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Imperfect Accounting and Reporting Bias

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ABSTRACT

Errors and bias are both inherent features of accounting. In theory, while errors discourage bias by lowering the value relevance of accounting, they can also facilitate bias by providing camouflage. Consistent with theory, we find a hump-shaped relation between a firm's propensity to engage in intentional misstatement and the prevalence of unintentional misstatements in the firm's

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industry for the whole economy and a majority of the industries. The result is robust to using firms' number of items in financial statements and exposure to complex accounting rules as alternative proxies for errors and to using the restatement amount in net income to quantify the magnitude of bias and errors. To directly test for the two effects of errors, we show that when errors are more prevalent, the market reacts less to firms' earnings surprises and bias is more difficult to detect. Our results highlight the imperfectness of accounting, advance understanding of firms' reporting incentives, and shed light on accounting standard setting.

JEL codes: G32; G34; G38; M40; M41; M48; M53

Keywords: accounting errors; reporting bias; fraud; accounting regulation; earnings response coefficient; fraud detection; textual analysis

1. Introduction

Accounting is a complex process that necessitates professional knowledge and substantial judgment. Setting aside possible bias, accounting is still imperfect and errors commonly occur. A 2007 *Wall Street Journal* article reports a record high of 1,420 financial restatements in 2006 involving nearly 10% of U.S. public companies, the majority of which are due to small companies correcting errors with no apparent intention to misreport (Posen [2007]). Hennes, Leone, and Miller [2008] (hereafter, HLM) classify 73.6% of U.S. Government Accountability Office (GAO) restatements as unintentional misapplications of generally accepted accounting principles (GAAP) and only 26.4% of them as intentional misapplications. Many more errors probably do not get corrected, but nonetheless affect reported accounting numbers.

One possible implication of reporting errors is that they shape firms' incentives for bias, or even fraud.[1] To see why, consider the world of Becker [1968], in which a firm manager commits fraud only if her benefits of manipulating earnings outweigh the costs. With accounting being imperfect in practice, both benefits and costs of the manager are likely to be functions of the error rate in the firm's financial reporting, because errors affect market participants' perceptions of accounting's information value, as well as their ability to discern the "correct" accounting numbers and detect fraud. For this reason, we expect reporting errors to yield significant effects on reporting bias. We develop this idea analytically and empirically in this paper.

We begin by building a one-period reporting game, extending Fischer and Verecchia [2000] (hereafter, FV). In the game, a risk-neutral firm manager makes a potentially biased earnings report to a risk-neutral market

[1] Throughout the paper, we use "errors" to refer to unintentional misapplications of GAAP and "bias" to refer to intentional misapplications of GAAP. Reporting bias rises to "fraud" when it results in a material misstatement that violates 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 regulations (such as Securities and Exchange Commission (SEC) Rule 10b-5).

after observing the firm's earnings. The earnings that the manager observes consist of the firm's true earnings and a noise term. This noise term is our theoretical construct of interest, which we interpret as 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 true earnings based on the firm's reported earnings and its prior beliefs.

We modify FV by allowing the noise term to affect the manager's cost of bias, which aims to capture the potential "camouflage effect" of accounting errors on bias. This effect arises because accounting noise, by making fraud detection more difficult, potentially lowers the manager's costs of manipulating earnings and facilitates opportunistic reporting.[2] There is, however, an offsetting effect. This effect is first described in FV: As noise in the accounting process increases, earnings become less value relevant to the market, which reduces the manager's benefits of biasing earnings and dampens her incentives to do so. We thus refer to this as the "value relevance–reducing effect." The properties of the errors' two effects determine the shape of the relation between the manager's propensity to bias earnings and errors' variance.

We observe a hump-shaped association between a firm's probability of engaging in an intentional misstatement in a quarter (our proxy for bias propensity) and the percentage of its industry peers engaging in unintentional misstatements in the same quarter (our primary proxy for errors' variance) for a broad sample of U.S. firms from 1996Q1 to 2005Q4 and a majority of industries in the sample. The latter proxy assumes that a larger variance makes possible extreme realizations of errors, which are more likely to be detected. Both proxies are constructed following HLM's approach, which classifies the misstatements covered by the GAO database into intentional and unintentional ones based on a combination of searches for fraud-related keywords, regulatory enforcement actions, and investigations. Thus, in this approach, bias and errors are defined as what the "policeman" says, consistent with our model, in which bias is subject to costs while errors are not. A hump-shaped association between bias and errors is consistent with the two counteracting effects that we model. The turning point of the observed association is high compared to the average error rate of the respective sample, which indicates that the camouflage effect likely outweighs the value relevance–reducing effect for a majority of our sample firms.

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[2] A similar camouflage effect is observed in U.S. tax law practices, that is, widespread errors in tax returns make it difficult to detect fraud. In FY2012, the IRS reported investigations of 2,987 tax frauds, which account for only 0.0015% of the 198 million taxpayers in the United States. 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 compared to the 17% of noncompliant taxpayers estimated by the IRS. The article adds that, because tax auditors are aware of the complexity of U.S. tax law, they "expect to find a few errors in every tax return and do not routinely suspect [tax fraud]" (available at http://www.nolo.com/legal-encyclopedia/negligence-versus-tax-fraud-irs-difference-29962.html).

We then explore the causes of errors to identify alternative proxies for their variance. Some attribute errors to transaction complexity. For example, Carol Stacey, former Chief Accountant of the SEC's Division of Corporate Finance, comments that reporting errors "often stem from the complexity of the company transactions themselves, and not necessarily from the accounting." Others fault today's lengthy and complicated 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" (both Harris [2007]). Regulators are fully aware of the challenges companies face with the prevailing standards. Hans Hoogervorst, Chairman of the International Accounting Standards Board, recently commented that he "was struck by the multitude of measurement techniques that both IFRSs [International Financial Reporting Standards] 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."[3]

We use firms' number of nonmissing items in their quarterly filings to proxy for errors' variance due to transaction complexity. To capture the variation in errors' variance caused by regulation ambiguity, we build an index based on the number of interpretations in rules that executives name as "potential minefields" (including rules on merger, hedge, lease, and warranty, see Harris [2007]) and firms' exposure to these rules.[4] We first conduct portfolio analyses to verify the relevance of the two proxies; we show that firms with a higher level of transaction complexity or a higher degree of exposure to ambiguous rules have larger error rates. Further, both proxies, either measured at the firm level or averaged within industries, are related to bias propensity in a hump-shaped fashion.

The relation between bias and errors is robust to including industry and year-quarter fixed effects, in addition to a long list of controls. The relation is also robust to using restatement amount–based measures of bias and errors and to controlling for the estimated mean and variance of CEOs' and other top executives' reporting objectives (proxied using their equity-based incentives, tenure, or vesting horizon). The relation continues to hold when using a firm's propensity to meet or marginally beat the analyst consensus forecast to proxy for bias, when adopting different definitions of the regulation ambiguity index, when controlling for firms'

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[3] The remarks are available at http://www.ifrs.org/Alerts/Conference/Pages/HH-speech-Amsterdam-June-2012.aspx.

[4] Practitioners strongly criticize these four rules for their lengthiness and difficulty of compliance. In addition to Harris [2007], the *Wall Street Journal* comments that FAS 133, the rule on hedging accounting, "... is so lengthy and complex that there is much debate about its application in many situations." The same article points out that 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 (Posen [2007]).

fundamental volatility, when deleting outliers, and when studying alternative sample periods and ways of clustering.

To provide further support for the relation, we directly test for the two underlying effects. Consistent with errors reducing the value relevance of reported earnings, firms in industries with a higher prevalence of errors are associated with lower earnings response coefficients. At the same time, intentional misstatements made by these firms are more difficult to detect, which supports the camouflage effect of errors.

The extant capital market literature studies reporting bias extensively (see Dechow, Ge, and Schrand [2010] for a review), possibly because bias can be costly to investors, particularly if it rises to the level of fraud (Karpoff, Lee, and Martin [2008], Dyck, Morse, and Zingales [2014]). In contrast, research on errors, which are as inherent to accounting as bias, is limited. Our paper contributes to this literature in three ways. Foremost, it demonstrates that errors, far from being extraneous, have important implications for earnings quality. We show that errors have competing effects on firms' incentives for bias. Second, each of the two effects we document carries its own implication: the value relevance–reducing effect suggests that errors affect pricing, and the camouflage effect suggests that errors raise the difficulty of regulatory enforcement. Third, we identify several proxies for errors that are new to the literature and potentially usable in other contexts. In particular, the proxy for errors due to regulation ambiguity speaks to the view held by many practitioners that the increasingly lengthy and complicated accounting rules lead to errors. Our results provide support for this view and suggest that accounting regulations could alter firms' reporting incentives through their effects on firms' error rates.

We are not the first to note the importance of accounting errors. The theoretical literature has long recognized the importance of measurement noise in accounting. Some theories imply an endogenous association between bias and noise in accounting (e.g., FV, Dye and Sridhar [2004], Stocken and Verrecchia [2004], Ewert and Wagenhofer [2005], Laux and Laux [2009], Friedman [2014]). Others take into account the role of accounting noise in agency conflicts and optimal contracting (e.g., Lambert and Larcker [1987], Banker and Datar [1989], Datar, Kulp, and Lambert [2001], Dutta and Reichelstein [2005]). Christensen [2010] argues that errors are as essential as bias in affecting beliefs. A handful of empirical studies also examine errors (e.g., DeFond and Jimbalvo [1991], Plumlee and Yohn [2010]). One notable study is HLM, which develops a novel approach to distinguish errors from bias and shows that removing error-related misstatements significantly improves the testing power of fraud-focused research.

2. *A Model of Reporting Bias*

We build on FV's theoretical framework to motivate our empirical analyses. FV do not feature a camouflage effect of errors on bias, so we extend their model to accommodate this effect. This extension allows us to analyze the two potential effects of errors on bias, derive testable hypotheses, and discuss the analytical assumptions underpinning each hypothesis.

Closely 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 true earnings v, which is normally distributed with mean zero and variance σ_v^2. The manager knows the distribution of v but does not observe its realization. As in FV, we assume that the firm's accounting system has measurement noise. We denote this noise n and assume that it follows a normal distribution of mean zero and variance σ_n^2. We interpret n as accounting errors in our empirical analyses. The manager privately observes the realization of measured earnings, $e = v + n$, where v and n are independent; she then makes an external report. The manager may have various incentives to influence the stock price by introducing some bias into her report. Let b represent her bias of choice, so the report she discloses to the market is $r = v + n + b$. The market observes neither v nor n, but it possesses the correct priors of their distributions. After receiving the manager's report r, the market sets the firm's stock price P based on r and its prior beliefs.

We assume that the manager chooses the optimal bias, such that:

$$b^* = \text{argmax}_b \ xP - \frac{c\left(\sigma_n^2\right)}{2} b^2 . \tag{1}$$

In this objective function, xP captures the manager's benefits of biasing the report, with x representing her reporting objective. Both the manager and the market know that x follows a normal distribution with mean μ_x and variance σ_x^2, but only the manager observes its realization.[5] The term $\frac{c(\sigma_n^2)}{2} b^2$ reflects the manager's costs of biasing the report that might arise from her litigation risk, psychic costs, and reputation loss. We assume $c(\sigma_n^2)$ to be a decreasing function of σ_n^2 (i.e., $\frac{dc}{d\sigma_n^2} < 0$) to account for errors' potential camouflage effect on bias. This assumption is motivated by Stocken and Verrecchia [2004], which find that the cost of bias increases with the precision of the reporting system in equilibrium, and by Friedman [2014], which assumes that the cost of bias is tied to the variance of the noise term through a CFO's endogenous reporting effort.

For any given σ_n^2, FV prove the existence of a linear equilibrium, in which

$$b\ \left(x,\ e; \sigma_n^2\right) = \frac{\beta^*}{c\left(\sigma_n^2\right)}\ x, \tag{2}$$

$$P\ \left(r; \sigma_n^2\right) = \beta^*\ r + \alpha, \tag{3}$$

[5] We follow FV and assume that the realization of x is known only to the manager. This assumption prevents the manager's reporting bias from being fully revealed. Our model would deliver a similar intuition if we instead assume x to be a known parameter but allow c to vary across managers, as in Dye and Sridhar [2004]. A manager-specific cost function could reflect her unique costs from "cheating" on reports that the market cannot perfectly observe.

where the coefficient $\frac{\beta^*}{c}$ in equation (2) solves the following equation:

$$\sigma_x^2\left(\frac{\beta}{c}\right)^3+\left(\frac{\beta}{c}\right)\left(\sigma_v^2+\sigma_n^2\right)-\sigma_v^2\varphi = 0. \quad (4)$$

We define $\varphi \equiv \frac{1}{c}$ as the inverse cost of bias. In equation (4) and the equations below, c and φ continue to be functions of σ_n^2; we use c and φ to denote $c(\sigma_n^2)$ and $\varphi(\sigma_n^2)$ for ease of notation. φ is an increasing function of σ_n^2 (i.e., $\frac{d\varphi}{d\sigma_n^2}>0$), given $\frac{d\varphi}{d\sigma_n^2} = -\frac{1}{c^2}\frac{dc}{d\sigma_n^2}$ and our assumption of $\frac{dc}{d\sigma_n^2}<0$.

Our particular interest is in how σ_n^2 affects the manager's choice of bias, that is, $b(x,\ e;\sigma_n^2)$ in equation (2). As x is assumed to be independent of σ_n^2, we focus on the effect of σ_n^2 on $\frac{\beta^*}{c}$ (a term we label "propensity to bias" or "bias propensity" hereafter). We solve for $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}$, our comparative static of interest, as

$$\frac{d\left(\frac{\beta^*}{c}\right)}{d\sigma_n^2} = \frac{\sigma_v^2\frac{d\varphi}{d\sigma_n^2}}{3\sigma_x^2\left(\frac{\beta^*}{c}\right)^2+\left(\sigma_v^2+\sigma_n^2\right)} + \frac{-\frac{\beta^*}{c}}{3\sigma_x^2\left(\frac{\beta^*}{c}\right)^2+\left(\sigma_v^2+\sigma_n^2\right)}. \quad (5)$$

This solution consists of two terms: The first term represents the marginal benefit (MB) from errors' camouflage effect, and the second term represents the marginal cost (MC) from errors' value relevance–reducing effect.[6] The two effects counteract each other, because the first term affects bias propensity positively while the second term affects it negatively. As the two terms share the same denominator, which is strictly positive, the relation between bias propensity and errors' variance depends on the relative magnitudes of the two terms' numerators, which in turn depend on (a) whether $\sigma_v^2\frac{d\varphi}{d\sigma_n^2}$ outweighs $\frac{\beta^*}{c}$ when $\sigma_n^2 = 0$, and (b) the sign of $\frac{d^2\varphi}{d(\sigma_n^2)^2}$.

