Do Accounting Errors Breed Fraud?

Vivian W. Fang\textsuperscript{a}\textsuperscript{*}
University of Minnesota

Allen H. Huang\textsuperscript{b}
Hong Kong University of Science and Technology

Wenyu Wang\textsuperscript{c}
Indiana University

Current draft: April 5, 2015

Abstract

This paper links accounting errors to firms’ incentives for fraud. While errors discourage fraud by lowering the value relevance of reported earnings, they also incentivize fraud by providing camouflage. We analyze the two effects in the framework of Fischer and Verrecchia (2000) and generate hypotheses. Using intentional and unintentional misstatements as empirical proxies for fraud and errors, respectively, we document a hump-shaped relationship between an industry’s prevalence of fraud and that of errors. This result is robust to using SEC enforcement actions or the likelihood of meeting or marginally beating analyst consensus forecasts as alternative proxies for fraud. Motivated by three causes of errors (i.e., transaction complexity, regulation ambiguity, and staffing deficiency), we use firms’ number of items in their quarterly filings, rules-based characteristics of accounting standards, and state boards’ CPA requirements as alternative proxies for errors. These proxies are associated with fraud in a similar fashion as errors. Our results highlight an important economic implication of accounting errors and shed light on the recent debate on “principles-based” versus “rules-based” accounting systems.

JEL classifications: G38; M40; M41; M48; M53

Keywords: U.S. GAAP; Accounting Restatements; Errors; Fraud; Principles-based; Rules-based

\textsuperscript{a}Please send correspondence to Email: fangw@umn.edu, Carlson School of Management, University of Minnesota, Minneapolis, MN 55455.

\textsuperscript{b}Email: allen.huang@ust.hk, The Hong Kong University of Science and Technology, Clear Water Bay, Kowloon, Hong Kong

\textsuperscript{c}Email: wenywang@indiana.edu, Kelley School of Business, Indiana University, Bloomington, IN 47405.
1. Introduction

Accounting errors are common in the U.S. corporate world.\textsuperscript{1} A 2007 Wall Street Journal article reports a record high of 1,420 financial restatements in 2006 involving almost 10% of U.S. public companies, the majority of which are due to small companies correcting errors with no apparent intention to misreport (WSJ, 2007). Hennes, Leone, and Miller (2008, hereafter HLM) classify 73.6% of the Government Accountability Office (GAO) restatements as errors and only 26.4% of them as intentional misapplications of GAAP (hereafter, bias or fraud).\textsuperscript{2} Considering that these figures are based on misstatements already restated, the actual incidence of reporting errors is only likely to be higher. Aside from being common, errors also represent an important construct in theory.\textsuperscript{3} Accounting is an information system in which errors are inherent. Although errors are not expected to affect the mean of reported earnings, they are essential for updating beliefs because their variance conveys information (Christensen, 2010).

The causes of accounting errors are multifaceted. Some attribute errors to the complexity of business transactions. In cases that involve inherently complicated items, such as derivatives and convertible securities, reporting mistakes might be difficult to avoid. Others fault today’s complex and sometimes retroactively applied accounting rules. CFO Magazine, for example, states that “An explosion in accounting errors – in part reflecting the difficulties of today’s complex rules – has forced nearly a quarter of U.S. companies to learn the art of the restatement”

\textsuperscript{1}Throughout the paper, we use “errors,” “accounting errors,” and “reporting errors” interchangeably to refer to unintentional misapplications of U.S. Generally Accepted Accounting Principles (GAAP). We also sometimes refer to such misapplications as “mistakes.”

\textsuperscript{2}In contrast to errors, we use the term “bias” or “fraud” to refer to intentional misapplications of GAAP. Technically speaking, a reporting bias rises to fraud only when it results in material misstatements that violate securities laws (such as Section 17a of the Securities Act of 1933 or Section 10 of the Securities Exchange Act of 1934) or related securities regulation (such as SEC Rule 10b-5). As HLM point out, however, recent auditing guidelines (e.g., SAS No. 82, AICPA 1998, etc.) increasingly broaden the definition of fraud and use it loosely to cover all intentional misstatements. We follow this use of the term for parsimony.

\textsuperscript{3}Accounting errors play a similar role in reporting games (e.g., Fischer and Verrecchia, 2000; Dye and Sridhar, 2004) as noise does in adverse selection models (e.g., Grossman and Stiglitz, 1980) and in higher order belief models (e.g., Morris and Shin, 1998; Morris and Shin, 2002).
(CFO, 2007). Regulators are fully aware of the challenges companies face with the prevailing standards. Hans Hoogervorst, Chairman of International Accounting Standards Board (IASB), recently commented that he “was struck by the multitude of measurement techniques that both IFRSs and US GAAP prescribe, from historic cost, through value-in-use, to fair value and many shades in between. In all, our standards employ about 20 variants based on historic cost or current value.” Yet, in a non-trivial number of cases, basic misapplications of GAAP occur even in instances that feature simple business transactions and accounting rules, indicating breakdowns in corporate controls and staffing competencies (Plumlee and Yohn, 2010).

Although the exact causes of accounting errors are up for debate, given their prevalence and information role, an investigation of their economic implications seems warranted. Research in this area is surprisingly lacking, especially compared to the rich tapestry of work on fraud (see Dechow, Ge, and Schrand (2010) for a review). In this paper, we take a first step in addressing the issue by linking accounting errors to firms’ incentives to commit fraud. Intuitively, such a link is quite plausible: If we view a manager’s decision to manipulate earnings as a tradeoff between her marginal benefit (MB) and the marginal cost (MC) of doing so, errors might affect both sides of the tradeoff. On the one hand, by adding noise to earnings reports, errors render the reports less value relevant to the market. We refer to this effect of errors as the “value-relevance reducing effect” and expect it to decrease the manager’s MB of manipulating earnings. On the other hand, by making it more difficult for market participants to detect fraud and prove intent (or stated differently, by allowing fraudulent firms to mingle), errors can also breed opportunities

---

4 As another example, the Wall Street Journal writes that some financial restatements are “the result of significant reinterpretations of complex accounting standards that could not realistically have been foreseen by company executives” and call for accounting standards that “should be applied prospectively, not retroactively, to reduce the number of unnecessary financial restatements that damage companies and confuse investors” (WSJ, 2007).

5 These remarks are from Hans Hoogervorst’s speech at the International Association for Accounting Education & Research conference in Amsterdam on June 20, 2012, available at http://www.ifrs.org/Alerts/Conference/Pages/HH-speech-Amsterdam-June-2012.aspx.
for intentional misreporting. We refer to this effect of errors as the “camouflage effect” and expect it to decrease the manager’s MC of manipulating earnings.

To formalize this intuition, we analyze the two effects in the framework of Fischer and Verrecchia (2000, hereafter FV). As in FV, we model a one-period game in which a risk-neutral manager makes a potentially biased earnings report to a risk-neutral market after observing the firm’s earnings. The earnings the manager observes consist of the firm’s terminal value and a noise term (the theoretical construct of interest, accounting errors). The manager reports to the market her observed earnings plus her bias of choice. The market forms a rational expectation of the firm’s terminal value based on its prior beliefs and the firm’s reported earnings.

We modify FV by introducing the noise term into the manager’s cost function. This modification takes into account errors’ potential camouflage effect on fraud, which is assumed to increase in errors at a decreasing rate. We defer the detailed discussion of the modified model to Section 2. The key predictions are that, if errors’ camouflage effect, at its maximum, outweighs their value-relevance reducing effect, there is a hump-shaped relationship between the manager’s propensity to bias and the errors’ variance; otherwise, the bias propensity strictly decreases in the errors’ variance. The empirical part of this paper focuses on testing these two predictions.

---

6 We draw this intuition from U.S. tax law practices, which present a similar situation, i.e., widespread errors in tax returns make it difficult to detect and prosecute tax fraud. In FY2012, the IRS reports investigations of 2,987 tax frauds, which account for only 0.0015% of the 198 million taxpayers in the U.S. In an article titled “Negligence Versus Tax Fraud: How the IRS Tells the Difference,” Nolo Press notes that the percentage of Americans convicted of tax crimes is strikingly small when compared to the 17% of non-compliant taxpayers estimated by the IRS. The article adds that, because tax auditors are aware of the complexity of tax law in the U.S., they “expect to find a few errors in every tax return and do not routinely suspect (tax fraud).” Even when tax fraud is suspected, establishing that the taxpayer willfully violated the tax law is still challenging, because of the difficulty in separating willful understatements of tax liability from inadvertent errors, especially in complicated areas of the law. Slemrod (2007) writes that “An overt act is necessary to give rise to the crime of income tax evasion; therefore, the government must show willfulness and an affirmative act intended to mislead. Some tax understatement is, however, inadvertent error, due to ignorance of or confusion about the tax law.”

7 In FV, the noise in reporting enters the manager’s objective function through its effect on the value relevance of reported earnings, and so it affects only the manager’s benefits from biasing the report. Our model differs from FV’s in that the noise term affects not only the manager’s benefits from biasing the report but also her costs. This modification allows us to generate a more complete picture of how errors might affect the manager’s choice of bias.
Mapping theoretical constructs to empirical proxies is challenging. In our core analysis, we use the percentage of intentional misstatements as a proxy for reporting bias and that of unintentional misstatements as a proxy for the manager’s (and the market’s) perceived variance of errors. The rationale of the latter is that a larger variance of errors makes possible the extreme realizations, which are more likely to be detected and corrected ex-post. This mapping opens up the possibility of endogeneity concerns due to measurement error (ME). The first ME arises because we construct both proxies from restatement databases, possibly underestimating the incidence of misstatements if they are either undetected or detected but not tracked by a database. This raises a concern that the detection rate might induce a positive association between the incidence of the intentional and unintentional misstatements we observe. We base our empirical proxies on the time of misstatement rather than the time of detection, which mitigates this concern. The second ME is related to the classification of misstatements into bias and errors. We rely on HLM’s approach to implement the classification. HLM conduct extensive tests to validate their approach but misclassifications remain possible. Misclassifying intentional misstatements as unintentional or vice versa induce a positive association between the two. Both endogeneity concerns are unlikely to explain a hump-shaped or a negative association between bias and errors that our model predicts. If the association is indeed hump-shaped, it puts a narrow bound on the potential sources of endogeneity: They would have to induce opposing effects on the sensitivity of bias to errors depending on the errors’ variance. Nevertheless, to minimize ME, we adopt alternative proxies for both bias and errors in subsequent tests.

The empirical findings provide strong support for a hump-shaped relationship between reporting bias and errors. Using the GAO misstatement sample from 1992Q1 to 2006Q4, we

---

8 The concern remains if the lag between the time of misstatement and the time of detection tends to be similar for the fraud committed and the errors made in the same period. As we discuss in Section 4.2, this is inconsistent with our finding that fraud takes more time to detect than errors, on average.
show that an industry’s percentage of intentional misstatements, our primary proxy for bias, first rises in the industry’s percentage of unintentional misstatements in a quarter and then drops: The turning point occurs when the percentage of unintentional misstatements nears 6.4%. The marginal effect of errors on bias is 0.5 when the percentage of unintentional misstatements is at its 25th percentile, decreasing to 0.41 at its median, 0.27 at its 75th percentile, and -0.23 at its 99th percentile. This finding is robust to using a contemporaneous specification and a lead-lag one.

We employ two alternative proxies for bias, replacing an industry’s percentage of intentional misstatements in a quarter with the percentage of the industry’s firms identified by the Securities and Exchange Commission (SEC) as having engaged in financial misconduct and its firms meeting or marginally beating analyst consensus forecasts. The first alternative proxy is calculated using the SEC enforcement action database of Karpoff et al. (2014), which has a lower omission rate of fraud-related misstatements than the GAO database. The second one is less subject to concerns related to the detection rate of misstatements. The results remain strong.

