To Tell the Truth: Management Forecasts in Periods of Accounting Fraud

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ABSTRACT

Using a sample of firms subject to Securities and Exchange Commission (SEC) Enforcement Actions, we compare changes in the incidence, news content, bias, and accuracy of fraud firms' management earnings forecasts to the changes observed in a sample of control firms matched on industry, size, and fraud risk. We find that, although managers of control firms significantly increase the number of their earnings forecasts over time, managers of fraud firms initially provide more forecasts during the fraud period, but, once the fraud period ends, managers of fraud firms decrease the quantity of their earnings forecasts both in the post-fraud period before the fraud is revealed and after the fraud is publicly known. Relative to control firms, managers of fraud firms are more likely to issue a significantly greater proportion of bad news forecasts during fraud than either before or after the fraud period, and issue less ex post optimistically biased and more accurate forecasts during the fraud period than they did prior to the fraud period. In combination, our results suggest that managers of fraud firms increase their use of credible earnings forecasts to manage investor expectations downward during periods of fraud while simultaneously fraudulently manipulating earnings to meet or beat market expectations. We also find that, relative to the control sample, the market responds more strongly to both the good news and bad news earnings forecasts of fraud firms, both during and after fraud, relative to the pre-fraud market response. Thus, public revelation of the fraud does not appear to taint the credibility of management forecasts. As a whole, the results suggest that management forecasts are of a high quality (traditionally defined) and perceived as credible while managers commit fraud.

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1. Introduction

Empirical accounting research related to earnings quality and voluntary disclosure quality has progressed, to a great extent, in isolation, even though accounting theory has long recognized the potential relation between the two. Recently, empirical findings suggest a complementary relation. For example, Lennox and Park (2006) find that firms with higher earnings response coefficients (a proxy for earnings quality) release management earnings forecasts more frequently (a proxy for voluntary disclosure quality). Using several alternative proxies for earnings quality (i.e., accruals magnitude, earnings variability, and predictive ability for cash flows), Francis et al. (2008) also find that firms with higher earnings quality have higher voluntary disclosure quality as measured by an index of disclosure derived from annual reports. More recently, Ball et al. (2009) extend the notion of a complementary relation by testing the "confirmation" hypothesis, a conjecture that reported, audited, backwards-looking outcomes discipline and hence enhance management forecast credibility. Specifically, they document that firms committing to higher audit fees (a proxy for earnings quality because it measures the extent of verification and hence the freedom from earnings manipulation) also issue management forecasts that are more frequent, more precise, and elicit larger price reactions.

We extend this literature by investigating an important context in which the relation between earnings quality and voluntary disclosure quality is likely unique – the context of accounting fraud. In most accounting frauds, managers interject bias into realized earnings numbers by violating generally accepted accounting principles governing earnings measurement. Thus, earnings quality declines, and a complementary relationship between earnings quality and voluntary disclosure quality implies lower voluntary disclosure quality as well. However, a key incentive to commit fraud, the desire to meet or beat earnings expectations, also creates an incentive for more frequent, less optimistically biased, and more accurate management earnings forecasts (an important voluntary disclosure) to manage the expectations that firms wish to beat. That is, in periods in which the incentive to meet or beat expectations has become so strong so that managers choose to commit fraud and damage earnings quality, voluntary disclosure quality (traditionally measured) can remain high, and may in fact increase due to an enhanced role of management forecasts in managing earnings expectations.

To investigate the association between fraud (our earnings quality proxy) and voluntary disclosure quality, we examine the management earnings forecast behavior of 119 firms that were subject to accounting-related Securities and Exchange Commission (SEC) Enforcement Actions during pre-fraud, fraud, post-fraud, and public periods, where public period is defined by public knowledge of the fraud (i.e., when regulatory proceedings are initiated and the public is informed of the alleged fraud).[1] Specifically, we compare changes over time in the incidence, news content, bias, and accuracy of fraud firms' management earnings forecasts to the changes observed in a sample of control firms matched on industry, size, and fraud risk. We find that relative to the pre-fraud period, managers of both fraud and matched non-fraud firms significantly increase the frequency of earnings forecasts during the fraud period. In addition, we find that relative to both the control firms and their own behavior in the pre-fraud period, firms that engage in fraud are more likely to issue management forecasts that contain bad news during the fraud period. The forecasts during fraud periods are also less *ex post* optimistically biased relative to the pre-fraud period, and more *ex post* accurate relative to the pre-fraud period. These results are consistent with managers of fraud firms using multiple tools (i.e., managing expectations downward while simultaneously manipulating earnings) to meet market expectations. As fraud firms move from the fraud periods to post-fraud and public periods, they significantly decrease the frequency of their forecasts and are less likely to issue forecasts that contain bad news relative to control firms. However, the fraud firms maintain the relatively lower bias and greater accuracy for the forecasts they issue in post-fraud and public periods.

We also examine investor assessment of the credibility of fraud period management forecasts by examining the stock market reaction to management forecasts in those periods compared to our sample of control firms. We find that, relative to the control sample, market responses to fraud firm forecasts are

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[1] Technically, the term "fraud" is a legal term that can only be determined by a court of law. However, we use "fraud" to refer to firms that face enforcement actions from the Securities and Exchange Commission for outside-

more pronounced for both good and bad news in fraud, post-fraud, and public periods relative to pre-fraud periods. This finding is in marked contrast to Hui and Lennox (2009), who find that investors discount actual earnings news in fraud periods even after they control for ex ante fraud risk (as we do via a control group matched to our fraud firms on industry, size, and fraud risk). These results suggest that investors perceive management forecasts as credible in fraud periods and are consistent with our finding that firms issue more accurate and less *ex post* optimistically biased forecasts during periods of fraud, thereby establishing a reputation for credible disclosure.[2]

Furthermore, our results suggest that the improvement in forecast quality demonstrated by fraud firms during the fraud period and maintained during post-fraud establishes a reputation for credible forecasting among investors that persists after the fraud ends. Public revelation of the fraud does not appear to taint the credibility of management forecasts. Interestingly, while the decrease in management forecast frequency we detect post-fraud is consistent with a reduced need to manage expectations, it is also consistent with a fear of drawing attention to the firm before the fraud is revealed. The further forecast frequency reduction in the public period is consistent with increased monitoring from regulators.[3]

This study contributes to the literature on the relation between voluntary disclosure and earnings quality, the literature that investigates the causes and consequences of fraudulent reporting[4], and the voluntary disclosure literature in general. With respect to the relation between earnings quality and voluntary disclosure, the conclusion of recent studies is that the relation is complementary. We extend this line of research using an unambiguous measure of the choice of earnings quality: the incidence of

[2] An alternative interpretation is that the market is fooled by accounting manipulations during fraud periods (Bardos et al. 2010) that simply make the management forecasts *appear* to be credible. However, this interpretation admits that managers can choose low earnings quality to cause the market to perceive that voluntary disclosure quality is high, and thus, expands the interpretation of Ball et al.'s (2009) confirmation hypothesis to add the idea that both earnings quality enhancing choices (e.g., paying higher audit fees to reduce the *ex ante* likelihood of fraud) and earnings quality destruction choices (e.g., commission of *ex post* fraud) can enhance investors' perception of management forecast credibility.

[3] A related potential alternative explanation is that new participants in the earnings measurement and disclosure process (i.e., new CEOs) wish to establish a reputation for credible forecasting in the presence of this increased monitoring. In a supplemental analysis, we control for management turnover and our results remain qualitatively similar.

[4] See Dechow et al. (1996), Healy and Palepu (2003), Palmrose and Scholz (2004), Desai et al. (2006), Erickson, Hanlon, and Maydew (2006), Efendi et al. (2007), Karpoff et al. (2008a, 2008b), and Dechow et al. (2010).

fraud. Contrary to findings in prior research, our results suggest that voluntary disclosure quality (as measured by accuracy, bias, and information content) and earnings quality are not complementary during periods of accounting fraud. Identifying different effects for alternative proxies for earnings quality is an important theme in Dechow et al. (2010). In addition to documenting a unique relation between earnings quality and voluntary disclosure quality when earnings quality is proxied by fraud, our findings and interpretations suggest that research into the relationship between fraud and voluntary disclosure quality requires a more precise definition of voluntary disclosure quality to permit unambiguous interpretation of the association of fraud-induced low earnings quality and voluntary disclosure quality.

With respect to understanding the effects of fraud, it is reasonable to believe that fraud might taint the credibility of the entire measurement and disclosure process. However, our results suggest that incentives to engage in quality voluntary disclosure while committing fraud remain strong, most likely because of management's incentive to meet market expectations and the usefulness of credible voluntary disclosure to lower investors' earnings expectations while concurrently increasing reported earnings (artificially) through fraudulent reporting. To our knowledge, ours is the first study to present evidence on whether the act of fraud influences the voluntary disclosure behavior of fraud firms in fraud periods.