We first consider $\sigma_v^2\frac{d\varphi}{d\sigma_n^2}|_{\sigma_n^2=0} > \frac{\beta^*}{c}|_{\sigma_n^2=0}$ for condition (a). This assumption suggests that the MB from the camouflage effect dominates the MC from the value relevance–reducing effect when σ_n^2 is low, leading to a positive relation between bias propensity and errors' variance initially. As σ_n^2 increases, how this relation evolves depends on condition (b). If $\frac{d^2\varphi}{d(\sigma_n^2)^2}<0$, such that the MB from the camouflage effect declines with σ_n^2, the MC from the value relevance–reducing effect will eventually take over and turn the relation to negative when σ_n^2 gets sufficiently high. Thus, we expect to see a hump-shaped relation between bias propensity and errors' variance.[7] Al-

[6] The first link is evident based on the definition of φ and our assumption that φ increases with σ_n^2. To see the second link, we can assume away the camouflage effect in our model and rewrite $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2} = \frac{-\frac{\beta^*}{c}}{3\sigma_x^2(\frac{\beta^*}{c})^2+(\sigma_v^2+\sigma_n^2)}$. It is then the same as the value relevance–reducing effect in FV, which is $\frac{d(\beta)}{d\sigma_n^2} = \frac{-\beta c^2}{3\beta^2\sigma_x^2+c^2(\sigma_v^2+\sigma_n^2)}$ with both sides divided by a constant c.

[7] Note that our model cannot predict a similar hump-shaped relation between bias propensity and the variance of firms' true earnings, σ_v^2. In FV's and our model, bias propensity strictly

ternatively, if $\frac{d^2\varphi}{d(\sigma_n^2)^2} > 0$, the MB from the camouflage effect dominates for all values of σ_n^2, and bias propensity strictly increases with errors' variance.

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

H1a: If the MB from the camouflage effect outweighs the MC from the value relevance–reducing effect when errors' variance is at its lower bound and the MB decreases with errors' variance, there exists a hump-shaped relation between bias propensity and errors' variance.

H1b: If the MB from the camouflage effect outweighs the MC from the value relevance–reducing effect when errors' variance is at its lower bound and the MB increases with errors' variance, bias propensity will strictly increase with errors' variance.

Next, we consider $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}|_{\sigma_n^2=0} < \frac{\beta^*}{c}|_{\sigma_n^2=0}$ for condition (a). Under this assumption, the MC from the value relevance–reducing effect dominates the MB from the camouflage effect when σ_n^2 is low, resulting in a negative relation between bias propensity and errors' variance initially. If $\frac{d^2\varphi}{d(\sigma_n^2)^2} > 0$, such that the MB from the camouflage effect increases with σ_n^2, it will gradually take over the MC from the value relevance–reducing effect and turn the relation to positive. This predicts a U-shaped relation between bias propensity and errors' variance. If $\frac{d^2\varphi}{d(\sigma_n^2)^2} < 0$ instead, the MB from the camouflage effect never outweighs the MC from the value relevance–reducing effect, leading to a negative relation between bias propensity and errors' variance for all values of σ_n^2.

This discussion generates two additional hypotheses stated as follows:

H2a: If the MC from the value relevance–reducing effect outweighs the MB from the camouflage effect when errors' variance is at its lower bound and the MB increases with errors' variance, there exists a U-shaped relation between bias propensity and errors' variance.

H2b: If the MC from the value relevance–reducing effect outweighs the MB from the camouflage effect when errors' variance is at its lower bound and the MB decreases with errors' variance, bias propensity will strictly decrease with errors' variance.

In appendix A, we prove the four hypotheses and plot their predictions in figures A.1–A.4, respectively. It is noteworthy that which figure emerges from the data depends on which hypothesis's underlying assumptions are met.[8]

increases with σ_v^2. Intuitively, this is because, unlike σ_n^2, σ_v^2 has a value relevance–increasing effect. The prediction does not change if we assume that σ_v^2 has a camouflage effect on bias. In fact, if the cost of bias decreases with σ_v^2, bias propensity will increase even faster with σ_v^2. Nevertheless, we assess the effect of σ_v^2 on our empirical findings in section 4.3.3.

[8] Consider, for example, a simple cost function $c = \frac{1}{(\sigma_n^2+a)^\gamma}$, or equivalently, an inverse cost function $\varphi = (\sigma_n^2 + a)^\gamma$. The parameter a determines how $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}|_{\sigma_n^2=0}$ compares to $\frac{\beta^*}{c}|_{\sigma_n^2=0}$

3. Data and Sample

This section describes the sample, variables used in our core analyses, and data sources used to construct these variables. Detailed variable definitions are provided 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 database of securities class action lawsuits, and Accounting and Auditing Enforcement Releases. We use the GAO database 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 this approach based on a combination of keyword searches for variants of the words “fraud” and “irregularity,” whether there is an SEC enforcement action, 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 definition of bias) 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 significantly more negative market reactions than those of errors.

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 collected manually by Burns and Kedia [2006] (also Burns, Kedia, and Lipson [2010]) and Files [2012], in that order. For the remaining ones, we review the firms’ filings (e.g., 8-Ks and 10-Ks) on the SEC’s Web site. Of the 2,705 GAO restatements, we are able to identify misstating periods for 2,646 of them; the rest are not included in our analyses. The sample restatements, announced by 2,114 firms between January 7, 1997 and June 29, 2006, cover 21,251 firm-quarters between 1992Q1 and 2006Q2 based on misstating periods. The incidence of misstatements may be underestimated for the beginning quarters, because restatements associated with these quarters may be announced prior to 1997. It may also be underestimated for the ending quarters, because there is typically a time lag between the time of misstatement and the time of detection. To correct for truncation bias, we limit our mis-

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in condition (a) and γ determines the sign of $\frac{d^2\varphi}{d(\sigma_n^2)^2}$ in condition (b). If $\gamma \in [0, 1)$ and $a < (\frac{\frac{\beta}{c}^*|_{\sigma_n^2=0}}{\gamma\sigma_v^2})^{\frac{1}{\gamma-1}}$ $(a > (\frac{\frac{\beta}{c}^*|_{\sigma_n^2=0}}{\gamma\sigma_v^2})^{\frac{1}{\gamma-1}})$, the assumptions of H1a (2b) are met; note that when $\gamma \in [0, 1)$, inequality flips when both sides of the equation for condition (a) are raised to the power of $\gamma - 1$. Instead, If $\gamma > 1$ and $a > (\frac{\frac{\beta}{c}^*|_{\sigma_n^2=0}}{\gamma\sigma_v^2})^{\frac{1}{\gamma-1}}$ $(a < (\frac{\frac{\beta}{c}^*|_{\sigma_n^2=0}}{\gamma\sigma_v^2})^{\frac{1}{\gamma-1}})$, the assumptions of H1b (2a) are met.

stating sample to 20,653 firm-quarters between 1996Q1 and 2005Q4. We report robust results using alternative sample cutoff points in section 4.3.3.

We conduct the core analyses at the firm-quarter level. To construct the sample, we first merge the misstating firm-quarters into the universe of Compustat firm-fiscal quarters and delete 3,944 firm-quarters that cannot be merged. We then merge Compustat firm-fiscal quarters with the proxies for errors and controls. Depending on data availability, the firm-quarter samples used in the core analyses range between 233,631 and 280,609 observations.

3.2 MEASURES OF BIAS PROPENSITY AND ERRORS' VARIANCE

To measure bias propensity, we define *Bias* as an indicator variable that equals 1 if HLM have identified the firm as having engaged in an intentional misstatement in a quarter, and 0 otherwise. This proxy is motivated by the idea that bias of a larger magnitude is more likely to get caught ex post.

To measure the variance of firms' reporting errors, we first define *Error%* as the percentage of firms with unintentional misstatements in a quarter for each of the Global Industry Classification Standard (GICS) 24 industry groups.[9] Like *Bias*, this proxy builds on the idea that, on average, a larger variance of errors is associated with a higher likelihood of an error being detected, because extreme realizations of errors are more likely.[10] Ideally, we would define this proxy at the firm level to be consistent with our model. A binary variable that denotes errors in a firm-quarter (analogous to *Bias*), however, would have a mechanical negative correlation with *Bias*, because a misstating firm in our sample is classified by HLM as either a bias or an error firm in a quarter but not both. Further, errors defined this way would drop out of a quadratic model that we later estimate, because the resulting proxy would be perfectly correlated with its squared term. We thus assume that firms in the same industry group share similar distributions of errors and estimate errors' variance at the industry level. To do so, we assign firm

[9] GICS is jointly developed by MSCI and Standard & Poor's; a list of GICS 10 industries/sectors and 24 industry groups and revision history are available at http://www.spindices.com/documents/index-policies/methodology-gics.pdf. We use GICS to define industries, because Bhojraj, Lee, and Oler [2003, p. 745], who run a horse race of the popular industry classification standards, find that "GICS classifications are significantly better at explaining stock return co-movements, as well as cross-sectional variations in valuation multiples, forecasted and realized growth rates, research and development expenditures, and various key financial ratios." GICS dates back to 1999; for firm-quarters prior to 1999 in our sample, we use the firms' earliest available GICS.

[10] One concern with *Error%* is that, even though income-increasing and income-decreasing errors are equally likely, we observe more income-increasing errors, because market participants might be more motivated to detect such errors. Observing one side of the errors' distribution does not necessarily bias our analysis, as long as it does not tilt the manager's and the market's perceptions of the true distribution; recall that both the manager and the market are assumed to know the true distribution of errors in FV. Empirically, multiplying *Error%* by an adjustment factor (such as two) to make it a more "correct" proxy would not change our inferences qualitatively.

i to its industry *j* and align firm *i*'s fiscal quarter to the closest calendar quarter (i.e., the calendar quarter that covers most of the days in a given fiscal quarter).

We further build two proxies, *NItems* and *RegAmbiguity*, to capture the variation in errors' variance that stems from transaction complexity and regulation ambiguity, respectively. Following Li [2008] and Lundholm, Rogo, and Zhang [2014], we calculate *NItems* as a firm's number of nonmissing items from the Compustat quarterly files. Unlike *Error%*, this proxy is available at both firm level and industry level when averaged within industry-quarters.

We build *RegAmbiguity* in three steps. First, we look up the accounting rules that apply to Merger and Acquisition (M&A) transactions, hedging transactions, leases, and warranties.[11] We define the annual ambiguity index of each rule as the rule's number of interpretations in a year (as provided in Mergenthaler [2009]), scaled by its number of interpretations in 1996, the first year of the sample period. This scaling is intended to control for the cross-sectional variation in the number of interpretations across rules and capture the change in the degree of ambiguity of a given rule over time.[12] Second, we identify the transactions that would expose a firm to these rules in a given quarter. We consider a firm to be exposed to merger rules if the firm reports goodwill on its balance sheet in the Compustat quarterly files, to hedge rules if we locate at least one variant of the keyword "hedge" in the firm's 10-Q filings, to the lease rule if the firm reports operating leases or capital leases in the Compustat annual files, and to the warranty rule if we locate the keyword "warranty" or "warranties" in the firm's 10-Q filings.[13] A firm's exposure to regulation ambiguity, *RegAmbiguity*, is therefore the sum of the ambiguity indexes of all rules that apply to the firm in a quarter. Similar to *NItems*, *RegAmbiguity* is available at both the firm and industry levels.

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[11] Merger rules include *FAS 141: Business Combinations* and *FAS 142: Goodwill and Other Intangible Assets* (or *APB 16: Business Combinations* and *APB 17: Intangible Assets* prior to 2001). Hedge rules include *FAS 133: Accounting for Derivative Instruments and Hedging Activities* (or *FAS 80: Accounting for Futures Contracts*, *FAS 105: Disclosure of Information About Financial Instruments with Off-Balance-Sheet Risk and Financial Instruments with Concentrations of Credit Risk*, and *FAS 119: Disclosure About Derivative Financial Instruments and Fair Value of Financial Instruments* prior to 2000). The lease rule and the warranty rule are *FAS 13: Accounting for Leases* and *FAS 5: Accounting for Contingencies*, respectively.

[12] Mergenthaler [2009] reports four rules-based characteristics: the number of words, the existence of bright line thresholds, the number of scope or legacy exceptions, and the number of interpretations. We focus on the number of interpretations, because the other three characteristics exhibit little time-series variation within each rule.

[13] To locate M&A transactions, we use the Compustat annual goodwill indicator (i.e., GDWL) to fill in the missing quarterly goodwill indicator (i.e., GDWLQ). To locate hedging transactions, we search for the keywords "hedging" and "hedge(s)" and exclude the keyword "hedge fund(s)." For leases, we use the Compustat annual files instead of quarterly files, because the indicators for operating leases and capital leases are both available only in the annual files.

3.3 CONTROLS

For controls, we first focus on those related to growth, as prior research shows that growth affects firms' bias incentives theoretically (e.g., Povel, Singh, and Winton [2007], Strobl [2013]) and empirically (e.g., Wang, Winton, and Yu [2010], Wang and Winton [2014]). We use three proxies for growth: the firm's seasonally adjusted quarterly sales growth (*SaleGrowth*), market-to-book ratio (*Q*), and the natural logarithm of market capitalization (*MV*). *Q* and *MV* are measured at the end of the quarter. We also include the number of analysts following the firm (*NAnalysts*), an indicator to denote equity issuance (*EquityIssue*), and the firm's share turnover (*Turnover*) in a quarter. Analyst coverage and incentives to issue equity affect the manager's propensity to bias (e.g., Degeorge, Patel, and Zeckauser [1999]; Teoh, Welch, and Wong [1998]), and trading activity affects the market's perception of the firm's fundamentals and the manager's reporting objective.

We further include four industry-quarter-level controls. Heinle and Verrecchia [2016] show that an industry's size affects the informativeness of its member firms' earnings reports, so we include the number of firms in an industry-quarter (*NFirms*) as a control. We then use the percentage of firms in an industry-quarter that are delisted due to bankruptcy (*Bankruptcy%*) to capture the industry-wide economic condition, which affects both bias and errors. Governance is another factor that can affect both bias and errors: Strong governance can decrease firms' error rates, as well as managers' bias propensity. While a firm's own governance system is endogenous, the average governance practice in the firm's industry is arguably more exogenous, because it is less subject to the firm management's control. We define two controls to capture the governance environment in which the firm operates: the average percentage of independent board directors (*IndBoard%*) and the average institutional ownership (*IO*) in the firm's industry in a quarter. Defining *IndBoard%* and *IO* at the firm level results in a smaller sample (due to data coverage) but does not affect our results.

In terms of data sources, we obtain firm financials and listing status from the Compustat quarterly and annual files, analyst coverage from I/B/E/S, equity issuance from the SDC Platinum database, firm returns and trading volume from the CRSP daily and monthly files, board member information from the Institutional Shareholder Services (ISS), and institutional ownership from the Thomson Institutional (13f) Holdings database.

