 and 2006 GAO restatement reports and contains restatements during the years 1997-2005. All variable definitions can be found in Appendix 2. All variables except *LOSSPER, AGE, PRE_RETURN* and indicator variables are winsorized at the 1 and 99 percentiles for the whole sample. T-tests (2-tailed) are calculated on the difference in means for the revenue and non-revenue restatement observations.

TABLE 4
Restatement sample correlations

Correlations (Spearman rank correlations above diagonal, Pearson below diagonal)

	REVENUE	*RRC SCORE*	*BTM*	*LOSSPER*	*SALEFCST*	*OM*	*GM*	*R&D*	*EARNVOL*	*CHSALES*	*PRERET*	*BIGN*	*LOGMVE*	*AR ACC*
REVENUE	1	0.236	-0.104	0.124	0.086	-0.124	0.129	0.228	0.044	0.078	-0.183	-0.005	-0.011	0.276
RRC SCORE	0.219	1	-0.152	0.189	0.189	-0.080	0.142	0.319	0.104	0.020	-0.052	0.092	0.159	0.314
BTM	-0.091	-0.135	1	-0.154	-0.089	0.121	-0.087	-0.198	0.090	-0.218	-0.048	0.039	-0.243	-0.172
LOSSPER	0.121	0.152	-0.121	1	-0.201	-0.637	-0.087	0.383	0.282	0.055	-0.192	-0.205	-0.419	0.222
SALEFCST	0.086	0.193	-0.132	-0.184	1	0.207	0.081	0.002	-0.041	0.098	0.004	0.243	0.531	0.096
OM	0.010	-0.001	0.057	-0.351	0.103	1	0.340	-0.342	-0.013	-0.093	0.151	0.241	0.447	-0.098
GM	0.031	0.042	0.045	-0.262	0.085	0.859	1	0.205	0.040	0.004	0.011	0.077	0.080	0.213
R&D	-0.002	0.032	-0.080	0.336	-0.054	-0.760	-0.739	1	0.044	0.055	-0.166	-0.039	-0.110	0.249
EARNVOL	0.023	-0.005	0.158	0.013	-0.055	0.040	0.024	-0.055	1	-0.169	-0.026	0.017	-0.117	-0.024
CHSALES	0.034	0.009	-0.128	0.224	0.016	-0.241	-0.149	0.161	-0.064	1	-0.096	0.000	0.148	0.293
PRERETURN	-0.092	-0.005	-0.065	-0.049	0.005	0.038	0.023	-0.036	0.014	-0.030	1	0.052	0.162	-0.168
BIGN	-0.005	0.095	0.016	-0.213	0.243	0.128	0.116	-0.076	0.009	-0.014	0.020	1	0.329	-0.025
LOGMVE	-0.002	0.158	-0.295	-0.371	0.511	0.149	0.117	-0.116	-0.100	0.085	0.073	0.326	1	0.028
AR ACCRUAL	0.226	0.234	-0.150	0.289	0.076	-0.127	-0.020	0.074	-0.043	0.366	-0.044	-0.043	0.022	1

This table contains Pearson and Spearman rank correlations for select variables of 1,188 restatement firms obtained from the 2002 and 2006 GAO reports on restatements. *REVENUE* is an indicator equal to one if the firm restated revenue and zero if the firm restated something other than revenue. All of the other variables are calculated as explained in Appendix 2.