Finally, while research on management earnings forecasts has examined the effects of shareholder litigation (Skinner 1997; Rogers and Van Buskirk 2009), managerial incentives (Aboody and Kasznik 2000; Rogers and Stocken 2005), proprietary information costs (Ajinkya et al. 2005; Wang 2007), and accounting conservatism (Hui et al. 2009) on firms' voluntary disclosure behavior, it has not addressed the question of how accounting fraud impacts managers' use of earnings forecasts. Also, prior research has examined the intertemporal relation between disclosure reputation and assessment of management forecast credibility (e.g., Baginski and Hassell 1990; Williams 1996; Mercer 2004; Rogers and Stocken 2005), but it has not investigated the effects of fraud on assessments of management earnings forecast credibility. We provide evidence concerning how investors respond to the issuance of subsequent voluntary disclosures once a fraud has become public knowledge. Specifically, our results suggest that once a firm has established a reputation for credible forecasting, the benefits to forecast credibility appear to be long-lived.[5]

The remainder of the paper proceeds as follows: Section 2 reviews the literature and develops our empirical predictions. The research design is specified in Section 3. We describe our sample of fraud and matched nonfraud firms in Section 4, and empirical results are presented in Section 5. Section 6 discusses additional analyses, and Section 7 concludes the paper.

2. Key Definitions, Assumptions, and Empirical Predictions

Prior to making empirical predictions, we discuss earnings quality and voluntary disclosure quality constructs, our proxies for the two constructs, and the assumptions under which the proxies are valid.

2.1. Earnings "Quality"

Dechow et al. (2010) note the existence of several alternative proxies for earnings quality, each with its own strengths and weaknesses. The primary strength of using SEC Accounting and Auditing Enforcement Releases (AAERs) as a proxy for low earnings quality is that an outside source, the SEC, has identified a problem with earnings quality, and thus, the researcher benefits from avoiding the potential misspecification (and resulting Type I errors) of a model of earnings quality. Further, as opposed to samples of restatements and internal control deficiencies, AAERs maximize the likelihood that the decline in earnings quality is intentional. This characteristic of AAERs is important for our study because voluntary disclosure quality is also a choice, and we are interested in the complementary nature of earnings quality and disclosure quality choices.

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[5] An independently developed concurrent study, Ettredge, Huang, and Zhang (2011) examine whether managers change their forecasting behavior subsequent to the public announcement of an accounting restatement. In contrast, our study examines whether the act of intentionally misreporting is associated with changes in managers' forecasting behavior before, during, or after the period in which managers commit fraud. In addition, we document the market's assessment of forecast credibility during fraud periods. We provide insights into the role that voluntary disclosures play in helping managers of fraudulent firms manage market expectations during and after fraud. We also examine whether the changes in managers' voluntary disclosure behavior persists into future periods, including the period after the fraud is revealed to the public.

The primary weakness of choosing AAERs as a measure of lower earnings quality is identifying the "high quality" condition. Dechow et al. (2010) note that a non-SEC enforcement control group might also contain firms that engage in overly aggressive earnings management but, for some reason, avoid SEC enforcement (a Type II error). Accordingly, we use the fraud firm as its own control by basing our primary tests on differences in voluntary disclosure behavior in fraud periods relative to periods in which the SEC either argues fraud has not been committed or that it is not sufficiently certain that fraud has been committed to say so. Therefore, our key assumption is that, given the SEC has chosen to charge a given firm with fraud and investigated it, the SEC's designation of the period in which the fraud was committed is reliable evidence that earnings quality was compromised in an egregious manner relative to periods designated as not containing fraud.

We also utilize a control group of firms matched on size, industry, and fraud risk (discussed later). But, the purpose of that control group is to control intertemporally for changes in expected voluntary disclosure characteristics (i.e., management forecasts frequency, bias, accuracy, tenor of news, and information content) of firms that fit the profile of high fraud risk firms based on corporate governance structures and changes in key financial statement variables.

2.2. Voluntary Disclosure "Quality"

Ball et al. (2009) document an association between higher audit fees and more frequent management forecasts, more specific management forecasts, and a greater price reaction to those forecasts. The first two proxies, frequency and specificity, are commonly used measures of management forecast quality (Bamber and Cheon 1998; Ajinkya et al. 2005; Francis et al. 2008; Rogers and Van Buskirk 2009). The proxy for management forecast credibility in equity markets, price reaction to the forecast, is also well-established (Pownall and Waymire 1989). Related to forecast specificity (to the extent that it measures uncertainty), management forecast bias and accuracy are additional measures of management forecast quality obtained by an *ex post* comparison of the forecast to realized earnings (Williams 1996; Rogers and Stocken 2005).

Consistent with prior literature, our empirical tests use frequency, bias, accuracy, and price reaction as measures of management forecast disclosure quality, and we draw conclusions assuming that the proxies are valid. Whenever possible, we consider alternative interpretations and what those interpretations teach us about the association between earnings quality and disclosure quality. This is necessary because each of these proxies has its strengths and weaknesses in general and in the specific context of fraud.

Frequency is a simple count of forecast incidence and, thus, is independent of whether actual earnings are measured in accordance with generally accepted accounting principles or fraudulently. However, more frequent forecasts are not necessarily less biased, more accurate, or more price informative. That is, in the context of Dechow et al.'s (2010) discussion of earnings quality, forecast frequency is divorced from any discernable decision task.

Bias and accuracy directly measure the ability of managers to forecast earnings, and thus (assuming a known mapping of earnings into prices), are directly linked to an investor's decision task. However, their measurement depends on realized earnings, which can be manipulated by management. That is, the earnings quality condition affects the *measurement* of voluntary disclosure quality. However, if the decision task of interest is predicting what earnings number will be revealed in the upcoming earnings release (a task that is independent of earnings quality), then management forecast bias and accuracy are valid measures of quality.[6] Alternatively, if the decision task of interest is predicting what *value-relevant* earnings will be revealed in the upcoming earnings release, then management forecast bias and accuracy remain valid measures of quality *if* the market does not differentially value the fraudulent component of earnings.

[6] Management earnings forecasts are fundamentally different from many other types of voluntary disclosure. Some voluntary disclosures are of non-mandated information. For example, disclosing an expansion strategy or attributing an expected earnings increase or decrease to some internal or external phenomenon represent disclosures that are not followed by a mandatorily disclosure of the same information. However, management earnings forecasts are simply early disclosures of forthcoming (often, shortly forthcoming) mandated earnings releases. The timing aspect of a management forecast permits sharing of management's private information, mitigation of private information acquisition by others, reduction of information asymmetry, and increase in share value.

Price reaction at the management forecast date has the advantage of being independent of realized earnings unless managers convey a forecast of what they know will be fraudulently reported earnings. Known forecasting of fraudulent earnings does not render price reactions as invalid measurements of management forecast credibility if the market discounts fraudulent earnings. Whether the market can ascertain fraud before it is publicly announced is an empirical question on which there are mixed results. Hui and Lennox (2009) find that investors respond less strongly to the positive earnings surprises of firms committing accounting fraud than the positive surprises of nonfraud firms. However, recent evidence from Bardos et al. (2010) suggests investors are unable to initially see through mistakes in materially misstated earnings and attach the same valuation to the component of a positive earnings surprise that will be restated as they do to the true earnings surprise.

2.3. Empirical Predictions

2.3.1. Frequency

While all managers have incentives to meet the market's expectations of earnings, the willingness of managers of fraud firms to engage in unlawful behavior suggests they face greater pressure to avoid missing market expectations than managers of other firms. Indeed, SAS No. 99 identifies external pressure as one of the three risk factors associated with fraudulent behavior (Skousen and Wright 2008). Similarly, Dechow et al. (1996) state that "influencing investor perceptions of firm value provides a primary motivation for earnings manipulation," (p.4) and Graham et al. (2005) find that managers view the meeting of earnings targets as essential to maintaining credibility with the market and preventing a decrease in stock price. Graham et al. (2005) also report that managers are frequently willing to make sacrifices in long-term economic value in order to meet current analyst and investor earnings expectations.

As an alternative to manipulating actual earnings, managers can also manage earnings expectations through voluntary disclosure (Ajinkya and Gift 1984). Soffer et al. (2000) document that managers strategically time the disclosure of bad news in order to walk down investors' earnings expectations to a beatable level, and Baik and Jiang (2006) find that managers' attempts to use pessimistic guidance to lower expectations often result in an increased probability of meeting analyst forecasts. Also, Brown and Higgins (2005) find that U.S. managers are more likely to use forecast guidance to avoid negative earnings surprises than managers in other countries, due to strong investor protection laws. Matsumoto (2002) and Burgstahler and Eames (2006) find evidence that managers often use a combination of increasing reported earnings through earnings management while lowering expectations through negative earnings guidance.

If managers of fraud firms face increased pressure to manage the market's expectations, we expect to observe a higher frequency of management earnings forecasts during periods of fraud than we observe for managers of matched nonfraud firms. Further, fraud is evidence that within GAAP earnings management is constrained, suggesting an enhanced role for management forecasts in meeting or beating expectations. Given that an increase in management forecast frequency is a measure of voluntary disclosure quality, this prediction is in contrast to the notion of a complementary relation between earnings quality and voluntary disclosure quality during periods of fraud.