3.4 DESCRIPTIVE STATISTICS

Table 1, panel A, reports the sample distribution of misstating firm-quarters separately for the 24 GICS industry groups and for the pooled sample. In the pooled sample, 5,268 firm-quarters are associated with intentional misstatements, representing 1.21% of the total Compustat firm-quarters. The number (percentage) of firm-quarters with unintentional misstatements is much higher at 11,940 (2.75%). Misstatements are spread broadly across industries, with Food & Staples Retailing and Semiconduc-

TABLE 1

Sample Distribution and Descriptive Statistics

Panel A: Sample distribution of total firm-quarters and misstating firm-quarters by industry groups

GICS Industry Groups	Total Number of Firm-Quarters	Number of Intentionally Misstating Firm-Quarters	Percentage of Intentionally Misstating Firm-Quarters	Number of Unintentionally Misstating Firm-Quarters	Percentage of Unintentionally Misstating Firm-Quarters
Energy	24,482	191	0.78	533	2.18
Materials	32,322	160	0.50	595	1.84
Capital goods	28,548	382	1.34	546	1.91
Commercial and professional services	20,767	328	1.58	677	3.26
Transportation	8,049	123	1.53	216	2.68
Automobiles and components	6,044	124	2.05	166	2.75
Consumer durables and apparel	18,462	213	1.15	334	1.81
Consumer services	13,127	161	1.23	712	5.42
Media	13,961	201	1.44	338	2.42
Retailing	18,537	289	1.56	1,306	7.05
Food and staples retailing	3,566	124	3.48	210	5.89
Food, beverage, and tobacco	10,375	158	1.52	218	2.10
Household and personal products	3,338	63	1.89	62	1.86
Health care equipment and services	27,978	425	1.52	714	2.55
Pharmaceuticals, biotechnology, and life sciences	21,393	107	0.50	381	1.78
Banks	34,449	224	0.65	812	2.36
Diversified financials	15,620	111	0.71	295	1.89
Insurance	9,570	208	2.17	250	2.61
Real estate	14,308	76	0.53	367	2.56
Software and services	42,139	744	1.77	1,356	3.22
Technology hardware and equipment	37,944	541	1.43	901	2.37

(*Continued*)

TABLE 1—*Continued*

Panel A: Sample distribution of total firm-quarters and misstating firm-quarters by industry groups

GICS Industry Groups	Total Number of Firm-Quarters	Number of Intentionally Misstating Firm-Quarters	Percentage of Intentionally Misstating Firm-Quarters	Number of Unintentionally Misstating Firm-Quarters	Percentage of Unintentionally Misstating Firm-Quarters
Semiconductors and semiconductor equipment	2,642	60	2.27	81	3.07
Telecommunication services	12,118	118	0.97	464	3.83
Utilities	14,098	137	0.97	406	2.88
Total	433,837	5,268	1.21	11,940	2.75

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

Variable	*N*	Mean	SD	1%	25%	Median	75%	99%
Firm-Level Variables								
$Bias_{i,q}$	280,609	0.01	0.12	0.00	0.00	0.00	0.00	1.00
$SaleGrowth_{i,q}$	280,609	0.31	1.15	−0.98	−0.04	0.09	0.30	8.38
$Q_{i,q}$	280,609	3.47	5.76	0.23	1.14	1.88	3.34	39.27
$MV_{i,q}$	280,609	5.02	2.24	−0.03	3.45	4.94	6.55	10.25
$NAnalysts_{i,q}$	280,609	3.52	5.41	0.00	0.00	1.00	5.00	24.00
$EquityIssue_{i,q}$	280,609	0.01	0.13	0.00	0.00	0.00	0.00	1.00
$Turnover_{i,q}$	280,609	2.89	3.82	0.00	0.41	1.57	3.67	19.06
Industry-Quarter-Level Variables								
$Error\%_{j,q}$	927	2.89	2.34	0	1.26	2.43	3.61	11.68
$NFirms_{j,q}$	927	0.46	0.27	0.09	0.25	0.37	0.66	1.21
$Bankruptcy\%_{j,q}$	927	0.00	0.01	0.00	0.00	0.00	0.00	0.00
$IndBoard\%_{j,q}$	927	62.45	7.34	45.98	56.85	62.54	68.26	78.39
$IO_{j,q}$	927	0.37	0.10	0.16	0.30	0.36	0.44	0.62
Alternative Proxies for Errors (available at both the firm and industry levels)								
$NItems_{i,q}$	259,761	1.09	0.37	0.64	0.79	0.86	1.46	1.94
$RegAmbiguity_{i,q}$	233,631	2.90	1.80	0.00	1.37	2.50	3.83	7.57
$NItems_{j,q}$	927	1.00	0.31	0.54	0.71	0.93	1.31	1.60
$RegAmbiguity_{j,q}$	927	2.89	1.06	1.03	2.03	2.79	3.76	5.13

Panel A reports the sample distribution of the Compustat firm-quarters, the intentionally misstating firm-quarters, and the unintentionally misstating firm-quarters for the 24 GICS industry groups. Panel B reports the number of observations (*N*), mean, standard deviation (SD), 1st percentile (1%), 25th percentile (25%), median, 75th percentile (75%), and 99th percentile (99%) for the variables used in the core analyses. Firm-level variables are measured for firm *i*-quarter *q*, an indicator variable to denote intentional misstatement (*Bias*), sales growth (*SaleGrowth*), market-to-book (*Q*), market capitalization (*MV*), number of analysts (*NAnalysts*), an indicator to denote equity issuance (*EquityIssue*), and share turnover (*Turnover*). Industry-quarter-level variables are measured for industry *j*-quarter *q*, percentage of firms that engage in unintentional misstatements (*Error%*), number of firms (*NFirms*), percentage of firms delisted due to bankruptcy (*Bankruptcy%*), average percentage of independent board directors (*IndBoard%*), and average institutional ownership (*IO*). Variables that are available at both firm and industry levels include the firm's number of nonmissing items in its quarterly financial statements (*NItems*) and degree of exposure to ambiguous accounting rules (*RegAmbiguity*). *Error%*, *Bankruptcy%*, and *IndBoard%* are in percentage points, *NFirms* is in thousands, and *NItems* is in hundreds. Detailed variable definitions are in appendix B. All continuous variables are winsorized at the top and bottom 1%; the only exception is *Bankruptcy%*, the magnitude of which is miniscule. The sample period is between 1996Q1 and 2005Q4.

tors & Semiconductor Equipment having the highest incidence of bias-related misstatements (3.48% and 2.27%, respectively) and Retailing and Food & Staples Retailing having the highest incidence of error-related misstatements (7.05% and 5.89%, respectively).

Table 1, panel B, reports descriptive statistics for the variables used in the core analyses. Intentional misstatements are infrequent: Firms that engage in such misstatements account for only 1% of the sample. Among the three proxies for errors' variance, *Error%*, the percentage of unintentionally misstating firms in an industry-quarter, has a mean of 2.89%. This proxy is available for 927 rather than 960 industry-quarters (24 industries × 10 years × 4 quarters) because the industry group Semiconductors & Semiconductor Equipment was added after 2003Q1 and because a handful of industry-quarters do not have data to calculate the board independence measure. At the firm level, *NItems* has a mean of 109 (out of a total of 362 data items that we use from the Compustat quarterly files), and *RegAmbiguity* has a mean of 2.9. During our sample period, a firm-quarter on average has a sales growth rate of 31% relative to the same quarter of the prior year, a market-to-book ratio of 3.47, market capitalization (in natural logarithm) of 5.02, 3.52 analysts following, and a share turnover of 2.89. The average percentage of firms issuing equity is 1%. Turning to the industry-quarter-level controls, the average number of firms in an industry group is 460, the average percentage of independent board directors is 62.45%, the average percentage of institutional ownership is 37%, and the percentage of firms delisted due to bankruptcy is minuscule.

4. The Relation Between Reporting Bias and Errors

4.1 THE RELATION BETWEEN BIAS PROPENSITY AND ERROR RATE

To test our hypotheses, we first examine the relation between a firm's bias propensity and the error rate of the firm's industry by estimating the following quadratic logit regression:[14]

$$Bias_{i,q} = \alpha + \beta_1 Error\%_{j,q} + \beta_2 Error\%^2_{j,q} + \varepsilon_{i,q}, \tag{6}$$

where subscript i indexes firms, j indexes GICS industry groups, and q indexes calendar quarters. Again, *Bias* measures firm i's probability of engaging in an intentional misstatement in quarter q, and *Error%* measures the percentage of firms that engage in unintentional misstatements in the firm's industry j in the same quarter. $Error\%^2$ is the squared term of *Error%*. We cluster standard errors by industry and year-quarter.

[14] We adopt a quadratic logit model, because it is sufficient to test our hypotheses. It also fits the data well based on three model selection criteria, including pseudo R-squared, the Akaike information criterion, and Bayesian information criterion: The quadratic model significantly outperforms a logit model with only linear regressors or a logit model that regresses bias propensity on the natural logarithm of one plus the error rate, and it performs similarly to or better than logit models with even higher order polynomial regressors.

TABLE 2
The Relation Between Reporting Bias and Errors

	(1)	(2)	(3)	(4)	(5)
Dependent Variables			$Bias_{i,q}$		
$Error\%_{j,q}$	**0.403*****	**0.415*****	**0.398*****	**0.247*****	**0.170*****
	(0.065)	(0.069)	(0.058)	(0.087)	(0.048)
$Error\%^2_{j,q}$	**−0.025*****	**−0.027*****	**−0.026*****	**−0.017*****	**−0.012*****
	(0.005)	(0.005)	(0.004)	(0.006)	(0.004)
$SaleGrowth_{i,q}$		−0.032	−0.021	−0.026	−0.012
		(0.036)	(0.037)	(0.035)	(0.037)
$Q_{j,q}$		−0.015**	−0.021**	−0.013*	−0.019**
		(0.008)	(0.009)	(0.007)	(0.008)
$MV_{i,q}$		0.187***	0.199***	0.185***	0.195***
		(0.030)	(0.032)	(0.029)	(0.031)
$NAnalysts_{i,q}$		0.035***	0.036***	0.035***	0.037***
		(0.009)	(0.009)	(0.008)	(0.008)
$EquityIssue_{i,q}$		0.163**	0.200**	0.176**	0.229***
		(0.080)	(0.078)	(0.082)	(0.086)
$Turnover_{i,q}$		0.051***	0.046***	0.055***	0.045***
		(0.011)	(0.011)	(0.011)	(0.011)
$NFirms_{j,q}$		0.189	0.120	0.100	0.028
		(0.262)	(0.346)	(0.339)	(0.387)
$Bankruptcy\%_{j,q}$		0.153	0.497	−1.719*	−1.680**
		(0.857)	(0.659)	(0.919)	(0.824)
$IndBoard\%_{j,q}$		−0.033***	−0.030**	−0.018	−0.008
		(0.011)	(0.013)	(0.012)	(0.016)
$IO_{j,q}$		0.256	−0.420	1.578	1.628
		(0.981)	(1.283)	(1.081)	(1.415)
Intercept	−5.274***	−4.453***	−4.836***	−7.705***	−9.048***
	(0.179)	(0.506)	(0.558)	(0.919)	(1.454)
Industry fixed effects			Yes		Yes
Year-quarter fixed effects				Yes	Yes
Number of observations	433,837	280,609	280,609	280,609	280,609
Pseudo-R^2	1.35%	6.63%	7.28%	7.31%	7.99%

This table reports the logit regression results on the relation between firm *i*'s bias propensity in quarter *q* (*Bias*) and the error rate of the firm's industry *j* in the same quarter (*Error%*). $Error\%^2$ is the squared term of *Error%*. Controls include firm *i*'s sales growth (*SaleGrowth*), market-to-book (*Q*), market capitalization (*MV*), number of analysts (*NAnalysts*), an indicator to denote equity issuance (*EquityIssue*), share turnover (*Turnover*), industry *j*'s number of firms (*NFirms*), percentage of firms delisted due to bankruptcy (*Bankruptcy%*), average percentage of independent board directors (*IndBoard%*), and average institutional ownership (*IO*). *Error%*, *Bankruptcy%*, and *IndBoard%* are in percentage points, and *NFirms* is in thousands. Detailed variable definitions are in appendix B. The sample period is between 1996Q1 and 2005Q4. Standard errors clustered by industry and year-quarter are displayed below the coefficient estimates in parentheses. The coefficient estimates on the key variables of interest are highlighted in bold. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

Column (1) of table 2 reports the regression results of estimating equation (6). As shown, *Error%* exhibits a positive coefficient and its squared term exhibits a negative coefficient, both significant at the 1% level. This is consistent with H1a that there exists a hump-shaped relation between *Bias* and *Error%*. The turning point of the hump is near *Error%* = 8.1% (i.e., $0.403/(2 \times 0.025)$), which is high relative to the sample mean of

Error%, 2.89%.[15] This suggests that, even though the underlying analytical relation between bias and errors might be hump-shaped, the empirically relevant range is the increasing, concave part of the hump. In other words, if errors indeed yield counteracting effects on firms' bias incentives as we model, the benefits from errors' camouflage effect outweigh the costs from their value relevance–reducing effect for a majority of our sample firms. In column (2) of table 2, we include the controls discussed in section 3.3. The coefficients on *Error%* and *Error%*^{2} are similar to those reported in column (1) in both magnitude and significance. The turning point is slightly lower at 7.6%.

In column (3) of table 2, we include industry fixed effects to control for omitted industry characteristics that are constant over time. The results are comparable to those reported in columns (1) and (2). In column (4), we replace industry fixed effects with year-quarter fixed effects to control for the intertemporal variation in errors induced by systematic shocks. Although the coefficients on *Error%* and *Error%*^{2} remain statistically significant at the 1% level, the magnitude of the coefficients is noticeably smaller, suggesting that errors are susceptible to shocks that affect multiple industries at the same time. Finally, in column (5), we include both industry and year-quarter fixed effects. The magnitude of the coefficients on *Error%* and *Error%*^{2} further decreases, but both coefficients remain statistically significant at the 1% level. The results in column (5) show that firms' bias propensity is at least partly explained by the industry-specific time-series variation in errors, which does not co-move across industries. In other words, error rates meaningfully explain firms' bias propensity above and beyond industry characteristics and systematic shocks. Compared to column (1), columns (3)–(5) have lower turning points, ranging from 7.1% to 7.8%.

Next, we gauge the economic impact of *Error%* on *Bias*. For a given *Error%*, we calculate its marginal effect on *Bias* while holding controls at the sample mean values (see footnote 15 for the formula of marginal effect in a quadratic logit model). Based on the coefficients in column (5) of table 2, the marginal effect of *Error%* on *Bias* is 0.11% when *Error%* is at its 25th percentile, 0.16% at its median, 0.1% at its 75th percentile, and −0.1% at its 99th percentile. These effects are sizable compared to the unconditional probability of firms' engaging in bias, 1%.[16]

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[15] Denote $F(x) = \mathit{Bias}$, $x = \mathit{Error\%}$, and $z = \mathit{Control}$; the marginal effect of *Error%* on *Bias* is given by $\frac{dF(x)}{dx} = \frac{e^{-(\alpha+\beta_1 x+\beta_2 x^2+\gamma' z)}}{[1+e^{-(\alpha+\beta_1 x+\beta_2 x^2+\gamma' z)}]^2}(\beta_1 + 2\beta_2 x)$ in a quadratic logit model and $\frac{dF(x)}{dx} = \beta_1 + 2\beta_2 x$ in a quadratic linear model. Thus, the turning point x^* occurs at the same point for both models when $\frac{dF(x)}{dx} = 0$; that is, $x^* = -\frac{\beta_1}{2\beta_2}$.