Next we explore the causes of errors and identify alternative proxies for errors. Errors arise from various sources, such as transaction complexity, regulation ambiguity, and staffing deficiency. We use three proxies – firms’ number of non-missing items in their quarterly filings, rules-based characteristics of accounting standards, and state boards’ CPA requirements for working experience – that are each motivated by a cause of errors. We verify that the prevalence of errors is positively associated with firms’ number of financial statement items and rules-based characteristics, and negatively associated with the stringency of CPA requirements. We then show that these proxies are associated with the prevalence of bias in a similar fashion as errors.

To the best of our knowledge, this paper is the first in the literature to link accounting errors to firms’ reporting incentives. We thus highlight the importance of errors by shedding
light on their economic implications. Our paper is related to a handful of studies that call attention to errors. On a theoretical front, Christensen (2010) argues that accounting research should take more notice of errors because they are just as essential as bias in affecting beliefs. HLM are the first to undertake a systematic empirical analysis of errors. They develop a novel approach to distinguish errors from fraud and demonstrate the importance of doing so for improving the testing power of fraud-focused research. Palmrose, Richardson, and Scholz (2004) show that the market reacts more negatively to announcements of fraud-related restatements than to those of error-related restatements. Our paper differs from these studies in that we focus on the errors’ implications for firms’ tendency to bias earnings. Plumlee and Yohn (2010) provide a thorough discussion of the causes of misstatements in general. We draw from their study to identify causes of error-related misstatements in particular.9

Our paper also speaks to the recent debate on the “principles-based” accounting system versus the “rules-based” accounting system (e.g., see Section 108 of the Sarbanes-Oxley Act of 2002). At the heart of this debate is whether a flexible, objectives-oriented approach should replace the concrete, yet rigid rules-based approach (see Schipper (2003) for a summary of the arguments on both sides).10 Those who defend the rules-based system argue that, in the absence of detailed implementation guidance, financial reporting is subject to interpretation, which means less comparability, verifiability, credibility, and ability to enforce. Others, however, contend that the increasingly lengthy and complicated accounting rules are the very reason for errors, as having too many “check-boxes” not only increases the number of possible dimensions for

9 Also tangentially related are studies that consider estimation errors in accruals (e.g., Dechow and Dichev, 2002; Hribar and Collins, 2002). These studies, however, focus on how to better measure accrual quality.
10 Schipper (2003) notes that it is not clear whether the current financial reporting system in the U.S. is rules-based to begin with. She observes that “U.S. financial reporting standards are in general based on principles, derived from the FASB’s Conceptual Framework, but they also contain elements – such as scope and treatment exceptions and detailed implementation guidance – that make them also appear to be rules-based.”
making mistakes but also discourage the use of professional judgment that might be more in line with the principles behind the rules.¹¹ Our paper highlights the need to understand the effect of accounting systems on errors. If, as we show, accounting standards with more rules-based characteristics, particularly with those that add to the difficulties in identifying and understanding the associated literature, on average increase the errors’ variance (or at least the variance perceived by the manager and the market), a regulatory shift to a more principles-based system could dampen incentives for fraud through its effect on errors.¹²

The paper outline progresses as follows. Section 2 presents a model to analyze how errors affect reporting bias and generate testable hypotheses. Section 3 describes the data source, sample, and variable measurement. Section 4 contains our empirical tests and Section 5 concludes.

2. A model of reporting bias extending FV

In this section, we analyze the two possible effects of errors on bias in the framework of FV and develop testable hypotheses. In particular, our goal is to lay out and discuss the analytical assumptions underpinning each of the hypotheses we subsequently test.

Following FV, we set up a one-period reporting game in which a risk-neutral firm manager makes a potentially biased earnings report to a perfectly competitive, risk-neutral market. The firm generates a terminal value \( \tilde{v} \), which is normally distributed with mean zero and

---

¹¹ Many practitioners hold this view. According to CFO Magazine, Chris Paisley, a former 3Com finance chief, comments that “The rules governing revenue recognition have gotten increasingly complicated, as have the rules covering tax accounting, to name a few.” Finance chiefs also cite rules on merger accounting, leasing, warranties, and stock options as being “potential minefields.” Robert Blakely, the former CFO of Fannie Mae, adds that “These days you have to be a tremendous student of the accounting rules to understand the subtleties” and that while working for Fannie Mae, he had “a whole staff that [did] nothing but work on accounting policies.”

¹² Several studies link rules-based accounting characteristics to earnings attributes (e.g., Nelson, Elliott, and Tarpley, 2002; Mergenthaler, 2009; Folsom et al., 2013). Unlike these studies, we focus on how the characteristics of accounting standards affect firms’ fraud incentives through their effects on errors.
variance $\sigma_v^2$ ($\sigma_v^2 > 0$). Neither the manager nor the market observes the realization of $\tilde{v}$, but both possess the correct priors of its distribution. The manager privately observes earnings, $\tilde{e} = \tilde{v} + \tilde{n}$, where $\tilde{v}$ and $\tilde{n}$ are independent. We interpret $\tilde{n}$ as accounting errors, which are normally distributed with mean zero and variance $\sigma_n^2$ ($\sigma_n^2 \geq 0$). The manager produces an earnings report $r$ to the market after observing $\tilde{e}$. The market does not observe $\tilde{e}$ but forms a rational expectation of the firm’s stock price $P$ based on its prior beliefs and the manager’s reported $r$:

$$P = E[\tilde{v}|r]$$

(1)

The manager has some discretion to bias the earnings she reports. The difference between $r$ and $\tilde{e}$ thus represents her bias of choice, $b = r - \tilde{e}$. In choosing the bias, the manager is assumed to maximize her objective function characterized below as:

$$xP - \frac{c}{2}b^2$$

(2)

$xP$ captures the manager’s benefits from biasing the report, with $x$ representing the manager’s reporting objective. The market does not observe the realization of $x$ but knows that it follows a normal distribution of mean zero and variance $\sigma_x^2$. $\frac{c}{2}b^2$ reflects the manager’s costs of biasing the report that might arise from her litigation risk, psychic costs, and reputation loss. $c$ is assumed to be a known positive parameter that is independent of the variance of errors $\sigma_n^2$. 13

To account for accounting errors’ potential camouflage effect on reporting bias, we modify $c$ by assuming that it is a function of $\sigma_n^2$ that decreases in $\sigma_n^2$ (i.e., $\frac{dc}{d\sigma_n^2} < 0$). 14
In Appendix A.1, we prove that FV is a special case if we instead assume \( \frac{dc}{d\sigma_n^2} = 0 \). We rewrite the manager’s objective function as:

\[
xP - \frac{c(\sigma_n^2)}{2} b^2 \quad (3)
\]

We then solve for the equilibrium of the modified model, which consists of the manager’s bias function \( b(e, x; \Phi) \) and the market’s pricing function \( P(r; \Phi) \), where \( \Phi = \{\sigma_v^2, \sigma_n^2, \sigma_x^2\} \). Assuming rational expectations, FV prove the existence of a linear equilibrium for any given \( \sigma_n^2 \) (we refer interested readers to Section IV of FV for the detailed proof):

\[
b(e, x; \Phi) = \frac{\beta}{c(\sigma_n^2)} x \quad (4)
\]

\[
P(r; \Phi) = \beta r + \alpha \quad (5)
\]

where the coefficient \( \beta \) solves the following equation:

\[
\beta^3 \sigma_x^2 + \beta (\sigma_v^2 + \sigma_n^2) c^2 - \sigma_v^2 c^2 = 0 \quad (6)
\]

In equation (6) and the equations below, \( c \) continues to depend on \( \sigma_n^2 \); we use \( c \) to denote \( c(\sigma_n^2) \) for ease of notation. Without loss of generality, we also normalize \( \sigma_x^2 \) to one below.

Our particular interest is how \( \sigma_n^2 \) affects the manager’s choice of bias, \( b(e, x; \Phi) \). As \( x \) is the realization of a random event that is independent of \( \sigma_n^2 \), we examine the effect of \( \sigma_n^2 \) on \( \frac{\beta}{c} \) (a term we refer to as the “bias propensity” or “propensity to bias” hereafter). We rewrite equation (6) in terms of \( \frac{\beta}{c} \) as:

\[
\left(\frac{\beta}{c}\right)^3 + \left(\frac{\beta}{c}\right) (\sigma_v^2 + \sigma_n^2) - \varphi = 0 \quad (7)
\]

To facilitate our analysis below, we define \( \varphi \equiv \frac{\sigma_x^2}{c} \) as the inverse cost function in equation 7. \( \varphi \) is an increasing function of \( \sigma_n^2 \) (i.e., \( \frac{d\varphi}{d\sigma_n^2} > 0 \)); this is easy to see with \( \frac{d\varphi}{d\sigma_n^2} = -\frac{\sigma_x^2}{c^2} \frac{dc}{d\sigma_n^2} \) and our
assumption that $\sigma_v^2 > 0$ and $\frac{dc}{d\sigma_n^2} < 0$. For any given parameter set $\Phi$, the solution $\frac{\beta^*}{c^*}$ to equation (7) constitutes the equilibrium solution. We verify that there is only one real value solution:

$$\frac{\beta^*}{c^*} = \left[ \frac{1}{2} \varphi + \Delta^2 \right]^{\frac{1}{2}} + \left[ \frac{1}{2} \varphi - \Delta^2 \right]^{\frac{1}{2}}$$

$$\Delta = \left( \frac{\sigma_v^2 + \sigma_n^2}{3} \right)^3 + \left( \frac{\varphi}{2} \right)^2$$

(8)

(9)

To study the effect of errors on bias propensity, we solve for $\frac{d(\frac{\beta^*}{c^*})}{d\sigma_n^2}$. Considering equation (7) as defining an implicit function of $\frac{\beta^*}{c^*}$, we take the derivative with respect to $\sigma_n^2$ on both sides:

$$3 \left( \frac{\beta^*}{c^*} \right)^2 \frac{d(\frac{\beta^*}{c^*})}{d\sigma_n^2} + \frac{\beta^*}{c^*} + (\sigma_v^2 + \sigma_n^2) \frac{d(\frac{\beta^*}{c^*})}{d\sigma_n^2} - \frac{d\varphi}{d\sigma_n^2} = 0$$

(10)

We can then solve for $\frac{d(\frac{\beta^*}{c^*})}{d\sigma_n^2}$, our comparative static of interest, from equation (10) as:

$$\frac{d(\frac{\beta^*}{c^*})}{d\sigma_n^2} = \frac{\frac{d\varphi}{d\sigma_n^2}}{3 \left( \frac{\beta^*}{c^*} \right)^2 + (\sigma_v^2 + \sigma_n^2)} - \frac{\frac{\beta^*}{c^*}}{3 \left( \frac{\beta^*}{c^*} \right)^2 + (\sigma_v^2 + \sigma_n^2)}$$

(11)

We can obtain the same solution by taking the derivative of equation (8) with respect to $\sigma_n^2$.