However, managers of fraud firms also have incentives to reduce their voluntary disclosures during fraud for two reasons. First, managers are exposed to legal penalties under SEC Rule 10b-5, which provides that the plaintiff must establish that managers' earnings forecasts were intentionally false or misleading. If the fraud is uncovered, managers whose voluntary disclosures are shown to have misled the market through overly optimistic forecasts or by failing to disclose materially adverse information are likely to face shareholder lawsuits under SEC Rule 10b-5. Second, bad news management forecasts disclose poor performance, a condition that managers are generally trying to hide via fraud. So, bad news forecasts might be suppressed. Thus, it is possible that the frequency of management earnings forecasts will decline during periods of fraud.

2.3.2. News Content

Managers' efforts to lower investor expectations should result in the issuance of forecasts that fall below current market expectations (Matsumoto 2002). Therefore, we expect that managers are more likely to issue disclosures that fall short of analyst expectations during periods of fraud. Evidence on our conjecture provides a gauge of the relative strength of competing incentives. While bad news forecasting is consistent with maximizing the likelihood of meeting or beating lowered expectations, it is not consistent with the notion that managers have incentives to hide or at least delay bad news. Dechow et al. (2010) suggest that managers of fraudulent firms attempt to hide declining performance and note that fraudulent firms have abnormally strong stock return performance in the years before the fraud begins. Accordingly, managers of fraudulent firms may be less likely to issue bad news forecasts in an effort to mask declining performance and maintain their firm's stock price. Further, Kothari et al. (2009) provide evidence that suggests that, on average, managers delay the disclosure of bad news and disclose good news in a timely manner.

2.3.3. Bias

In addition to controlling the overall news content of their forecasts, managers have the ability to bias their earnings forecasts (Hirst et al. 2008). However, Rogers and Stocken (2005) note that managers' abilities to bias their forecasts are limited because investors are able to use the subsequent earnings report to determine whether management is providing credible forecasts. To the extent that fraud allows managers to hide or at least delay the revelation of declining performance, the act of fraud would be associated with more optimistically biased forecasts. Consistent with this notion, Rogers and Stocken (2005) find that managers are more likely to strategically bias their forecasts, according to their incentives, when it is more difficult for investors to assess the credibility of the forecasts. In contrast, the act of fraud is potentially associated with less optimistically biased forecasts because, as discussed above, managers are likely to be concerned with the legal liability associated with issuing false or misleading forecasts under SEC Rule 10b-5 and may not wish to suffer the capital market consequences of falling short of a management forecast. In addition, prior research suggests that managers develop a forecasting reputation based on their prior forecasts (Williams 1996), which suggests that optimistically biased management forecasts will potentially taint management's forecasting reputation and limit managers' ability to use earnings forecasts to meet or beat expectations in the future.

2.3.4 Accuracy

Finally, we examine whether managers' strategic incentives influence the accuracy of their forecasts during fraud. Although managers have incentives to disregard forecast accuracy and issue forecasts in a strategic manner, we expect that fraud will be associated with more accurate forecasts for two reasons. First, as discussed above, managers are able to minimize their legal liability under SEC Rule 10b-5 by providing accurate forecasts. Second, prior research suggests that managers with greater accounting flexibility are more likely to issue accurate forecasts (Kasznik 1999). Given that managers engaging in financial statement fraud have more control over reported "actual" earnings than managers of nonfraud firms, they should be more capable of ensuring that reported earnings are in line with their own forecasts than managers of nonfraud firms. In addition, accurate forecasts likely strengthen management's forecasting reputation and enhance the role of forecasts in meeting or beating expectations.

2.4. Investor Assessment of Management Earnings Forecast Credibility

Bardos et al. (2010) find evidence that investors are initially unable to see through mistakes in materially misstated earnings and attach the same valuation to the component of a positive earnings surprise that will be restated as they do to the true earnings surprise. However, Hui and Lennox (2009) find that investors respond less strongly to the positive earnings surprises of firms committing accounting fraud than the positive surprises of nonfraud firms. This result suggests that even before a fraud is revealed publicly, investors discount the earnings of firms that are later revealed to have reported fraudulently. Based on this evidence, we would also expect the market to view the earnings forecasts of fraud firms as less credible than the forecasts of nonfraud firms during the fraud period.

Earnings forecasts of fraud firms issued during the public period could also be viewed by the market as either more or less credible than those of nonfraud firms. Specifically, the market may discount the credibility of fraud firms' forecasts in the public period because managers' willingness to engage in deceitful behavior is now known publicly. After investors learn that managers have deceived them, investors may find it difficult to trust the subsequent forecasts issued by those same managers.

Alternatively, investors may view the revelation of fraud as the beginning of managers' efforts to develop a stronger future reputation. For example, prior research has found that accounting fraud often leads to significant management turnover (Karpoff et al. 2008a).[7] To the extent that firms make a substantial effort post-fraud to regain the trust of investors, including the use of managerial turnover, their subsequent forecasts may have more credibility with the market than those of other firms. In addition, if fraud firms establish a reputation for accurate forecasts during the fraud period, this reputational effect may persist into subsequent periods.

3. Research Design

3.1. Management Forecast Properties

To investigate the association between accounting fraud and changes in firms' disclosure behavior, we follow Rogers and Van Buskirk (2009) in regressing proxies for firms' disclosure behavior on a series of indicator variables that represent different time periods relative to the event of interest, which in our setting is the fraud period. Our initial model is as follows:

$$DiscProxy = \beta_0 + \beta_1\, PreFraudPeriod + \beta_2\, PostFraudPeriod + \beta_3\, PublicPeriod + \varepsilon \qquad (1)$$

The dependent variable, *DiscProxy*, represents various measures of management forecast quality in different regressions. *Frequency* is defined as the average number of forecasts per quarter issued by the firm during a given time period. *BadNewsD*, a dummy variable equal to one if the earnings forecast contains negative news, and zero otherwise, where news content is determined by comparing the forecast to the most recent consensus analyst forecast; *Bias*, equal to the management EPS forecast minus reported EPS scaled by the stock price as of two days before the forecast; and *F_AbsError*, measured as the absolute value of *Bias*. Consistent with prior research, larger values of *F_AbsError* indicate less accurate, and thus lower quality, forecasts (Ajinkya et al. 2005; Bamber et al. 2010).

[7] In additional analysis (discussed later), we control for executive turnover and find that our inferences remain the same.

In equation (1), we use indicator variables that are designed to capture changes in disclosure behavior relative to the fraud period (the benchmark period). We define the fraud period based on information from SEC Enforcement Actions and examine three separate time periods that surround the fraud period (see Figure 1). *PreFraudPeriod* is an indicator variable set equal to one during the twelve months preceding the fraud, and zero otherwise. *PostFraudPeriod* is an indicator variable set equal to one for the period after the fraud, but before the fraud becomes public knowledge, and zero otherwise. Finally, *PublicPeriod* is an indicator variable set equal to one during the twelve months after the fraud becomes public knowledge, and zero otherwise.[8]

Using equation (1), we can observe changes in the disclosure behavior of fraud firms by examining the coefficients on the various time periods (β_1 to β_3) relative to the fraud period (the base group). However, both the decision to commit fraud and the decision to change forecasting behavior are endogenous firm choices. Accordingly, we match each fraud firm with a nonfraud firm based on industry, size, and *ex ante* fraud risk. This ensures that observed changes in disclosure behavior are driven by the fraud event itself, and not other factors that high fraud risk firms have in common.[9] Details of this matching procedure are presented in Section 4.1.

We assign each control firm to pre-fraud, fraud, post-fraud, and public time periods that correspond to those of the fraud firm with which it is paired. We then augment equation (1) by including two indicator variables to distinguish between the fraud firms and matched firms. In the augmented equation (2), the indicator variable *Fraud* equals one if the observation represents a firm that committed

[8] Kedia and Rajgopal (KR, 2011) present a timeline of SEC events as depicted in Karpoff et al. (2008a) in their Figure 1 (p. 265). To enhance the comparison of our paper to theirs, our pre-fraud period is the period left of the KR "violation period." Our fraud period is the same as the KR "violation period." Our post-fraud period is the period between the end of the KR "violation date" and the date of the "initial regulatory proceeding" in KR. Our public period is the period after the initial regulatory proceeding, which is the point at which it is known publicly that the SEC is initiating an enforcement action. The SEC typically conducts an informal and\or formal investigation (which is generally not known publicly) before the Enforcement Action is announced on the initial regulatory proceeding date and does not move forward with an Enforcement Action unless they believe there is evidence of egregious misreporting.