[16] The marginal effect in a quadratic logit model does not necessarily decrease monotonically with x as in a quadratic linear model when $\beta_2 < 0$, because the term $\frac{e^{-(\alpha+\beta_1 x+\beta_2 x^2+\gamma' z)}}{[1+e^{-(\alpha+\beta_1 x+\beta_2 x^2+\gamma' z)}]^2}$ in the previously derived $\frac{dF(x)}{dx}$ varies with x too.

Among the controls, *Q* is negatively related to *Bias* in columns (2)–(5), which suggests that firms lacking growth opportunities are more likely to engage in reporting bias. *MV* is positively related to *Bias*, suggesting that either large firms are more likely to bias their earnings reports or the reporting bias in these firms is more likely to be detected. Further, *NAnalysts*, *EquityIssue*, and *Turnover* are positively correlated with *Bias*, consistent with the view that capital market pressure (stemming from analysts, the need for equity financing, or momentum trading) increases managers' bias propensity.

4.2 THE RELATION BETWEEN BIAS PROPENSITY AND ALTERNATIVE PROXIES FOR ERRORS

4.2.1. The Relevance of Alternative Proxies to Errors: Portfolio Analysis. We use *Error%* as the proxy for errors' variance in table 2. While intuitive, this proxy is available only at the industry level. We now consider two proxies for errors' variance that are also available at the firm level, and thus correspond better to the σ_n^2 that we model.

The first proxy, *NItems*, is defined as the number of nonmissing items in firms' quarterly financial statements. This proxy is intended to capture errors' variance that stems from transaction complexity. Presumably, when a firm has more complex transactions, it needs to create more line items on its financial statements to account for the transactions and/or disclose more details in footnotes. We thus expect a larger value of *NItems* to reflect a higher level of transaction complexity, which should in turn lead to a higher incidence of errors. Confirming our expectation, *NItems*, averaged within industry-quarters, has a Pearson correlation with *Error%* of 0.36 and a Spearman correlation with *Error%* of 0.46, both significant at the 1% level.[17]

The second proxy, *RegAmbiguity*, aims to capture the effect of regulation on errors. Many practitioners hold the view that increasingly lengthy and complicated accounting rules are to blame for errors, because of (1) the rules' lack of clarity, (2) the difficulties in identifying all relevant accounting literature associated with certain rules, and (3) the complexity of the literature (see Scott Taub's remarks). In particular, financial executives find rules on merger accounting, hedge accounting, leasing, and warranties challenging to understand and follow (Harris [2007]).[18] We define an annual ambiguity index for each of these rules based on the rule's number

[17] We assume that a larger *NItems* indicates greater transaction complexity and creates more opportunities for errors. Chen, Miao, and Shevlin [2015] find that *NItems* is positively related to disclosure quality *after* controlling for transaction complexity. An overall positive correlation between *NItems* and *Error%* suggests that, while higher disclosure quality could mean fewer errors, the primary effect of *NItems* on *Error%* is through transaction complexity.

[18] A summary of Scott Taub's remarks is available at http://www.sec.gov/news/speech/2006/spch111706sat.htm. Other named rules include the ones on revenue recognition and tax accounting; we do not use these rules in calculating *RegAmbiguity* because they are applicable to all firms.

of interpretations. *RegAmbiguity* is then defined as the sum of the ambiguity indexes of all rules that apply to a firm in a quarter (see section 3.2 for the detailed definition of this proxy).

Consistent with practitioners' view that these rules have become increasingly lengthy and complicated, *RegAmbiguity*, averaged within industry-quarters, increases monotonically from 1.46 in 1996 to 4.26 in 2005 in our sample. It is also strongly associated with *Error%*: The Pearson coefficient is 0.38 and the Spearman coefficient is 0.6, both significant at the 1% level. This suggests that the incidence of errors, on average, increases with rule ambiguity captured by the rule's number of interpretations.

We conduct several portfolio analyses to further confirm the relevance of the two proxies to errors. Panel A.1 of table 3 sorts the sample into quartiles based on *NItems*. As the panel shows, the percentage of error-related misstatements, *Error%*, increases monotonically from the bottom quartile to the top quartile. In fact, *Error%* in the top quartile is six times greater than that in the bottom quartile (i.e., 5.58% vs. 0.75%), and the difference is significant at the 1% level. Panel A.2 of table 3 sorts the sample into quartiles based on industry-quarter adjusted *NItems* (i.e., a firm's quarterly *NItems* minus the mean *NItems* of the industry-quarter to which the firm-quarter belongs). *Error%* still increases monotonically with the adjusted *NItems*, but the difference in *Error%* between the top and the bottom quartiles is smaller (5.08% vs. 1.47%, significant at the 1% level). This result suggests that, like *Error%*, *NItems* exhibits significant cross-industry and intertemporal variation. Panels A.3 and A.4 of table 3 repeat the analyses in panels A.1 and A.2 with *RegAmbiguity* and industry-quarter adjusted *RegAmbiguity*, respectively, and reveal a similar pattern. *Error%* in the top quartile of *RegAmbiguity* (adjusted *RegAmbiguity*) is 5.25% (4.94%), significantly higher than the corresponding value in the bottom quartile, 1.26% (2.52%).

Panels B.1–B.4 of table 3 sort the sample based on the four components of *RegAmbiguity*. We create three sets of portfolios within each panel. In columns (1) and (2) of panels B.1–B.4, we calculate and compare *Error%* based on whether firm-quarters are exposed to rules on merger, hedge, lease, and warranty in the pooled sample, respectively. In columns (3) and (4) of panels B.1–B.4, we first group firm-quarters into industry-quarters and then conduct paired *t*-tests to compare *Error%* based on whether firm-quarters are exposed to a particular rule within each industry-quarter. This approach aims to isolate the effect of regulation ambiguity on firms' error rates above and beyond industry characteristics and systematic shocks. In columns (5) and (6) of panels B.1–B.4, we first create 2 × 2 portfolios by sorting on firms' *MV* and then on *NItems* within each industry-quarter, and next conduct paired *t*-tests to compare *Error%* based on whether firm-quarters are exposed to a particular rule within each portfolio. This approach further controls for the effects of firm size and financial statement complexity on error rates. The results from all panels continue to show higher *Error%* for firms that need to apply these potentially ambiguous rules in a quarter than for firms that do not. As we add more controls in the

TABLE 3

The Relevance of Alternative Proxies for Errors: Portfolio Analyses

Panel A: Portfolio analyses based on *NItems* and *RegAmbiguity*

A.1: Raw Value	(1) 1st Quartile of *NItems*	(2) 2nd Quartile of *NItems*	(3) 3rd Quartile of *NItems*	(4) 4th Quartile of *NItems*	(4)–(1)
Error%	0.75%	1.94%	2.85%	5.58%	**4.83%*****
Number of observations	105,586	103,382	109,552	105,593	
A.2: Subtracting industry-quarter mean					
	1st Quartile of *NItems*	2nd Quartile of *NItems*	3rd Quartile of *NItems*	4th Quartile of *NItems*	
Error%	1.47%	1.92%	2.68%	5.08%	**3.61%*****
Number of observations	106,224	105,836	106,023	106,030	
A.3: Raw value					
	1st Quartile of *RegAmbiguity*	2nd Quartile of *RegAmbiguity*	3rd Quartile of *RegAmbiguity*	4th Quartile of *RegAmbiguity*	
Error%	1.26%	2.41%	4.09%	5.25%	**3.99%*****
Number of observations	81,519	82,258	84,893	81,895	
A.4: Subtracting industry-quarter mean					
	1st Quartile of *RegAmbiguity*	2nd Quartile of *RegAmbiguity*	3rd Quartile of *RegAmbiguity*	4th Quartile of *RegAmbiguity*	
Error%	2.52%	2.69%	2.89%	4.94%	**2.42%*****
Number of observations	82,678	82,616	82,602	82,669	

Panel B: Portfolio analyses based on exposure to rules on goodwill, hedge, lease, and warranty

	Raw Value		Portfolios Within Industry-Quarter		2 × 2 Size:*NItems* Portfolios Within Industry-Quarter	
B.1	(1) No Goodwill	(2) Goodwill	(3) No Goodwill	(4) Goodwill	(5) No Goodwill	(6) Goodwill
Error%	2.13%	3.56%	2.88%	3.58%	4.00%	4.30%
Number of Observations	306,718	151,092	906	906	3,693	3,693
	(2)–(1)	**1.43%*****	(4)–(3)	**0.70%*****	(6)–(5)	**0.30%*****

(*Continued*)

TABLE 3—*Continued*

Panel B: Portfolio analyses based on exposure to rules on goodwill, hedge, lease, and warranty

	Raw Value		Portfolios Within Industry-Quarter		2 × 2 Size: *NItems* Portfolios Within Industry-Quarter	
	(1)	(2)	(3)	(4)	(5)	(6)
B.2	No Hedging	Hedging	No Hedging	Hedging	No Hedging	Hedging
Error%	2.40%	4.45%	3.00%	4.68%	3.73%	5.04%
Number of observations	205,636	134,013	906	906	3,643	3,643
	(2)–(1)	**2.05%*****	(4)–(3)	**1.69%*****	(6)–(5)	**1.31%*****
B.3						
	No Lease	Lease	No Lease	Lease	No Lease	Lease
Error%	1.33%	2.84%	1.45%	3.21%	3.33%	3.84%
Number of observations	72,608	385,202	888	888	1,397	1,397
	(2)–(1)	**1.51%*****	(4)–(3)	**1.76%*****	(6)–(5)	**0.50%***
B.4						
	No Warranty	Warranty	No Warranty	Warranty	No Warranty	Warranty
Error%	2.88%	4.12%	3.37%	4.52%	3.88%	4.91%
Number of observations	248,930	90,719	906	906	3,704	3,704
	(2)–(1)	**1.24%*****	(4)–(3)	**1.16%*****	(6)–(5)	**1.04%*****

Panel A reports the percentage of firms that engage in unintentional misstatements in a quarter (*Error%*) for various subsamples of firms. Panel A.1 forms quartiles based on firms' nonmissing items in their quarterly financial statements (*NItems*). Panel A.2 forms quartiles based on adjusted *NItems*. Adjusted *NItems* is calculated as a firm's *NItems* in a quarter minus the mean *NItems* in the industry-quarter to which the firm-quarter belongs. Panel A.3 forms quartiles based on firms' *RegAmbiguity*. Panels A.4 forms quartiles based on adjusted *RegAmbiguity*. Adjusted *RegAmbiguity* is calculated as a firm's *RegAmbiguity* in a quarter minus the mean *RegAmbiguity* in the industry-quarter to which the firm-quarter belongs. The last column of each panel, labeled as (4)–(1), tests whether *Error%* in column (4) exceeds *Error%* in column (1). Panel B reports the percentage of firms that engage in unintentional misstatements in a quarter (*Error%*) for various subsamples of firms. Columns (1) and (2) of panel B.1 form subsamples based on firms' exposure to merger rules in the pooled sample. Columns (3) and (4) of panel B.1 form subsamples based on firms' exposure to merger rules within each industry-quarter. Columns (5) and (6) of panel B.1 first create 2 × 2 portfolios by sorting on firm size (*MV*) and then on firms' nonmissing items in their quarterly financial statements (*NItems*) within each industry-quarter, and next, they form subsamples based on firms' exposure to merger rules within each portfolio. Panels B.2–B.4 are structured analogously to panel B.1, based on firms' exposure to hedge rules, the lease rule, and the warranty rule, respectively. The last row of each panel tests whether *Error%* in column (2) exceeds *Error%* in column (1) using unpaired *t*-tests, whether *Error%* in column (4) exceeds *Error%* in column (3) using paired *t*-tests, and whether *Error%* in column (6) exceeds *Error%* in column (5) using paired *t*-tests, respectively. Detailed variable definitions are in appendix B. The sample period is between 1996Q1 and 2005Q4. The *t*-statistics are highlighted in bold. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

TABLE 4
The Relation Between Reporting Bias and Errors: Alternative Proxies for Errors

	(1)	(2)	(3)	(4)
Dependent Variables		$Bias_{i,q}$		
$NItems_{j,q}$	**7.741****			
	(3.682)			
$NItems^2{}_{j,q}$	**−3.953****			
	(1.636)			
$RegAmbiguity_{j,q}$		**0.862*****		
		(0.299)		
$RegAmbiguity^2{}_{j,q}$		**−0.088***		
		(0.048)		
$NItems_{i,q}$			**4.072*****	
			(1.413)	
$NItems^2{}_{i,q}$			**−1.203****	
			(0.521)	
$RegAmbiguity_{i,q}$				**0.321*****
				(0.074)
$RegAmbiguity^2{}_{i,q}$				**−0.029*****
				(0.007)
Controls	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year-Quarter Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	280,609	280,609	259,761	233,631
Pseudo R^2	7.57%	7.93%	7.70%	7.79%

This table reports the logit regression results on the relation between firm *i*'s bias propensity in quarter *q* (*Bias*) and alternative proxies for errors. In column (1), variance of errors is measured as the number of nonmissing items in quarterly financial statements (*NItems*), averaged for firms in industry *j*-quarter *q*. In column (2), variance of errors is measured as the degree of exposure to ambiguous accounting rules (*RegAmbiguity*), averaged for firms in industry *j*-quarter *q*. In column (3), variance of errors is measured as *NItems* for firm *i*-quarter *q*. In column (4), variance of errors is measured as *RegAmbiguity* for firm *i*-quarter *q*. $NItems^2$ and $RegAmbiguity^2$ are the squared terms of *NItems* and *RegAmbiguity*, respectively. Controls include firm *i*'s sales growth (*SaleGrowth*), market-to-book (*Q*), market capitalization (*MV*), number of analysts (*NAnalysts*), an indicator to denote equity issuance (*EquityIssue*), share turnover (*Turnover*), industry *j*'s number of firms (*NFirms*), percentage of firms delisted due to bankruptcy (*Bankruptcy*%), average percentage of independent board directors (*IndBoard*%), and average institutional ownership (*IO*). *Error*%, *Bankruptcy*%, and *IndBoard*% are in percentage points, *NFirms* is in thousands, and *NItems* is in hundreds. Detailed variable definitions are in appendix B. The sample period is between 1996Q1 and 2005Q4. Standard errors clustered by industry and year-quarter are displayed below the coefficient estimates in parentheses. The coefficient estimates on the key variables of interest are highlighted in bold. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

sorting, the difference in *Error*% between the non-rule exposing group and the rule-exposing group decreases in magnitude but remains statistically significant at the 10% level or lower. The only exception is that the difference in *Error*% between firms with exposure to the lease rule and those without is slightly larger when compared within industry-quarters than when compared in the pooled sample.

