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The Market's Valuation of Fraudulently Reported Earnings

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Abstract: This study examines the market valuation of accounting earnings during the period *before* it is publicly revealed that the earnings are fraudulent. Using both cross-sectional and time-series valuation models, we first find that the market accords less weight to earnings when the accounting numbers are fraudulent. We also show that the market better anticipates the presence of fraud when there is information in the public domain indicating a high *ex-ante* risk of fraud. Our findings suggest that investors are able to accurately assess the probability of fraud and that such assessments affect the market's valuation of earnings even before it is publicly announced that fraud has occurred.

Keywords: accounting fraud, market valuation, earnings coefficient

1. INTRODUCTION

Can investors see through accounting fraud or are they fooled? At first, it might appear that investors are fooled. Managers commit accounting fraud to sustain excessively high stock valuations for their companies (Jensen, 2005), but this is possible only if investors are fooled by the fraudulent reporting. Indeed, managers would have little incentive to commit fraud if investors could easily identify what managers were doing, and so the very presence of fraudulent behavior suggests that it must be difficult for investors to unravel misstated accounting numbers. On the other hand, it is naïve to believe that investors are *completely* fooled by fraudulent reporting. Investors have strong incentives to become informed in order to avoid the trading losses that stem from holding the overvalued stocks of fraudulent companies. To the extent that investors are able to accurately predict the presence of fraud, we expect their

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assessments of the risk of fraud will condition the way in which they value a company's reported earnings.

We begin by presenting a theoretical model in which investors are partially informed about the presence of fraud. Investors understand that the reported profitability of a fraud company is likely to be overstated, which causes them to rationally lower their assessment of the company's true profitability. This affects the market valuation of reported earnings, because a company with a lower expected profitability is more likely to discontinue its operations in the future by exercising the abandonment/adaptation option. This anticipated contraction in the scale of operations lowers the coefficient on earnings in valuation regressions (Burgstahler and Dichev, 1997). We thus predict that the weight accorded to reported earnings in the valuation model will be lower for fraud companies than for non-fraud companies if investors are able to accurately judge which companies are most likely to be fraudulent.

To test this prediction, we identify companies that received an Accounting and Auditing Enforcement Release (AAER) from the Securities and Exchange Commission (SEC) claiming that managers had intentionally misstated their accounts.[1] We then pinpoint the quarters in which the earnings are fraudulent but there has not yet been any public announcement of an accounting impropriety. This yields a sample of 1,248 fraud quarters. We compare the earnings coefficient in the valuation model between this fraud sample and a control sample of 257,616 quarters in which the reported earnings are not alleged to be fraudulent. We also conduct a time-series comparison in which the control sample comprises 2,491 quarters before the fraud companies commenced their fraudulent activities. In this time-series analysis, we use each fraud company as a control for itself and test whether the earnings coefficient is lower during fraud periods than in the quarters before fraud commenced.

Our results are consistent with the predictions of the theoretical model. Specifically, the cross-sectional results reveal that the earnings coefficient is significantly smaller in the fraud sample than in the control sample of non-fraud companies. This suggests that investors are able to accurately identify which companies are most likely to commit fraud even before fraud has been publicly announced to the market. Further, the time-series tests indicate that the earnings coefficient is significantly larger during the pre-fraud period than during the fraud period. It thus appears that investors are able to discriminate between fraudulently reported earnings and earnings reported by the same company before it commenced misreporting. Overall, we conclude that investors are not completely fooled by the fraudulent activities of managers. Rather, they are apparently able to determine which companies have the highest risk of fraud and pinpoint when fraud is most likely to take place.[2]

1 Fraudulent accounting refers to the manipulation of reported accounting numbers beyond generally accepted accounting principles (GAAP). Strictly speaking, AAERs represent the SEC's allegation of fraud, but we follow the literature by referring to them as actual cases of fraud. There is broad consensus in the literature that AAERs represent egregious violations of GAAP (Feroz et al., 1991; Dechow et al., 1996; Beneish, 1999; and Miller, 2006). Isolating accounting manipulations using a sample of AAERs also helps to avoid any coding bias on the part of the researcher in evaluating whether a certain event amounts to fraud (Erickson et al., 2006).

2 This does not necessarily mean that investors consciously make explicit predictions of fraud risk. Rather, they act *as if* they are assessing such risk when they decide on their response to reported earnings. This "as if" qualifier is common in accounting and economics research – for example, it is often assumed that individuals act as if they are maximizing utility even though most people are not consciously aware of the utility concept. Similarly, we argue that investors act as if they are making assessments of fraud risk even though they may not be aware that they are doing so.

We go on to investigate how investors become informed about the risk of fraud. Specifically, we investigate whether investors use relevant publicly available information cues to assess the risk of fraud. We estimate the *ex-ante* risk of fraud using a statistical model that utilizes the independent variables identified in past fraud prediction studies (e.g., accruals). These independent variables are publicly observable to investors at the time of earnings releases and before the public revelation of fraud. If investors use the same public information as in our fraud prediction model, the probability of fraud predicted by the model should be associated with a significantly smaller earnings response coefficient.

Consistent with this prediction, we find that the earnings coefficient is significantly smaller when the statistical model predicts a high *ex-ante* probability of fraud. This finding holds in both the cross-sectional and time-series tests. Thus, investors apparently use publicly available information about the risk of fraud when they value a company's reported earnings. Further, we show that the *ex-post* fraud variable remains incrementally significant in explaining the lower earnings coefficient after controlling for the *ex-ante* risk of fraud. This suggests that investors also use other fraud-relevant information, beyond the independent variables included in our statistical model. Thus, when benchmarked against the statistical model, investors seem to be relatively well informed about the presence of fraud. In a supplementary analysis, we investigate whether investors are better informed about the risk of fraud when the extent of analyst following is larger and when the level of institutional ownership is higher. We find that the earnings coefficient during the fraud period is more heavily discounted when analyst following and institutional ownership are greater, suggesting that these factors are associated with investors being more accurately informed about the risk of fraud.

This study makes four key contributions to the literature. First, it provides a direct link between fraudulent attempts by managers to mislead investors and the rational responses of investors who have incentives to find out whether they are being duped. Our findings indicate that investors can partly anticipate when reported earnings are likely to be fraudulent. However, we also show that investors lack perfect foresight, and that it is still possible for managers to (partially) dupe investors. This finding makes sense because if fraudulent behavior were readily identifiable then managers would have little incentive to commit fraud in the first place. From a regulatory standpoint, our evidence suggests that the risk to investors arising from fraudulent financial reporting is lower than might be expected, given that rational investors are able to anticipate which companies are most likely to engage in fraud. However, we caution that our research findings are based on average results and regulators may perhaps be more concerned about specific types of fraud, such as those that affect relatively unsophisticated investors.

Second, this study finds that the ability of investors to detect the risk of fraud is dependent on the external information environment. Our results indicate that investors can more fully anticipate the occurrence of fraud and make corresponding adjustments to their valuations in richer informational settings that are characterized by a greater presence of analysts and institutional investors.

Third, our study offers important insights for the earnings management literature, which typically assumes that opportunistic reporting through accruals manipulation is easily detectable *ex-ante* from the financial reporting numbers. This assumption is questionable because opportunistic reporting would not occur if it could be easily unraveled to reveal the true earnings number. To overcome this logical inconsistency, we use an *ex-post* measure of opportunistic financial reporting (i.e., fraud) that is not easily identified by scrutinizing abnormal accruals.[3] A further advantage of looking at fraud rather than accruals is that we isolate a setting in which financial reporting is clearly opportunistic, whereas accruals may also signal managers' private information (Tucker and Zarowin, 2006). A fundamental insight of this study is that investors are partially but not fully informed about opportunistic reporting, and thus investors are unable to fully unravel managers' opportunistic reporting choices.

Finally, most fraud studies focus on what happens to companies and managers *after* the public announcement of accounting manipulation (Agrawal et al., 1999; Farber, 2005; Srinivasan, 2005; Desai et al., 2006; Fich and Shivdasani, 2007; and Wilson 2008). In contrast, this study contributes to the literature by investigating how the market prices fraudulent earnings news *before* a company makes any public disclosure of an accounting fraud.

The remainder of the paper is organized as follows. Section 2 presents a theoretical model of the market pricing of fraudulent earnings and develops the study's two main hypotheses. Section 3 discusses the sample and provides the main results, while Section 4 reports the findings from supplementary analyses. Section 5 concludes.

2. HYPOTHESIS DEVELOPMENT

In this section, we theoretically examine a situation in which investors are partially informed about the risk of fraud. We demonstrate how the value relevance of earnings changes for companies that are suspected of fraudulent reporting. Based on our theoretical predictions, we then formulate hypotheses and design regression models for the empirical analysis.