[9] Prior research also suggests that disclosure choices are driven by firm performance (e.g., Miller 2002). To examine whether our results are robust to changes in firm performance, we perform supplemental analyses in which we match firms based on size, industry, and return on assets at the beginning of the fraud period. Inferences remain the same under the alternative matching procedure.

fraud, and zero otherwise, and the indicator variable *Match* equals one if the observation is from a matched firm, and zero otherwise. Additionally, we include firm size, defined as the natural log of market value of equity, book-to-market ratio, analyst following, and industry fixed effects to control for other factors that may have an effect on firms' disclosure behavior.[10] All continuous variables are winsorized at the 1^{st} and 99^{th} percentiles to alleviate the effects of outliers on the analysis. Our final regression model is as follows, with standard errors clustered by firm and year to control for dependency in the error terms (Gow et al. 2010; Petersen 2009):

$$\begin{aligned} \mathit{DiscProxy} = {} & \beta_0 + \beta_1\, \mathit{Fraud\ x\ PreFraudPeriod} + \beta_2\, \mathit{Fraud\ x\ PostFraudPeriod} \\ & + \beta_3\, \mathit{Fraud\ x\ PublicPeriod} + \beta_4\, \mathit{Match\ x\ PreFraudPeriod} \\ & + \beta_5\, \mathit{Match\ x\ FraudPeriod} + \beta_6\, \mathit{Match\ x\ PostFraudPeriod} \\ & + \beta_7\, \mathit{Match\ x\ PublicPeriod} + \Gamma_i\, \mathit{CONTROLS} + \varepsilon \end{aligned} \quad (2)$$

The benchmark group in equation (2) (captured by the intercept) is fraud firms during the fraud period. Therefore, the coefficients on the fraud firm variables, β_1, β_2, and β_3, represent the change in the fraud firms' disclosure behavior from the fraud period to the pre-fraud, post-fraud, or public period, respectively. To capture the change in disclosure for the matched firms, the coefficients for the matched firms in the nonfraud periods (β_4, β_6, and β_7) can be compared to the matched firms' disclosure behavior during the fraud period (β_5).

Because we are primarily interested in the abnormal change in the disclosure behavior of fraud firms (that is, the change incremental to that observed in comparable nonfraud firms), we test our hypotheses by comparing the coefficients on the fraud firm variables to the combined coefficients on the matched firm variables using F-tests. For example, to examine whether a change in disclosure behavior from the fraud period to the public period is different for fraud firms than for matched firms, we perform an F-test on the difference between β_3 and (β_7 - β_5). A positive difference represents a larger change in disclosure for the fraud firms relative to the change in disclosure behavior for the matched firms from the

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[10] Our results are robust to including additional control variables in equation (2). Specifically, inferences remain the same when we control for firm performance (return on assets) during the period, management forecast horizon, and whether the forecast was for quarterly or annual earnings.

fraud period to the public period. Figure 2 details how the coefficients from equation (2) map into the F-tests upon which we base our inferences. By focusing our analysis on F-tests comparing changes in the disclosure behavior of fraud firms over time relative to those observed in the matched firms, we are able to better isolate the changes in disclosure behavior that are due exclusively to the fraud event itself.

3.2. Investor Assessment of Management Forecast Credibility

Next, we examine the impact of accounting fraud on investor assessment of management forecast credibility. Following prior research (e.g., Pownall and Waymire 1989), we use the market reaction to the news contained in a forecast as a proxy for forecast credibility, where news is defined as the forecast's deviation from the most recent consensus analyst forecast. To investigate how the act of fraudulent reporting impacts the market reaction to management earnings forecasts, we estimate the following regression, again with standard errors clustered by firm and year:

$$\begin{aligned} CAR = {} & \gamma_0 + \gamma_1\, GoodNews + \gamma_2\, BadNews + \gamma_3\, Fraud \\ & + \gamma_4\, Fraud \times GoodNews + \gamma_5\, Fraud \times BadNews \\ & + \gamma_6\, Period + \gamma_7\, Period \times GoodNews + \gamma_8\, Period \times BadNews \\ & + \gamma_9\, Period \times Fraud \times GoodNews + \gamma_{10}\, Period \times Fraud \times BadNews \\ & + \Gamma_i\, CONTROLS + \varepsilon \end{aligned} \tag{3}$$

The dependent variable in the above regression, *CAR*, is the firm's three day, size-adjusted stock return centered on the day the management forecast is issued. *ForecastNews* is the management forecast minus the current consensus analyst forecast, scaled by the stock price as of two days before the forecast. *GoodNews* equals *ForecastNews* when *ForecastNews* is greater than zero, ranked by year and scaled to range between zero and one, and zero otherwise. *BadNews* equals the absolute value of *ForecastNews* when *ForecastNews* is less than zero, ranked by year and scaled to range between zero and one, and zero otherwise.[11] *Fraud* is an indicator variable equal to one for fraud firms, and zero for matched firms.[12]

[11] Results are qualitatively similar when the raw values of *GoodNews* and *BadNews* are used in place of the rankings.

[12] As described above and in Section 4.1, match firms are identified based on industry, size, and *ex ante* fraud risk. It is especially important to identify comparable match firms based on *ex ante* fraud risk because investors'

Period is defined contextually. For example, when we compare the fraud period to the pre-fraud period, *Period* equals one in the fraud period and zero in the pre-fraud period. Coefficients of primary interest are γ_9, which measures the change between periods of interest in information content of good news forecasts by fraud firms relative to control firms, and γ_{10}, which measures the same effect for bad news forecasts.

The other variables in equation (3) are included to control for additional factors that have been shown to affect the market reaction to management earnings forecasts. *Shock* is defined as the absolute value of *ForecastNews*. *Precision* is a count variable set equal to two for point estimates, one for range estimates, zero for open-ended forecasts, and missing for qualitative forecasts. *Horizon* is an indicator variable set equal to one for quarterly forecasts, and zero for annual forecasts. *Size* and *BTM* are defined as the natural log of market value of equity and book-to-market ratio, respectively. Again, all continuous variables are winsorized at the first and 99th percentiles.

4. Sample Description

4.1. Sample Selection

Our initial sample of fraud firms is based on 396 firms subject to SEC enforcement actions for fraud periods beginning after 1997.[13] From this initial sample, we remove 68 firms whose public periods end after 2008, where the public period is defined as the year after the existence of the fraud becomes public knowledge. We also require each firm to issue at least one earnings forecast, obtained from First Call's Company Issued Guidance Database, between the pre-fraud and public periods, resulting in the elimination of an additional 146 firms.[14]

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perceptions of fraud risk potentially cause the market to discount the credibility of management's earnings forecasts. Accordingly, matching on *ex ante* fraud risk reduces that likelihood that any differential market response to the forecasts of fraud firms relative to nonfraud firms is driven by differences is investors' perceptions of the likelihood that a firm is committing fraud.

[13] Our sample of SEC enforcement actions comes from hand collected samples obtained from Karpoff et al. (2008a,b) and from Audit Integrity. We require the fraud period to begin after 1997 to ensure availability of management earnings forecast data from First Call.

[14] Following Ajinkya et al. (2005), we require that all sample firms (both fraud and match firms) have analyst coverage on the First Call Analyst Forecast Database during the sample period to ensure that our sample firms are covered by First Call during the sample period.

Next, we match each of the remaining 182 fraud firms with a nonfraud firm based on industry, size, and a fraud risk measure commercially produced by Audit Integrity called Accounting and Governance Risk (AGR). Price et al. (2011) find that AGR detects and predicts fraud as well or better than risk proxies developed in the academic literature, including Dechow et al.'s (2011) F-score. We begin our matching procedure by identifying all nonfraud firms with the same 2 digit SIC code as the fraud firm.[15] We then retain those firms with total assets within 25% of the fraud firm's total assets as of the beginning of the fraud period. Out of the remaining possible matches, we keep the firm with the closest AGR score to that of the fraud firm.

As discussed in the previous section, we match our fraud and nonfraud firms on ex ante fraud risk because we are interested in the effects of the fraud itself on changes in firms' disclosure behavior, not effects driven by other firm characteristics that might be common among firms that operate in a high fraud risk environment. Thus, matching firms on fraud risk provides us with the most conservative method for isolating the effects of the fraud itself from other firm characteristics when conducting our analyses. We lose 63 additional observations due to missing AGR scores or the inability to find a suitable match firm based on the above criteria. The resulting 119 fraud firms and their corresponding matched firms become our final sample. Table 1 summarizes the sample selection procedure.

4.2. Descriptive Statistics

Table 2 provides various descriptive statistics for our sample. As seen in Panel A, the majority of the frauds begin between 1998 and 2001. The frauds in our sample begin in 2003 or earlier due to our data requirement that a firm's public period must end before 2009 to be included in the final sample. Our fraud firms also appear to be concentrated in the manufacturing (SIC 20-39) and services (SIC 70-88) industries (Table 2, Panel B). Panels C and D of Table 2 display characteristics of the fraud and nonfraud matched firms, respectively. The average fraud is just over two years in length, and it is roughly two and a half years after the fraud has ended before it becomes public knowledge. Importantly, untabulated

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[15] We match 14 of our firms on 1 digit SIC codes due to the inability to find suitable matches using 2 digit SIC codes.

analysis suggests that the fraud and matched firms are similar in terms of size (both market value of equity and total assets), fraud risk (AGR), and economic performance (ROA), which suggests that our matching procedure is effective.