TABLE 5
Logistic regression estimates of revenue restatement model

	Prediction	Revenue Restatement Coefficient		Z-statistic	Marginal Effects
RRC SCORE	+	0.357	***	4.86	0.088
Value Relevance					
BTM	-	-0.28	*	-1.9	-0.031
LOSSPER	+	0.426		1.51	0.026
SALESFCST	+	0.496	***	2.59	0.089
OM	+	0.045		1.19	0.031
GM	+	-0.047		-0.81	-0.020
R&D	+	-0.069		-0.88	-0.017
EARNVOL	+	0.005		1.06	0.013
Governance					
CHSALES	-	-0.313	*	-1.73	-0.029
PRERETURN	-	-0.275	**	-2.34	-0.050
BIGN	?	-0.412	*	-1.69	-0.084
AUDITOR	?	0.265		1.26	0.052
LOGMVE	?	0.024		0.49	0.009
Other					
AR ACCRUAL	+	5.147	***	3.21	0.057
Intercept		-1.997	***	-2.93	
Industry & Year (not presented)					
N		1188			
Chi^2		163.09	***		
Psuedo R^2		0.159			
Correctly Classified		75.8%			

This table presents estimates of a logistic regression model where the dependent variable is one if the firm restated revenue and zero if the firm restated something other than revenue. All variables are as explained in Appendix 2. Z-statistics are presented using Huber/White robust standard errors with firm-level clustering to adjust standard errors for multiple restatements from the same firm. Marginal effects are calculated for each continuous variable as the change in the predicted probability as the variable moves one standard deviation centered at the mean, holding all other variables constant at their mean values. Marginal effects for indicator variables are similarly calculated, but with the change in the predicted probability calculated as the indicator variable moves from zero to one. Results for industry and year indicators are not shown but are included in the model. *, **, *** indicate statistical significance of the coefficient at the 10, 5, or 1 percent level.

TABLE 6
Attributes of misreporting univariate logistic regressions

	MISS GROWTH	*MISS FCST*	*OVERSTATEMENT*	*MULTIPLE*
RRC SCORE	0.318	0.041	0.007	0.071
	1.64	0.25	0.06	0.74
Intercept	-3.173 ***	-1.977 ***	1.412 ***	-0.913 ***
	-10.44	-8.52	9.83	-7.2
N	345	217	348	348
chi2	2.62	0.06	0.00	0.54
Pseudo R2	0.019	0.00	0.00	0.001

This table contains univariate logistic regression estimates to determine whether complex revenue recognition is associated with attributes of the restatement that indicate manipulation. The sample of restatements contains restatements during the years 1997-2005. *MISS GROWTH* is an indicator equal to one if first restating period had positive sales growth prior to the restatement and zero or negative sales growth after the restatement, and zero otherwise. *MISS FCST* is an indicator equal to one if for the first restating period (1) the firm had an analyst revenue forecast, (2) the firm had previously beat the analyst revenue forecast for that period, and (3) the restatement caused the firm to miss for that period, and zero otherwise. *OVERSTATEMENT* is an indicator equal to one if the net effect of the restatement over the restatement periods was an overstatement, and zero otherwise. *MULTIPLE* is an indicator equal to one if the firm's restatement included additional areas of restatement besides revenue, and zero otherwise. *, **, *** indicate statistical significance of the statistic at the 10, 5, or 1 percent level using 2-tailed tests.

TABLE 7
Consequences of misreporting descriptive statistics

Panel A: Descriptive Statistics

Variable	N	Mean	Std. dev.	25th pctl.	Median	75th pctl.
RRC SCORE	348	0.445	1.22	-0.373	0.316	1.138
AAER	348	0.201	0.401	0	0	0
CAR	348	-0.100	0.205	-0.187	-0.054	0.013
PRERETURN	348	-0.191	0.954	-0.704	-0.352	0.032
POSTRETURN	348	-0.213	0.802	-0.623	-0.328	0.001
CEOLEFT	348	0.310	0.463	0	0	1
LOGMVE	348	5.659	1.822	4.368	5.458	6.734
RESTLEN	348	8.175	6.487	3	7	12
CHREV	348	-0.057	0.121	-0.068	-0.017	-0.002
CHNI	348	-0.134	1.493	-0.190	-0.008	0.115
BTM	348	0.496	0.534	0.165	0.395	0.712
ROA	348	-0.145	0.426	-0.147	-0.015	0.038
MISS FCST	348	0.078	0.268	0	0	0