(i) Theoretical Model

Consider the valuation problem for a company that has just released its financial report for period t. We first describe the valuation problem for a non-fraud company, which serves as a base scenario, and then extend the problem to incorporate the possibility of fraud.[4] The non-fraud company reports its earnings (X_t) and its equity book value (B_t) for period t. The company's profitability in period t is then $q_t = X_t/B_t$. Going forward, we assume that profitability evolves according to the following process:[5]

$$\tilde{q}_{t+1} = a + bq_t + \tilde{e}_{t+1}, \tag{1}$$

where $a \geq 0$ is a constant, $b > 0$ is a persistence parameter, and $\tilde{e}_{t+1}$ is a zero-mean disturbance term.

3 Accruals variables have relatively low explanatory power in models that predict the incidence of accounting fraud (Dechow et al., 1996; and Beneish, 1997).

4 We do not explicitly model the company's reporting choice, assuming instead that its report is either fraudulent or truthful. We keep the model simple given that our purpose is to examine how the market reacts to financial reporting of a (suspected) fraud company. Fully endogenizing the fraud choice is likely to complicate the model structure considerably as that would require specifying the cost and benefit functions facing the firm's manager. Moreover, there are likely multiple ways of representing such functions; e.g., managers may fraudulently overstate their earnings to earn higher cash compensation, to avoid dismissal or to engage in profitable stock trades.

5 Similar dynamic processes for q_t are assumed in the literature (e.g., Ohlson 1995; Zhang 2000; and Callen et al., 2005).

At $t+1$ the company chooses either: (1) to discontinue its operations and apply its resources to another business with an adaptation value of B_t (as in Burgstahler and Dichev, 1997), or (2) to continue its current operations with a value equal to kX_{t+1}, where k is the earnings capitalization factor. As shown in Burgstahler and Dichev (1997) and Zhang (2000), the optimal decision is for the company to exercise the adaptation option if its profitability (q_{t+1}) falls below a critical point, which equals $q^* \equiv 1/k$ in this setting, and to stay in business otherwise.

Assuming risk neutrality, the company's market value at t (V_t) incorporates both the expected adaptation value $B_t \Pr(q_{t+1} < 1/k)$ and the expected value of staying in business $k\int_{q_{t+1}\geq 1/k} X_{t+1} f(q_{t+1})\,dq_{t+1}$. In general, valuation also incorporates information conveyed by the company through sources other than financial statements. Let $u_t \in [0, \infty)$ be the value that investors attach to this other information. The total value of the non-fraud company in period t is then $V_t = B_t \Pr(q_{t+1} < 1/k) + k\int_{q_{t+1}\geq 1/k} X_{t+1} f(q_{t+1})\,dq_{t+1} + u_t$. Utilizing the link between q_{t+1} and q_t described in equation (1) and rearranging, we get[6]

$$\begin{aligned}
V_t &= \Pr(q_{t+1} < 1/k)B_t + \Pr(q_{t+1} \geq 1/k)k(aB_t + bX_t) + k\int_{q_{t+1}\geq 1/k} X^u_{t+1} f(q_{t+1})\,dq_{t+1} + u_t \\
&= kb\Pr(e_{t+1} \geq 1/k - a - bq_t)X_t + [1 - (1 - ka)\Pr(e_{t+1} \geq 1/k - a - bq_t)]B_t \\
&\quad + k\int_{q_{t+1}\geq 1/k} X^u_{t+1} f(e_{t+1})\,de_{t+1} + u_t
\end{aligned}$$

where $X^u_{t+1} \equiv B_t e_{t+1}$ is the company's unexpected earnings in period $t+1$.

This equation shows that the company's value is a function of reported earnings (X_t), book value (B_t), and a third component ($k\int_{q_{t+1}\geq 1/k} X^u_{t+1} f(e_{t+1})\,de_{t+1}$). Empirically, this third component tends to be small relative to the other two components.[7] Thus, the non-fraud company's market value can be approximated using the following expression:

$$V_t \approx w_1(q_t)X_t + w_2(q_t)B_t + u_t. \tag{2}$$

The earnings coefficient, $w_1 \equiv kb\Pr(e_{t+1} \geq 1/k - a - bq_t)$, is increasing in profitability (q_t), a prediction confirmed in empirical studies (e.g., Burgstahler and Dichev, 1997; Barth et al., 1998; and Collins et al., 1999). The book value coefficient, $w_2 \equiv 1 - (1 - ka)\Pr(e_{t+1} \geq 1/k - a - bq_t)$, is decreasing (increasing) in q_t if a is smaller (larger) than $1/k$.[8]

We now extend this model to the situation in which a company intentionally overstates its earnings but investors are uncertain about the precise magnitude of the

6 For simplicity, we assume $B_t = B_{t+1}$ in the analysis.

7 The unconditional expected value of unexpected earnings is, by definition, zero. For a company that is highly likely to continue its operations (which is true for the vast majority of companies in our sample), the conditional expected value will be close to the unconditional expected value (i.e., zero).

8 Typically, the constant part of the profitability process (a) is small relative to $1/k$ (which may be interpreted as the cost of capital for a company in a steady-state operation), and thus the coefficient on the book value would normally be decreasing in profitability. However, we do not require this assumption for our main predictions because our focus is on the earnings coefficient, which is unambiguously increasing in profitability.

earnings overstatement. Their belief is that the overstatement, F_t, is distributed within $[F_l, F_h]$, with $F_h > F_l > 0$, and with a probability density $f(.)$. Investors rationally subtract the expected magnitude of the overstatement $(\tilde{F}_t)$ from reported earnings (X_t) when assessing true earnings. Investors expect that the true earnings of a fraud company are $X_t - \tilde{F}_t$ when the company reports earnings X_t, while the true book value is expected to be $B_t - \tilde{F}_t$.

Letting $\tilde{X}'_t = X_t - \tilde{F}_t$ and $\tilde{B}'_t = B_t - \tilde{F}_t$, investors believe the company's true profitability is $\tilde{q}'_t \equiv \tilde{X}'_t/\tilde{B}'_t = (X_t - \tilde{F}_t)/(B_t - \tilde{F}_t)$. Typically, earnings are less than book value $(X_t < B_t)$, and thus the reported profitability of a fraud company exceeds its true profitability (i.e., $\tilde{q}'_t < q_t$). Let s be the difference between a fraud company's reported and true profitability. Then $\forall \tilde{F}_t > 0$, we have $\tilde{s}_t \equiv q_t - \tilde{q}'_t = \frac{(B_t - X_t)\tilde{F}_t}{B_t(B_t - \tilde{F}_t)} > 0$.

In addition to misstating its financial statements, the fraud company can issue other information (u_t) that is misleading about its value. For simplicity, we assume the other information of a fraud company is equal to its true value (u_t) plus a constant, $u_o \geq 0$. Letting $\bar{u}_t^F$ and $\bar{u}_t^{NF}$ be the means of the other information for fraud and non-fraud companies, respectively, then $\bar{u}_t^F = \bar{u}_t^{NF} + u_o$.

If investors know for certain that a company is reporting fraudulently (but are uncertain about the magnitude of fraud $\tilde{F}_t$), then their valuation of the fraud company, conditional on (X_t, B_t, u_t), is

$$\begin{aligned} V_t &= E_{\tilde{F}}[w_1(\tilde{q}'_t)\tilde{X}'_t + w_2(\tilde{q}'_t)(\tilde{B}'_t)] + u_t \\ &= w_1(q_t)X_t + w_2(q_t)B_t - E_{\tilde{F}}\left([w_1(q_t - \tilde{s}_t) + w_2(q_t - \tilde{s}_t)]\tilde{F}_t\right) \\ &\quad - (w_1(q_t) - E_{\tilde{F}}[w_1(q_t - \tilde{s}_t)])\, X_t + (E_{\tilde{F}}[w_2(q_t - \tilde{s}_t)] - w_2(q_t))\, B_t + u_t, \end{aligned} \tag{3}$$

where $E_{\tilde{F}}(.)$ is the expectation operator of the distribution of $\tilde{F}_t$.

In general, however, investors lack perfect foresight and cannot be certain whether or not a company is committing a fraud. Letting $p < 1$ be the investor assessment of the probability of fraud, the market value of a *suspected* fraud company is a weighted average of equations (2) and (3): [9]

$$\begin{aligned} V_t = {} & w_1(q_t)X_t + w_2(q_t)B_t + u_t - p\,u_o - pE_{\tilde{F}}\left([w_1(q_t - \tilde{s}_t) + w_2(q_t - \tilde{s}_t)]\tilde{F}_t\right) \\ & - p\,(w_1(q_t) - E_{\tilde{F}}[w_1(q_t - \tilde{s}_t)])\, X_t + p\,(E_{\tilde{F}}[w_2(q_t - \tilde{s}_t)] - w_2(q_t))B_t. \end{aligned} \tag{4}$$

Observe that equation (4) simplifies to equation (2) when investors assess the probability of fraud (p) to be zero.