This solution consists of two terms: The first term represents errors’ camouflage effect and the second term errors’ value-relevance reducing effect.\(^{15}\) As the two terms share a strictly positive denominator, the relationship between bias propensity and errors’ variance depends on the relative magnitude of the two terms’ numerators, which in turn depends on (a) the sign of the second derivative of $\varphi$ with respect to $\sigma_n^2$, and (b) whether $\frac{d\varphi}{d\sigma_n^2}$ outweighs $\frac{\beta^*}{c^*}$ when $\sigma_n^2 = 0$. We

\(^{15}\)To see this, consider the partial effect of errors’ variance on bias propensity through the value-relevance reducing effect. If we shut down errors’ camouflage effect, our model becomes exactly the same as FV’s and we can solve $\frac{d(\frac{\beta^*}{c^*})}{d\sigma_n^2} = \frac{-\frac{\beta^*}{c^*}}{3 \left( \frac{\beta^*}{c^*} \right)^2 + (\sigma_v^2 + \sigma_n^2)}$. This maps to the effect FV presents on p.238, which is $\frac{d(\beta)}{d\sigma_n^2} = \frac{-\beta_c^2}{3\beta^2\sigma_x^2 + \sigma_n^2(\sigma_v^2 + \sigma_n^2)}$, with $\sigma_x^2$ normalized to one and both sides divided by $c$ (since $c$ is a constant term in FV that is independent of $\sigma_n^2$).
consider $\frac{d^2 \varphi}{d(\sigma_n^2)^2} < 0$ to be the most realistic assumption for condition (a). Condition (b) compares $\frac{d \varphi}{d \sigma_n^2} \big|_{\sigma_n^2=0}$, when $\frac{d \varphi}{d \sigma_n^2}$ is at its maximum (because $\frac{d \varphi}{d \sigma_n^2} > 0$ and $\frac{d^2 \varphi}{d(\sigma_n^2)^2} < 0$), and $\frac{\beta^*}{c} \big|_{\sigma_n^2=0}$. If condition (b) is met, errors’ camouflage effect dominates when $\sigma_n^2$ is low, leading to a positive relationship between bias propensity and errors in this regime. As $\sigma_n^2$ increases, the camouflage effect declines and the value-relevance reducing effect of errors gradually takes over, eventually turning the relationship to negative. The counteracting effects give rise to a hump-shaped relationship between bias propensity and the errors’ variance. Alternatively, if condition (b) is not met, errors’ value-relevance reducing effect strictly dominates in the whole regime of $\sigma_n^2$.

With this discussion, the model generates two hypotheses, as follows,

**Hypothesis 1:** If accounting errors’ camouflage effect increases in the errors’ variance at a decreasing rate and this effect, at its maximum, outweighs errors’ value-relevance reducing effect, there exists a hump-shaped relationship between bias propensity and errors’ variance.

We can also express Hypothesis 1 in mathematical terms. That is, if $\frac{d \varphi}{d \sigma_n^2} > 0$ and $\frac{d^2 \varphi}{d(\sigma_n^2)^2} < 0$ for any $\sigma_n^2 \in [0, \overline{\sigma_n^2}]$ and if $\frac{d \varphi}{d \sigma_n^2} \big|_{\sigma_n^2=0} > \frac{\beta^*}{c} \big|_{\sigma_n^2=0}$, there exists a $\overline{\sigma_n^2}$ such that $\frac{\beta^*}{c}$ increases in $\sigma_n^2$ when $\sigma_n^2 < \overline{\sigma_n^2}$ and decreases in $\sigma_n^2$ when $\sigma_n^2 > \overline{\sigma_n^2}$.

**Hypothesis 2:** If accounting errors’ camouflage effect increases in the errors’ variance at a decreasing rate and this effect, at its maximum, does not outweigh errors’ value-relevance reducing effect, bias propensity will strictly decrease in errors’ variance.

---

16 If $\frac{d^2 \varphi}{d(\sigma_n^2)^2} \geq 0$, the camouflage effect of errors increases in $\sigma_n^2$ at a constant or increasing rate, which means that $\varphi$, the inverse cost of biasing earnings, approaches positive infinity when $\sigma_n^2$ does. As $\varphi$ approaches positive infinity, the cost of biasing earnings approaches zero. The cost is unlikely to be zero, however, because even if the errors’ variance is infinitely large, firms can still get caught for engaging in fraud.
Or expressed in mathematical terms, if \( \frac{d \phi}{d \sigma_n^2} > 0 \) and \( \frac{d^2 \phi}{d(\sigma_n^2)^2} < 0 \) for any \( \sigma_n^2 \in [0, \sigma_n^2] \) and if

\[
\frac{d \phi}{d \sigma_n^2} \bigg|_{\sigma_n^2=0} \leq \frac{\beta^*}{c^*} \bigg|_{\sigma_n^2=0} \cdot \frac{\beta^*}{c^*} \text{ is strictly decreasing in } \sigma_n^2.
\]

We graphically illustrate the two hypotheses in Figure 1. Proofs are in Appendix A.2 and A.3, respectively.

3. Data and Sample

This section specifies the data sources and describes the sample and main variables used in our core analysis. Detailed definitions of all variables are in Appendix B.

3.1 Sample selection

Several available databases track corporate restatements over different time periods, including the GAO Financial Restatement Database, Audit Analytics (AA), the Securities Class Action Clearinghouse (SCAC) database of securities class action lawsuits, and Accounting and Auditing Enforcement Releases (AAERs). We use the GAO database as the starting point to construct our sample, because it is the only database that has a readily available approach to classify its restatements according to managerial intent. HLM develop the approach based on a combination of keyword searches for variants of the words “fraud” and “irregularity,” whether there exists an enforcement action by the SEC, and whether there is an investigation into a misstating firm’s accounting matters. They validate this approach in two ways. First, they show that most of the irregularities (equivalent to our definitions of bias and fraud) they classify are followed by fraud-related class action lawsuits, while only one error is followed by such a lawsuit. Second, they show that announcements of irregularities trigger a significantly more negative market reaction than those of errors. For controls, we obtain the quarterly U.S. real
GDP growth rate from the U.S. Bureau of Economic Analysis and firm financials from the Compustat quarterly.

The GAO database does not compile misstating periods for its restatements. To identify misstating periods, we first search the GAO restatements in AA, which provides misstating periods for its restatement sample. For the ones we cannot locate in AA, we use the misstating periods manually collected by Burns and Kedia (2006) (also Burns, Kedia, and Lipson, 2010) and Files (2012), in that order. For the remaining ones, we make an additional attempt by reviewing the firms’ filings (e.g., 8-Ks, 10-Ks, etc.) on the SEC’s website. Out of the 2,705 misstatements in GAO, we are able to identify misstating periods for 2,649 of them; the rest are not included in our analyses. The sample restatements, announced by 2,115 firms between January 7th, 1997 and June 29th, 2006, cover 21,238 firm-quarters based on misstating periods.

We conduct most of our analyses on the industry-calendar quarter level. To construct the sample, we first merge the 21,238 misstating firm-quarters into the universe of Compustat firm-fiscal quarters and delete 3,448 of them that cannot be merged. We then sort Compustat firm-fiscal quarters, with and without misstating events, into industry-calendar quarters by aligning a firm’s fiscal quarter to the closest calendar quarter, and merge with controls. Industries are based on the Global Industry Classification Standard (GICS), including Energy (#10), Materials (#15), Industrials (#20), Consumer Discretionary (#25), Consumer Staples (#30), Health Care (#35), Financials (#40), Information Technology (#45), Telecommunication Services (#50), and Utilities (#55). Our final sample for the core analysis consists of 600 observations, covering ten GICS industries and 60 calendar quarters from 1992Q1 to 2006Q4.\footnote{GICS is an industry classification standard jointly developed by MSCI and Standard & Poor’s. We use GICS because Bhojraj, Lee, and Oler (2003), who run a horse race of the popular industry classification standards, find that “GICS classifications are significantly better at explaining stock return comovements, as well as cross-sectional variations in valuation multiples, forecasted and realized growth rates, research and development expenditures, and...}
3.2 Measurement of bias propensity, variance of accounting errors, and controls

Testing Hypothesis 1 and Hypothesis 2 calls for proxies for the firm’s bias propensity and the accounting errors’ variance. We use an industry’s percentage of fraud-related misstatements, i.e., the ratio of the number of firms with intentional misstatements identified by HLM to the total number of Compustat firms in a quarter, as our primary proxy for the industry firms’ propensity to bias. We express the measure in percentage points and denote it as $\text{Bias\%}$. As alternative proxies for bias propensity, we also use an industry’s percentage of firms flagged by the SEC as having engaged in financial misconduct in the quarter ($\text{Misconduct\%}$, in percentage points) and the percentage of firms meeting or beating mean analyst forecasts by up to one cent ($\text{Beat1ct\%}$, in percentage points). SEC enforcement actions are manually collected by Karpoff et al. (2014), and the quarterly reported earnings per share (EPS) and analyst consensus forecast are from the Institutional Brokers’ Estimate System (I/B/E/S) database. We do not use any discretionary accrual-based measures, because most discretionary accrual models use the industry norm as a benchmark to isolate cross-sectional variation, explicitly assuming that the average bias within an industry is zero in any period (Owens, Wu, and Zimmerman, 2013).

Empirically measuring the errors’ variance is challenging. An ideal proxy would require us to obtain the firms’ terminal values and their bias-free earnings, neither of which are directly observable. We assume that a larger variance of errors is associated with a higher likelihood of an average error being detected and corrected, because extreme realizations of errors are more likely. Based on this assumption, we use an industry’s percentage of error-related misstatements, i.e., the ratio of the number of firms with unintentional misstatements identified by HLM to the various key financial ratios.” Our results are robust to using Fama-French 12 industry specifications or the North American Industry Classification System (NAICS). GICS dates back only to 1999; for firm-quarters prior to 1999 in our sample, we use the closest one available.
total number of Compustat firms in a quarter, to proxy for the errors’ variance. We denote the measure as $Bias\%$ and also express it in percentage points.

For controls, we focus on those related to growth (or investment opportunities), as previous research indicates that growth affects firms’ incentives for fraud both theoretically (e.g., Povel, Singh, and Winton, 2007; Strobl, 2013) and empirically (e.g., Wang, Winton, and Yu, 2010; Wang and Winton, 2014). We employ one economy-wide growth measure, the quarterly real GDP growth that is seasonally adjusted ($GDPGrowth$), and two industry-wide growth measures, the industry’s weighted average sales growth in a given quarter ($SaleGrowth_avg$, defined as the weighted average of its firms’ quarterly growth rates in sales with the weights being the firms’ market capitalization at the end of the quarter) and the industry’s median market-to-book ratio ($MB$).

3.3 Descriptive statistics

Table 1 Panel A reports the sample distribution of intentionally and unintentionally misstating firm-quarters separately for the ten GICS industries and for the pooled sample. In our final sample, 5,474 firm-quarters are associated with intentional misstatements identified by HLM, representing 0.92% of the entire cross-section of Compustat firm-quarters. The number (percentage) of firm-quarters with unintentional misstatements is much higher at 12,208 (2.05%). Misstatements are spread broadly across industries, with Consumer Staples and Information Technology having the highest incidence of fraud-related misstatements (1.47% and 1.30%, respectively) and Consumer Discretionary and Telecommunication Services having the highest incidence of error-related misstatements (both 2.97%).

Table 1 Panel B reports descriptive statistics for the variables used in our core analysis. The percentages of intentionally and unintentionally misstating firms, $Bias\%$ and $Error\%$, are
slightly lower at 0.79% and 1.87%, respectively, averaged across industry-quarters. *Misconduct*%, the percentage of intentionally misstating firm-quarters calculated using Karpoff et al.’s (2014) SEC enforcement action data, has a higher average than *Bias*% at 1.12%. This is consistent with Karpoff et al.’s observation that the GAO database has a relatively high omission rate. The average percentage of firms meeting or marginally beating analyst consensus forecasts in an industry-quarter, *Beat1ct*%, is 16.15%. During our sample period, the average growth rate in seasonally adjusted real GDP is 0.82%. An industry-quarter has an average growth rate of 4% in sales revenue and an average market-to-book ratio of 1.92.

4. **Empirical Results**

4.1 *Relationship between reporting bias and reporting errors: univariate plots*

We begin our analysis by plotting an industry-quarter’s percentage of firms with fraud-related misstatements, *Bias*%, against its percentage of firms with error-related misstatements, *Error*%. Figure 2 reports the plot. The best fit for the data is a hump-shaped curve in which *Bias*% increases in *Error*% till *Error*% reaches about 6.5%; then it decreases in *Error*%.

In Figure 3, we repeat the plot for each of the ten GICS industries and make two observations. First, consistent with the plot for the pooled sample, a similar hump-shaped curve appears in five out of the ten industries, namely Industrials, Consumer Discretionary, Consumer Staples, Telecommunication Services, and Utilities. Second, for the rest of the industries, *Bias*% strictly increases in *Error*%. Compared to the industries for which we observe a hump-shaped fit, these industries have a low rate of *Error*% – Energy, Materials, and Health Care have *Error*% topped

---

18 In generating the best fit, we request MATLAB to fit the data using a quadratic function that nests linear, hump-shaped, and U-shaped functions.
at 3.9%, Financials at 4.3%, and Information Technology at 5.5% – which suggests that we might be observing only the upward part of the hump for these industries.