4.3. Univariate Analysis of Intertemporal Disclosure Trends

Prior to performing our main tests with appropriate controls, we examine simple time series trends in the management earnings forecast disclosure characteristics (other than information content to equity markets). Table 3 shows an increase in disclosures per quarter for fraud firms in the fraud period relative to the pre-fraud period, followed by monotonic decreases in the post-fraud and public periods. Matched firms substantially increase their disclosures per quarter in a monotonic fashion over the four periods presented. As we show in Figure 1, the mean number of months from the beginning of the pre-fraud period to the end of the public period is 83, approximately seven years. This relatively long period motivates the use of the control group matched on industry, size, and fraud risk to capture general trends in forecast disclosure frequencies over time. The only other systematic change observable from Table 3 is the intertemporal behavior of the percentage of management forecasts that are bad news. Fraud firms release fewer bad news management forecasts in the pre-fraud period relative to matched firms. This condition reverses in the fraud and post-fraud periods.

5. Main Results

In Table 4, Panel A, we present the results of estimating Equation (2). As mentioned in Section 3, we focus our discussion on the results of F-tests of "differences in differences" derived from the Table 4, Panel A regressions and presented in Table 4, Panel B.

5.1. Management Forecast Frequency

The results for forecast frequency are presented in the first column of Table 4, Panel B. Coefficient β_1 on *Fraud*PreFraudPeriod* is negative and significant, indicating that fraud firms experience a significant increase in the average number of forecasts issued per quarter from the pre-fraud period to the fraud period ($p = 0.047$). However, this increase does not appear to be abnormal, or incremental to that observed in the matched firms over the same time frame, as the incremental change for fraud firms is not statistically different from zero ($p = 0.265$).

In examining the change in forecast frequency from the fraud period to both the post-fraud period and the public period, we find significant incremental changes for fraud firms relative to nonfraud firms. Relative to the nonfraud firms, fraud firms significantly decrease the frequency of their management earnings forecasts from the fraud period to both the post-fraud and public periods. Specifically, the incremental changes of -0.388 and -0.643 for the post-fraud period and public period, respectively, indicate an initial 38.8% decrease in the disclosure levels of fraud firms once the fraud itself has come to an end, after controlling for any changes in the disclosure behavior of the matched firms, with an additional 25.5% abnormal decrease in forecast frequency after the fraud becomes public knowledge. The decreases are significant ($p = 0.003$ and $p = 0.001$, respectively).

Overall, our results suggest that both fraud and nonfraud firms significantly increase disclosure during periods of fraud. However, relative to nonfraud firms, firms that engage in fraud significantly reduce the frequency of their management earnings forecasts subsequent to the fraud. The decrease in management earnings forecasts is most pronounced after the fraud has been revealed to the general public (the public period), which suggests that managers of fraud firms exhibit more cautious behavior subsequent to the fraud, and especially once the fraud becomes public knowledge.

5.2. Management Forecast News Content

The second column of Table 4, Panel B examines changes in the tendency to issue bad news forecasts across periods. The negative and significant β_1 coefficient indicates that managers of fraud firms are more likely to issue forecasts that fall short of market expectations during periods of fraud. In contrast, the difference between β_4 and β_5 is not statistically different from zero, which indicates that nonfraud firms do not experience a significant change in the probability of issuing a bad news forecast during their pseudo-fraud period. The difference in differences test is significantly negative ($p = 0.001$), which indicates that the increase in the probability of issuing a bad news forecast is significantly higher for fraud firms relative to nonfraud firms.

In both the post-fraud and public periods, fraud firms are not significantly more likely to issue a bad news forecast relative to the fraud period (i.e., β_2 and β_3 are not significant). In contrast, nonfraud firms are significantly more likely to issue bad news forecasts once the pseudo-fraud period ends (significantly positive β_6 - β_5 and β_7 - β_5). The differences-in-differences are both significantly negative ($p = 0.063$ and $p = 0.033$, respectively). In summary, for fraud firms, the tendency to skew management earnings forecasts toward bad news increases in the fraud period and decreases in the post-fraud and public periods. These results are consistent with managers of fraud firms increasing their use of voluntary forecasts to lower analysts' earnings expectations during periods of accounting fraud.

5.3. Management Forecast Bias

The third column of Table 4, Panel B presents the results of F-tests examining abnormal changes in the bias of forecasts issued by fraud firms over time with larger values of *Bias* indicating more optimistically biased forecasts. Coefficient β_1 (which measures bias in the pre-forecast period relative to the fraud period) is positive and significant, which suggests that managers of fraud firms provide less optimistically biased forecasts during periods of fraud. In contrast, the change in bias for the matched firms is insignificant, which indicates that matched firms did not alter the level of bias in their forecasts during the pseudo-fraud period. In addition, the incremental change from the fraud period to the pre-fraud period (i.e., the difference in differences) indicates that managers of fraudulent firms significantly reduce the optimism in their forecasts during periods of fraud ($p = 0.018$). This finding is consistent with managers of fraudulent firms attempting to minimize their legal exposure under SEC Rule 10b-5 by providing less optimistic forecast during periods of fraud. Further, the differences in the forecast bias of fraud firms between the fraud period and both the post-fraud period and public period are insignificant, suggesting that managers continue to issue less optimistically biased forecasts once the fraud concludes.

5.4. Management Forecast Accuracy

The final column of Panel B presents the results for forecast accuracy with larger values of *F_AbsError* representing less accurate forecasts. Consistent with expectations, the coefficient β_1 is positive and significant, which suggests that managers of fraud firms provide more accurate forecasts when they are committing fraud relative to the pre-fraud period. In contrast, the change in accuracy for the matched firms is insignificant, which indicates that matched firms did not alter the level of accuracy in their forecasts during the pseudo-fraud period. The test of fraud firms incremental change relative to the match firms is positive and significant ($p = 0.006$), which is consistent with managers of fraud firms issuing more accurate forecasts during periods of fraud because, relative to the pre-fraud period, they fear additional legal exposure, and in addition, credible forecasting is necessary to management market expectations. Furthermore, fraudulent accounting practices can be used to meet their forecasted earnings number. We also find a marginally significant incremental change for fraud firms from the fraud period to the post-fraud period of 0.015 ($p = .091$), but no significant abnormal change when comparing the fraud period to the public period. This result suggests that the accuracy of fraud firms' management earnings forecasts remains relatively constant after the fraud ends but before the public is aware of the fraud.

Our findings regarding changes in the frequency, news content, bias, and accuracy of management issued forecasts during periods of accounting fraud provide evidence that managers of fraud firms actively attempt to manage market expectations through the use of voluntary earnings forecasts. We find that relative to matched firms, fraud firms decrease their disclosure levels after the fraud period, issue more bad news during fraud than before or after the fraud period, and issue less optimistically biased and more accurate forecasts during fraud than they did previously. More frequent, less biased, and more accurate management forecasts are traditionally considered *higher* quality management forecasts.

5.5. Management Forecast Credibility in the Equity Market

Table 5 presents the results of estimating equation (3). The coefficients of primary interest are γ_9 on the *Period x Fraud x GoodNews* interaction and γ_{10} on the *Period x Fraud x BadNews* interaction. These coefficients capture the change across periods in the pricing of fraud firms' good and bad news management forecasts relative to the matched control firms (i.e., differences in differences).

In Panel A, *Period* equals one for the fraud period, and zero for the designated non-fraud period. In the first column, the designated non-fraud period is the pre-fraud period. Coefficients γ_9 and γ_{10} are significantly positive ($p = 0.055$) and negative ($p = 0.002$), respectively, when measuring price reactions to good and bad news in the fraud relative to the pre-fraud period. Therefore, the market treats both good and bad news management earnings forecasts issued by fraud firms as more credible during fraud periods relative to the pre-fraud periods. The designated non-fraud periods in the second and third columns are the post-fraud period and public period, respectively. In both columns, we find that the coefficients on γ_9 and γ_{10} are not statistically different from zero, which suggests that there is not a significant change in investors' perceptions of the credibility of management earnings forecasts issued by fraud firms in the post-fraud and public periods (i.e., we are unable to reject the null hypothesis that post-fraud and public period management forecasts are not viewed as more or less credible by the equity market).

Table 5, Panel B, recasts the same analysis in a different way. *Period* equals one for the pre-fraud period, and zero for the other periods. The significantly negative γ_9 in each column means that the price reaction to good news in fraud, post-fraud, and public periods is more positive than the price reaction to good news in the pre-fraud period. The significantly positive γ_{10} in each column means that the price reaction to bad news in fraud, post-fraud, and public periods is more negative than the price reaction to bad news in the pre-fraud period.

In summary, the price reaction tests are consistent with the tests on bias and accuracy. Management earnings forecast quality increases during the fraud period, and that increase persists into the post-fraud period and even into the period in which the public is aware of the fraud.