A comparison of equations (4) and (2) shows that the market value of a suspected fraud company deviates from that of a non-fraud company in four ways. First, investors subtract pu_0 from the suspected company's other information (u_t) because they believe there is a risk that this information is fraudulent. Despite this rational unraveling of the fraud company's other information, the company can fool investors and raise its market valuation by disclosing a higher value of u_t as long as investors are unsure whether the company is fraudulent (i.e., $p < 1$).

9 We do not model how investors assess p. In reality, we would expect investors to assess the probability of fraud based on all of the information available to them, which includes, but is not limited to, information provided by the company. For simplicity, we assume that p is independent of F.

Second, investors understand that the reported earnings and reported book values of fraud companies are overstated. This leads to a lower market valuation for a company that is suspected of being fraudulent $(-pE_{\tilde{F}}([w_1(q_t - \tilde{s}_t) + w_2(q_t - \tilde{s}_t)]\tilde{F}_t) < 0)$.

Third, investors' beliefs affect the weight accorded to a company's reported earnings since investors understand that the true profitability of a fraud company is less than its reported profitability (i.e., $\tilde{s}_t > 0$). As the coefficient on earnings (w_1) is increasing in a company's expected profitability, investors place less weight on the reported earnings of a company suspected of being fraudulent $(w_1(q_t) > E_{\tilde{F}}[w_1(q_t - \tilde{s}_t)]$. The economic intuition is that investors understand a fraud company is more likely to discontinue its operations and thus its earnings are less value relevant. This implies that suspected fraud companies have a smaller earnings coefficient $(-p\ (w_1(q_t) - E_{\tilde{F}}[w_1(q_t - \tilde{s}_t)]) < 0)$.

Finally, investors' beliefs affect the weight accorded to a company's reported book value. However, the sign of the effect is ambiguous because the coefficient on book value (w_2)can be either decreasing or increasing in a company's expected profitability. If $a < 1/k$, the book value coefficient is decreasing in the company's expected profitability. In this situation, investors believe that a fraud company is more likely to discontinue operations and so the company's book value is more value relevant $(p\ (E_{\tilde{F}}[w_2(q_t - \tilde{s}_t)] - w_2(q_t)) > 0)$. The opposite prediction holds if $a > 1/k$.

(ii) Research Design

Before a company is revealed to be fraudulent, investors are uncertain about whether a fraud is taking place. Investors form *ex-ante* assessments about the risk of fraud and these assessments turn out to be correct or incorrect *ex-post.* Investors' *ex-ante* beliefs about the risk of fraud are not observable so we instead use an *ex-post* fraud dummy variable ($Fraud_{it}$) as a proxy for these beliefs. To the extent that rational investors are informed about the risk of fraud, they should assess that the probability of fraud is higher for fraud companies ($Fraud_{it} = 1$) than for companies not engaging in fraud ($Fraud_{it} = 0$). Thus, the *ex-post* fraud dummy variable is a valid proxy for investors' *ex-ante* beliefs under the assumption that investors are rational.

We test the predictions in equation (4) by estimating the following regression model:

$$V_{it} = b_0 + b_1 X_{it} + b_2 B_{it} + b_3 Fraud_{it} + b_4 X_{it} \times Fraud_{it} + b_5 B_{it} \times Fraud_{it}, \tag{5}$$

where $Fraud_{it}$ is a dummy variable equal to one if company i committed accounting fraud during period t, and zero otherwise.

When a company is believed to be non-fraudulent ($p = 0$), equation (4) simplifies to equation (2), while equation (5) simplifies to $V_{it} = b_0 + b_1 X_{it} + b_2 B_{it}$. The slope coefficient on earnings (b_1) is then equal to $w_1(q_t)$ in equation (2) while the book value coefficient (b_2) is $w_2(q_t)$. Consistent with this theoretical model, past research finds the earnings and book value coefficients are typically positive ($b_1 > 0$ and $b_2 > 0$).

The coefficients b_3, b_4, and b_5 in equation (5) reflect investors' assessments of both the probability of fraud (p) and the magnitude of the expected earnings overstatement

$(\tilde{F}_t)$. From equations (4) and (5), the coefficient on the $Fraud_{it}$ dummy variable in the valuation model is:

$$b_3 = (1-p)u_o - pE_{\tilde{F}}\{[w_1(q_t - \tilde{s}_t) + w_2(q_t - \tilde{s}_t)]\tilde{F}_t\}.$$

The sign of b_3 can be either positive or negative so we do not form a signed prediction for the coefficient on the $Fraud_{it}$ dummy variable.

The coefficient on the interaction between reported earnings and fraud ($X_{it} \times Fraud_{it}$) is b_4 in equation (5). This corresponds to $-p\ (w_1(q_t) - E_{\tilde{F}}[w_1(q_t - \tilde{s}_t)])$ in equation (4). Mathematically, this expression is negative because $w_1(q_t)$is an increasing function of q_t. Intuitively, the sign is negative because investors rationally anticipate that the reported profitability of a fraud company is overstated. This, in turn, means that a suspected fraud company is expected to have a higher probability of abandoning its operations, making earnings less value relevant. This real-option effect leads us to predict that b_4 is negative in equation (5). That is, the coefficient on earnings in the valuation model is significantly smaller for companies that are suspected of being fraudulent $(-p(w_1(q_t) - E_{\tilde{F}}[w_1(q_t - \tilde{s}_t)]) < 0$ in equation (4). Under the assumption that investors form rational expectations about the risk of fraud, we have the following hypothesis:

H$_1$: The earnings coefficient is significantly smaller for companies that commit fraud than for companies that do not commit fraud.

The interaction between the reported book value and fraud has the coefficient b_5 in equation (5). This corresponds to $p\ (E_{\tilde{F}}[w_2(q_t - \tilde{s}_t)] - w_2(q_t))$ in equation (4) and, as explained earlier, the sign of this expression is ambiguous. Accordingly, we do not make a signed prediction about the coefficient on the interaction between book value and fraud ($B_{it} \times Fraud$).

(iii) The Ex-ante Risk of Fraud

Evidence affirming H$_1$ would indicate that investors distinguish between the reported earnings of fraud and non-fraud companies. However, this still leaves the question as to *how* investors become informed about fraud risk. The necessary information cues must be observable to investors when the financial statements are released to the market and before the fraudulent reporting is publicly revealed.

Statistical models of fraud prediction reveal that fraud companies are systematically different from non-fraud companies in their operating environments and accounting practices (e.g., Dechow et al., 1996; Erickson et al., 2006; Johnson et al., 2009; and Dechow et al., 2011). These risk characteristics can be publicly observed *before* fraud is publicly announced, and investors can therefore use these information cues to assess the risk of fraud. If investors rely on these public information sources, we expect the earnings coefficient to be smaller when the *ex-ante* risk of fraud is high. This leads to our second hypothesis.

H$_2$: The earnings coefficient is significantly smaller when the company has a higher *ex-ante* risk of fraud.

To test H_2, we replace the $Fraud_{it}$ dummy variable in equation (5) with a dummy variable (Hi_Risk_{it}) that takes a value of one if the company has a high *ex-ante* risk of fraud, and zero otherwise:

$$V_{it} = b_0 + b_1 X_{it} + b_2 B_{it} + b_3 Hi\_Risk_{it} + b_4 X_{it} \times Hi\_Risk_{it} + b_5 B_{it} \times Hi\_Risk_{it}. \quad (6)$$

In accordance with H_2, we expect the earnings coefficient to be smaller for companies that are deemed to have a high risk of fraud, i.e., $b_4 < 0$.

To construct the *ex-ante* risk variable (Hi_Risk_{it}), we estimate a logit model of fraud. (The independent variables are taken from the prior fraud prediction literature and are discussed in Section 3(*iii*)). We use the coefficients to predict the likelihood of fraud and we then convert this continuous fraud probability to a dummy variable. (We use a dummy rather than a continuous variable in order to facilitate a comparison of the coefficients in equations (6) and (5)). The Hi_Risk_{it} variable takes a value of one (zero) if the company's F-score from the fraud prediction model is greater (less) than one. Following Dechow et al. (2011), the F-score is defined to be the predicted probability of fraud divided by the proportion of fraud observations within the sample.[10] Higher F-Scores indicate a higher *ex-ante* risk of fraudulent reporting.

(iv) Errors in Predicting Fraud

Two types of prediction error arise when the risk of fraud is assessed *ex-ante*. A type I error occurs if the company is not fraudulent but the *ex-ante* risk of fraud is assessed as being high ($Fraud_{it} = 0$ and $Hi\_Risk_{it} = 1$). A type II error arises when a company is believed to have a low risk of fraud but it later turns out to be fraudulent ($Fraud_{it} = 1$ and $Hi\_Risk_{it} = 0$). There is no prediction error when the *ex-ante* assessment of fraud risk is consistent with the *ex-post* outcome (either $Fraud_{it} = 1$ and $Hi\_Risk_{it} = 1$, or $Fraud_{it} = 0$ and $Hi\_Risk_{it} = 0$).