4.2.2. The Relation Between Bias Propensity and Alternative Proxies for Errors: Regression Analysis. Next, we relate *NItems* and *RegAmbiguity* to *Bias* in multivariate regression analyses. We first reestimate equation (6), replacing *Error*% with industry-quarter-level *NItems*. Table 4, column (1), reports the regression results including controls, as well as industry and year-quarter fixed effects. If *NItems* indeed captures the variation in errors' variance due to transaction complexity, it should behave similarly to *Error%*. As shown, *NItems* has a positive coefficient and its squared term has a negative coefficient, both significant at the 5% level. The turning point is near *NItems* = 98. The marginal effect is 3% when *NItems* is at its 25th percentile, 2% at its median, −3% at its 75th percentile, and −2% at its 99th percentile.[19] Column (2) repeats the analysis with industry-quarter-level *RegAmbiguity*. We again observe a hump-shaped relation between *Bias* and *RegAmbiguity*. The turning point occurs when *RegAmbiguity* = 4.87. The marginal effect is 0.4% when *RegAmbiguity* is at its 25th percentile, 0.5% at its median, 0.4% at its 75th percentile, and −0.1% at its 99th percentile. In these two columns, we give all firms of an industry-quarter equal weights in calculating *NItems* and *RegAmbiguity*. In table OA1 of the online appendix, we redefine the two proxies for an industry-quarter either as the median values or the market cap–weighted average values of firm-level *NItems* and *RegAmbiguity* observations from the industry-quarter. The results are qualitatively similar.

So far, we use only industry-quarter-level proxies for errors' variance in the regression analyses. With *NItems* and *RegAmbiguity* available at the firm level, we are able to conduct two analyses using firm-level proxies for errors' variance, which are more closely linked to our model. In column (3) of table 4, we reestimate equation (6) and regress *Bias* on firm-level *NItems* and its squared term $NItems^2$. We continue to include all controls and both industry and year-quarter fixed effects. A hump-shaped relation between *Bias* and firm-level *NItems* remains, and the turning point is now higher at *NItems* = 169. The marginal effect is 1.2% when *NItems* is at its 25th percentile, 1.3% at its median, 1.5% at its 75^{th} percentile, and −1% at its 99th percentile. In column (4), we repeat the analysis with firm-level *RegAmbiguity*. Again, we observe a hump-shaped relation between bias and firm-level *RegAmbiguity*. The turning point is near *RegAmbiguity* = 5.52. The marginal effect is 0.2% when *RegAmbiguity* is at its 25th percentile, 0.19% at its median, 0.14% at its 75th percentile, and −0.14% at its 99th percentile.

4.3 ADDITIONAL ANALYSES

4.3.1. Restatement Amount–Based Measures. Our primary proxies for bias propensity and errors' variance, *Bias* and *Error%*, are based on the incidence of misstatements. In this section, we seek to quantify the magnitude of bias and errors' variance. We face at least two challenges. First, a misstatement often has widespread effects on the books, making it difficult to identify and weigh the effects across accounts and statements. Second, compared to incidence-based measures, restatement amount–based measures are likely to be more susceptible to the effects of firm heterogeneity,

[19] Again, these marginal effects do not monotonically decrease because we estimate a quadratic logit model. For the derivation of marginal effect in such a model and a more detailed explanation, see footnotes 15 and 16.

because the former only require the unconditional probability of detection to be higher for more severe misstatements.[20]

Given the two challenges, we first define *Bias_amt* to capture the magnitude of bias in a firm-quarter. For an intentionally misstating firm, *Bias_amt* is calculated as the firm's magnitude of restatement in net income in the misstating quarter, scaled by the standard deviation of its quarterly net income over the last five years. *Bias_amt* is coded as zero for all other firm-quarters. We further define two measures to capture the magnitude of errors' variance in an industry-quarter. *Error_amt* is the average restatement amount in an industry-quarter (with restatement amount defined as the magnitude of the restatement in net income for a firm that engages in an unintentional misstatement in the quarter scaled by the standard deviation of its quarterly net income over the last five years and zero for all other firms). *Error_std* is similarly defined but uses the standard deviation of the restatement amount rather than its average magnitude. Restatement amounts are obtained from the Compustat unrestated quarterly files.[21]

Column (1) of table 5 reports the ordinary least squares (OLS) results replacing *Bias* and *Error%* with *Bias_amt* and *Error_amt* in equation (6), with controls and fixed effects included. Column (2) of table 5 replaces *Error_amt* with *Error_std*. The results in both columns are qualitatively similar to those reported in tables 2 and 4.

4.3.2. Controlling for Reporting Objectives. In this section, we assess the robustness of our core results to controlling for the distribution of the manager's reporting objective, that is, the x term in FV's model (and our model). The x term might confound our empirical analysis, because its variance, σ_x^2, affects $\frac{\beta}{c}$ in FV and x may be related to the proxies for bias propensity that we use if they are closer to $\frac{\beta}{c}x$ than to $\frac{\beta}{c}$.

FV list several factors to motivate the x term, including managers' compensation contracts, time horizon, rate of time preference, and degree of risk aversion. We focus on capturing the first two factors, because the other two are difficult to measure empirically. Specifically, we calculate, for each industry-quarter, the average CEO pay-for-performance sensitivity (*PPS_avg*), scaled wealth-performance sensitivity (*WPS_avg*), tenure

[20] Intuitively, the variance of firms' true earnings, σ_v^2, affects what constitute bias and errors of larger magnitude. A \$10,000 restatement in net income, for example, might be considered large for a firm with a \$20,000 standard deviation in net income but trivial for a firm with a \$2,000,000 standard deviation in net income.

[21] We acknowledge two limitations of *Bias_amt*, *Error_amt*, and *Error_std*. First, while focusing on the bottom line of the income statement allows us to capture the magnitude of misstatements in the single most important metric that influences market expectations and share prices (Kothari [2001]), we do not capture the effects of misstatement on other statements (such as balance sheet). Second, while scaling by earnings' variance helps remove the firm heterogeneity that defines the magnitude of bias propensity and errors' variance, it might not fully remove this heterogeneity.

TABLE 5
The Relation Between Reporting Bias and Errors: Restatement Amount–Based Proxies

	(1)	(2)
Dependent Variables	$Bias\_amt_{i,q}$	
$Error\_amt_{j,q}$	**0.721*****	
	(0.061)	
$Error\_amt^2_{j,q}$	**−1.880*****	
	(0.183)	
$Error\_std_{j,q}$		**0.013****
		(0.006)
$Error\_std^2_{j,q}$		**−0.001****
		(0.000)
Controls	Yes	Yes
Industry fixed effects	Yes	Yes
Year-quarter fixed effects	Yes	Yes
Number of observations	280,205	280,205
Adjusted R^2	0.1%	0.1%

This table reports the ordinary least squares (OLS) regression results on the relation between firm i's bias propensity in quarter q and variance of errors of the firm's industry j in the same quarter. Bias propensity is measured as the restatement amount in net income for an intentionally misstating firm i, scaled by the standard deviation of its quarterly net income in the last five years, and zero for all other firms (*Bias_amt*). In column (1), variance of errors is measured as the average scaled restatement in net income for firms in industry j-quarter q, with a firm's scaled restatement calculated as the firm's raw restatement amount divided by the standard deviation of its quarterly net income in the last five years (*Error_amt*). In column (2), variance of errors is measured as the standard deviation of the scaled restatement in net income for firms in industry j-quarter q, with a firm's scaled restatement calculated as the firm's raw restatement amount divided by the standard deviation of its quarterly net income in the last five years (*Error_std*). $Error\_amt^2$ and $Error\_std^2$ are the squared terms of *Error_amt* and *Error_std*, respectively. Controls include firm i's sales growth (*SaleGrowth*), market-to-book (Q), market capitalization (*MV*), number of analysts (*NAnalysts*), an indicator to denote equity issuance (*EquityIssue*), share turnover (*Turnover*), industry j's number of firms (*NFirms*), percentage of firms delisted due to bankruptcy (*Bankruptcy%*), average percentage of independent board directors (*IndBoard%*), and average institutional ownership (*IO*). *Error%*, *Bankruptcy%*, and *IndBoard%* are in percentage points, and *NFirms* is in thousands. Detailed variable definitions are in appendix B. The sample period is between 1996Q1 and 2005Q4. Standard errors clustered by industry and year-quarter are displayed below the coefficient estimates in parentheses. The coefficient estimates on the key variables of interest are highlighted in bold. *** and ** indicate significance at the 1% and 5% levels, respectively, using two-tailed tests.

(*Tenure_avg*), and length of vesting period in years (*Vesting_avg*) as proxies for the mean values of the x term. The first two proxies, calculated following Core and Guay [2002] and Edmans, Gabaix, and Landier [2009], respectively, capture CEOs' reporting objectives that might arise from the performance-contingent components of their compensation contracts. The last two proxies are shown to be related to CEO horizon (see Pan, Wang, and Weisbach [2016] on CEO tenure and Gopalan et al. [2014] and Edmans, Fang, and Lewellen [2017] on vesting horizon and impending vesting). We similarly calculate the standard deviation of CEO pay-for-performance sensitivity (*PPS_std*), scaled wealth-performance sensitivity (*WPS_std*), tenure (*Tenure_std*), and vesting period length (*Vesting_std*) within each industry-quarter as proxies for the variance of the x term. In table 6, we alternately include these measures as additional controls in equation (6), individually and jointly. The four proxies for the mean values of the x term load significantly in the expected direction in their respective regressions, suggesting that more equity incentives and shorter time

TABLE 6
The Relation Between Reporting Bias and Errors: Controlling for Reporting Objective

	(1)	(2)	(3)	(4)	(5)
Dependent Variables			$Bias_{i,q}$		
$Error\%_{j,q}$	**0.143*****	**0.145*****	**0.114****	**0.121****	**0.293*****
	(0.051)	(0.052)	(0.049)	(0.054)	(0.086)
$Error\%^2_{j,q}$	**−0.010*****	**−0.010****	**−0.008****	**−0.009****	**−0.018*****
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
$PPS\_avg_{j,q}$	0.001**				0.000
	(0.000)				(0.000)
$PPS\_std_{j,q}$	−0.000				0.000**
	(0.000)				(0.000)
$WPS\_avg_{j,q}$		0.003*			0.002
		(0.002)			(0.002)
$WPS\_std_{j,q}$		−0.009			−0.009
		(0.009)			(0.008)
$Tenure\_avg_{j,q}$			−0.131**		−0.111*
			(0.062)		(0.060)
$Tenure\_std_{j,q}$			0.179***		0.184***
			(0.060)		(0.068)
$Vesting\_avg_{j,q}$				−0.044*	−0.012*
				(0.024)	(0.006)
$Vesting\_std_{j,q}$				0.007	−0.095
				(0.034)	(0.059)
Controls	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes
Number of observations	278,961	280,609	278,390	239,799	238,550
Pseudo-R^2	8.00%	8.03%	8.09%	7.64%	7.34%

This table reports the logit regression results on the relation between firm *i*'s bias propensity in quarter *q* (*Bias*) and the error rate of the firm's industry *j* in the same quarter (*Error%*), controlling for the distribution of the reporting objective. $Error\%^2$ is the squared term of *Error%*. The distribution of the reporting objective is captured using the average and the standard deviation of the CEO pay-for-performance sensitivity for industry *j*-quarter *q* (*PPS_avg* and *PPS_std*) in column (1), the average and the standard deviation of the CEO scaled wealth-performance sensitivity for industry *j*-quarter *q* (*WPS_avg* and *WPS_std*) in column (2), the average and the standard deviation of CEO tenure for industry *j*-quarter *q* (*Tenure_avg* and *Tenure_std*) in column (3), the average and the standard deviation of CEO vesting period length for industry *j*-quarter *q* (*Vesting_avg* and *Vesting_std*) in column (4), and all of these measures in column (5), respectively. Controls include firm *i*'s sales growth (*SaleGrowth*), market-to-book (*Q*), market capitalization (*MV*), number of analysts (*NAnalysts*), an indicator to denote equity issuance (*EquityIssue*), share turnover (*Turnover*), industry *j*'s number of firms (*NFirms*), percentage of firms delisted due to bankruptcy (*Bankruptcy%*), average percentage of independent board directors (*IndBoard%*), and average institutional ownership (*IO*). *Error%*, *Bankruptcy%*, and *IndBoard%* are in percentage points, *NFirms* is in thousands, and *PPS_avg*, *PPS_std*, *WPS_avg*, and *WPS_std* are in tens. Detailed variable definitions are in appendix B. The sample period is between 1996Q1 and 2005Q4. Standard errors clustered by industry and year-quarter are displayed below the coefficient estimates in parentheses. The coefficient estimates on the key variables of interest are highlighted in bold. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

horizon increase bias propensity. The results on *Error%* and $Error\%^2$ are unaffected. We further calculate proxies to capture the distribution of the reporting objectives that might arise from CFOs' and other top executives' tenure and vesting periods when data are available. The results, in table OA2 of the online appendix, are not sensitive to controlling for these proxies. In table OA3, we control for the CEOs' reporting objectives measured at the firm level instead of the industry level. The results are robust despite smaller samples. We do not control for CEOs' vesting periods in this table due to limited data availability.

4.3.3. Robustness Checks. We now check the robustness of our core results to within-industry regressions, an alternative measure of reporting bias, several alternative definitions of the regulation ambiguity index, additional controls for fundamental volatility, outlier controls, and different sample periods and ways of clustering.

First, we reestimate equation (6) within each of the GICS 24 industry groups. Table OA4 of the online appendix reports the results from the within-industry regressions. Of the 24 GICS industries, we observe a hump-shaped relation between bias and errors in 17; an increasing, concave relation in two; an increasing, linear relation in two; and an insignificant relation in three. Therefore, the hump-shaped relation is applicable to a majority (i.e., 71%) of the industries.

Second, we repeat the analyses in table 2 with an alternative measure of bias, that is, an indicator variable that denotes whether a firm meets or beats the analyst consensus forecast by up to one cent in a quarter. A firm's tendency to meet or marginally beat the analyst consensus forecast is a widely accepted measure of earnings management (e.g., Bartov, Givoly, and Hayn [2002], Brown and Caylor [2005]). Unlike *Bias*, this measure is not affected by the detection rate of misstatements or the omission rate of restatement databases. Table OA5 of the online appendix reports results with this measure, which are qualitatively similar to those reported in table 2.