6. Additional Analysis

6.1. Management Turnover

Prior research suggests that accounting fraud often leads to significant management turnover (Karpoff et al. 2008a). Because prior research suggests that managers play a significant role in their firms' disclosure policies (Bamber et al. 2010), it is necessary to examine whether our results are robust to controlling for management turnover. We identify firms that experience a change in CEO or CFO during or after the fraud period and create an indicator variable (*Turnover*) equal to one if the firm changed its CEO or CFO and zero otherwise. We find that the coefficient on *Turnover* is insignificant in most model specifications and that all our inferences remain the same.

6.2. Additional Characteristics of Management Forecasts

In supplemental tests, we investigate changes in additional attributes of management issued forecasts during accounting fraud. Specifically, we examine changes in the precision, specificity, and horizon of forecasts issued during and after periods of fraud. We measure forecast precision using a count variable set equal to four for point forecasts, three for range forecasts, two for open-ended forecasts, and one for qualitative guidance. Forecast specificity is defined as the high end minus the low end of range forecasts, scaled by the stock price as of two days before the forecast. Specificity is set equal to zero for point forecasts and missing for open-ended and qualitative forecasts. Thus, a larger value of precision indicates a more precise forecast, while a higher value of specificity indicates a less specific forecast. Horizon is first measured as the number of days between the date the forecast is issued and the fiscal period end date. As a second measure of horizon, we use an indicator variable set equal to one for quarterly forecasts, and zero for annual forecasts.

In untabulated analysis, we observe no significant incremental changes in the precision, specificity, or our first measure of the horizon of management issued forecasts for fraud firms relative to matched firms from the fraud period to the pre-fraud, post-fraud, or public periods. However, we do find that compared to nonfraud firms, fraud firms issue significantly more quarterly forecasts relative to annual forecasts during the fraud period than they did previously (incremental change of -0.748; $p = 0.002$). It appears that as managers use earnings guidance to manage market expectations during periods of fraud, they focus primarily on short-term quarterly expectations.

6.3. Alternative Matching Procedure

In our primary analysis, we match fraud and nonfraud firms on size, industry, and *ex ante* fraud risk using a commercially produced risk measure called Accounting and Governance Risk (AGR). We do this because matching firms on fraud risk is likely to provide us with the most conservative method for isolating the effects of the fraud itself from other firm characteristics common among firms with high fraud risk when investigating changes in disclosure behavior.

However, economic performance has been shown to be a potentially significant determinant of a firm's disclosure behavior (Miller 2002; Roger and Van Buskirk 2009). As economic performance is also a determinant of accounting fraud, it is likely that the performance of our sample of fraud firms has a non-random distribution, and thus the observed changes in disclosure behavior could be attributable to changes in performance rather than the act of committing fraud. To ensure that this is not the case, we replicate our primary analysis, again matching firms on industry and size, but replacing fraud risk (AGR) with return on assets (ROA). This setting provides us with fraud and nonfraud firms that have similar performance levels in the year before the fraud began. Inferences remain the same.

7. Conclusion

Using a sample of firms that were subject to Securities and Exchange Commission (SEC) Enforcement Actions, we compare changes in the incidence, news content, bias, and accuracy of fraud firms' management earnings forecasts to the changes observed in a sample of control firms matched on industry, size, and fraud risk. We find that relative to the period before the fraud begins, managers of both fraud and matched nonfraud firms significantly increase the number of earnings forecasts during the fraud period. However, once the fraud period ends (and before the fraud is known publicly), we find that while managers of nonfraud firms continue to increase the frequency of their forecasts, managers of fraud firms decrease the quantity of their earnings forecasts, and the difference between fraud and nonfraud firms is significant. Similarly, after the fraud becomes publicly known, managers of fraud (nonfraud) firms further decrease (increase) the frequency of their management forecasts, and again the difference is significant. Thus, the decision to commit fraud is associated with significant changes in voluntary disclosure behavior. Lower forecast frequencies post-fraud are consistent with a fear of drawing attention to the firm before the fraud is revealed. The further forecast frequency reduction in the public period is consistent with increased monitoring from regulators. A related potential alternative explanation is that new participants in the earnings measurement and disclosure process wish to establish a reputation for credible forecasting in the presence of this increased monitoring.

When managers choose to issue an earnings forecast, we find that relative to managers of matched nonfraud firms, managers of fraud firms are more likely to issue a significantly greater proportion of bad news forecasts during fraud than either before or after the fraud period, and issue less ex post optimistically biased and more accurate forecasts during the fraud period than they did prior to the fraud period. In combination, our results suggest that managers of fraud firms increase their use of earnings forecasts to manage investor expectations downward during periods of fraud. These results are consistent with managers of fraud firms using multiple tools (i.e., credibly managing expectations downward while simultaneously fraudulently manipulating earnings) to meet market expectations.

We also find that, relative to the control sample, the market responds more strongly to both the good news and bad news earnings forecasts of fraud firms, both during and after fraud, relative to the pre-fraud period market response. These results are likely attributable to our previous finding that firms issue more accurate forecasts during periods of fraud, thereby establishing a reputation for credible disclosure that persists after the fraud ends. Thus, public revelation of the fraud does not appear to taint the credibility of management forecasts. The results are also consistent with other recent evidence that suggests investors are initially unable to see through mistakes in materially misstated earnings (Bardos et al. 2010).

As a whole, the results suggest that management forecasts are of a high quality (traditionally defined) and perceived as credible while managers commit fraud. If managers achieve this observable accuracy and low optimistic bias by fraud, then managers can choose low earnings quality to cause the market to perceive that voluntary disclosure quality is high.

Our findings and interpretations suggest that research into the relationship between fraud and voluntary disclosure quality requires a more precise definition of voluntary disclosure quality to permit unambiguous interpretation of the association of fraud-induced low earnings quality and voluntary disclosure quality. At issue is the question of how voluntary disclosure quality should be defined when it is being tested for association with the underlying determinant of its content, earnings. Our findings suggest that *traditionally defined* measures of management earnings forecast quality and earnings quality are not complements during periods of fraud.

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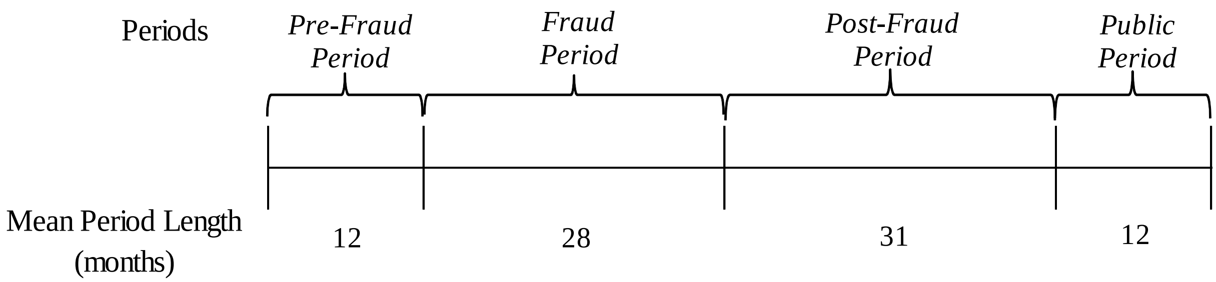
Figure 1
Fraud Timeline



The pre-fraud period consists of the 12 month period ending the first day of the fraud period. The post-fraud period begins the day the fraud period ends and continues until the fraud is made public. The public period consists of the 12 month period beginning the day the fraud is made public.

Figure 2

Mapping Equation (2) Coefficients into F-Tests

Model: $DiscProxy = \beta_0 + \beta_1\ Fraud\ x\ PreFraudPeriod + \beta_2\ Fraud\ x\ PostFraudPeriod$
$+ \beta_3\ Fraud\ x\ PublicPeriod + \beta_4\ Match\ x\ PreFraudPeriod$
$+ \beta_5\ Match\ x\ FraudPeriod + \beta_6\ Match\ x\ PostFraudPeriod$
$+ \beta_7\ Match\ x\ PublicPeriod + \Gamma_i\ CONTROLS + \varepsilon$

Changes in Disclosure (F-tests):	Fraud Period to Pre-Fraud Period	Fraud Period to Post-Fraud Period	Fraud Period to Public Period
Fraud Firms	β_1	β_2	β_3
Match Firms	$\beta_4 - \beta_5$	$\beta_6 - \beta_5$	$\beta_7 - \beta_5$
Incremental Change for Fraud Firms	$\beta_1 - (\beta_4 - \beta_5)$	$\beta_2 - (\beta_6 - \beta_5)$	$\beta_3 - (\beta_7 - \beta_5)$

Alternative disclosure proxies (*DiscProxy*) are: Frequency = average # of forecasts issued per quarter during the period; BadNewsD = 1 if (forecast - consensus analyst forecast) < 0, 0 otherwise; Bias = (forecast - actual EPS) / stock price two days before forecast; *F_AbsError* = absolute value of Bias. *Fraud* = 1 for fraud firms, 0 otherwise; *Match* = 1 for matched firms, 0 otherwise; *PreFraudPeriod* = 1 if forecast is issued during 12 months before beginning of fraud; *FraudPeriod* = 1 if forecast is issued during the fraud; *PostFraudPeriod* = 1 if forecast is issued after the fraud period but before the fraud becomes public knowledge; *PublicPeriod* = 1 if forecast is issued during the 12 months after the fraud becomes public knowledge. Controls are: *Size* = natural log of the market value of equity; *BTM* = book value of common equity divided by market value of common equity; *Analyst Following* = 1 + the natural log of the number of analysts following the firm prior to the forecast; Industry fixed effects.