We examine the implications of these four situations by including both the *ex-ante* and *ex-post* fraud variables in the valuation model:

$$\begin{aligned} V_{it} = {} & b_0 + b_1 X_{it} + b_2 B_{it} + b_3 Fraud_{it} + b_4 X_{it} \times Fraud_{it} + b_5 B_{it} \times Fraud_{it} \\ & + b_6 Hi\_Risk_{it} + b_7 X_{it} \times Hi\_Risk_{it} + b_8 B_{it} \times Hi\_Risk_{it}. \end{aligned} \quad (7)$$

The statistical model gives the correct classification if it predicts a high risk of fraud for a company that is actually committing fraud ($Fraud_{it} = 1$; $Hi\_Risk_{it} = 1$). The model generates a type II prediction error if a fraud company is assessed as having a low risk of fraud ($Fraud_{it} = 1$; $Hi\_Risk_{it} = 0$).[11] The statistical model relies only on publicly observable indicators of fraud risk whereas investors can obtain other private information that is relevant to assessing the risk of fraud. Therefore, investors' beliefs about the risk of fraud should be more accurate than the predictions of the

10 In untabulated robustness tests, we find that our main results continue to hold if we instead use the median F-score or we use the 90^{th} percentile value to identify companies that are predicted to have very high fraud risk.

11 We caution that the analysis of type II prediction errors is somewhat problematic because it is likely that some accounting frauds are not discovered by the SEC. This caveat applies more generally to the AAER literature and is not unique to our study.

statistical model. In this case, the $Fraud_{it}$ dummy would load in equation (7) even after controlling for the statistical model's estimates of the *ex-ante* risk of fraud. We expect that $b_4 < 0$ if investors use other information not included in our statistical model when assessing which companies are more likely to be engaging in fraud.[12]

In equation (7), the earnings coefficient is $b_1 + b_7$ for a non-fraud company that is assessed as having a high risk of fraud ($Fraud_{it} = 0$ and $Hi\_Risk_{it} = 1$): this corresponds to a type I error. In contrast, the earnings coefficient is b_1 for a non-fraud company that is correctly classified ($Fraud_{it} = Hi\_Risk_{it} = 0$). The coefficient b_7 thus captures the effect of a type I error on the earnings coefficient. We expect that $b_7 < 0$ if investors and the statistical model commit similar type I errors; that is, investors discount the reported earnings of high-risk companies that are not actually fraudulent.

3. SAMPLE AND MAIN RESULTS

(i) Sample

We identify the fraud commencement date, the fraud end date and the first public announcement of an accounting impropriety. The start and end dates indicate whether a fraud is taking place, while the announcement date allows us to identify whether investors have been publicly informed. These three dates are important because our goal is to test whether investors are informed about the presence of fraud *before* the fraud is publicly announced to the market. The time-line for these three dates is illustrated in Figure 1.

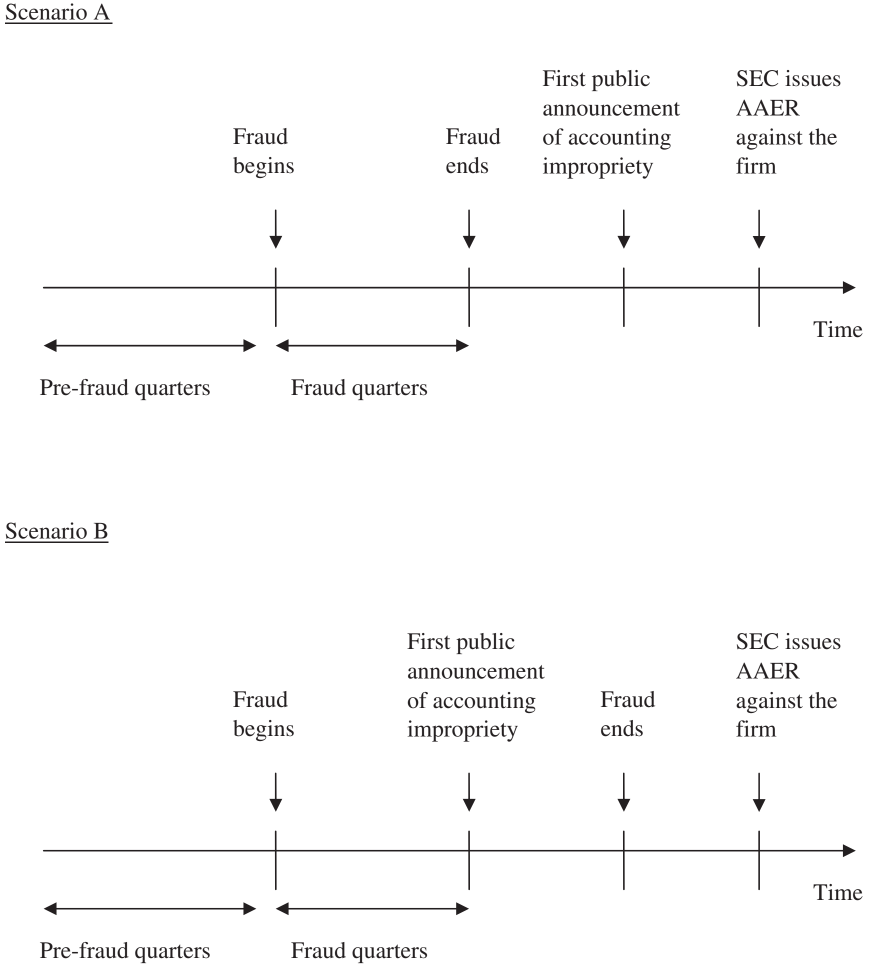
We identify the fraud commencement and fraud end dates by reading through the AAERs issued by the SEC. In some cases, the information in the AAERs does not allow us to identify when the fraud period begins or ends, and these observations are eliminated from the sample. We then search all of the press releases and SEC filings on Lexis-Nexis to determine the date of the first public revelation of accounting impropriety.

We emphasize that the date of the first public announcement is not necessarily the date on which investors would have recognized that the accounting problems amount to a fraud. To illustrate this point, consider Qwest, one of the AAER companies in our fraud sample. The first public disclosure of accounting problems occurred when Morgan Stanley issued a research report on June 20, 2001 criticizing Qwest's accounting practices. Morgan Stanley's report was initially rebuffed by Qwest, and it was only later that the full extent of the company's accounting manipulation became apparent and a fraud was alleged by the SEC. With the benefit of hindsight, we know that June 20, 2001 was the first occasion on which there was any public indication of accounting impropriety at Qwest. Although the full extent of the fraudulent reporting would not have been known at that time, we use June 20, 2001 as the announcement

12 Understandably it is difficult for academic researchers to identify private sources of information on fraud risk as we only have access to publicly available information. However, the study by Dyck et al. (2010) is useful for thinking about potential sources of private information. Dyck et al. (2010) find that the parties who uncover fraud include: the firm's own management (34.3%), analysts (11.1%), auditors (7.4%), clients or competitors (4.2%), employees (12.0%), shareholders (2.3%), the SEC (4.6%), other regulatory agencies (9.3%), law firms (2.3%), media (10.2%) and short sellers (2.3%). Some of these parties are likely to use public sources of information to assess the risk of fraud: e.g., analysts, auditors, the SEC, other regulatory agencies, media. On the other hand, other parties are likely to rely more on private information sources; e.g., management, employees.

Figure 1

Alternative time-lines for companies subject to AAERs



date for Qwest given that it was the first time any questions were publicly raised about the propriety of its accounting. We adopt the same approach to identifying the first public disclosure dates of the other fraud companies in our sample.

As illustrated in Figure 1, our fraud sample consists of the quarters during the fraud period and before the first public disclosure date. Typically, the first public disclosure occurs after the end of the fraudulent reporting, and thus the fraud sample includes all of the quarters of the fraud period (Scenario A in Figure 1). However, in some cases the first public disclosure occurs before the end of the fraud period, and we then exclude any fraud quarters subsequent to the first public disclosure (Scenario B). Consequently, all of the quarters in our fraud sample relate to the period *before* any public disclosure of accounting impropriety.

Panel A of Table 1 outlines the procedure for deriving the sample. We start with the 2,489 AAERs issued by the SEC between January 1, 1982 and September 28, 2006.