In Figure 4, we plot Beat1ct%, an industry-quarter’s percentage of firms meeting or marginally beating analyst consensus against Error% for the pooled sample. Beat1ct% is less affected by the detection rate of misstatements than Bias%. We observe a similar pattern: Beat1ct% increases in Error% till Error% reaches about 4.5%; then it decreases in Error%. When we plot Beat1ct% by GICS industries, a hump-shaped curve exists in six of them. The plots are similar if we plot Misconduct% against Error%. We do not report them for brevity.

Overall, Figures 2–4 suggest that the propensity to bias systematically varies with the prevalence of reporting errors. The general patterns in these figures point to Hypothesis 1, which predicts a hump-shaped relationship between reporting bias and errors, rather than Hypothesis 2, which predicts that bias strictly decreases in errors. In the next section, we more rigorously examine the relationship between bias and errors in multivariate analyses.

4.2 Relationship between reporting bias and reporting errors: multivariate analyses

To examine whether the relationship between reporting bias and reporting errors is indeed hump-shaped as predicted by Hypothesis 1, we estimate the following model:

\[
\text{Bias}_{j,q} = \alpha + \beta_1 \text{Error}^\%_{j,q} + \beta_2 \text{Error}^\%_{j,q}^2 + \text{IND}_{j} + \varepsilon_{j,q}
\] (12)

where subscript \(j\) indexes GICS industries and \(q\) indexes calendar quarters. Again, Bias% and Error% denote industry \(j\)’s percentages of firms identified by HLM as having engaged in intentional and unintentional misstatements in quarter \(q\), respectively. Error%\(^2\) is the squared term of Error%. We include industry fixed effects and cluster standard errors by industry and quarter. A positive \(\hat{\beta}_1\) and a negative \(\hat{\beta}_2\) would support Hypothesis 1, while a negative \(\hat{\beta}_1\) and a non-positive \(\hat{\beta}_2\) would support Hypothesis 2.
Column (1) of Table 2 Panel A reports the ordinary least squares (OLS) regression results of estimating equation (12). As shown, Error% exhibits a positive coefficient and its squared term a negative coefficient, both significant at the 1% level. This is consistent with Hypothesis 1 and the univariate plots that there exists a hump-shaped relationship between Bias% and Error%. In Column (2) of Table 2, we include the three controls discussed in Section 3.2, namely the seasonally adjusted quarterly real GDP growth rate GDPGrowth, the industry’s quarterly growth rate in sales SaleGrowth_avg, and the industry’s median market-to-book ratio MB, all measured during or at the end of quarter \( q \). The results are not substantially affected. Based on the coefficients in Column (2), the turning point of the hump is near Error% = 6.4% (i.e., \( 0.513/(2\times0.04) \)), confirming our observation from Figure 2. In terms of economic significance, the marginal effect of Error% on Bias% is 0.5 when Error% is at its 25\(^{th}\) percentile, which decreases to 0.41 at its median, 0.27 at its 75\(^{th}\) percentile, and -0.23 at its 99\(^{th}\) percentile.

In Columns (1) and (2), we estimate a contemporaneous specification with both Bias% and Error% calculated in quarter \( q \). This is closely linked to our model, a one-period reporting game, in which we assume that the manager possesses the correct priors of her own company’s accounting errors of the period while choosing the bias for the period’s earnings. Next we estimate a lead-lag specification. This relaxes our model’s assumption by allowing the manager to form an expectation of the errors’ variance in a given period based on what she infers from the previous period’s earnings of her own company and those reported by industry peers, particularly if the variance tends to persist between periods. In our sample, Error% is highly autocorrelated: \( \text{Error}_{j,q} \% \) and \( \text{Error}_{j,q+1} \% \) have a Pearson and a Spearman correlation of 0.97, significant at the
1% level. We rerun equation (12) replacing $\text{Fraud}_{j,q}$ with $\text{Fraud}_{j,q+1}$. The regression results reported in Columns (3)–(4), without and with controls respectively, are very similar.

For our analysis in Table 3, we rely on the GAO database to identify fraud- and error-related misstatements because it is the only restatement database that has a readily available approach to classify its sample according to managerial intent. Karpoff et al. (2014) note, however, that the GAO database has a relatively high omission rate. As a result, both $\text{Bias}\%$ and $\text{Error}\%$ are underestimated. It is difficult to assert the direction in which this measurement error biases our results. As an attempt to minimize it, we use $\text{Misconduct}\%$ as an alternative proxy for bias. $\text{Misconduct}\%$ is an industry’s percentage of firms flagged by the SEC as having engaged in financial misconduct in a quarter, calculated using Karpoff et al.’s (2014) SEC enforcement action data. Column (1) of Table 3 reports the regression results replacing $\text{Bias}\%$ with $\text{Misconduct}\%$ in equation (12), with controls included. Column (2) repeats the regression using a lead-lag specification. The results are consistent with those reported in Table 2 and suggest a hump-shaped relationship between $\text{Misconduct}\%$ and $\text{Error}\%$. Based on the coefficients in Column (1), the turning point is near $\text{Error}\% = 5.2\%$ (i.e., $0.537/(2\times0.052)$). The marginal effect is 0.52 when $\text{Error}\%$ is at its 25th percentile, decreasing to 0.4 at its median, 0.23 at its 75th percentile, and -0.43 at its 99th percentile.

---

19 The high autocorrelation of $\text{Error}_{j,q}\%$ is not surprising, because a misstatement usually spans several consecutive quarters. By adding industry fixed effects, we identify based on the variation of $\text{Error}_{j,q}\%$ within an industry over time so a high autocorrelation of the variable, if anything, should only work against us.

20 The sample size is 590 in Table 3 Columns (3) and (4), compared to 600 in Columns (1) and (2). Because $\text{Bias}\%$ and $\text{Error}\%$ are available only from 1992Q1 to 2006Q4, lagging $\text{Error}\%$ by one quarter relative to $\text{Bias}\%$ results in a loss of one quarter’s observations for all ten GICS industries.

21 Karpoff et al. (2014) build a comprehensive database of financial misconduct from seven sources, namely the SEC’s website; the Department of Justice; the Wolters Kluwer Law & Business Securities (Federal) electronic library; the Lexis-Nexis’ FEDSEC:SECREL and FEDSEC:CASES library; the PACER database; the SEC’s Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system; and the Lexis-Nexis’ All News and Dow Jones’ Factiva news source. They define a misstatement as financial misconduct if it involves one or more violations of Section 13(b)(2)(a), Section 13(b)(2)(b), or Section 13(b)(5) of the Securities and Exchange Act of 1934. This definition is along the line of irregularities that HLM define and fraud/bias that we define. In building this database, they seek to remove extraneous events, which are equivalent to errors, as we and HLM define them.
A second measurement error is related to the fact that the GAO, or any financial misconduct database, can only track misstatements that are subsequently detected. In other words, Bias\% and/or Error\% are underestimated if any misstatement goes undetected. One particular concern is that, the detection rate of misstatements, which may depend on internal control strength, auditor competency, and regulatory enforcement intensity, among others, induces a spurious relationship between Bias\% and Error\%. This concern is more likely if the lag between the time of misstatement and the time of detection is similar across fraud and errors. In our sample, the time difference between the start of the misstating period and the restatement announcement date for fraud-related misstatements is about 29\% longer than that of the error-related misstatements (1,079 days versus 834 days, significantly different at the 1\% level). Nevertheless, to assess the robustness of our results, we use a proxy for bias that depends less on the detection rate of misstatements, i.e., Beat1ct\%, the percentage of firms meeting or marginally beating analyst consensus forecasts in an industry-quarter. A firm’s tendency to meet or marginally beat analyst consensus forecast is a widely accepted measure of earnings management (e.g., Bartov, Givoly, and Hayn, 2002; Brown and Caylor, 2005). In Columns (3) and (4) of Table 3, we reestimate equation (12), replacing Fraud_{j,q}\% with Beat1ct_{j,q}\% and Beat1ct_{j,q+1}\%, including controls. The results are again similar. Based on Column (3), the turning point is near Error\% = 4.7\% (i.e., 1.675/(2\times0.18)), consistent with the observation from Figure 4. The marginal effect is 1.61 when Error\% is at its 25\textsuperscript{th} percentile, 1.19 at its median, 0.6 at its 75\textsuperscript{th} percentile, and -1.67 at its 99\textsuperscript{th} percentile.

In summary, the results in this section point to a hump-shaped relationship between an industry’s incidence of fraud and the industry’s incidence of errors and are robust to using alternative proxies for fraud. These results provide support for Hypothesis 1, which posits that
errors have counteracting effects on firms’ incentives for fraud, i.e., the camouflage effect and the value-relevance reducing effect, and which effect dominates depends on the level of the errors’ variance. The result, however, are inconsistent with Hypothesis 2, which posits that the value-relevance reducing effect of errors strictly outweighs the camouflage effect. Overall, our results suggest that by providing camouflage, accounting errors can incentivize fraud, and this effect dominates the value-relevance reducing effect when errors are not prevalent.

4.3 **Relationship between reporting bias and reporting errors: causes of errors**

In this section, we explore the causes of accounting errors and relate them to firms’ reporting incentives. The causes we identify below serve as alternative proxies for errors. These proxies do not rely on the coverage of restatement databases or detection rate of misstatements, which helps minimize measurement error in our primary proxy for errors, Error%. Although our earlier finding on the relationship between the incidence of fraud and errors does not depend on the sources of errors, an investigation into the sources may be of independent interest. If firms’ propensity to bias indeed systematically varies with errors as we show, this analysis locates the areas policymakers can potentially target if they are to alter firms’ incentives for fraud through changing the likelihood of firms making reporting mistakes.

We draw the causes of accounting errors from Plumlee and Yohn (2010); the remarks by Scott Taub, Acting Chief Accountant of the SEC from 2006-2007;\(^\text{22}\) and anecdotal evidence. Plumlee and Yohn (2010) list transaction complexity, characteristics of accounting standards, and internal company errors as three primary reasons for errors. Transaction complexity is intrinsic to firms’ business operations. Carol Stacey, Chief Accountant of the SEC’s Division of Corporate Finance from 1996-2007, comments that reporting errors “often stem from the

---

complexity of the company transactions themselves, and not necessarily from the accounting.” She cites convertible securities as an example of business items that are simply difficult to account for (CFO, 2007). Regulation ambiguity is believed to be another driver of reporting errors. Practitioners who blame accounting regulation for errors often point to (1) a lack of clarity in the standards, (2) difficulties in identifying all of the relevant accounting literature associated with certain standards, and (3) the complexity of the literature (see Scott Taub’s remarks). Setting aside transaction complexity and regulation ambiguity, basic misapplications of GAAP still commonly occur. Scott Taub notes that “well over half of the errors that resulted in restatements were caused by ordinary books and records deficiencies or by simple misapplications of the accounting standards.” Most of these misapplications are honest mistakes made by accounting staff due to a lack of knowledge, a lack of training, or just incompetency. We refer to these cases as errors caused by staffing deficiency.

Next, we seek empirical proxies separately for the three causes: transaction complexity, regulation ambiguity, and staffing deficiency. We conjecture that when a firm has more complex transactions, the firm will need to set up different items/lines on its financial statements to account for the transactions and/or disclose more details in the footnotes. To capture the degree of complexity of an industry firms’ business transactions, we obtain sample firms’ numbers of non-missing items from Compustat quarterly files and average the numbers within industry-

---

23 As an example for the lack of clarity in accounting standards, when Fannie Mae was under investigation by the SEC for its accounting practices in late 2004, the company claimed that it made honest mistakes in the implementation of FAS 133. FAS 133 is a relatively new standard governing the accounting for derivative instruments and hedging activities. The Wall Street Journal states, “…this standard is so lengthy and complex that there is much debate about its application in many situations.” As another example, many companies made mistakes in their accounting for leases before the SEC’s Chief Accountant articulated a significant reinterpretation of the accounting standard for leases in 2005 (both WSJ, 2007).