Table 1
Sample Selection Procedure

	Fraud Firms
Initial sample of SEC Enforcement Actions with fraud periods beginning after 1997	396
Less:	
Firms with public periods ending after 2008	(68)
Firms who did not issue guidance during event window*	(146)
Firms without AGR fraud risk scores	(56)
Firms without an industry/size/fraud risk matched firm	(7)
Final sample	119

The pre-fraud period consists of the 12 month period ending the first day of the fraud period. The post-fraud period begins the day the fraud period ends and continues until the fraud is made public. The public period consists of the 12 month period beginning the day the fraud is made public. A firm's event window spans from the beginning of the pre-fraud period through the end of the public period.

*This includes firms not followed by at least one analyst in First Call's Analyst Forecast database during their entire event window (Ajinkya et al. 2005).

Table 2
Descriptive Statistics

Panel A: Frauds by year

Year fraud began	Number of firms	Percent
1998	21	17.6%
1999	22	18.5%
2000	39	32.8%
2001	24	20.2%
2002	6	5.0%
2003	7	5.9%
Total	119	100.0%

Panel B: Industry composition

Industry	Number of firms	Percent
Mining (10-14)	1	1%
Construction (15-17)	1	1%
Manufacturing (20-39)	50	42%
Transportation and communications (40-48)	3	3%
Wholesale trade (50-51)	14	12%
Retail trade (52-59)	8	7%
Financial (60-67)	12	10%
Services (70-88)	24	20%
Misc.	6	5%
Total	119	100%

Panel C: Characteristics of fraud firms

Variable	Mean	Median	Std. Dev.	First Quartile	Third Quartile
Length of fraud period (months)	27.9	24.3	18.9	12.1	39.5
Length of post period (months)	31.4	29.6	17.5	22.1	42.5
Market value of equity ($ millions)	6,687	662	18,638	177	3,702
Total assets ($ millions)	6,419	518	26,837	142	2,885
Return on assets	0.01	0.04	0.18	0.00	0.08
Book-to-market ratio	0.56	0.40	0.65	0.21	0.64
AGR score	57	60	27	34	80

Table 2 (continued)

Panel D: Characteristics of match firms

Variable	Mean	Median	Std. Dev.	First Quartile	Third Quartile
Market value of equity ($ millions)	7,642	576	28,892	151	2,940
Total assets ($ millions)	6,158	481	25,917	138	2,577
Return on assets	0.01	0.04	0.25	0.01	0.08
Book-to-market ratio	0.50	0.40	0.47	0.20	0.75
AGR score	55	57	25	36	75

Panel A presents the distribution of the fraud firms over time, based on the year the fraud began. Panel B displays the distribution of the fraud firms over 2-digit SIC codes. Variables in Panels C and D are calculated as of the end of the year prior to the beginning of the fraud period.

Table 3
Time-Series Behavior of Mean Values of Disclosure Frequency, News Content, Ex Post Bias, and Ex Post Absolute Forecast Error for Fraud Firms Relative to Firms Matched on Fraud Risk

		Pre-fraud	Fraud	Post-fraud	Public
Disclosures per quarter:	Fraud firms	0.519	0.859	0.685	0.492
	Matched firms	0.313	0.682	0.937	1.063
	Difference	0.206	0.177	-.252	-.571
	p-value	**0.018**	0.133	**0.036**	**0.001**
Bad news percentage:	Fraud firms	26.56%	44.92%	48.23%	45.41%
	Matched firms	37.96%	27.79%	38.14%	44.72%
	Difference	-11.40%	17.13%	10.09%	0.69%
	p-value	**0.040**	**0.001**	**0.001**	0.863
Ex post bias:	Fraud firms	0.027	0.018	0.050	0.013
	Matched firms	0.021	0.027	0.013	0.016
	Difference	0.006	-0.009	0.037	-0.003
	p-value	0.560	0.243	0.104	0.674
Ex post absolute forecast error:	Fraud firms	0.029	0.023	0.056	0.020
	Matched firms	0.024	0.029	0.017	0.020
	Difference	0.005	-0.006	0.039	0.000
	p-value	0.621	0.461	**0.087**	0.918

Differences are presented in bold when they are significant at the $\alpha = 0.10$ level using a two-tailed test.

P-values are calculated using two-tailed t-tests of means for Disclosures Per Quarter, Ex Post Bias, and Ex Post Absolute Forecast Error, and χ^2 of equal proportions for Bad News Percentage.

The pre-fraud period consists of the 12 month period ending the first day of the fraud period. The post-fraud period begins the day the fraud period ends and continues until the fraud is made public. The public period consists of the 12 month period beginning the day the fraud is made public.

Table 4

Panel A: Regression Analysis of Disclosure Characteristics and Fraud

Model: $DiscProxy = \beta_0 + \beta_1\ Fraud\ x\ PreFraudPeriod + \beta_2\ Fraud\ x\ PostFraudPeriod$
$+ \beta_3\ Fraud\ x\ PublicPeriod + \beta_4\ Match\ x\ PreFraudPeriod$
$+ \beta_5\ Match\ x\ FraudPeriod + \beta_6\ Match\ x\ PostFraudPeriod$
$+ \beta_7\ Match\ x\ PublicPeriod + \Gamma_i\ CONTROLS + \varepsilon$

	Management Forecast Characteristic			
	Frequency	*BadNewsD*	*Bias*	*F_AbsError*
Intercept (β_0)	-0.413 (0.006)	-4.714 (0.001)	0.103 (0.001)	0.107 (0.001)
Fraud x PreFraudPeriod (β_1)	-0.212 (0.047)	-0.935 (0.004)	0.019 (0.020)	0.016 (0.028)
Fraud x PostFraudPeriod (β_2)	-0.166 (0.189)	0.091 (0.364)	0.007 (0.218)	0.009 (0.095)
Fraud x PublicPeriod (β_3)	-0.323 (0.038)	0.196 (0.361)	-0.003 (0.526)	-0.001 (0.834)
Match x PreFraudPeriod (β_4)	-0.514 (0.001)	-0.231 (0.593)	-0.002 (0.721)	-0.005 (0.384)
Match x FraudPeriod (β_5)	-0.195 (0.109)	-0.724 (0.001)	0.005 (0.477)	0.004 (0.540)
Match x PostFraudPeriod (β_6)	0.027 (0.818)	-0.206 (0.350)	-0.003 (0.607)	-0.002 (0.607)
Match x PublicPeriod (β_7)	0.125 (0.478)	0.130 (0.607)	-0.001 (0.868)	-0.002 (0.760)
Size	0.135 (0.001)	0.110 (0.107)	-0.009 (0.001)	-0.01 (0.001)
BTM	-0.002 (0.979)	0.421 (0.060)	0.003 (0.789)	0.003 (0.760)
Analyst Following	0.000 (0.953)	0.003 (0.829)	0.001 (0.219)	0.001 (0.183)
N	895	4,296	4,192	4,192
Adj. R^2	25.6%	5.2%	7.7%	8.8%
Type of Regression	OLS	Logistic	OLS	OLS

Table entries are estimates with two-tailed p-values in parentheses

Table 4

Panel B: F-Tests of Changes in Disclosure Characteristics During Periods of Fraud

Model: $DiscProxy = \beta_0 + \beta_1$ *Fraud x PreFraudPeriod* + β_2 *Fraud x PostFraudPeriod* + β_3 *Fraud x PublicPeriod* + β_4 *Match x PreFraudPeriod* + β_5 *Match x FraudPeriod* + β_6 *Match x PostFraudPeriod* + β_7 *Match x PublicPeriod* + Γ_i *CONTROLS* + ε

Changes in Disclosure (F-tests):	*Frequency*	*BadNewsD*	*Bias*	*F_AbsError*
Fraud Period to Pre-Fraud Period[1]				
Fraud Firms (β_1)	-0.212 (0.047)	-0.935 (0.004)	0.019 (0.020)	0.016 (0.028)
Matched Firms ($\beta_4 - \beta_5$)	-0.319 (0.004)	0.493 (0.242)	-0.007 (0.325)	-0.009 (0.180)
Change between periods for fraud firms relative to matched firms *($\beta_1 - (\beta_4 - \beta_5)$)*	0.107 (0.265)	-1.428 **(0.001)**	0.026 **(0.018)**	0.025 **(0.006)**
Fraud Period to Post-Fraud Period				
Fraud Firms (β_2)	-0.166 (0.189)	0.091 (0.364)	0.007 (0.218)	0.009 (0.095)
Matched Firms ($\beta_6 - \beta_5$)	0.222 (0.005)	0.518 (0.020)	-0.008 (0.236)	-0.006 (0.269)
Change between periods for fraud firms relative to matched firms *($\beta_2 - (\beta_6 - \beta_5)$)*	-0.388 **(0.003)**	-0.427 **(0.063)**	0.015 (0.129)	0.015 **(0.091)**
Fraud Period to Public Period				
Fraud Firms (β_3)	-0.323 (0.038)	0.196 (0.361)	-0.003 (0.526)	-0.001 (0.834)
Matched Firms ($\beta_7 - \beta_5$)	0.320 (0.011)	0.854 (0.003)	-0.006 (0.454)	-0.006 (0.433)
Change between periods for fraud firms relative to matched firms *($\beta_3 - (\beta_7 - \beta_5)$)*	-0.643 **(0.001)**	-0.658 **(0.033)**	0.003 (0.768)	0.005 (0.604)

[1]A negative coefficient in this comparison indicates an *increase* in the disclosure proxy of interest when moving from the pre-fraud to the fraud period.