Table 1
Sample Selection and Fraud Duration

Panel A: Sample Selection

	Number of AAERs
Number of Accounting and Auditing Enforcement Releases (AAERs) January 1st, 1982–September 28th, 2006	2,489
Less: Multiple AAERs relating to a single instance of fraud	(1,686)
Less: AAERs that do not involve financial statement fraud, or that do not precisely identify the fraud period	(229)
Less: AAERs with missing variables in Compustat and CRSP	(349)
Less: AAERs from banks or insurance companies	(22)
Total number of fraud companies in the final sample	212
Total number of fraud fiscal quarters in the final sample	1,248
Total number of non-fraud companies in the cross-sectional tests	9,633
Total number of non-fraud quarters in the cross-sectional tests	257,616

Panel B: Duration of the Fraud Period

Fraud Period	*Number of Fraud Companies*	*% of Fraud Sample*
< = 4 quarters	118	55.7%
5 to 8 quarters	55	25.9%
9 to 12 quarters	21	9.9%
> 12 quarters	18	8.5%
Total	212	100%

The SEC often issues multiple AAERs for a single instance of fraud so the number of frauds is much smaller than the total number of AAERs. For example, the Qwest fraud resulted in the issuance of 16 AAERs. We drop all frauds that do not involve financial reporting and we also drop frauds where the AAERs fail to disclose the start and end of the fraud period. We impose the restriction that data are available in COMPUSTAT and CRSP and we follow past research by dropping 22 frauds involving banks or insurance companies.[13] This leaves us with a final sample of 212 fraud companies and 1,248 fraud quarters.[14] After imposing similar data requirements on companies that did not receive AAERs, we obtain a control sample of 9,633 companies that were not accused of fraud (257,616 non-fraud quarters).

We test our hypotheses using both cross-sectional and time-series models. In the cross-sectional analysis, we test whether the earnings coefficients are smaller in the 1,248 fraud quarters than in the 257,616 non-fraud quarters. In the time-series tests, we examine whether the earnings coefficients are smaller during fraud than during the 10-year period before the commencement of fraud (i.e., 2,491 pre-fraud quarters).

Panel B of Table 1 reports the duration of the fraud period for the 212 companies that received an AAER. In most instances (55.7%), the fraudulent reporting lasts no longer than 1 year, but in 8.5% of cases it persists for at least 3 years before any public disclosure of accounting impropriety.

13 Our main results remain robust if we include banks and insurance companies in the sample.
14 The size of the fraud sample in our study (1,248 fraud quarters) is similar to Dechow et al. (2011) who estimate models using 498, 453 and 363 company–year observations in their fraud samples.

Table 2

The Market Valuation of Fraudulently Reported Earnings

	Predicted Sign	*Cross-sectional Tests* (1)	(2)	*Time-series Tests* (3)	(4)
Constant	?	33.775	33.771	26.073	26.281
		(14.60)***	(14.60)***	(3.71)***	(3.76)***
X_{it}	+	11.957	11.954	10.543	10.487
		(37.56)***	(37.56)***	(4.20)***	(4.27)***
B_{it}	+	0.700	0.701	0.916	0.932
		(36.70)***	(36.82)***	(4.00)***	(4.35)***
$Fraud_{it}$	?	1.616	2.669	−2.312	−1.916
		(1.03)	(1.81)*	(−1.08)	(−1.00)
$X_{it} \times Fraud_{it}$	−	−5.477	−5.212	−6.399	−6.186
		(−3.51)***	(−3.15)***	(−2.40)**	(−2.49)**
$B_{it} \times Fraud_{it}$	?	0.185		0.065	
		(1.36)		(0.35)	
Non-Fraud quarters		257,616	257,616	2,491	2,491
Fraud quarters		1,248	1,248	1,248	1,248
Adj R^2 (%)		37.05	37.07	58.61	58.61
Economic effect on V_{it} of a one standard deviation increase in X_{it} around the median value of X_{it}					
Non-fraud Quarters		33.9%	33.9%	29.9%	29.7%
Fraud Quarters		18.4%	19.1%	11.8%	12.2%
Difference		15.5%	14.8%	18.1%	17.5%
The ERCs:					
Fraud Quarters: b_1+b_4		6.480	6.742	4.144	4.301
Non-fraud Quarters: b_1		11.957	11.954	10.543	10.487

Note:

The dependent variable (V_{it}) is the closing stock price on the first day after the quarterly earnings announcement.

$$V_{it} = b_0 + b_1 X_{it} + b_2 B_{it} + b_3 Fraud_{it} + b_4 X_{it} \times Fraud_{it} + b_5 B_{it} \times Fraud_{it}. \tag{5}$$

V_{it} = the closing stock price of company i on the first day after its earnings announcement in quarter t; X_{it} = the reported quarterly earnings per share of company i in quarter t; B_{it} = the reported book value per share of company i in quarter t. $Fraud_{it}$ = one if company i issues fraudulently misstated accounts in quarter t; = zero otherwise. The treatment sample comprises 1,248 fraud quarters. The control sample comprises 257,616 non-fraud quarters in the cross-sectional tests, and 2,491 pre-fraud quarters in the time-series tests. Dummy variables for every year, quarter and four-digit SIC fixed effects are included but the results are not reported. T-statistics are calculated based on Huber/White/sandwich robust standard errors and clustering at the company level.

***, ** and * indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

(ii) The Market's Valuation of Fraudulently Reported Earnings (H_1)

We begin by testing whether the coefficient on reported earnings in the valuation model is lower when companies are engaging in fraud (H_1). We start with the cross-sectional analysis, which utilizes the 1,248 fraud quarters and the control sample of 257,616 non-fraud quarters. Because our sample comprises multiple quarterly observations that relate to a given company, we control for time-series dependence in the residuals by estimating robust standard errors that are adjusted for clustering on each company (Petersen, 2009).

The cross-sectional tests are reported in columns (1) and (2) of Table 2. Consistent with past research, we find that the earnings coefficient is significantly positive for companies not committing fraud (t-stats. = 37.56 in both columns). In column (1), the earnings coefficient is 11.957 for the non-fraud quarters compared with just 6.480 (= 11.957 – 5.477) for the fraud quarters. The earnings coefficient remains positive for the fraud companies, but its magnitude is significantly attenuated. In column (1), the difference in the earnings coefficient between the fraud and non-fraud quarters is large (–5.477) and statistically significant at the 1% level (t-stat. = –3.51). The results are similar in column (2), in which we drop the insignificant interaction between book value and fraud. The significant negative coefficients for the interaction between reported earnings and fraud ($X_{it} \times Fraud_{it}$) are consistent with our prediction in H_1 that investors accord less weight to earnings when the financial statements are fraudulent. It follows that investors perceive reported earnings as being less value relevant for companies that are engaging in fraud. Thus, stock prices reflect the presence of fraud even before the accounting problems are publicly disclosed.

In contrast to the results for reported earnings, we find no significant difference in the coefficients on book value between the fraud and non-fraud quarters. This insignificant result is not unexpected, as our model gives an unambiguous prediction for the coefficient on $B_{it} \times Fraud_{it}$. The $Fraud_{it}$ intercepts in columns (1) and (2) are positive, implying that fraud companies have slightly higher market valuations than non-fraud companies, after controlling for their reported earnings and reported book value. However, the $Fraud_{it}$ intercepts are significantly different from zero (at the 10% level) in column (2) only.

Columns (3) and (4) of Table 2 report the time-series results in which we compare the fraud quarters and pre-fraud quarters. In these tests, each fraud company is used as a control for itself by comparing the market valuation of the company during the fraud and pre-fraud periods. Although the control sample is much smaller than in the cross-sectional tests, the results are very similar. In particular, column (3) reveals that the earnings coefficient is 10.543 during the pre-fraud quarters, but is much lower at just 4.144 (= 10.543 – 6.399) during the fraud period. Thus, the weight that the market places on reported earnings is much lower after fraud commences. The difference in the earnings coefficients between the two periods is not only large (–6.399), but is also statistically significant (t-stat. = –2.40).[15]

In summary, we find that investors accord less weight to earnings for companies that are engaging in fraud. This finding holds regardless of whether the comparison is with companies that are not involved in fraud or with the same fraud companies over time (fraud quarters versus pre-fraud quarters). These findings suggest that investors can accurately identify which companies are most likely to engage in fraud and they can also pinpoint when the frauds are likely to occur.

(iii) Ex-ante Fraud Risk and the Market's Valuation of Reported Earnings (H_2)

In this section, we test whether the earnings coefficient is smaller for companies that are assessed as having a high *ex-ante* risk of fraud (H_2). We posit that investors rely on public information cues about fraud risk when deciding how much weight to

15 These time series tests help to allay concerns that our results might be attributable to cross-sectional differences between the fraud and non-fraud samples. As a further control, we match each fraud observation to a corresponding no-fraud observation, where the one-to-one matching is based on industry, year and size (total assets). Consistent with H_1, the untabulated results reveal significant negative coefficients for the $X_{it} \times Fraud_{it}$ interaction variable (t-stats. = –2.72, –2.62).

accord reported earnings. We thus expect that an *ex-ante* measure of fraud risk will be associated with a smaller earnings response coefficient.