24 We use the term “staffing deficiency” to stress the honest aspect of these misstatements, which is narrower than the term “internal company errors” in Plumlee and Yohn (2010). Unlike us, they are interested in studying the causes of all misstatements, such that an internal company error in their study could be a fraud-related misstatement that arises from internal control weakness.
quarters. This follows Li (2008) and Lundholm, Rogo, Zhang (2014), who use the number of non-missing items from Compustat annual files as a proxy for financial complexity. We denote the resulting measure as \( N_{\text{Items}} \), a larger value of which corresponds to a greater degree of transaction complexity in an industry-quarter. There is a total of 362 quarterly data items in Compustat; in our sample, \( N_{\text{Items}} \) has a mean of 94.23 and a standard deviation of 33.24.

For regulation ambiguity, we use the rules-based characteristics (\( RBC \)) score developed by Mergenthaler (2009). The \( RBC \) score focuses on identifying the characteristics of rules-based accounting standards as opposed to principle-based standards. Specifically, the score, calculated for each accounting rule, is the sum of four indicator variables: \( BLT \), \( Exception \), \( Guidance \), and \( Details \). \( BLT \) equals one if a rule has any bright-line thresholds, and zero otherwise; \( Exception \) equals one if the rule has any scope or legacy exceptions, and zero otherwise; \( Guidance \) equals one if the rule is in the top decile of all rules in terms of the number of implementation guidance, and zero otherwise; and \( Details \) equals one if the rule is in the top decile of all rules in terms of the number of words in the standard, and zero otherwise. We average the \( RBC \) scores of all accounting rules in effect during a given quarter and denote it as \( RulesbasedAccStd \). The average \( RulesbasedAccStd \) in our sample is 0.97. Ex-ante, it is not clear how this measure would affect the incidence of errors: Although the last three characteristics (i.e., a higher \( Exception \), \( Guidance \), and \( Details \)) could very well add to the difficulties in identifying accounting literature and the complexity of the literature, bright-line thresholds (i.e., a higher \( BLT \)) may actually improve clarity.

Last, we turn to staffing deficiency. Here we intend to capture the extent of honest mistakes made by accounting staff due to a lack of knowledge or training. We use the variation in the CPA licensure requirements by the states where firms are headquartered. Firms hire CPAs
to prepare or assist in preparing financial statements, because a full reporting CPA license is required for an accounting staff to sign off on financial statements in most states. To obtain the license, a candidate must meet the state board of accountancy’s educational and professional requirements, and pass the Uniform CPA Exam. Stricter requirements hold the candidate to a higher level of knowledge and/or training. Assuming that firms prepare financial statements in the states where their headquarters are located, we expect their likelihood of reporting mistakes to decrease with the stringency of the states’ CPA requirements. We obtain the CPA licensure requirements from the AICPA’s website and firms’ historical headquarters locations from Compact Disclosure. We focus on one aspect of the requirements: the number of years of public accounting working experience, which we label as WorkExp. WorkExp ranges from one to four years in our sample, with an average of 1.27. Because WorkExp is coded on the state level rather than industry level, we conduct the analysis using this variable on the state-quarter level.

We first check the correlations between Error% and each of the proxies described above to see whether they are relevant. NItems has a Pearson correlation with Error% of 0.45 and a Spearman correlation of 0.46, both significant at the 1% level. This is consistent with our conjecture that the number of items on an average industry firm’s quarterly financial statements can be used as a proxy for transaction complexity, which is positively related to the industry’s incidence of reporting errors. Error% is strongly associated with RulesbasedAccStd: The Pearson coefficient is 0.62 and the Spearman coefficient is 0.63, both significant at the 1% level. This

---

25 This is true regardless of whether firms hire accounting staff locally or from another state. In the case of an out-of-state hire, the staff is usually required to fulfill the working experience requirements of the new state and get her license transferred.

26 We do not use education requirements for two reasons. First, education requirements have little variation across states. All states require either 120 (equivalent to a bachelor’s degree) or 150 credit hours. We cannot use a binary proxy for errors because a binary nature variable is perfectly correlated with its squared term. Second, working experience requirements, i.e., training on the job, are likely more relevant than education requirements. This is corroborated by the fact that if a CPA wishes to transfer her license to another state, she typically needs to fulfill the working experience requirements of the new state but not the education requirements.
suggested that rules-based characteristics, on average, contribute to reporting errors or at least the ones detected. As to the measure of CPA requirements, WorkExp has a negative Pearson (Spearman) correlation with Error% of -0.07 (-0.04), also significant at the 1% (5%) level. This suggests that stricter requirements for professional licensure in states where firms’ headquarters are located reduce the incidence of reporting mistakes.

In Table 4, we relate the transaction complexity measure, NItems, to the incidence of fraud, Bias%. We first estimate a lead-lag specification replacing Error% and its squared term Error%2 in equation (12) with NItems and NItems2 in Column (1). If NItems indeed captures the variation in the errors’ variance due to transaction complexity, it should behave similarly as Error% in a regression of Bias%. As expected, NItems exhibits a significantly positive coefficient, and its squared term has a significantly negative coefficient. In Columns (2)-(3), we repeat the analysis in Column (1), replacing Bias% with Misconduct% and Beat1ct%. The results are consistent with those reported in Column (1). Based on Column (1)’s coefficients, the turning point is near NItems = 76.5 (i.e., 0.153/(2×0.001)). This compares to 94.23, the mean of NItems in our sample, at which the marginal effect is -0.04.

Next, we relate RulesbasedAccStd, our proxy for errors caused by regulation ambiguity, to Bias%. In Table 5, we repeat equation (12), replacing Error% and its squared term Error%2 with RulesbasedAccStd and RulesbasedAccStd2. We multiply RulesbasedAccStd by 100 to make it comparable to the dependent variable Bias%, which is in percentage points. Consistent with RulesbasedAccStd having a positive association with Error%, we observe a hump-shaped relationship between all three proxies for bias and RulesbasedAccStd. Based on Column (1)’s coefficients, the turning point is near RulesbasedAccStd = 1.1 (i.e., 0.888/(2×0.004)/100). This is slightly higher than the mean of RulesbasedAccStd, 0.97, at which the marginal effect is 0.11.
We conduct two robustness checks for Table 5. In the first robustness check, we repeat the analyses with each of the four rules-based characteristics: BLT, Exception, Guidance, and Details. Most of the explanatory power of RulesbasedAccStd appears to come from the last three characteristics: BLT in itself is not associated with Error%. In the second robustness check, we repeat the analyses controlling for NItems, our proxy for transaction complexity, and its squared term. This is to address the concern that, in some areas of reporting, such as leases, income taxes, derivatives and hedging, and convertible securities, it is difficult to separate regulation ambiguity from transaction complexity. The results continue to hold.

Finally, we relate the working experience requirement measure to Bias%. In Table 6, we repeat equation (12) with WorkExp and its squared term. Because WorkExp is negatively correlated with Error%, to ease the interpretation of the coefficients, we take the inverse of the measure and denote it as InvWorkExp. We again multiply InvWorkExp by 100 to make it comparable to the dependent variable Bias%. As expected, we observe a hump-shaped relationship between all three proxies for bias and InvWorkExp. Based on Column (1)’s coefficients, the turning point is near InvWorkExp = 44.5 (i.e., 0.089/(2×0.001)), which corresponds to WorkExp of 2.2 years. The marginal effect is -0.07 at WorkExp’s mean, 1.27.

5. Conclusion

Accounting errors are largely understudied in capital market research. Existing studies of misstatements typically focus on the fraud-related ones, either completely overlooking the error-related ones or considering them as extraneous events that need to be removed. As Christensen (2010) points out, however, “Accounting should pay more attention to errors, as errors are

27 We acknowledge that, to the extent that Nitems fails to completely control for transaction complexity, Table 5 might pick up the effects of both transaction complexity and regulation ambiguity.
essential for the updating of beliefs.” In this paper, we give primary attention to accounting errors and link them to firms’ reporting incentives. We do so in two ways. Theoretically, we extend Fischer and Verrecchia (2000) to provide a framework for discussing how errors might affect firms’ propensity to bias. Empirically, we document a hump-shaped relationship between reporting bias and errors that supports our model’s prediction.

Our results are robust to using the likelihood of a firm flagged by the SEC as having engaged in financial misconduct or the likelihood of meeting or marginally beating analyst consensus forecasts as alternative proxies for fraud. Motivated by three typical causes of errors, i.e., transaction complexity, regulation ambiguity, and staffing deficiency, we use firms’ number of non-missing items in their quarterly filings, rules-based characteristics of accounting standards, and state boards’ CPA requirements as alternative proxies for errors. We show that the number of financial statement items, rules-based accounting characteristics, particularly those that add to the difficulties in identifying and understanding accounting literature, and the number of years of working experience required for the CPA license are correlated with the incidence of errors. More importantly, they are associated with the incidence of fraud in a similar fashion as the incidence of errors.

Our results highlight an important economic implication of accounting errors. Recall that, in our model, a hump-shaped relationship arises only if errors have counteracting effects on firms’ propensity to bias: The camouflage effect dominates when the errors’ variance is low and the value-relevance reducing effect takes over when the variance is sufficiently high. Our observation of such a relationship in the data confirms the existence of the two effects. Further, the turning point of the hump is relatively high compared to the average incidence of errors in the pooled sample and in individual industries, suggesting that, at least in some industries, the
most likely effect of a decrease in the errors’ variance is to reduce firms’ incentives for fraud. Based on our analysis of the errors’ causes, regulators can potentially alter characteristics of the accounting standards and professional requirements to reduce these incentives.

Our inferences are subject to caveats. Admittedly, managerial reporting intent is difficult to capture. Although our results are robust to using several alternative proxies for both reporting bias and errors, endogeneity due to measurement error remains possible. More research in this area is warranted, particularly if alternative approaches of classifying misstatements based on managerial intent and better instruments for accounting errors become available.
Appendix A: Proofs

Proof 1: If \( \frac{d\varphi}{d\sigma^2_n} = 0 \) for any \( \sigma^2_n \in [0, \overline{\sigma^2_n}] \), \( \frac{\beta^*}{c^*} \) is a monotonically decreasing function of \( \sigma^2_n \).

Proof 1 nests the conclusion in Fischer and Verrecchia (2000) as a special case of the modified model. Substituting \( \frac{d\varphi}{d\sigma^2_n} = 0 \) into equation (11) of Section 2, we get

\[
\frac{d \left( \frac{\beta^*}{c^*} \right)}{d\sigma^2_n} = \frac{-\beta^*}{3 \left( \frac{\beta^*}{c^*} \right)^2 + (\sigma^2_n + \sigma^2_n)} \leq 0
\]

that holds for any \( \sigma^2_n \in [0, \overline{\sigma^2_n}] \) when \( \frac{\beta^*}{c^*} \geq 0 \). Note that \( \frac{\beta^*}{c^*} \big|_{\sigma^2_n=0} > 0 \), so the trajectory of \( \frac{\beta^*}{c^*} \) starts from a positive point and remains decreasing in \( \sigma^2_n \) as long as \( \frac{\beta^*}{c^*} > 0 \). Now we prove by contradiction that \( \frac{\beta^*}{c^*} \) will never go negative. Assume that \( \frac{\beta^*}{c^*} \) becomes negative at some point of \( \sigma^2_n \). By the continuity of \( \frac{\beta^*}{c^*} \), it must imply that the trajectory of \( \frac{\beta^*}{c^*} \) crosses zero at some point. If \( \frac{\beta^*}{c^*} \) ever hits zero, however, \( \frac{d \left( \frac{\beta^*}{c^*} \right)}{d\sigma^2_n} \) becomes zero, and therefore \( \frac{\beta^*}{c^*} \) will stay at zero and never go negative. This conclusion contradicts the assumption that \( \frac{\beta^*}{c^*} \) becomes negative at some point of \( \sigma^2_n \), and thus \( \frac{\beta^*}{c^*} \geq 0 \) holds for \( \sigma^2_n \in [0, \overline{\sigma^2_n}] \) and \( \frac{d \left( \frac{\beta^*}{c^*} \right)}{d\sigma^2_n} \) never turns positive. Q.E.D.