The incremental changes of interest are presented in **bold** when they are significant at the 0.10 level using a two-tailed test.

Table 4 (continued)

All continuous variables are winsorized at the first and 99th percentiles to alleviate the effects of outliers on the analysis. T-statistics are calculated using White's (1980) heteroscedasticity robust standard errors clustered by firm and year to control for dependency in the error terms.

Variable Definitions: *Frequency* = average # of forecasts issued per quarter during the period; *BadNewsD* = 1 if (forecast - consensus analyst forecast) < 0, 0 otherwise; *Bias* = (forecast - actual EPS) / stock price two days before forecast; *F_AbsError* = absolute value of Bias; *Fraud* = 1 for fraud firms, 0 otherwise; *Match* = 1 for matched firms, 0 otherwise; Pre-Fraud Period = 1 if forecast is issued during 12 months before beginning of fraud; *FraudPeriod* = 1 if forecast is issued during the fraud; *PostFraudPeriod* = 1 if forecast is issued after the fraud period but before the fraud becomes public knowledge; *PublicPeriod* = 1 if forecast is issued during the 12 months after the fraud becomes public knowledge; *Size* = natural log of the market value of equity; *BTM* = book value of common equity divided by market value of common equity; *Analyst Following* = 1 + the natural log of the number of analysts following the firm prior to the forecast; Industry fixed effects not reported.

Table 5
Management Forecast Credibility Before, During, and After Fraud

$$CAR = \gamma_0 + \gamma_1\, GoodNews + \gamma_2\, BadNews + \gamma_3\, Fraud + \gamma_4\, Fraud \times GoodNews + \gamma_5\, Fraud \times BadNews$$
$$+ \gamma_6\, Period + \gamma_7\, Period \times GoodNews + \gamma_8\, Period \times BadNews$$
$$+ \gamma_9\, Period \times Fraud \times GoodNews + \gamma_{10}\, Period \times Fraud \times BadNews$$
$$+ \Gamma_i\, CONTROLS + \varepsilon$$

(Table entries are estimated coefficients with two-tailed p-values in parentheses. P-values < 0.10 are in bold type.)

Panel A: Price reactions in Fraud Period relative to price reactions in:			
	Pre-fraud Period (*Period* = 1 for fraud period and 0 for pre-fraud period)	Post-Fraud (*Period* = 1 for fraud period and 0 for post-fraud period)	Public (*Period* = 1 for fraud period and 0 for public period)
Intercept (γ_0)	0.007 (0.621)	0.025 (0.126)	0.013 (0.462)
GoodNews (γ_1)	0.064 (0.202)	0.030 (0.160)	0.054 **(0.018)**
BadNews (γ_2)	-0.155 **(0.000)**	-0.114 **(0.000)**	-0.128 **(0.000)**
Fraud (γ_3)	-0.024 (0.126)	-0.030 **(0.023)**	-0.031 **(0.044)**
Fraud x GoodNews (γ_4)	0.020 **(0.000)**	0.063 **(0.004)**	0.091 **(0.000)**
Fraud x BadNews (γ_5)	0.097 **(0.071)**	0.009 (0.539)	0.027 (0.179)
Period (γ_6)	-0.024 (0.126)	-0.040 **(0.003)**	-0.026 (0.148)
Period x GoodNews (γ_7)	-0.002 (0.974)	0.043 **(0.011)**	0.014 (0.626)
Period x BadNews (γ_8)	0.099 **(0.026)**	0.048 (0.147)	0.063 **(0.022)**
Period x Fraud x GoodNews (γ_9)	0.066 **(0.055)**	0.025 (0.258)	0.001 (0.962)
Period x Fraud x BadNews (γ_{10})	-0.112 **(0.002)**	-0.015 (0.548)	-0.032 (0.261)
ForecastNews x Shock	-0.190 (0.789)	-0.171 (0.903)	-0.429 (0.518)
ForecastNews x Precision	-0.164 (0.219)	0.075 (0.656)	-0.068 (0.710)
ForecastNews x Horizon	0.385 **(0.042)**	0.257 **(0.000)**	0.234 **(0.089)**
ForecastNews x Size	0.012 (0.764)	-0.021 (0.582)	-0.017 (0.665)
ForecastNews x BTM	0.418 **(0.039)**	0.158 (0.278)	0.492 **(0.005)**
Adj. R^2	0.110	0.124	0.129
N	1,839	3,311	2,249

Table 5 continued

Panel B: Price reactions in Pre-Fraud Period relative to price reactions in:			
	Fraud Period (*Period* = 1 for pre-fraud period and 0 for fraud period)	Post-Fraud (*Period* = 1 for pre-fraud period and 0 for post-fraud period)	Public (*Period* = 1 for pre-fraud period and 0 for public period)
Intercept (γ_0)	0.017 (0.280)	0.018 (0.202)	0.001 (0.974)
GoodNews (γ_1)	0.062 **(0.000)**	0.039 **(0.026)**	0.073 **(0.005)**
BadNews (γ_2)	-0.056 **(0.032)**	-0.106 **(0.000)**	-0.115 **(0.000)**
Fraud (γ_3)	-0.024 (0.117)	-0.016 (0.419)	0.010 (0.627)
Fraud x GoodNews (γ_4)	0.086 **(0.008)**	0.048 **(0.079)**	0.035 (0.278)
Fraud x BadNews (γ_5)	-0.014 (0.560)	-0.007 (0.740)	-0.020 (0.460)
Period (γ_6)	0.024 (0.126)	-0.010 (0.423)	-0.007 (0.715)
Period x GoodNews (γ_7)	0.002 (0.974)	0.027 (0.391)	0.007 (0.906)
Period x BadNews (γ_8)	-0.099 **(0.026)**	-0.054 (0.378)	-0.026 (0.410)
Period x Fraud x GoodNews (γ_9)	-0.066 **(0.055)**	-0.051 **(0.010)**	-0.061 **(0.029)**
Period x Fraud x BadNews (γ_{10})	0.112 **(0.002)**	0.098 **(0.089)**	0.078 **(0.000)**
ForecastNews x Shock	-0.190 (0.789)	-0.151 (0.905)	-0.328 (0.708)
ForecastNews x Precision	-0.164 (0.219)	0.284 **(0.016)**	0.202 (0.208)
ForecastNews x Horizon	0.385 **(0.042)**	0.312 **(0.084)**	0.248 (0.437)
ForecastNews x Size	0.012 (0.764)	-0.047 (0.124)	-0.064 **(0.046)**
ForecastNews x BTM	0.418 **(0.039)**	-0.003 (0.973)	0.475 **(0.003)**
Adj. R^2	0.110	0.138	0.167
N	1,839	2,072	1,010

Table 5 continued

All continuous variables are winsorized at the first and 99th percentiles to alleviate the effects of outliers on the analysis. T-statistics are calculated using White's (1980) heteroscedasticity robust standard errors clustered by firm and year to control for dependency in the error terms. The pre-fraud period consists of the 12 month period ending the first day of the fraud period. The post-fraud period begins the day the fraud period ends and continues until the fraud is made public. The public period consists of the 12 month period beginning the day the fraud is made public. *CAR* = cumulative, size-adjusted security return on days -1, 0, and +1; *ForecastNews* = (forecast - consensus analyst forecast) / stock price two days before forecast; *GoodNews* = ForecastNews when ForecastNews > 0, and zero otherwise, ranked by year and scaled to range between 0 and 1; *BadNews* = Absolute value of ForecastNews when Forecast News < 0, and zero otherwise, ranked by year and scaled to range between 0 and 1; *Fraud* = 1 for fraud firms and zero for match firms; *Shock* = the absolute value of ForecastNews; *Precision* = 2 if forecast is a point estimate, 1 if a range estimate, and 0 if open-ended; *Horizon* = 1 for quarterly forecasts and 0 for annual forecasts; *Size* = natural log of the market value of equity; *BTM* = book value of common equity divided by market value of common equity.