We begin by estimating a statistical model that predicts the likelihood of fraud. Following Dechow et al. (2011), the independent variables in this model include working capital accruals ($RSST\_ACC_{it}$), changes in receivables (CH_REC_{it}), changes in inventory (CH_INV_{it}), changes in cash sales (CH_CS_{it}), changes in earnings (CH_EARN_{it}), and the issuance of securities during the year ($ISSUE_{it}$). We also include two risk variables that are found to be significant predictors of fraud: return volatility (RET_VOL_{it}) and earnings volatility ($EARN\_VOL_{it}$). Finally, we follow earlier fraud studies by including variables for the company's auditor ($Bigaudit_{it}$), the log of total assets ($SIZE_{it}$), the company's age (AGE_{it}), prior year's returns (Lag_Return_{it}) and leverage ($Leverage_{it}$).

The fraud prediction model is reported in Table A1 of the Appendix and the results are generally consistent with past research.[16] The model has a type I error rate of 32.6% and a type II error rate of 33.6%. In other words, 67.4% of fraud companies and 66.4% of non-fraud companies are correctly classified by the model (see Table A2 of the Appendix). This level of predictive accuracy is similar to Dechow et al. (2011) who obtain correct classification rates of 63.36–65.78% for fraud companies and 60.86–65.03% for non-fraud companies. We use the coefficient estimates to classify each company-quarter as having either a high *ex-ante* risk of fraud ($Hi\_Risk_{it} = 1$) or a low risk ($Hi\_Risk_{it} = 0$). We then estimate the valuation model shown in equation (6). The cross-sectional results are reported in column (1) of Table 3 and the time-series tests are shown in column (3).

Consistent with H_2, we find that the earnings coefficient in the valuation model is significantly smaller for quarters that are assessed to be high risk. The coefficient on $X_{it} \times Hi\_Risk_{it}$ in column (1) is –1.503 and statistically significant (*t*-stat. = –3.66). Similar results are obtained from the time-series analysis in column (3), which compares the fraud quarters with the pre-fraud quarters. The earnings coefficient is 10.227 for the quarters in which the risk of fraud is believed to be low, but it is only 4.690 (= 10.227 – 5.537) when the risk of fraud is deemed to be high. The effect of fraud risk on the earnings coefficient is statistically significant. Overall, the results support the prediction in H_2 that the valuation weight on reported earnings is significantly less when public information cues point toward a high risk of fraud.

We next explore the valuation implications of type I and type II prediction errors. Specifically, we estimate equation (7), which allows reported earnings to interact with both the *ex-ante* risk of fraud (Hi_Risk_{it}) and the *ex-post* fraud variable ($Fraud_{it}$). The purpose of this model is to test whether investors are better informed about the risk of fraud when benchmarked against the predictions generated by our statistical model.

The cross-sectional and time-series results for equation (7) are reported in columns (2) and (4) of Table 3. Both sets of results reveal that the $X_{it} \times Fraud_{it}$ interaction variable has negative coefficients that are statistically significant (*t*-stats. = –3.53, –2.50). These coefficients capture the impact of fraud when the *ex-ante* risk of fraud is assessed as being low (i.e., $Hi\_Risk_{it} = 0$). They indicate that investors place less

16 An exception is that the $Bigaudit_{it}$ coefficient is insignificant in Table A1 whereas Lennox and Pittman (2010) find that companies audited by Non-Big Four audit firms are significantly more likely to commit fraud. The difference is likely attributable to sampling since Lennox and Pittman (2010) have data on 508 fraud companies whereas our sample consists of just 212 fraud companies. The difference in sample sizes arises because we require returns data from CRSP and many fraud companies are not covered by CRSP, particularly the fraud companies that are audited by non-Big Four firms.

Table 3

Ex-ante Fraud Risk and the Market Valuation of Reported Earnings

	Predicted Sign	*Cross-sectional Tests* Eq. (6) (1)	Eq. (7) (2)	*Time-series Tests* Eq. (6) (3)	Eq. (7) (4)
Constant	?	34.440	34.429	55.992	47.952
		(15.92)***	(15.91)***	(6.29)***	(5.74)***
X_{it}	+	12.149	12.147	10.227	11.695
		(31.91)***	(31.87)***	(3.72)***	(3.76)***
B_{it}	+	0.644	0.645	0.823	0.804
		(33.93)***	(33.89)***	(3.46)***	(3.26)***
$Fraud_{it}$	?		1.281		−1.326
			(0.82)		(−0.63)
$X_{it} \times Fraud_{it}$	−		−4.878		−5.798
			(−3.53)***		(−2.50)**
$B_{it} \times Fraud_{it}$	?		0.091		0.042
			(0.73)***		(0.22)
Hi_Risk_{it}	?	4.359	4.350	6.490	6.431
		(21.68)***	(21.71)***	(2.67)	(2.65)*
$X_{it} \times Hi\_Risk_{it}$	−	−1.503	−0.693	−5.537	−1.721
		(−3.66)***	(−2.15)**	(−2.11)**	(−1.67)*
$B_{it} \times Hi\_Risk_{it}$	?	0.278	0.276	0.102	0.086
		(10.50)***	(10.44)***	(0.50)	(0.43)
Non-fraud Quarters		234,789	234,789	2,269	2,269
Fraud Quarters		1,149	1,149	1,149	1,149
Adj R^2 (%)		39.54	39.68	60.59	60.91
The ERCs:					
Predicted Fraud Quarters: b_1+b_4		10.646		4.690	
Predicted Fraud Quarters: b_1+b_6			11.454		9.974
Non-fraud Quarters: b_1		12.149	12.147	10.227	11.695

Note:

The dependent variable (V_{it}) is the closing stock price on the first day after the quarterly earnings announcement.

$$V_{it} = b_0 + b_1 X_{it} + b_2 B_{it} + b_3 Hi\_Risk_{it} + b_4 X_{it} \times Hi\_Risk_{it} + b_5 B_{it} \times Hi\_Risk_{it}. \quad (6)$$

$$V_{it} = b_0 + b_1 X_{it} + b_2 B_{it} + b_3 Fraud_{it} + b_4 X_{it} \times Fraud_{it} + b_5 B_{it} \times Fraud_{it} + b_6 Hi\_Risk_{it} + b_7 X_{it} \times Hi\_Risk_{it} + b_8 B_{it} \times Hi\_Risk_{it}. \quad (7)$$

V_{it} = the closing stock price of company i on the first day after its earnings announcement in quarter t; X_{it} = the reported quarterly earnings per share of company i in quarter t; B_{it} = the reported book value per share of company i in quarter t. $Fraud_{it}$ = one if company i issues fraudulently misstated accounts in quarter t; = zero otherwise. Hi_Risk_{it} = one if the F-score from the fraud prediction model is greater (less) than one (zero) for company i in quarter t. Following Dechow et al. (2010), the F-score is defined to be the predicted probability of fraud (i.e., $[\exp(\beta X)/(1+\exp(\beta X))]$) divided by the proportion of fraud observations in the sample (i.e., the number of fraud observations divided by the total number of observations). The results of the fraud model are reported in Table A1 of the Appendix while its predictive accuracy is shown in Table A2. The treatment sample comprises 1,149 fraud quarters. The control sample comprises 234,789 non-fraud quarters in the cross-sectional tests, and 2,269 pre-fraud quarters in the time-series tests. Dummy variables for every year, quarter and four-digit SIC fixed effects are included but the results are not reported. T-statistics are calculated based on Huber/White/sandwich robust standard errors and clustering at the company level. ***, ** and * indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

weight on fraudulent earnings even when the statistical model incorrectly classifies the fraud companies as having low fraud risk (type II errors). This in turn suggests that investors are more accurately informed about the risk of fraud than our statistical prediction model. This may be because investors rely on private information when deciding how to weight a company's reported earnings, whereas our statistical model utilizes only publicly available information. Alternatively, investors may be using public information cues that are not included in our statistical model but that are relevant to assessing fraud risk. In either case, our results indicate that, when benchmarked against the statistical model, investors are accurately informed about the prevailing risk of fraud.

We also test whether the coefficients on the $X_{it} \times Hi\_Risk_{it}$ interaction variable remain significant after controlling for the interaction between reported earnings and the *ex-post* fraud outcome variable. The $X_{it} \times Hi\_Risk_{it}$ coefficient captures the incremental impact of *ex-ante* fraud risk when companies are not actually fraudulent ($Fraud_{it} = 0$). In column (2), the $X_{it} \times Hi\_Risk_{it}$ coefficient is negative and significant at the 5% level (*t*-stat. = –2.15). Thus, the earnings coefficient is significantly smaller when non-fraud companies are assessed as having high fraud risk, which corresponds to the situation in which our statistical model commits a type I prediction error. The $X_{it} \times Hi\_Risk_{it}$ coefficient is also negative (–0.991) in the time-series model reported in column (4), but it is only significant at the 10% level. These findings suggest that investors accord less weight to reported earnings when the statistical model commits type I errors (i.e., non-fraud companies are assessed as having high risk).