Proof 2: If \( \frac{d\varphi}{d\sigma^2_n} > 0 \) and \( \frac{d^2\varphi}{d(\sigma^2_n)^2} < 0 \) for any \( \sigma^2_n \in [0, \overline{\sigma^2_n}] \) and if \( \frac{d\varphi}{d\sigma^2_n} \big|_{\sigma^2_n=0} > \frac{\beta^*}{c^*} \big|_{\sigma^2_n=0} \), there exists a \( \sigma^2_n^* \) such that \( \frac{\beta^*}{c^*} \) increases in \( \sigma^2_n \) when \( \sigma^2_n \leq \sigma^2_n^* \) and decreases in \( \sigma^2_n \) when \( \sigma^2_n > \sigma^2_n^* \).

We prove Hypothesis 1 below.

Since \( \frac{d\varphi}{d\sigma^2_n} \big|_{\sigma^2_n=0} > \frac{\beta^*}{c^*} \big|_{\sigma^2_n=0} \), the trajectory of \( \frac{\beta^*}{c^*} \) lies below the trajectory of \( \frac{d\varphi}{d\sigma^2_n} \) at the starting point \( \sigma^2_n = 0 \) and \( \frac{\beta^*}{c^*} \) is increasing in \( \sigma^2_n \) as long as \( \frac{d\varphi}{d\sigma^2_n} > \frac{\beta^*}{c^*} \). Meanwhile, \( \frac{d\varphi}{d\sigma^2_n} \) is decreasing in \( \sigma^2_n \) because \( \frac{d^2\varphi}{d(\sigma^2_n)^2} < 0 \), so the trajectory of \( \frac{\beta^*}{c^*} \) and the trajectory of \( \frac{d\varphi}{d\sigma^2_n} \) must cross at some point \( \sigma^2_n = \sigma^2_n^* \), such that \( \sigma^2_n^* \) solves the equation:

\[
\frac{d\varphi}{d\sigma^2_n} = \frac{\beta^*}{c^*}
\]

Substituting in the solution of \( \frac{\beta^*}{c^*} \) defined in equation (8) of Section 2, \( \sigma^2_n^* \) is solved from the following equation:

\[
\frac{d\varphi}{d\sigma^2_n} = \left[ \frac{1}{2} \varphi + \Delta^2 \right]^{\frac{1}{3}} + \left[ \frac{1}{2} \varphi - \Delta^2 \right]^{\frac{1}{3}}
\]

where \( \Delta \) is defined in equation (9) of Section 2.
At the crossing point $\sigma_n^2 = \sigma_n^{2*}$, $\frac{d(\beta^*)}{d\sigma_n^2} = 0$ and $\frac{d^2 \phi}{d(\sigma_n^2)^2} < 0$, so $\frac{\beta^*}{c^*}$ reaches its maximum, and the trajectory of $\frac{d \phi}{d \sigma_n^2}$ moves below $\frac{\beta^*}{c^*}$ right beyond $\sigma_n^2 = \sigma_n^{2*}$, as shown in Figure 1. Equation (11) then implies that $\frac{\beta^*}{c^*}$ becomes decreasing in $\sigma_n^2$ right beyond $\sigma_n^2 = \sigma_n^{2*}$. Equation (11) also implies that if $\frac{\beta^*}{c^*}$ approaches $\frac{d \phi}{d \sigma_n^2}$, $\frac{d(\beta^*)}{d\sigma_n^2}$ approaches zero. Since $\frac{d^2 \phi}{d(\sigma_n^2)^2} < 0$ holds for all $\sigma_n^2$, the trajectory of $\frac{d \phi}{d \sigma_n^2}$ must decline faster than the trajectory of $\frac{\beta^*}{c^*}$ when the distance between $\frac{\beta^*}{c^*}$ and $\frac{d \phi}{d \sigma_n^2}$ is sufficiently small, which makes the two trajectories diverge, such that the two trajectories never cross again in the regime of $\sigma_n^2 > \sigma_n^{2*}$, and therefore $\frac{\beta^*}{c^*}$ remains a decreasing function of $\sigma_n^2$ for all $\sigma_n^2 > \sigma_n^{2*}$. Q.E.D.

**Proof 3:** If $\frac{d \phi}{d \sigma_n^2} > 0$ and $\frac{d^2 \phi}{d(\sigma_n^2)^2} < 0$ for any $\sigma_n^2 \in [0, \sigma_n^2]$ and if $\frac{d \phi}{d \sigma_n^2} |_{\sigma_n^2=0} \leq \frac{\beta^*}{c^*} |_{\sigma_n^2=0}$, $\frac{\beta^*}{c^*}$ is monotonically decreasing in $\sigma_n^2$.

We prove *Hypothesis 2* below.

Since $\frac{d \phi}{d \sigma_n^2} |_{\sigma_n^2=0} \leq \frac{\beta^*}{c^*} |_{\sigma_n^2=0}$, the trajectory of $\frac{\beta^*}{c^*}$ lies above the trajectory of $\frac{d \phi}{d \sigma_n^2}$ at the starting point $\sigma_n^2 = 0$ and $\frac{\beta^*}{c^*}$ is decreasing in $\sigma_n^2$ as long as $\frac{d \phi}{d \sigma_n^2} < \frac{\beta^*}{c^*}$. Equation (11) implies that if $\frac{\beta^*}{c^*}$ approaches $\frac{d \phi}{d \sigma_n^2}$, $\frac{d(\beta^*)}{d\sigma_n^2}$ approaches zero. Since $\frac{d^2 \phi}{d(\sigma_n^2)^2} < 0$ holds for all $\sigma_n^2$, the trajectory of $\frac{d \phi}{d \sigma_n^2}$ must decline faster than the trajectory of $\frac{\beta^*}{c^*}$ when the distance between $\frac{\beta^*}{c^*}$ and $\frac{d \phi}{d \sigma_n^2}$ is sufficiently small, which makes the two trajectories diverge, such that the distance between $\frac{\beta^*}{c^*}$ and $\frac{d \phi}{d \sigma_n^2}$ never decreases to zero and the two trajectories never cross for all $\sigma_n^2 \in [0, \sigma_n^2]$. Therefore, $\frac{\beta^*}{c^*}$ is a decreasing function of $\sigma_n^2$ for all $\sigma_n^2 \in [0, \sigma_n^2]$. Q.E.D.
Appendix B: Variable Definition

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Key variables of interest</strong></td>
<td></td>
</tr>
<tr>
<td>Bias%_{j,q}</td>
<td>Industry $j$’s percentage of firms identified by HLM as having engaged in intentional misstatements in quarter $q$, in percentage points. HLM classify the restatement sample of the GAO Financial Restatement Database according to managerial reporting intent, using a combination of keyword searches for variants of the words “fraud” and “irregularity,” a search for whether there exists an enforcement action by the SEC, and a search for whether there is an investigation into a misstating firm’s accounting matters. Misstating periods of the GAO restatement sample are collected first from AA, and then supplemented with the data collected manually by Burns and Kedia (2006) (also Burns, Kedia, and Lipson, 2010) and Files (2012), in that order. We manually collect the remaining ones from firms’ filings (e.g., 8-Ks, 10-Ks, etc.) on the SEC’s website;</td>
</tr>
<tr>
<td>Error%_{j,q}</td>
<td>Industry $j$’s percentage of firms identified by HLM as having engaged in unintentional misstatements in quarter $q$, in percentage points. The sample selection is similar to that for Bias%_{j,q};</td>
</tr>
<tr>
<td><strong>Alternative proxies for bias/fraud</strong></td>
<td></td>
</tr>
<tr>
<td>Misconduct%_{j,q}</td>
<td>Industry $j$’s percentage of firms identified by the SEC as having engaged in financial misconduct in quarter $q$, in percentage points. The SEC enforcement actions and the violation beginning and ending periods are manually collected by Karpoff et al. (2014);</td>
</tr>
<tr>
<td>Beat1ct%_{j,q}</td>
<td>Industry $j$’s percentage of firms that have their reported EPS falling between analyst consensus forecast and that plus one cent in quarter $q$, in percentage points. EPS and analyst consensus forecast are obtained from the I/B/E/S unadjusted summary file;</td>
</tr>
<tr>
<td><strong>Alternative proxies for errors</strong></td>
<td></td>
</tr>
<tr>
<td>NItems_{j,q}</td>
<td>The average number of firms’ non-missing items in their quarterly financial statements in industry $j$ in quarter $q$. The financial statement items are obtained from Compustat quarterly files;</td>
</tr>
<tr>
<td>RulesbasedAccStd_{q}</td>
<td>The average RBC scores of all accounting rules in effect in quarter $q$. The RBC score of each accounting rule, developed by Mergenthaler (2009), is the sum of four indicator variables multiplied by 100: BLT that equals one if the rule has any bright-line thresholds, and zero otherwise; Exception that equals one if the rule has any scope or legacy exceptions, and zero otherwise; Guidance that equals one if the rule is in the top decile of all rules in terms of the number of implementation guidance, and zero otherwise; and Details that equals one if the rule is in the top decile of all rules in terms of the number of words in the standard, and zero otherwise;</td>
</tr>
<tr>
<td>WorkExpr_{s,q}</td>
<td>The number of years of working experience in public accounting required by state $s$ for obtaining the CPA license in quarter $q$. Firms are sorted into states based on their historical headquarters locations in quarter $q$ according to Compact Disclosure. CPA license requirements are obtained from the AICPA website. InvWorkExpr_{s,q} is the inverse of WorkExpr_{s,q}, multiplied by 100;</td>
</tr>
<tr>
<td><strong>Control variables</strong></td>
<td></td>
</tr>
<tr>
<td>GDPGrowth_{q}</td>
<td>The seasonally adjusted U.S. real GDP growth rate in quarter $q$, in percentage points, obtained from the U.S. Bureau of Economic Analysis;</td>
</tr>
<tr>
<td>SaleGrowth_{avg}_{j,q}</td>
<td>The average sales revenue growth rate of all firms in industry $j$ in quarter $q$, calculated as each firm’s sales revenue (SALEQ) in quarter $q$ divided by its sales</td>
</tr>
</tbody>
</table>
revenue in quarter $q-1$ minus one, weighted by its market value of equity (PRCCQ×CSHPRQ) at the end of quarter $q$. SaleGrowth_avg$_{s,q}$ is similar to SaleGrowth_avg$_{j,q}$ but calculated for all firms in state $s$ in quarter $q$. Firms are sorted into states based on their historical headquarters locations in quarter $q$.

$MB_{j,q}$

The median market-to-book ratio of industry $j$ in quarter $q$, where the market-to-book ratio of each firm is its market value of equity (PRCCQ×CSHPRQ) scaled by its book value of equity (CEQQ), both measured at the end of quarter $q$. $MB_{s,q}$ is similar to $MB_{j,q}$ but calculated for all firms in state $s$ in quarter $q$. Firms are sorted into states based on their historical headquarters locations in quarter $q$. 

---

32
References


CFO MAGAZINE. “Say Again.” April 1, 2007.