Panel B: Consequences of Misreporting Variables by Revenue Recognition Complexity

	High Revenue Recognition Complexity						Low Revenue Recognition Complexity							
Variable	N	Mean	Std. dev.	25th pctl.	Median	75th pctl.	N	Mean	Std. dev.	25th pctl.	Median	75th pctl.	Difference	t-test
RRC SCORE	173	1.394	0.881	0.684	1.139	1.805	175	-0.492	0.667	-0.788	-0.364	0.015	1.886	22.50
AAER	173	0.162	0.369	0	0	0	175	0.240	0.428	0	0	0	-0.078	-1.82
CAR	173	-0.080	0.192	-0.153	-0.045	0.022	175	-0.119	0.216	-0.222	-0.064	0.001	0.039	1.78
CEO LEFT	173	0.301	0.460	0	0	1	175	0.320	0.468	0	0	1	-0.019	-0.39

This table contains descriptive statistics for the sample of revenue restatements (Panel A) and consequences of misreporting variables by revenue recognition complexity (Panel B). The sample of restatements is obtained from the 2002 and 2006 GAO restatement reports and contains restatements during the years 1997-2005. In Panel B, the sample is divided based on revenue recognition complexity relative to the mean revenue recognition complexity for the sample. T-tests are calculated using 2-tailed tests. All variables are previously defined in Appendix 2.

TABLE 8
Consequences of misreporting regression results

	Prediction	AAER	Prediction	CAR	Prediction	CEO Turnover
RRC SCORE	-	-0.361 ***	+	0.023 ***	-	-0.177
		-2.85		2.61		-1.38
BIGN	+	0.967				
		1.58				
MISSFCST	+	0.043				
		0.09				
RESTLEN	+	0.01				
		0.46				
MULTIPLE	+	0.077	-	0.030		
		0.19		0.92		
AUDITOR	?	0.833 **	?	-0.017	?	0.388
		2.43		-0.80		1.34
LOGMVE	+	0.199 **	?	-0.004	?	-0.150 *
		2.29		-0.64		-1.82
CHREV	-	-3.649 ***	+	0.391 ***	-	-0.415
		-3.18		3.07		-0.39
CHNI	-	0.178 *	+	0.005	-	0.058
		1.93		0.84		0.74
AAER			-	-0.126 ***	+	0.626 *
				-4.02		1.86
BTM			+	0.005		
				0.22		
PRERETURN			-	-0.036 ***	-	-0.373
				-3.96		-1.15
POSTRETURN					-	-0.540 **
						-1.96
ROA					-	-0.879 **
						-2.13
CAR					-	-0.606
						-0.90
Intercept		-5.190 ***		-0.028		-1.193
		-4.69		-0.32		-0.95
Industry (not presented)						
N		348		348		348
Chi^2 / F		31.77 ***		4.58 ***		38.05 ***
Pseudo R^2 / R^2		0.108		0.209		0.123

This table contains logistic and OLS regression estimates using a sample of 348 revenue restatement firms to determine if revenue recognition complexity affects the consequences of restatement to the firm/managers. The first model (AAER) estimates a logistic regression with the dependent variable set to one if the revenue restatement was accompanied by an SEC AAER and zero otherwise. The second model (CAR) is an OLS regression of 5-day cumulative abnormal annoucement returns on restatement and firm characteristics. Finally, the third (CEO Turnover) estimates a logistic regression with a dependent variable set to one if the CEO departs anytime in the two years following the restatement announcement and zero otherwise. All control variables are as explained in Appendix 2. Z-statistics (for Logistic) and t-statistics (for OLS) are listed below each coefficient. I use Huber/White Robust standard errors with firm-level clustering to control for multiple restatements by the same firm. *, **, *** indicate statistical significance of the coefficient at the 10, 5, or 1 percent level.