In summary, there are two main takeaways from Table 3. First, consistent with H_2, investors accord less weight to reported earnings when the *ex-ante* probability of fraud is high. This suggests that investors use public information cues that are similar to those used in our statistical model of fraud prediction. Second, the results suggest that investors use other fraud-relevant information that is absent from our statistical model. Thus, investors appear to be accurately informed about the prevailing risk of fraud when benchmarked against the statistical model.

4. INFORMATION ENVIRONMENT

We expect investors to be more accurately informed about the risk of fraud when there are reliable outside sources of information about the company. In contrast, investors are less well informed about fraud if they depend only on information provided by management. We therefore investigate whether a company's external information environment affects the market valuation of fraudulent earnings. We utilize two alternative proxies for the information environment: analyst following and institutional ownership (Walther, 1997).

(i) Analyst Following

Analysts typically follow companies on a continual basis and scrutinize management and financial reports to determine whether there are inconsistencies with industry practice (Yu, 2008). Although the detection of fraudulent accounting is not the primary goal of analysts, they are in an advantageous position to find it because they have training in finance and accounting, together with detailed knowledge of the industries that they cover. Consistent with this notion, Miller (2006) finds that the press helps to publicize accounting fraud by rebroadcasting information that originally came from analysts. He demonstrates that analysts are the most important source of information for articles in the press when such articles do not originate from the journalists' own investigations. Dyck et al. (2010) also find that analysts are directly involved in the process by which some accounting frauds are uncovered.

On the other hand, analysts may lack strong incentives to warn investors about a high risk of fraud since analysts have incentives to maintain good relations with management in order to keep their investment banking business or to maintain access to private information about the company (Lin and McNichols, 1998; Michaely and Womak, 1999; and Ke and Yu, 2006). Consistent with this pessimistic view, it has been found that analyst earnings forecasts and stock recommendations apparently do not alert investors to the presence of opportunistic earnings management (Bradshaw et al., 2001; and Teoh and Wong, 2002).

We explore these alternative viewpoints about the informational role of analysts by partitioning the sample according to the extent of analyst following. The Hi_Follow_{it}variable takes a value of one if analyst following during the quarter is above the sample median, and zero otherwise:

$$V_{it} = b_0 + b_1 X_{it} + b_2 B_{it} + b_3 Fraud_{it} + b_4 X_{it} \times Fraud_{it} + b_5 B_{it} \times Fraud_{it} + \ b_5 Hi\_Follow_{it} \\ + b_6 Fraud_{it} \times Hi\_Follow_{it} + b_7 X_{it} \times Hi\_Follow_{it} + \ b_8 X_{it} \times Fraud_{it} \times Hi\_Follow_{it}. \tag{8}$$

In equation (8), the b_4 coefficient captures the valuation discount on fraudulently reported earnings when the analyst following is small ($Hi\_Follow_{it} = 0$). In contrast, the discount is equal to $b_4 + b_8$ when the analyst following is large ($Hi\_Follow_{it} = 1$). If investors are more accurately informed about the risk of fraud when analyst following is large, then the coefficient on fraudulent earnings will be smaller (i.e., $b_8 < 0$).

The cross-sectional and time-series results for equation (8) are reported in Table 4. In column (1), the b_4 coefficient is negative (–3.267) but statistically significant at just the 10% level. It is insignificant in column (2). This provides only weak evidence of the discounting of fraudulently reported earnings when analyst following is small. In contrast, the valuation discount is much larger when the fraud companies have a large analyst following, with a total discount of –8.020 and –9.343 in columns (1) and (2). More importantly, the coefficient on fraudulent earnings is significantly smaller (i.e., b_8<0) when analyst following is large (t-stats. = –2.80, –2.55). It would thus appear that the earnings of fraud companies with high analyst following are not valued at the premium that other high-following companies command. We caution, however, that this does not necessarily mean that investors obtain their fraud-relevant information directly from analysts.[17] Rather, the analyst following variable may simply reflect that companies with a larger analyst following operate in a more transparent information environment, which allows investors to better pinpoint the occurrence of fraud.

17 Table 4 also reveals significant positive coefficients for analyst following and for the interaction between analyst following and reported earnings. These findings are consistent with analysts choosing to follow companies that have higher market valuations and report more informative earnings (McNichols and O'Brien, 1997).

Table 4
Analyst Following and the Market Valuation of Fraudulently Reported Earnings

	Predicted Sign	*Cross-sectional Test Eq. (10) (1)*	*Time-series Test Eq. (10) (2)*
Constant	?	26.952	12.173
		(13.13)***	(2.07)**
X_{it}	+	7.689	5.735
		(23.91)***	(1.44)
B_{it}	+	0.625	0.384
		(34.32)***	(1.66)*
$Fraud_{it}$	?	1.038	−4.984
		(0.92)	(−1.24)
$X_{it} \times Fraud_{it}$	−	−3.267	−1.764
		(−1.84)*	(−1.61)
$B_{it} \times Fraud_{it}$	?	0.053	0.021
		(0.41)	(0.12)
Hi_Follow_{it}	+	6.794	7.317
		(30.63)***	(2.06)**
$Fraud_{it} \times Hi\_Follow_{it}$	?	2.981	5.498
		(1.10)	(1.27)
$X_{it} \times Hi\_Follow_{it}$	+	8.784	9.512
		(16.51)***	(1.62)
$X_{it} \times Fraud_{it} \times Hi\_Follow_{it}$	−	−4.753	−7.579
		(−2.80)***	(−2.55)***
Non-fraud Quarters		257,616	2,491
Fraud Quarters		1,248	1,248
Adj R^2 (%)		42.83	63.92
The ERCs:			
Low Follow Fraud Quarters: b_1+b_4		4.422	3.971
Low Follow Non-fraud Quarters: b_1		7.689	5.735
High Follow Fraud Quarters: $b_1 + b_4 + b_7 + b_8$		6.463	5.904
High Follow Non-fraud Quarters: $b_1 + b_7$		14.483	15.247

Note:
The dependent variable (V_{it}) is the closing stock price on the first day after the quarterly earnings announcement.

$$V_{it} = b_0 + b_1X_{it} + b_2B_{it} + b_3Fraud_{it} + b_4X_{it} \times Fraud_{it} + b_5B_{it} \times Fraud_{it} + b_5Hi\_Follow_{it} + b_6Fraud_{it} \times Hi\_Follow_{it} + b_7X_{it} \times Hi\_Follow_{it} + b_8X_{it} \times Fraud_{it} \times Hi\_Follow_{it}. \quad (8)$$

V_{it} = the closing stock price of company i on the first day after its earnings announcement in quarter t; X_{it} = the reported quarterly earnings per share of company i in quarter t; B_{it} = the reported book value per share of company i in quarter t. $Fraud_{it}$ = one if company i issues fraudulently misstated accounts in quarter t; = zero otherwise. Hi_Follow_{it} = one if the number of analyst following is above the median; = zero if the number of analyst following is below the median. The treatment sample comprises 1,248 fraud quarters. The control sample comprises 257,616 non-fraud quarters in the cross-sectional tests, and 2,491 pre-fraud quarters in the time-series tests. Dummy variables for every year, quarter and four-digit SIC fixed effects are included but the results are not reported. T-statistics are calculated based on Huber/White/sandwich robust standard errors and clustering at the company level.
***, ** and * indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

(ii) Institutional Ownership

Compared with other types of investors, institutions have a greater demand for timely information dissemination and gravitate toward stocks that have faster information dissemination (D'Souza et al., 2010). Institutions have a high demand for information both as a basis for investment decisions and to satisfy standards of

Table 5

Institutional Ownership and the Market Valuation of Fraudulently Reported Earnings

	Predicted Sign	*Cross-sectional Test Eq. (11) (1)*	*Time-series Test Eq. (11) (2)*
Constant	?	26.034	11.587
		(10.79)***	(1.67)*
X_{it}	+	7.901	7.005
		(25.31)***	(3.13)***
B_{it}	+	0.590	0.851
		(32.86)***	(3.92)***
$Fraud_{it}$	?	0.725	–2.972
		(0.61)	(–1.45)
$X_{it} \times Fraud_{it}$	–	−1.787	−2.545
		(−0.87)	(−2.84)***
$B_{it} \times Fraud_{it}$	?	0.201	0.290
		(1.51)	(1.84)*
Hi_Inst_{it}	+	6.903	6.077
		(30.96)***	(2.19)**
$Fraud_{it} \times Hi\_Inst_{it}$	?	1.145	−1.697
		(0.49)	(−0.78)
$X_{it} \times Hi\_Inst_{it}$	+	6.905	6.226
		(14.32)***	(1.70)*
$X_{it} \times Fraud_{it} \times Hi\_Inst_{it}$	−	−6.911	−6.649
		(−2.71)***	(−2.49)**
Non-fraud Quarters		257,616	2,491
Fraud Quarters		1,248	1,248
Adj R^2 (%)		42.04	62.79
The ERCs:			
Low Inst Fraud Quarters: b_1+b_4		6.114	4.460
Low Inst Non-fraud Quarters: b_1		7.901	7.005
High Inst Fraud Quarters: $b_1+b_4+b_7+b_8$		6.108	4.037
High Inst Non-fraud Quarters: b_1+b_7		14.806	13.231