Figure 1 – Predicted relationship between bias propensity and errors’ variance by *Hypothesis 1* and *Hypothesis 2*

This figure plots the relationship between the manager’s reporting bias propensity ($\frac{\beta^*}{c^*}$) and the accounting errors’ variance ($\sigma_n^2$), as predicted by *Hypothesis 1* and *Hypothesis 2*. $\varphi$ represents the inverse cost of bias and equals $\frac{\sigma_v^2}{c}$, where $\sigma_v^2$ is the variance of the firm’s terminal value and $c$ is the cost of bias. Both hypotheses assume that the camouflage effect of accounting errors increases in the errors’ variance at a decreasing rate (i.e., $\frac{d\varphi}{d\sigma_n^2} > 0$ and $\frac{d^2\varphi}{d(\sigma_n^2)^2} < 0$). *Hypothesis 1* further assumes that the camouflage effect, at its maximum, outweighs the value-relevance reducing effect (i.e., $\frac{d\varphi}{d\sigma_n^2} \big|_{\sigma_n^2=0} > \frac{\beta^*}{c^*} \big|_{\sigma_n^2=0}$), while *Hypothesis 2* assumes the opposite (i.e., $\frac{d\varphi}{d\sigma_n^2} \big|_{\sigma_n^2=0} \leq \frac{\beta^*}{c^*} \big|_{\sigma_n^2=0}$).
Figure 2 – The relationship between the percentage of intentional misstatements and the percentage of the unintentional misstatements for the pooled sample

This figure plots Bias% and Error%, an industry’s percentages of firms identified by HLM as having engaged in intentional and unintentional misstatements in a quarter, respectively. Detailed definitions of all variables are in Appendix B. The sample period is between 1992Q1 and 2006Q4.
Figure 3 – The relationship between the percentage of intentional misstatements and the percentage of the unintentional misstatements by industries

This figure plots Bias% and Error%, separately for the ten GICS sectors/industries, an industry’s percentages of firms identified by HLM as having engaged in intentional and unintentional misstatements in a quarter, respectively. Detailed definitions of all variables are in Appendix B. The sample period is between 1992Q1 and 2006Q4.
Figure 4 – The relationship between the percentage of firms meeting/marginally beating analyst consensus and the percentage of unintentional misstatements for the pooled sample

This figure plots Beat1ct%, an industry’s percentage of firms that meet or marginally beat analyst consensus EPS forecasts in a quarter, and Error%, an industry’s percentage of firms identified by HLM as having engaged in unintentional misstatements during the quarter. Detailed definitions of all variables are in Appendix B. The sample is between 1992Q1 and 2006Q4.
<table>
<thead>
<tr>
<th>GICS Sector/Industries</th>
<th>Total number of firm-quarters</th>
<th>Number of intentionally misstating firm-quarters</th>
<th>Avg. % of intentionally misstating firm-quarters</th>
<th>Number of unintentionally misstating firm-quarters</th>
<th>Avg. % of unintentionally misstating firm-quarters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy</td>
<td>34,320</td>
<td>198</td>
<td>0.58%</td>
<td>537</td>
<td>1.56%</td>
</tr>
<tr>
<td>Materials</td>
<td>45,198</td>
<td>179</td>
<td>0.40%</td>
<td>596</td>
<td>1.32%</td>
</tr>
<tr>
<td>Industrials</td>
<td>80,489</td>
<td>869</td>
<td>1.08%</td>
<td>1,490</td>
<td>1.85%</td>
</tr>
<tr>
<td>Consumer Discretionary</td>
<td>98,152</td>
<td>1,001</td>
<td>1.02%</td>
<td>2,920</td>
<td>2.97%</td>
</tr>
<tr>
<td>Consumer Staples</td>
<td>24,266</td>
<td>357</td>
<td>1.47%</td>
<td>496</td>
<td>2.04%</td>
</tr>
<tr>
<td>Health Care</td>
<td>67,072</td>
<td>553</td>
<td>0.82%</td>
<td>1,117</td>
<td>1.67%</td>
</tr>
<tr>
<td>Financials</td>
<td>101,774</td>
<td>657</td>
<td>0.65%</td>
<td>1,765</td>
<td>1.73%</td>
</tr>
<tr>
<td>Information Technology</td>
<td>107,829</td>
<td>1,405</td>
<td>1.30%</td>
<td>2,417</td>
<td>2.24%</td>
</tr>
<tr>
<td>Telecom. Services</td>
<td>15,603</td>
<td>118</td>
<td>0.76%</td>
<td>464</td>
<td>2.97%</td>
</tr>
<tr>
<td>Utilities</td>
<td>20,457</td>
<td>137</td>
<td>0.67%</td>
<td>406</td>
<td>1.98%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>595,160</strong></td>
<td><strong>5,474</strong></td>
<td><strong>0.92%</strong></td>
<td><strong>12,208</strong></td>
<td><strong>2.05%</strong></td>
</tr>
</tbody>
</table>

This panel reports the sample distribution of misstating firm-quarters and Compustat firm-quarters for the ten GICS sectors/industries. Intentional and unintentional misstatements are identified by HLM. The sample period is between 1992Q1 and 2006Q4.
Table 1 – Continued

Panel B: Descriptive statistics of the variables used in the core analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>1%</th>
<th>25%</th>
<th>Median</th>
<th>75%</th>
<th>99%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bias%_{j,q}</td>
<td>600</td>
<td>0.79</td>
<td>0.79</td>
<td>0.00</td>
<td>0.05</td>
<td>0.54</td>
<td>1.32</td>
<td>3.07</td>
</tr>
<tr>
<td>Error%_{j,q}</td>
<td>600</td>
<td>1.87</td>
<td>2.03</td>
<td>0.00</td>
<td>0.17</td>
<td>1.35</td>
<td>3.00</td>
<td>9.29</td>
</tr>
<tr>
<td>Misconduct%_{j,q}</td>
<td>600</td>
<td>1.12</td>
<td>0.84</td>
<td>0.00</td>
<td>0.50</td>
<td>0.92</td>
<td>1.58</td>
<td>3.42</td>
</tr>
<tr>
<td>Beat1ct%_{j,q}</td>
<td>600</td>
<td>16.15</td>
<td>5.87</td>
<td>4.05</td>
<td>11.75</td>
<td>16.19</td>
<td>20.28</td>
<td>29.85</td>
</tr>
<tr>
<td>GDPGrowth_{q}</td>
<td>600</td>
<td>0.82</td>
<td>0.47</td>
<td>-0.31</td>
<td>0.52</td>
<td>0.83</td>
<td>1.11</td>
<td>1.88</td>
</tr>
<tr>
<td>SaleGrowth_avg_{j,q}</td>
<td>600</td>
<td>0.04</td>
<td>0.07</td>
<td>-0.11</td>
<td>0.00</td>
<td>0.04</td>
<td>0.08</td>
<td>0.24</td>
</tr>
<tr>
<td>MB_{j,q}</td>
<td>600</td>
<td>1.92</td>
<td>0.59</td>
<td>0.91</td>
<td>1.50</td>
<td>1.80</td>
<td>2.22</td>
<td>3.54</td>
</tr>
</tbody>
</table>

This panel reports the number of observations (N), mean, standard deviation (SD), 1\textsuperscript{st} percentile (1%), 25\textsuperscript{th} percentile (25%), median, 75\textsuperscript{th} percentile (75%), and 99\textsuperscript{th} percentile (99%) for the variables used in our core analysis. The variables include an industry’s percentage of firms identified by HLM as having engaged in intentional misstatements in a quarter (Bias\%), an industry’s percentages of firms identified by HLM as having engaged in unintentional misstatements in a quarter (Error\%), an industry’s percentage of firms identified by the SEC as having engaged in financial misconduct in a quarter (Misconduct\%), an industry’s percentage of firms that meet or marginally beat analyst consensus EPS forecasts in a quarter (Beat1ct\%), the seasonally adjusted quarterly U.S. real GDP growth (GDPGrowth\_), the market-cap weighted average industry quarterly sales growth (SaleGrowth\_avg), and the industry median market-to-book ratio (MB). Detailed variable definitions are in Appendix B. All continuous variables are winsorized at the top and bottom 1\%. The sample period is between 1992Q1 and 2006Q4.
Table 2 – The relationship between the percentage of intentional misstatements and the percentage of the unintentional misstatements: multivariate analysis

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Error%(_{j,q})</td>
<td>0.535***</td>
<td>0.513***</td>
<td>0.513***</td>
<td>0.485***</td>
</tr>
<tr>
<td></td>
<td>(0.078)</td>
<td>(0.075)</td>
<td>(0.081)</td>
<td>(0.079)</td>
</tr>
<tr>
<td>Error%(_{j,q})^2</td>
<td>-0.040***</td>
<td>-0.040***</td>
<td>-0.040***</td>
<td>-0.040***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>GDPGrowth(_q)</td>
<td>-0.083</td>
<td>0.437</td>
<td>0.267</td>
<td>0.397</td>
</tr>
<tr>
<td>SaleGrowth_avg(_{j,q})</td>
<td>-0.033</td>
<td>-0.004</td>
<td>(0.074)</td>
<td>(0.090)</td>
</tr>
<tr>
<td>MB(_{j,q})</td>
<td>-0.182*</td>
<td>-0.232**</td>
<td>(0.103)</td>
<td>(0.113)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.086</td>
<td>0.323</td>
<td>-0.054</td>
<td>0.408*</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.212)</td>
<td>(0.076)</td>
<td>(0.237)</td>
</tr>
</tbody>
</table>

Industry fixed effects | Yes | Yes | Yes | Yes |
# of Obs. | 600 | 600 | 590 | 590 |
Adjusted R\(^2\) | 0.670 | 0.679 | 0.595 | 0.608 |

Column (1) of this table reports the pooled ordinary least squares (OLS) regression results on the relationship between industry \(j\)'s percentage of firms identified by HLM as having engaged in intentional misstatements in quarter \(q\) (\(\text{Fraud}_{j,q}\)% and industry \(j\)'s percentages of firms identified by HLM as having engaged in unintentional misstatements in quarter \(q\) (\(\text{Error}_{j,q}\)% and its squared term (\(\text{Error}_{j,q}^2\)). Column (2) includes the seasonally adjusted quarterly U.S. real GDP growth (\(\text{GDPGrowth}_q\)), the market-cap weighted average industry quarterly sales growth (\(\text{SaleGrowth}_{avg,j,q}\)), and the industry median market-to-book ratio (\(\text{MB}_{j,q}\)) as control variables. Columns (3)-(4) are analogous to Columns (1)-(2) but replace \(\text{Fraud}_{j,q}\)% with \(\text{Fraud}_{j,q+1}\)% for quarter \(q+1\). Detailed definitions of all variables are in Appendix B. The sample period is between 1992Q1 and 2006Q4. We do not report coefficient estimates on industry fixed effects for brevity. # of Obs. denotes the number of observations. Coefficient estimates are shown in bold, and their standard errors clustered by industry and quarter are displayed in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.
Table 3 – The relationship between the likelihood of financial misconduct / the likelihood of meeting/marginally beating analyst consensus and the percentage of the unintentional misstatements: multivariate analysis

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>(1) Misconduct%(_{j,q})</th>
<th>(2) Misconduct%(_{j,q+1})</th>
<th>(3) Beat1ct%(_{j,q})</th>
<th>(4) Beat1ct%(_{j,q+1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Error(_{j,q})</td>
<td>0.537***</td>
<td>0.538***</td>
<td>1.675***</td>
<td>1.410***</td>
</tr>
<tr>
<td></td>
<td>(0.091)</td>
<td>(0.098)</td>
<td>(0.374)</td>
<td>(0.372)</td>
</tr>
<tr>
<td>Error(_{j,q})^2</td>
<td>-0.052***</td>
<td>-0.054***</td>
<td>-0.180***</td>
<td>-0.160***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.014)</td>
<td>(0.047)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>GDPGrowth(_{q})</td>
<td>0.243</td>
<td>0.384</td>
<td>-2.120</td>
<td>-1.115</td>
</tr>
<tr>
<td></td>
<td>(0.210)</td>
<td>(0.282)</td>
<td>(2.868)</td>
<td>(2.197)</td>
</tr>
<tr>
<td>SaleGrowth_avg(_{j,q})</td>
<td>-0.170**</td>
<td>-0.123</td>
<td>0.668*</td>
<td>0.376</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.089)</td>
<td>(0.354)</td>
<td>(0.349)</td>
</tr>
<tr>
<td>MB(_{j,q})</td>
<td>-0.136</td>
<td>-0.167</td>
<td>-0.966</td>
<td>-1.257</td>
</tr>
<tr>
<td></td>
<td>(0.108)</td>
<td>(0.110)</td>
<td>(0.845)</td>
<td>(0.791)</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.160***</td>
<td>1.194***</td>
<td>10.990***</td>
<td>12.052***</td>
</tr>
<tr>
<td></td>
<td>(0.231)</td>
<td>(0.239)</td>
<td>(1.673)</td>
<td>(1.720)</td>
</tr>
</tbody>
</table>