Third, we adopt alternative definitions of the regulation ambiguity index. We first redefine *RegAmbiguity* to capture changes in each set of rules from either 1996 or the prior year. The results are qualitatively similar and reported in table OA6, panel A of the online appendix. We then redefine *RegAmbituity* as the unscaled changes in each set of rules' number of interpretations (from either 1996 or the prior year). The results are also robust and tabulated in table OA6, panel B. Last, we redefine *RegAmbiguity* to exclude merger rules, hedge rules, and both, respectively. This is to address the concern that the increasingly lengthy and complicated accounting rules also reflect an increasing complexity of the underlying transactions (e.g., Schipper [2003]). In particular, rules on merger and hedging transactions might need to add more interpretations to accommodate the increasing difficulty in valuing intangible assets and the development of financial derivatives. The results, reported in table OA6, panel C, remain robust.

Fourth, we consider additional controls for fundamental volatility. For a given firm-quarter, we first calculate the firm-level control as the standard deviation of the firm's quarterly net income over the last five years. We then calculate the industry-quarter-level control as the standard deviation of the net income of all firms in the firm's industry-quarter. Table OA7 of the online appendix reports robust results controlling for the two proxies individually and jointly.

Fifth, we assess the effects of outliers. Columns (1) and (2) of table OA8 of the online appendix report similar results when we remove industry-quarters with error rates equal to or above the 99th percentile and the 95th percentile of the sample, respectively. In column (3), we remove sample observations from Consumer Services, Retailing, Food & Staples Retailing, and Telecommunication Services, the four industry groups with the highest error rates, and the results remain robust. In column (4), we remove 55 firms with both intentional and unintentional misstatements within four quarters from the sample. These firms could induce a spurious relation between bias and errors, because investigations into these firms' accounting errors may have led to the discovery of their reporting bias or vice versa. In our sample, these firms are associated with 1,847 firm-quarters, and the results are robust to removing these firm-quarters.

Sixth, we limit the samples in our core analyses to firm-quarters between 1996Q1 and 2005Q4 to mitigate truncation bias and ensure data availability to calculate all controls. We now define alternative sample periods to check for robustness. In column (1) of table OA9 of the online appendix, we assume a one-year lag between the time of misstatement and the time of detection for misstatements that occurred in the beginning and the ending quarters of the sample, and limit the sample to firm-quarters between 1996Q1 and 2005Q2. The results using this sample are similar to those reported in table 2. The results are also similar if we include firm-quarters between 1995Q1 and 2004Q2, thus assuming a two-year lag, or include firm-quarters between 1995Q1 and 2004Q4, as columns (2) and (3) show. In the last column, we include all firm-quarters between 1992Q1 and 2006Q2 without correcting for truncation bias. The results are again robust. Note that we omit *IndBoard%* as a control in columns (2)–(4), because the ISS data start in 1996.

Finally, we experiment with an alternative way of clustering. In the core analyses, we cluster standard errors by industry and year-quarter to avoid inflating *t*-statistics (Petersen [2009]), because reporting bias might be autocorrelated over time within an industry or correlated across industries in a given quarter. In table OA10 of the online appendix, we repeat the analyses in column (5) of table 2 and those in table 4, but instead cluster standard errors by firm and year-quarter. Clustering by firm helps correct the bias in standard errors if bias is autocorrelated over time within a firm. The results are similar to those previously reported.

In summary, our results show a hump-shaped relation between firms' bias propensity and errors' variance that is measured at either the industry or the firm level. This relation is robust to using alternative proxies for bias and errors and to including various controls and fixed effects. A hump-shaped relation between bias and errors is consistent with errors having counteracting effects on bias. Further, the empirically relevant range we observe is the increasing, concave part of the hump, suggesting that the camouflage effect likely dominates the value relevance–reducing effect for a majority of our sample firms.

5. *The Value Relevance–Reducing Effect and the Camouflage Effect*

In this section, we seek to bolster our earlier findings by directly testing for the two effects of errors on bias, namely, the value relevance–reducing effect and the camouflage effect.

First, we test for the value relevance–reducing effect by studying the market reaction at earnings announcements. This effect predicts that the sensitivity of price to earnings decreases with errors' variance, so we expect to find a lower earnings response coefficient (ERC) when errors are more prevalent.[22] We estimate the following model at the firm-quarter level:

$$CAR_{i,q} = \alpha + \beta_1 UE_{i,q} + \beta_2 Error\%_{j,q} + \beta_3 Error\%_{j,q} \times UE_{i,q} + Control\_ERC + \varepsilon_{i,q}. \tag{7}$$

CAR is the cumulative three-day market-adjusted return, centered on firm *i*'s earnings announcement date. *UE* is the unexpected earnings (or earnings surprises), calculated as the difference between the firm's EPS of quarter *q* and its EPS of quarter *q*-4, scaled by price 10 days before the earnings announcement. *Error%* is defined as before. For this analysis, we exclude firm-quarters for which the financial statements are subsequently restated.

Control_ERC contains a number of controls that prior literature uses in ERC models (e.g., Hayn [1995], Chen, Cheng, and Lo [2014]), including an indicator variable to denote firms that report a loss for a quarter (*Loss*), an indicator variable to denote the fourth quarter of a fiscal year (*Q4*), market capitalization (*MV*), market-to-book ratio (*Q*), and stock beta estimated over (−365, −60) days relative to earnings announcement dates (*Beta*), as well as the interaction terms between these variables and *UE*. It also includes *NFirms*, the size of the industry to which the firm belongs, and its interaction with *UE*. We continue to include industry and year-quarter fixed effects.

The results of estimating equation (7) are reported in table 7. Column (1) excludes *Error%* and its interaction with *UE*. The coefficient on *UE* is significantly positive, consistent with higher unexpected earnings

[22] Here we intend to examine the effect of an industry's error rate on its member firms' ERC. In related studies, Wilson [2008] and Chen, Cheng, and Lo [2014] investigate whether firms with material restatements experience a significant decrease in their future ERC, and Palmrose, Richardson, and Scholz [2004] investigate whether the market reacts more negatively to announcements of bias-related restatements than to those of error-related restatements.

TABLE 7

The Effect of Reporting Errors on ERC

	(1)	(2)	(3)
Dependent Variables		$CAR_{i,q}$	
$UE_{i,q}$	0.202***	0.214***	0.214***
	(0.017)	(0.016)	(0.016)
$Error\%_{j,q}$		−0.000	
		(0.000)	
$Error\%_{j,q} \times UE_{i,q}$		**−0.003*****	
		(0.001)	
$Error\%_{j,q-1}$			−0.000
			(0.000)
$Error\%_{j,q-1} \times UE_{i,q}$			**−0.003*****
			(0.001)
$Loss_{i,q}$	−0.024***	−0.024***	−0.024***
	(0.001)	(0.001)	(0.001)
$Loss_{i,q} \times UE_{i,q}$	−0.101***	−0.101***	−0.101***
	(0.008)	(0.008)	(0.008)
$Q4_{i,q}$	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
$Q4_{i,q} \times UE_{i,q}$	−0.024***	−0.025***	−0.024***
	(0.007)	(0.006)	(0.006)
$MV_{i,q}$	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)
$MV_{i,q} \times UE_{i,q}$	−0.011***	−0.012***	−0.012***
	(0.002)	(0.002)	(0.002)
$Q_{j,q}$	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)
$MB_{i,q} \times UE_{i,q}$	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
$Beta_{i,q}$	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)
$Beta_{i,q} \times UE_{i,q}$	−0.003	−0.002	−0.002
	(0.003)	(0.003)	(0.003)
$NFirms_{j,q}$	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
$NFirms_{j,q} \times UE_{i,q}$	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
Intercept	0.010***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)
Industry fixed effects	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes
Number of observations	221,241	221,241	221,241
Adjusted R^2	2.94%	2.95%	2.95%

This table reports the OLS regression results on the relation between the market reaction at earnings announcements (*CAR*) and unexpected earnings (*UE*), and the relation between *CAR* and *UE*'s interaction with variance of errors. Variance of errors is measured as industry *j*'s percentage of firms that engage in unintentional misstatements (*Error%*) in quarter *q* and quarter $q-1$ in columns (2) and (3), respectively. Controls, measured for firm *i*-quarter *q*, include an indicator variable to denote loss firms (*Loss*), an indicator variable to denote the fourth fiscal quarter (*Q4*), market capitalization (*MV*), market-to-book (*Q*), stock beta (*Beta*), number of firms in the firm's industry (*NFirms*), and the interaction between these variables and *UE*. *Error%* is in percentage points, and *NFirms* is in thousands. Detailed variable definitions are in appendix B. The sample period is between 1996Q1 and 2005Q4. Standard errors clustered by industry and year-quarter are displayed below the coefficient estimates in parentheses. The coefficient estimates on the key variables of interest are highlighted in bold. *** and ** indicate significance at the 1% and 5% levels, respectively, using two-tailed tests.

leading to a more favorable market reaction. Coefficients on controls are generally consistent with those in prior literature. Column (2) includes *Error%* and its interaction with *UE*. Our prediction is $\beta_3 < 0$. Consistent with our prediction, the coefficient on this interaction term is negative and significant at the 1% level, indicating that the market indeed responds less to a firm's earnings surprise when accounting errors are more prevalent in its industry. In column (3), we repeat the analysis, lagging *Error%* by one quarter relative to the quarter for which we measure *CAR* to allow the market to form an expectation of the errors' variance based on what it infers from the prior quarter. The results are similar.

We conduct three additional analyses to check for robustness. First, we follow Hirshleifer, Lim, and Teoh [2009] and estimate a model that augments equation (7) by also interacting *UE* with industry and year-quarter fixed effects. The results are consistent with those in table 7 and reported in table OA11 of the online appendix. Second, we redefine *UE* as the difference between the firm's EPS of a given quarter and the latest mean analyst consensus forecast prior to the earnings announcement, scaled by price 10 days before the earnings announcement. The results, reported in table OA12, remain robust, despite a smaller sample. Third, we measure *CAR* over alternative windows surrounding the earnings announcements. If it is indeed the accounting noise in a firm's report (as opposed to the uncertainty in firm fundamentals) that attenuates the market reaction at earnings announcements, the observed effect should be relatively persistent when we widen the measurement window of announcement returns. Table OA13 reports robust results measuring *CAR* over longer windows of up to 40 trading days after earnings announcements.

Next, we test for errors' camouflage effect. This effect posits that a manager's costs of biasing reported earnings decrease with errors' variance, because it is more difficult for market participants to detect fraud when errors are more prevalent. We estimate a Cox proportional odds model (Allison [1995]), specified as

$$Undetected_{i,q} = \alpha + \beta_1 Error\%_i + Control\_Detect + \varepsilon_{i,q}. \tag{8}$$

In building the sample for this analysis, we include, for each intentionally misstating firm i, all quarters from the one in which the misstatement begins till the one in which it is detected. *Undetected* indicates whether a misstating firm survives detection in quarter q, which equals 0 for the quarter in which the misstatement is detected and 1 for all quarters prior to that. *Error%* is the error rate of the firm's industry for the quarter in which the firm engages in misstatement; for misstatements that span multiple quarters, *Error%* is the error rate of the firm's industry averaged over all misstating quarters. *Control_Detect* includes controls used in Karpoff and Lou [2010] and Fang, Huang, and Karpoff [2016] that are shown to affect the probability of fraud detection. *Qtrs* measures the time elapsed since a misstatement begins, which equals the number of quarters from the beginning of the misstatement to quarter q. Its squared term, $Qtrs^2$, is included for

TABLE 8

The Effect of Reporting Errors on the Detection of Reporting Bias

Dependent Variables	$Undetected_{i,q}$
$Error\%_i$	**0.318*** **
	(0.081)
$Qtrs_{i,q}$	−0.183***
	(0.023)
$Qtrs^2_{i,q}$	0.005***
	(0.001)
$Size_{i,q}$	0.117***
	(0.044)
$Q_{j,q}$	0.003
	(0.018)
$Momentum_{i,q}$	0.543***
	(0.114)
$BiasCAR_i$	1.274***
	(0.303)
$NFirms_{j,q}$	−0.001
	(0.001)
Intercept	−0.101
	(0.717)
Industry fixed effects	Yes
Year-quarter fixed effects	Yes
Number of observations	5,702
Pseudo-R^2	16.01%

This table reports the logit regression results on the relation between the probability of an intentionally misstating firm i surviving detection in quarter q after the misstatement begins but before it is detected (*Undetected*) and the error rate of the firm's industry j in the misstating quarter(s) (*Error%*). The regression is estimated using the subsample of firms that engage in intentional misstatements. Controls, measured for firm i-quarter q, include the number of quarters from the beginning of the misstatement to quarter q (*Qtrs*), its squared term ($Qtrs^2$), total assets (*Size*), market-to-book (Q), stock momentum (*Momentum*), market reaction at the initial announcement of the misstatement (*BiasCAR*), and number of firms in the firm's industry (*NFirms*). *Error%* is in percentage points, and *NFirms* is in thousands. Detailed variable definitions are in appendix B. The sample period is between 1996Q1 and 2005Q4. Standard errors clustered by firm are displayed below the coefficient estimates in parentheses. The coefficient estimate on the key variable of interest is highlighted in bold. *** indicates significance at the 1% level, using two-tailed tests.

possible nonlinearity in the relation between the probability of survival and *Qtrs*. *Size* and Q are firms' total assets and market-to-book ratio of quarter q, *Momentum* is the buy-and-hold return over the past 12 months, and *BiasCAR* is the cumulative three-day market-adjusted return centered on the initial revelation date of the misstatement. We continue to include *NFirms* and fixed effects.

Table 8 presents the logit regression results of estimating equation (8). Our particular interest is in the coefficient on *Error%*. As shown, it is positive and significant at the 1% level, indicating that intentional misstatements by firms in industries with higher error rates are more difficult to detect, exactly as the camouflage effect would predict.[23]

[23] Although we cluster the standard errors by firm in table 8 because the sample is at the firm level, the results are similar if we cluster by industry and year-quarter.

To summarize, this section provides empirical support for the two key effects that we model. The results from the first test demonstrate that errors decrease the sensitivity of stock price to unexpected earnings at earnings announcements, consistent with the value relevance–reducing effect of errors. The results from the second test highlight the camouflage effect of errors: Errors make it more difficult to detect intentional misstatements. Together, these results help validate our model's assumptions and corroborate our findings in section 4.

6. *Conclusion*

Accounting is an imperfect information system, and both bias and errors are inherent to it. Accounting theories recognize the importance of errors in addition to bias. Christensen [2010], in particular, points out that "Accounting should pay more attention to errors, as errors are essential for the updating of beliefs." The empirical literature, however, gives scant attention to errors. Existing studies of corporate misstatements tend to focus on bias-related errors, either overlooking error-related ones or considering them as extraneous events that need to be removed. In this paper, we give primary attention to errors and link them to firms' reporting incentives.