Note:
The dependent variable (V_{it}) is the closing stock price on the first day after the quarterly earnings announcement.

$$V_{it} = b_0 + b_1X_{it} + b_2B_{it} + b_3Fraud_{it} + b_4X_{it} \times Fraud_{it} + b_5B_{it} \times Fraud_{it} + b_5Hi\_Inst_{it} + b_6Fraud_{it} \times Hi\_Inst_{it} + b_7X_{it} \times Hi\_Inst_{it} + b_8X_{it} \times Fraud_{it} \times Hi\_Inst_{it}. \quad (9)$$

V_{it} = the closing stock price of company i on the first day after its earnings announcement in quarter t; X_{it} = the reported quarterly earnings per share of company i in quarter t; B_{it} = the reported book value per share of company i in quarter t. $Fraud_{it}$ = one if company i issues fraudulently misstated accounts in quarter t; = zero otherwise. Hi_Inst_{it} = one if the percentage of institutional holding is above the median; = zero if the percentage of institutional holding is below the median. The treatment sample comprises 1,248 fraud quarters. The control sample comprises 257,616 non-fraud quarters in the cross-sectional tests, and 2,491 pre-fraud quarters in the time-series tests. Dummy variables for every year, quarter and four-digit SIC fixed effects are included but the results are not reported. T-statistics are calculated based on Huber/White/sandwich robust standard errors and clustering at the company level.
***, ** and * indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

fiduciary responsibility (O'Brien and Bhushan, 1990). Thus, the level of institutional ownership is a reasonable measure of the overall quality of a company's information environment. We therefore compare the market pricing of fraudulent earnings when institutional ownership is high versus when it is low. Specifically, we estimate equation (9) using institutional ownership as an alternative proxy for a company's information environment:

$$V_{it} = b_0 + b_1 X_{it} + b_2 B_{it} + b_3 Fraud_{it} + b_4 X_{it} \times Fraud_{it} + b_5 B_{it} \times Fraud_{it} + b_5 Hi\_Inst_{it} + b_6 Fraud_{it} \times Hi\_Inst_{it} + b_7 X_{it} \times Hi\_Inst_{it} + b_8 X_{it} \times Fraud_{it} \times Hi\_Inst_{it} \quad (9)$$

The Hi_Inst_{it} variable equals one if the percentage of institutional ownership is above the median, and zero otherwise.

The results are reported in Table 5. The $X_{it} \times Fraud_{it} \times Hi\_Inst_{it}$ coefficient is negative and significant at the 1% (5%) level in the cross-sectional (time-series) tests. This indicates that a lower valuation weight is placed on fraudulently reported earnings when institutional ownership is high. Again, this points toward investors being better able to identify fraudulent earnings information when the company operates in a richer information environment.

5. CONCLUSION

A large body of accounting literature examines the manipulation of reported earnings by managers, with most studies assuming that this behavior is opportunistic. Opportunistic reporting is unlikely to be easily unraveled by investors because if the market could easily see through earnings management and undo it, then managers would have little incentive to report opportunistically in the first place. Moreover, managers have an incentive to hide their opportunistic reporting from investors, particularly if their goal is to maintain the market's over-valuation of their company. On the other hand, investors have strong incentives to become informed about the risk of misreporting in order to avoid making costly investment decisions.

We infer whether investors are accurately informed by examining the weight that the market accords fraudulent earnings before any allegations of accounting impropriety have been made public. Our theoretical model generates the prediction that the weight on reported earnings is lower if investors rationally perceive a high risk of fraud. As predicted, we find that the earnings coefficient in the valuation model is significantly smaller for companies engaged in fraud. We also demonstrate that investors place less weight on reported earnings when there are public information cues indicating a high *ex-ante* risk of fraud. Additional supplementary tests indicate that investors are better informed about the risk of fraud when companies operate within richer information environments; i.e., when analyst following is greater or the level of institutional ownership higher.

In summary, investors are often characterized as the unfortunate, ill-informed victims of management deception, rather than as sophisticated agents who can partially unravel opportunistic reporting. In contrast, our results suggest investors understand that the reported earnings of fraud companies are less sustainable even though they may not know the exact reasons why. Thus, stock prices reflect the presence of fraud long before the accounting problems are publicly disclosed. Indeed the logic of our arguments can be applied to other situations where a company's true performance is temporarily hidden, but will be subsequently revealed. We leave it to future research to determine whether similar empirical findings hold outside of the fraud setting.

APPENDIX

Table A1

The Fraud Prediction Model

	Predicted sign	
Constant	?	−7.845
		(−40.89)***
RSST_ACC	+	0.680
		(4.13)***
CH_REC	+	3.011
		(6.93)***
CH_INV	+	4.218
		(7.81)***
CH_CS	+	0.141
		(4.01)***
CH_EARN	−	−2.847
		(−11.15)***
ISSUE	+	1.174
		(4.36)***
VOLA	+	1.903
		(3.35)***
RETSTD	+	4.095
		(8.03)***
Bigaudit	−	0.112
		(1.09)
SIZE	+	0.196
		(10.55)***
Age	−	−0.093
		(−3.11)***
Lag_Return	?	0.164
		(4.42)***
Leverage	+	1.444
		(11.28)***
Non-Fraud Quarters		234,789
Fraud Quarters		1,149

Note:
The dependent variable ($Fraud_{it}$) is dummy variable one if the reported earnings are fraudulent.
$Fraud_{it} = b_0 + b_1 RSST\_ACC_{it} + b_2 CH\_REC_{it} + b_3 CH\_INV_{it} + b_4 CH\_CS_{it} + b_5 CH\_EARN_{it} + b_5 ISSUE_{it} + b_6 VOLA_{it} + b_7 RETSTD + b_8 Bigaudit_{it} + b_9 SIZE_{it} + b_{10} Age_{it} + b_{11} Lag\_Return_{it} + b_{12} Leverage_{it}$
***, ** and * indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

Table A1
Continue

RSST accruals = (ΔWC + ΔNCO + ΔFIN)/Average total assets, where WC = [CA (DATA 4) – CASH and STI (DATA 1)] – [CL (DATA 5) – STD (DATA 34)]; NCO = [Assets (DATA 6) – CA (DATA 4) – LTI (DATA 32)] – [Total Liabilities (DATA 181) – CL (DATA 5) – LTD (DATA 9)]; FIN = [STI (DATA 193) + LTI (DATA 32)] – [LTD (DATA 9) + STD (DATA 34) + PRE Stock (DATA 130)]. *CH_REC* = Δreceivables (DATA 2)/Average total assets. *CH_INV* = Δinventory (DATA 3)/Average total assets. *CH_CS* = Percentage change in cash sales [Sales (DATA 12)-ΔAR(DATA 2)]. *CH_EARN* = (Earnings$_t$ (DATA 18)/Average total assets$_t$) – (Earnings$_{t-1}$/Average total assets$_{t-1}$). *ISSUE* = an indicator variable coded 1 if the firm issued securities during the manipulation year (an indicator variable coded 1 if DATA 108 > 0 or DATA111 > 0). *VOLA* = rank of the variance of EPS during the 5 years with a minimum of eight quarters available before the quarter, scaled by the number of observations. *RETSTD* = rank of the variance of the daily stock return during the fiscal quarter, scaled by the number of available observations. Industry (4-digit SIC) and year fixed effects are also included, but not reported. *Bigaudit* = one if the company is audited by one of the Big Five companies or their predecessors, zero otherwise. *SIZE* = the log of total assets. *Age* = log of firm age. *Lag_Return* = Previous year's annual buy-and-hold return minus the annual buy-and-hold value weighted market return. *Leverage* = Long-term debt (DATA 9)/ Total assets (DATA 6). The treatment sample comprises 1,149 fraud quarters and the control sample comprises 234,789 non-fraud quarters. The model is estimated using logistic regression.
***, ** and * indicate two-tailed significance at the 1%, 5%, and 10% levels, respectively.

Table A2
The Predictive Accuracy of the Fraud Model in Table A1

		Predicted Outcome		
		Fraud	*No-fraud*	*Total*
Actual outcome	Fraud	774	375	1,149
		(Correct classification = 67.4%)	(Type I error = 32.6%)	(100.0%)
	No-fraud	79,137	156,649	235,786
		(Type II error = 33.6%)	(Correct classification = 66.4%)	(100.0%)
	Total	79,911	157,024	236,935

Note:
The logit model generates a predicted fraud (no-fraud) outcome when the F-score is greater (less) than one. Following Dechow et al. (2010), the F-score is defined to be the predicted probability of fraud [$\exp(\beta X)/(1+\exp(\beta X))$] divided by the unconditional probability of fraud [number of fraud firms/total number of firms].

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