Industry fixed effects | Yes | Yes | Yes | Yes |
# of Obs. | 600 | 600 | 600 | 600 |
Adjusted R^2 | 0.705 | 0.689 | 0.634 | 0.625 |

This table reports the pooled OLS regression results on the relationship between two alternative proxies for bias propensity, namely industry \(j\)'s percentage of firms identified by the SEC as having engaged in financial misconduct in quarters \(q\) and \(q+1\) (\(\text{Misconduct}\%_{j,q}, \text{Misconduct}\%_{j,q+1}\)) and industry \(j\)'s percentage of firms that meet or marginally beat analyst consensus EPS forecasts in quarter \(q\) and \(q+1\) (\(\text{Beat1ct}\%_{j,q}, \text{Beat1ct}\%_{j,q+1}\)), and industry \(j\)'s percentage of firms identified by HLM as having engaged in unintentional misstatements in quarter \(q\) (\(\text{Error}\%_{j,q}\)) and its squared term (\(\text{Error}\%_{j,q}^2\)). All columns include the seasonally adjusted quarterly U.S. real GDP growth (\(\text{GDPGrowth}_q\)), the market-cap weighted average industry quarterly sales growth (\(\text{SaleGrowth}\_\text{avg,}\_j,\_q\)), and the industry median market-to-book ratio (\(\text{MB}_{j,q}\)) as control variables. Detailed definitions of all variables are in Appendix B. The sample period is between 1992Q1 and 2006Q4. We do not report coefficient estimates on industry fixed effects for brevity. # of Obs. denotes the number of observations. Coefficient estimates are shown in bold, and their standard errors clustered by industry and quarter are displayed in parentheses below the estimates. "***", "**", and '*' indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.
Table 4 – The relationship between proxies for bias propensity and transaction complexity

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>(1) $Bias%_{j,q+1}$</th>
<th>(2) $Misconduct%_{j,q+1}$</th>
<th>(3) $Beat1ct%_{j,q+1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$NItems_{j,q}$</td>
<td>0.153***</td>
<td>0.146***</td>
<td>0.280**</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.027)</td>
<td>(0.121)</td>
</tr>
<tr>
<td>$NItems_{j,q}^2$</td>
<td>-0.001***</td>
<td>-0.001***</td>
<td>-0.001**</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>$GDPGrowth_q$</td>
<td>0.766**</td>
<td>0.738***</td>
<td>0.230</td>
</tr>
<tr>
<td></td>
<td>(0.330)</td>
<td>(0.228)</td>
<td>(1.892)</td>
</tr>
<tr>
<td>$SaleGrowth_{avg_{j,q}}$</td>
<td>-0.096</td>
<td>-0.169</td>
<td>-0.225</td>
</tr>
<tr>
<td></td>
<td>(0.106)</td>
<td>(0.111)</td>
<td>(0.343)</td>
</tr>
<tr>
<td>$MB_{j,q}$</td>
<td>-0.170</td>
<td>0.031</td>
<td>-1.298</td>
</tr>
<tr>
<td></td>
<td>(0.122)</td>
<td>(0.170)</td>
<td>(0.989)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-6.325***</td>
<td>-5.689***</td>
<td>1.912</td>
</tr>
<tr>
<td></td>
<td>(1.309)</td>
<td>(1.380)</td>
<td>(6.114)</td>
</tr>
</tbody>
</table>

Industry fixed effects Yes Yes Yes
# of Obs. 531 540 540
Adjusted R² 0.533 0.626 0.655

This table reports the pooled OLS regression results on the relationship between the three proxies for bias propensity, namely industry $j$’s percentage of firms identified by HLM as having engaged in intentional misstatement in quarter $q+1$ ($Bias\%_{j,q+1}$), industry $j$’s percentage of firms identified by the SEC as having engaged in financial misconduct in quarter $q+1$ ($Misconduct\%_{j,q+1}$), and industry $j$’s percentage of firms that meet or marginally beat analyst consensus EPS forecasts in quarter $q+1$ ($Beat1ct\%_{j,q+1}$), and our proxy for transaction complexity, i.e., the average number of firms’ non-missing items in their quarterly financial statements in industry $j$ in quarter $q$ ($NItems_{j,q}$) and its squared term ($NItems_{j,q}^2$). All columns include the seasonally adjusted quarterly U.S. real GDP growth ($GDPGrowth_q$), the market-cap weighted average industry quarterly sales growth ($SaleGrowth_{avg_{j,q}}$), and the industry median market-to-book ratio ($MB_{j,q}$) as control variables. Detailed definitions of all variables are in Appendix B. The sample period is between 1992Q1 and 2006Q4. We do not report coefficient estimates on industry fixed effects for brevity. # of Obs. denotes the number of observations. Coefficient estimates are shown in bold, and their standard errors clustered by industry and quarter are displayed in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.
### Table 5 – The relationship between proxies for bias propensity and regulation ambiguity

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>(1) Bias(%_{j,q+1})</th>
<th>(2) Misconduct(%_{j,q+1})</th>
<th>(3) Beat1ct(%_{j,q+1})</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.888**</td>
<td>0.658***</td>
<td>4.375***</td>
</tr>
<tr>
<td></td>
<td>(0.199)</td>
<td>(0.155)</td>
<td>(0.792)</td>
</tr>
<tr>
<td>RulesbasedAccStd(_q_2)</td>
<td>-0.004***</td>
<td>-0.003***</td>
<td>-0.023***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>GDPGrowth(<em>q</em>)</td>
<td>0.092</td>
<td>0.167</td>
<td>-3.420**</td>
</tr>
<tr>
<td></td>
<td>(0.313)</td>
<td>(0.300)</td>
<td>(1.316)</td>
</tr>
<tr>
<td>SaleGrowth(<em>{avg,j,q</em>})</td>
<td>-0.029</td>
<td>-0.090</td>
<td>-0.151</td>
</tr>
<tr>
<td></td>
<td>(0.107)</td>
<td>(0.112)</td>
<td>(0.432)</td>
</tr>
<tr>
<td>MB(<em>{j,q</em>})</td>
<td>-0.576***</td>
<td>-0.416**</td>
<td>-1.848**</td>
</tr>
<tr>
<td></td>
<td>(0.116)</td>
<td>(0.164)</td>
<td>(0.814)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-41.910***</td>
<td>-30.624***</td>
<td>-194.112***</td>
</tr>
<tr>
<td></td>
<td>(9.325)</td>
<td>(7.309)</td>
<td>(38.206)</td>
</tr>
</tbody>
</table>

| Industry fixed effects | Yes | Yes | Yes |
| # of Obs.              | 590 | 600 | 600 |
| Adjusted R\(^2\)      | 0.559 | 0.611 | 0.674 |

This table reports the pooled OLS regression results on the relationship between the three proxies for bias propensity, namely industry \(j\)’s percentage of firms identified by HLM as having engaged in intentional misstatement in quarter \(q+1\) (Bias\(\%_{j,q+1}\)), industry \(j\)’s percentage of firms identified by the SEC as having engaged in financial misconduct in quarter \(q+1\) (Misconduct\(\%_{j,q+1}\)), and industry \(j\)’s percentage of firms that meet or marginally beat analyst consensus EPS forecasts in quarter \(q+1\) (Beat1ct\(\%_{j,q+1}\)), and our proxy for regulation ambiguity, i.e., the quarterly rules-based characteristics score measure developed in Mergenthaler (2009) (RulesbasedAccStd\(_q_\)) and its squared term (RulesbasedAccStd\(_q_2\)). All columns include the seasonally adjusted quarterly U.S. real GDP growth (GDPGrowth\(_q_\)), the market-cap weighted average industry quarterly sales growth (SaleGrowth\(_{avg,j,q_}\)), and the industry median market-to-book ratio (MB\(_{j,q_}\)) as control variables. Detailed definitions of all variables are in Appendix B. The sample period is between 1992Q1 and 2006Q4. We do not report coefficient estimates on industry fixed effects for brevity. # of Obs. denotes the number of observations. Coefficient estimates are shown in bold, and their standard errors clustered by industry and quarter are displayed in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.
Table 6 – The relationship between proxies for bias propensity and staffing deficiency

<table>
<thead>
<tr>
<th>Dependent Variables</th>
<th>(1) $\text{Bias}_{s,q+1}$</th>
<th>(2) $\text{Misconduct}_{s,q+1}$</th>
<th>(3) $\text{Beat1ct}_{s,q+1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{InvWorkExpr}_{s,q}$</td>
<td>0.089***</td>
<td>0.091***</td>
<td>1.558***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.028)</td>
<td>(0.109)</td>
</tr>
<tr>
<td>$\text{InvWorkExpr}_{s,q}^2$</td>
<td>-0.001***</td>
<td>-0.001***</td>
<td>-0.011***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>$\text{GDPGrowth}_{q}$</td>
<td>-0.020</td>
<td>-0.220</td>
<td>0.924</td>
</tr>
<tr>
<td></td>
<td>(0.166)</td>
<td>(0.185)</td>
<td>(0.702)</td>
</tr>
<tr>
<td>$\text{SaleGrowth_avg}_{s,q}$</td>
<td>-0.239∗</td>
<td>0.359</td>
<td>-2.574∗</td>
</tr>
<tr>
<td></td>
<td>(0.116)</td>
<td>(0.266)</td>
<td>(1.442)</td>
</tr>
<tr>
<td>$\text{MB}_{s,q}$</td>
<td>-0.721***</td>
<td>-0.407∗</td>
<td>-0.849</td>
</tr>
<tr>
<td></td>
<td>(0.227)</td>
<td>(0.241)</td>
<td>(1.077)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.935∗</td>
<td>-1.325∗</td>
<td>-31.548***</td>
</tr>
<tr>
<td></td>
<td>(0.442)</td>
<td>(0.533)</td>
<td>(2.180)</td>
</tr>
<tr>
<td># of Obs.</td>
<td>2,957</td>
<td>3,011</td>
<td>3,011</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.039</td>
<td>0.023</td>
<td>0.015</td>
</tr>
</tbody>
</table>

This table reports the pooled OLS regression results on the relationship between the three proxies for bias propensity, namely state $s$’ percentage of firms identified by HLM as having engaged in intentional misstatement in quarter $q+1$ ($\text{Bias}_{s,q+1}$), state $s$’ percentage of firms identified by the SEC as having engaged in financial misconduct in quarter $q+1$ ($\text{Misconduct}_{s,q+1}$), and state $s$’ percentage of firms that meet or marginally beat analyst consensus EPS forecasts in quarter $q+1$ ($\text{Beat1ct}_{s,q+1}$), and our proxy for staffing deficiency, i.e., the inverse of the number of years of working experience in public accounting required by state $s$ for obtaining the CPA license in quarter $q$ ($\text{InvWorkExpr}_{s,q}$). All columns include the seasonally adjusted quarterly U.S. real GDP growth ($\text{GDPGrowth}_{q}$), the market-cap weighted average state quarterly sales growth ($\text{SaleGrowth\_avg}_{s,q}$), and the state median market-to-book ratio ($\text{MB}_{s,q}$) as control variables. Detailed definitions of all variables are in Appendix B. The sample period is between 1992Q1 and 2006Q4. # of Obs. denotes the number of observations. Coefficient estimates are shown in bold, and their standard errors clustered by industry and quarter are displayed in parentheses below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.