We first document a hump-shaped relation between a firm's propensity to bias reported earnings and the error rate in the firm's industry. We then use firms' number of nonmissing items in their quarterly filings and firms' degree of exposure to potentially ambiguous accounting rules as alternative proxies to capture errors' variance that stems from transaction complexity and regulation ambiguity. We confirm the relevance of these two proxies to the incidence of errors and show that both proxies are related to firms' bias propensity in the same way that the incidence of errors is. The hump-shaped relation is also robust to using restatement amount–based measures to quantify the magnitude of bias propensity and errors' variance, as well as to controlling for the distribution of managers' reporting objectives. The hump-shaped relation exists in the pooled sample and a majority of the industries. The turning point of the observed hump is high compared to the average error rate in the respective samples, suggesting that, in our sample, the most likely effect of a decrease in errors' variance is to lower firms' incentives to bias reported earnings.

The results highlight important economic implications of accounting errors. In our model, a hump-shaped relation arises only if errors have counteracting effects on firms' bias propensity: The camouflage effect dominates when errors' variance is low, and the value relevance–reducing effect takes over when variance is high. Our observation of such a relation in the data is consistent with the existence of the two effects. As further support, we show that firms in industries with more prevalent errors have lower earnings response coefficients, and intentional misstatements by such firms are more difficult to catch.

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

This paper leaves several questions unanswered. First, staffing deficiency is often noted as another major contributor to reporting errors. In the same speech mentioned earlier, for example, Scott Taub remarks 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." In this study, however, we are unable to identify a good proxy for staffing deficiency. Second, a study of the relative importance of transaction complexity and regulation ambiguity as two causes of errors would be intriguing, but it is beyond the scope of this paper. These questions might be interesting to examine for future research.

APPENDIX A

Proofs and Graphical Illustrations

H1a (in mathematical terms): If $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}|_{\sigma_n^2=0} > \frac{\beta^*}{c}|_{\sigma_n^2=0}$ and if $\frac{d\varphi}{d\sigma_n^2} > 0$ and $\frac{d^2\varphi}{d(\sigma_n^2)^2} < 0$ for any $\sigma_n^2 \in [0, \overline{\sigma_n^2}]$, given a sufficiently high $\overline{\sigma_n^2}$, there exists a σ_n^{*2} such that $\frac{\beta^*}{c}$ increases with σ_n^2 when $\sigma_n^2 \leq \sigma_n^{*2}$ and

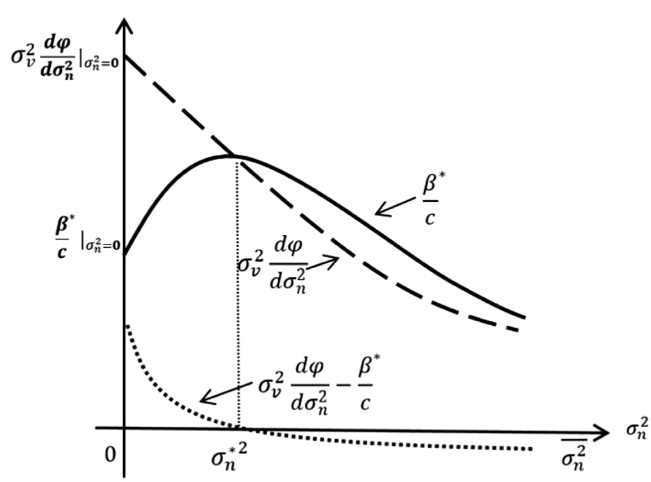

FIG. A.1.—A generic plot that depicts possible trajectories of $\frac{\beta^*}{c}$, $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}$, and $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$ to illustrate H1a.

decreases with σ_n^2 when $\sigma_n^2 > \sigma_n^{*2}$, where $\sigma_n^{*^2}$ is the turning point that solves the equation $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} = \frac{\beta^*}{c}$.

Proof. We focus on equation (5) of section 2, which we reproduce as follows:

$$\frac{d\left(\frac{\beta^*}{c}\right)}{d\sigma_n^2} = \frac{\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}}{3\sigma_x^2\left(\frac{\beta^*}{c}\right)^2 + \left(\sigma_v^2 + \sigma_n^2\right)} + \frac{-\frac{\beta^*}{c}}{3\sigma_x^2\left(\frac{\beta^*}{c}\right)^2 + \left(\sigma_v^2 + \sigma_n^2\right)}. \quad \text{(A.1)}$$

The two terms on the right-hand side of equation (A.1) share the same denominator, which is strictly positive, so the sign of $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}$ is determined by $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$.

The proof next analyzes the sign of $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$ for $\sigma_n^2 \in [0\ ,\ \overline{\sigma_n^2}]$, and figure A.1, as a generic plot, illustrates the intuition of the proof. In the figure, the solid line and the dashed line depict possible trajectories of $\frac{\beta^*}{c}$ and $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}$, respectively. The dotted line draws the difference between the two lines, which represents $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$ and is proportional to $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}$, as shown in equation (A.1).

First, the assumption $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}|_{\sigma_n^2=0} > \frac{\beta^*}{c}|_{\sigma_n^2=0}$ holds that $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$ starts out positive, as the figure shows. As σ_n^2 increases, there exists a connected regime in which $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$ remains positive because of its continuity. Equation (A.1) implies that $\frac{\beta^*}{c}$ increases with σ_n^2 in this regime, as $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2} > 0$. The function $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$itself, however, decreases with σ_n^2 in the regime, because (1) $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}$ decreases with σ_n^2 by the assumption of $\frac{d^2\varphi}{d(\sigma_n^2)^2} < 0$, and (2) $-\frac{\beta^*}{c}$ decreases with σ_n^2, given that $\frac{\beta^*}{c}$ increases with σ_n^2.

Second, assuming that $\overline{\sigma_n^2}$ is sufficiently high, we prove that there exists a local maximum point σ_n^{*2} at which $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2} = 0$ and $\frac{d^2(\frac{\beta^*}{c})}{d(\sigma_n^2)^2} < 0$. Given that $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$ is continuous and decreases with σ_n^2 when the function itself is positive, there must exist a critical point σ_n^{*2} at which $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c} = 0$. Equation (A.1) then implies that $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2} = 0$ when $\sigma_n^2 = \sigma_n^{*2}$. The second-order derivative of $\frac{\beta^*}{c}$ with respect to σ_n^2 can be derived as follows:

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

$$-\frac{\left(\sigma_v^2\frac{d\varphi}{d\sigma_n^2}-\frac{\beta^*}{c}\right)\left(6\sigma_x^2\left(\frac{\beta^*}{c}\right)\frac{d\left(\frac{\beta^*}{c}\right)}{d\sigma_n^2}+1\right)}{\left[3\sigma_x^2\left(\frac{\beta^*}{c}\right)^2+\left(\sigma_v^2+\sigma_n^2\right)\right]^2}. \tag{A.2}$$

Because $\sigma_v^2\frac{d\varphi}{d\sigma_n^2}-\frac{\beta^*}{c}=0$ and $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}=0$ when $\sigma_n^2=\sigma_n^{*2}$, the second-order derivative at this point is

$$\frac{d^2\left(\frac{\beta^*}{c}\right)}{d\left(\sigma_n^2\right)^2}|_{\sigma_n^2=\sigma_n^{*2}}=\left.\frac{\sigma_v^2\frac{d^2\varphi}{d\left(\sigma_n^2\right)^2}}{3\sigma_x^2\left(\frac{\beta^*}{c}\right)^2+\left(\sigma_v^2+\sigma_n^2\right)}\right|_{\sigma_n^2=\sigma_n^{*2}}. \tag{A.3}$$

Under the assumption of $\frac{d^2\varphi}{d(\sigma_n^2)^2}<0$, equation (A.3) is strictly negative. Hence, at the point of $\sigma_n^2=\sigma_n^{*2}$, the bias propensity, $\frac{\beta^*}{c}$, reaches its local maximum. We also illustrate this point in figure A.1.

Third, we prove that $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}$ remains negative for any $\sigma_n^2\in(\sigma_n^{*2},\ \overline{\sigma_n^2}]$; that is, σ_n^{*2} is also the global maximum point. First, note that σ_n^{*2} is a local maximum point as we prove above, so there exists a positive ε such that $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}<0$ for any $\sigma_n^2\in(\sigma_n^{*2},\ \sigma_n^{*2}+\ \varepsilon)$. Now we prove that $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}<0$ holds for any $\sigma_n^2\in(\sigma_n^{*2},\ \overline{\sigma_n^2}]$. To see this, substitute $\sigma_v^2\frac{d\varphi}{d\sigma_n^2}-\frac{\beta^*}{c}=\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}\ (3\sigma_x^2(\frac{\beta^*}{c})^2+(\sigma_v^2+\sigma_n^2))$ derived from equation (A.1) into equation (A.2), and we get

$$\frac{d^2\left(\frac{\beta^*}{c}\right)}{d\left(\sigma_n^2\right)^2}=\frac{\sigma_v^2\frac{d^2\varphi}{d\left(\sigma_n^2\right)^2}-\left(2+6\left(\frac{\beta^*}{c}\right)\frac{d\left(\frac{\beta^*}{c}\right)}{d\sigma_n^2}\right)\frac{d\left(\frac{\beta^*}{c}\right)}{d\sigma_n^2}}{3\sigma_x^2\left(\frac{\beta^*}{c}\right)^2+\left(\sigma_v^2+\sigma_n^2\right)}. \tag{A.4}$$

If $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}$ ever approaches zero from a negative value, $\frac{d^2(\frac{\beta^*}{c})}{d(\sigma_n^2)^2}$ approaches the value of $\frac{\sigma_v^2\frac{d^2\varphi}{d(\sigma_n^2)^2}}{3\sigma_x^2(\frac{\beta^*}{c})^2+(\sigma_v^2+\sigma_n^2)}$, which is strictly negative, because $\frac{d^2\varphi}{d(\sigma_n^2)^2}<0$. This means that if the trajectory of $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}$ starts with a negative value, $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}$ never turns positive, because when $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}$ gets sufficiently close to zero from the negative, its local derivative, $\frac{d^2(\frac{\beta^*}{c})}{d(\sigma_n^2)^2}$, becomes negative and prevents $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}$ from reaching zero. As a result, $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}<0$ holds for any $\sigma_n^2\in[\sigma_n^{*2},\ \overline{\sigma_n^2}]$, and $\frac{\beta^*}{c}$ decreases with σ_n^2 in this regime. $\square$

H1b (in mathematical terms): If $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}|_{\sigma_n^2=0} > \frac{\beta^*}{c}|_{\sigma_n^2=0}$ and if $\frac{d\varphi}{d\sigma_n^2} > 0$ and $\frac{d^2\varphi}{d(\sigma_n^2)^2} > 0$ for any $\sigma_n^2 \in [0, \overline{\sigma_n^2}]$, $\frac{\beta^*}{c}$ strictly increases with σ_n^2.

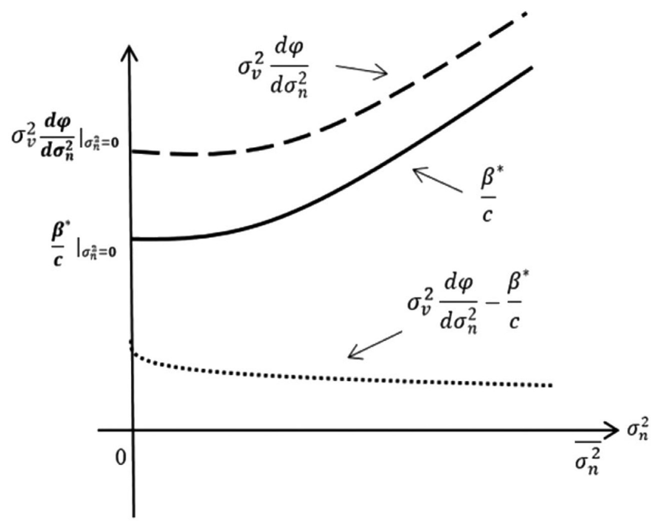

FIG. A.2.—A generic plot that depicts possible trajectories of $\frac{\beta^*}{c}$, $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}$, and $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$ to illustrate H1b.

Proof. If $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}|_{\sigma_n^2=0} > \frac{\beta^*}{c}|_{\sigma_n^2=0}$, $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$ starts out positive, so $\frac{\beta^*}{c}$ increases with σ_n^2 initially. Since $\frac{d^2\varphi}{d(\sigma_n^2)^2} > 0$, $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}$ also increases with σ_n^2. It is easy to verify that $\frac{\beta^*}{c}$ can never catch up with $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}$. This is because whenever $\frac{\beta^*}{c}$ approaches $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}$ from below, $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$ decreases and approaches zero, preventing $\frac{\beta^*}{c}$ from reaching $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}$. Hence, $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$ is always positive, and $\frac{\beta^*}{c}$ strictly increases with σ_n^2. □

H2a (in mathematical terms): If $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}|_{\sigma_n^2=0} < \frac{\beta^*}{c}|_{\sigma_n^2=0}$ and if $\frac{d\varphi}{d\sigma_n^2} > 0$ and $\frac{d^2\varphi}{d(\sigma_n^2)^2} > 0$ for any $\sigma_n^2 \in [0, \overline{\sigma_n^2}]$, given a sufficiently high $\overline{\sigma_n^2}$, there exists a σ_n^{*2} such that $\frac{\beta^*}{c}$ decreases with σ_n^2 when $\sigma_n^2 \leq \sigma_n^{*2}$ and increases with σ_n^2 when $\sigma_n^2 > \sigma_n^{*2}$, where σ_n^{*2} is the turning point that solves the equation $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} = \frac{\beta^*}{c}$.

Proof. The proof of this prediction closely follows that of H1a and also involves three steps. First, it is easy to see that if $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}|_{\sigma_n^2=0} <$

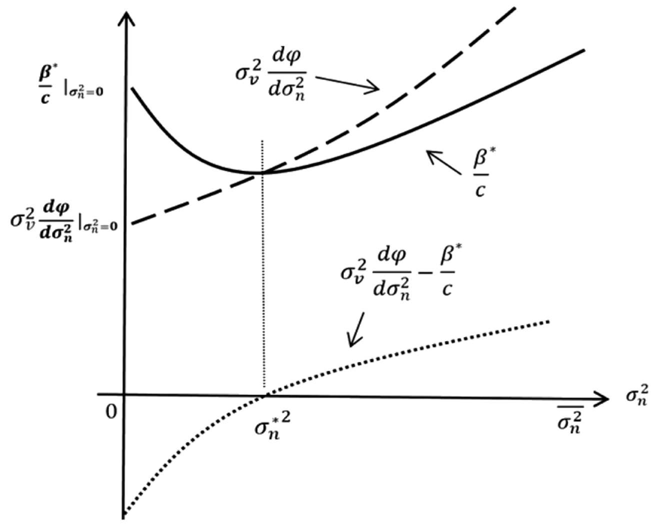

FIG. A.3.—A generic plot that depicts possible trajectories of $\frac{\beta^*}{c}$, $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}$, and $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$ to illustrate H2a.

$\frac{\beta^*}{c}|_{\sigma_n^2=0}$, $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$ starts out negative, $\frac{\beta^*}{c}$ decreases with σ_n^2 initially. The term $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$, however, increases with σ_n^2, because $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}$ increases with σ_n^2 (by the assumption $\frac{d^2\varphi}{d(\sigma_n^2)^2} > 0$) and $-\frac{\beta^*}{c}$ increases with σ_n^2. Second, following an argument similar to that in the proof of H1a, we can prove that there exists a σ_n^{*2} such that $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} = \frac{\beta^*}{c}$ (so $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2} = 0$) and $\frac{d^2(\frac{\beta^*}{c})}{d(\sigma_n^2)^2} > 0$, and thus σ_n^{*2} is the local minimal point. Third, we can prove that σ_n^{*2} is also the global minimal point; that is, $\frac{\beta^*}{c}$ decreases with σ_n^2 when $\sigma_n^2 \leq \sigma_n^{*2}$ and increases with σ_n^2 when $\sigma_n^2 > \sigma_n^{*2}$. □

H2b (in mathematical terms): If $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}|_{\sigma_n^2=0} < \frac{\beta^*}{c}|_{\sigma_n^2=0}$ and if $\frac{d\varphi}{d\sigma_n^2} > 0$ and $\frac{d^2\varphi}{d(\sigma_n^2)^2} < 0$ for any $\sigma_n^2 \in [0\,,\ \overline{\sigma_n^2}]$, $\frac{\beta^*}{c}$ strictly decreases with σ_n^2.

Proof. The proof of this prediction closely follows that of H1b. The assumption $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}|_{\sigma_n^2=0} < \frac{\beta^*}{c}|_{\sigma_n^2=0}$ holds that $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$ starts out negative, as figure A.4 shows. By the same logic laid out in the third step of the proof to Hypothesis 1a, when $\frac{d(\frac{\beta^*}{c})}{d\sigma_n^2}$ starts out negative, it never turns positive if $\frac{d\varphi}{d\sigma_n^2} > 0$ and $\frac{d^2\varphi}{d(\sigma_n^2)^2} < 0$ hold for any $\sigma_n^2 \in [0\,,\ \overline{\sigma_n^2}]$. Therefore, $\frac{\beta^*}{c}$ strictly decreases with σ_n^2. □

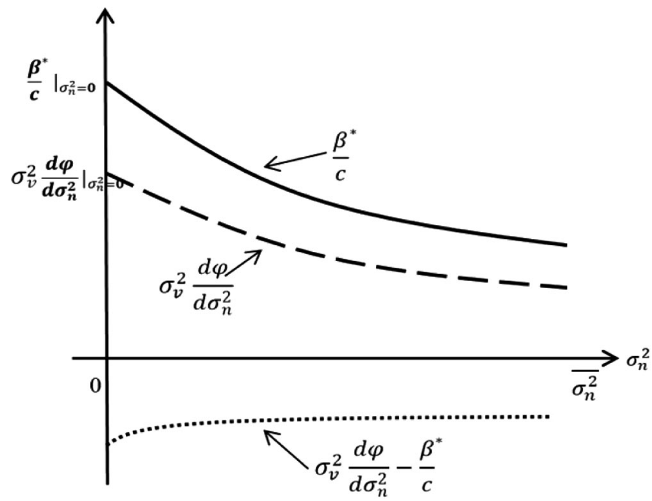

FIG. A.4.—A generic plot that depicts possible trajectories of $\frac{\beta^*}{c}$, $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2}$, and $\sigma_v^2 \frac{d\varphi}{d\sigma_n^2} - \frac{\beta^*}{c}$ to illustrate H2b.

APPENDIX B
Variable Definitions

Variable Name	Definition
Proxies for Bias Propensity in the Core Analyses	
$Bias_{i,q}$	An indicator variable that equals 1 if firm *i* has been identified by HLM as engaging in an intentional misstatement in quarter *q*, and 0 otherwise. HLM classify the restatement sample of the GAO Financial Restatement Database according to managerial intent, using a combination of keyword searches for variants of the words “fraud” and “irregularity,” whether there is an SEC enforcement action, and whether there is an investigation into a misstating firm’s accounting matters. Misstating periods are collected first from AA and then supplemented with data collected manually by Burns and Kedia [2006] (also Burns, Kedia, and Lipson [2010]) and Files [2012], in that order. We collect the remaining data from firms’ filings (e.g., 8-Ks and 10-Ks) on the SEC’s Web site.
$Bias\_amt_{i,q}$	The restatement amount in net income by firm *i*, scaled by the standard deviation of its net income (NIQR if it is restated and NIQ if not restated) over the last five years if firm *i* engages in an intentional misstatement in quarter *q*, or 0 otherwise. The restatement amount is calculated as the absolute difference between the restated net income (NIQR) and the unrestated net income (NIQ), both obtained from the Compustat unrestated quarterly files.

(Continued)

APPENDIX B—*Continued*

Variable Name	Definition
Proxies for Errors' Variance in the Core Analyses	
$Error\%_{j,q}$	Industry *j*'s percentage of firms identified by HLM as engaging in unintentional misstatements in quarter *q*, in percentage points. The sample selection is similar to that for $Bias_{i,q}$.
$NItems_{j,q}$ ($NItems_{i,q}$)	$NItems_{j,q}$ is the average $NItems_{i,q}$ for industry *j*-quarter *q*. $NItems_{i,q}$ is firm *i*'s number of nonmissing items in its quarterly financial statements in quarter *q*, in hundreds. The financial statement items are obtained from the Compustat quarterly files.
$RegAmbiguity_{j,q}$ ($RegAmbiguity_{i,q}$)	$RegAmbiguity_{j,q}$ is the average $RegAmbiguity_{i,q}$ for industry *j*-quarter *q*. $RegAmbiguity_{i,q}$ is the sum of $M\&A_{i,q} \times M\&ARuleAmbiguity_q$, $Hedge_{i,q} \times HedgeRuleAmbiguity_q$, $Lease_{i,q} \times LeaseRuleAmbiguity_q$, and $Warranty_{i,q} \times WarrantyRuleAmbiguity_q$ for firm *i*-quarter *q*. $M\&A_{i,q}$ equals 1 if firm *i* reports goodwill on its balance sheet (based on GDWLQ in the Compustat quarterly files and GDWL in the annual files if GDWLQ is missing) in quarter *q*, and 0 otherwise. $Hedge_{i,q}$ equals 1 if we locate the keyword "hedging" or "hedge(s)," but not "hedge fund(s)" in firm *i*'s 10-Q filings in quarter *q*, and 0 otherwise. $Lease_{i,q}$ equals 1 if firm *i* reports operating leases or capital leases (i.e., if it reports a nonmissing value in MRC1, MRC2, MRC3, MRC4, MRC5, MRCTA or CLD2, CLD3, CLD4, CLD5, DCLO, all from the Compustat annual files) in quarter *q*, and 0 otherwise. $Warranty_{i,q}$ equals 1 if we locate the keyword "warranty" or "warranties" in firm *i*'s 10-Q filings in quarter *q*, and 0 otherwise. $M\&ARuleAmbiguity_q$ is the sum of the number of interpretations in *FAS 141*: *Business Combinations* and *FAS 142*: *Goodwill and Other Intangible Assets* (or *APB 16: Business Combinations* and *APB 17: Intangible Assets* prior to 2001) in the year to which quarter *q* belongs, scaled by the sum of the number of interpretations in APB 16 and APB 17 in 1996, the first year of our sample period. $HedgeRuleAmbiguity_q$ is the number of interpretations in *FAS 133: Accounting for Derivative Instruments and Hedging Activities* (or the sum of the number of interpretations in *FAS 80: Accounting for Futures Contracts*, *FAS 105: Disclosure of Information About Financial Instruments with Off-Balance-Sheet Risk and Financial Instruments with Concentrations of Credit Risk*, and *FAS 119: Disclosure About Derivative Financial Instruments and Fair Value of Financial Instruments* prior to 2000) in the year to which quarter *q* belongs, scaled by the sum of the number of interpretations in FAS 80, FAS 105, and FAS 119 in 1996. $LeaseRuleAmbiguity_q$ is the number of interpretations in *FAS 13: Accounting for Leases* in the year to which quarter *q* belongs, scaled by the rule's number of interpretations in 1996. $WarrantyRuleAmbiguity_q$ is the number of interpretations in *FAS 5: Accounting for Contingencies* in the year to which quarter *q* belongs, scaled by the rule's number of interpretations in 1996.

(Continued)

APPENDIX B—*Continued*

Variable Name	Definition
$Error\_amt_{j,q}$ ($Error\_std_{j,q}$)	$Error\_amt_{j,q}$ is the average scaled restatement in net income for industry j-quarter q. For firms that engage in unintentional misstatements, scaled restatement is calculated as the magnitude of the raw restatement amount divided by the standard deviation of its quarterly net income over the last five years. Scaled restatement is zero for all other firms. $Error\_std_{j,q}$ is defined similarly as $Error\_amt_{j,q}$ but uses the standard deviation of the scaled restatement in net income, rather than its average. The restatement amount is calculated as the absolute difference between the restated net income and the unrestated net income, both obtained from the Compustat unrestated quarterly files.
Control Variables in the Core Analyses	
$SaleGrowth_{i,q}$	Firm i's sales revenue (SALEQ) in quarter q divided by its sales revenue in quarter q-4 minus one.
$Q_{j,q}$	Firm i's market value of equity divided by its book value of equity (CEQQ), both measured at the end of quarter q.
$MV_{i,q}$	The natural logarithm of the market value of equity of firm i at the end of quarter q.
$NAnalysts_{i,q}$	The number of analysts in I/B/E/S that issue at least one forecast for firm i during quarter q.
$EquityIssue_{i,q}$	An indicator variable that equals 1 if firm i issues equity in quarter q, and 0 otherwise. Equity issuance data are obtained from the SDC Platinum database.
$Turnover_{i,q}$	Firm i's total number of shares traded (VOL) during quarter q scaled by its number of shares outstanding (SHROUT) at the end of quarter q, both obtained from the CRSP monthly files.
$NFirms_{j,q}$	The number of firms in industry j-quarter q, in thousands.
$Bankruptcy\%_{j,q}$	The percentage of firms in industry j-quarter q that are delisted due to bankruptcy (i.e., DLRSN equals 02 in the Compustat quarterly files), in percentage points.
$IndBoard\%_{j,q}$	The average $IndBoard\%_{i,q}$ for industry j-quarter q, in percentage points. $IndBoard\%_{i,q}$ is firm i's number of independent board directors labeled by the ISS divided by its total number of board directors in the year to which quarter q belongs.
$IO_{j,q}$	The average $IO_{i,q}$ for industry j-quarter q. $IO_{i,q}$ is firm i's shares held by all institutional investors, divided by the total shares outstanding, both measured at the end of quarter q. Institutional ownership is from the Thomson Institutional (13f) Holdings database, and the total shares outstanding is from the CRSP monthly files (adjusted for stock splits and other distributions).
$PPS\_avg_{j,q}$ ($PPS\_std_{j,q}$)	The average and the standard deviation of CEO $PPS_{i,q}$ for industry j-quarter q, respectively. $PPS_{i,q}$ is the CEO's pay-for-performance sensitivity for firm i in the year to which quarter q belongs, in tens, calculated following Core and Guay [2002].
$WPS\_avg_{j,q}$ ($WPS\_std_{j,q}$)	The average and the standard deviation of CEO $WPS_{i,q}$ for industry j-quarter q, respectively. $WPS_{i,q}$ is the CEO's scaled wealth-performance sensitivity for firm i in the year to which quarter q belongs, in tens, calculated following Edmans, Gabaix, and Landier [2009].

(Continued)

APPENDIX B—*Continued*

Variable Name	Definition
$Tenure\_avg_{j,q}$ ($Tenure\_std_{j,q}$)	The average and the standard deviation of CEO tenure for industry *j*-quarter *q*. CEO tenure is the number of years elapsed between the year in which he/she became CEO of the firm and the year to which quarter *q* belongs, as tracked in ExecuComp.
$Vesting\_avg_{j,q}$ ($Vesting\_std_{j,q}$)	The average and the standard deviation of $Vesting_{i,q}$ for industry *j*-quarter *q*. $Vesting_{i,q}$ is approximated using the weighted average vesting period of a CEO's newly granted options in firm *i*-quarter *q*. The length of an option grant's vesting period is measured from the grant date to the date on which the option becomes exercisable, in years. The weight is the value of each option grant, calculated using the Black-Scholes option pricing model. All option grant data are from Thomson Reuters Insiders Data, and the inputs (i.e., dividend yield, risk-free interest rate, and volatility) to the Black-Scholes formula are obtained from the Compustat annual and quarterly files or calculated from the CRSP daily files.
Additional Variables in the ERC Test	
$CAR_{i,q}$	The cumulative three-day market-adjusted return centered on the earnings announcement date of firm *i*-quarter *q*, with the daily market–adjusted return calculated as the raw return minus the corresponding return on CRSP value-weighted index.
$UE_{i,q}$	The EPS of firm *i*-quarter *q* minus the EPS of firm *i*-quarter *q-4*, scaled by price 10 days before the earnings announcement date of firm *i*-quarter *q*.
$Loss_{i,q}$	An indicator variable that equals 1 if the EPS of firm *i*-quarter *q* is less than 0, and 0 otherwise.
$Q4_{i,q}$	An indicator variable that equals 1 if quarter *q* is the fourth quarter of firm *i*'s fiscal year, and 0 otherwise.
$Beta_{i,q}$	The market beta estimated using daily returns over (−365, −60) days relative to the earnings announcement date of firm *i*-quarter *q*.
Additional Variables in the Fraud Detection Test	
$Undetected_{i,q}$	An indicator variable that denotes whether an intentionally misstating firm *i* survives detection in quarter *q*, which equals 0 for a quarter in which the misstatement is detected and 1 for all quarters prior to that.
$Error\%_i$	For firm *i* that engages in an intentional misstatement in a single quarter, the percentage of firms that engages in unintentional misstatements in the firm's industry for that quarter; for firm *i* that engages in an intentional misstatement that spans multiple quarters, the percentage of firms that engage in unintentional misstatements in the firm's industry, averaged over all misstating quarters.
$Qtrs_{i,q}$	The number of quarters from the quarter in which firm *i*'s misstatement begins to quarter *q*.
$Size_{i,q}$	The natural logarithm of an intentionally misstating firm *i*'s book value of assets (ATQ) at the end of quarter *q*.
$Momentum_{i,q}$	An intentionally misstating firm *i*'s buy-and-hold return, measured over the 12 months prior to quarter *q*.
$BiasCAR_i$	The cumulative three-day market-adjusted return centered on the date when firm *i*'s misstatement is initially revealed, with the daily market–adjusted return calculated as the raw return minus the corresponding return on the CRSP value-weighted index.

This appendix describes the calculation of variables used in the paper. All scaling is done to improve the readability of the coefficients in the regression analyses.

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