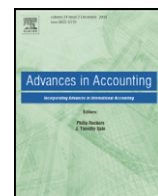




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The relation between earnings management and financial statement fraud[☆]

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ABSTRACT

This paper provides new evidence on the characteristics of firms that commit financial statement fraud. We examine how previous earnings management impacts the likelihood that a firm will commit financial statement fraud and in doing so develop three new fraud predictors. Using a sample of 54 fraud and 54 non-fraud firms, we find that fraud firms are more likely to have managed earnings in prior years and that earnings management in prior years is associated with a higher likelihood that firms that meet or beat analyst forecasts or that inflate revenue are committing fraud. We further find that fraud firms are more likely to meet or beat analyst forecasts and inflate revenue than non-fraud firms are even when there is no evidence of prior earnings management. This paper contributes to the fraud detection literature and the earnings management literature, and can help practitioners and regulators develop better fraud detection models.

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1. Introduction

The Association of Certified Fraud Examiners (ACFE, 2008) estimates that occupational fraud, or fraud in the workplace, costs the U.S. economy \$994 billion per year. Within occupational fraud, financial statement fraud¹ has the highest per case cost and total cost to the defrauded organizations, with an estimated total cost of \$572 billion per year in the U.S.² In addition to the direct impact on the defrauded organizations, fraud adversely impacts employees, shareholders and creditors. Financial statement fraud (henceforth fraud) also has broader, indirect negative effects on market participants by undermining the reliability of corporate financial statements and confidence in financial markets, resulting in higher risk premiums and less efficient capital markets.

Research about fraud antecedents and detection is important because it adds to the understanding about fraud, which has the potential to improve auditors' and regulators' ability to detect fraud either directly or by serving as a foundation to future fraud research that does. Improved fraud detection can help defrauded organizations,

and their employees, shareholders, and creditors curb costs associated with fraud, and can also help improve market efficiency. This knowledge is also of interest to auditors when providing assurance regarding whether financial statements are free of material misstatements caused by fraud, especially during client selection and continuation judgments, and audit planning.

This research contributes to the literature on fraud antecedents by examining the relation between earnings management and fraud. Firms can manipulate financial statements by managing earnings using discretionary accruals or by committing fraud. However, as accruals reverse over time (Healy, 1985), firms that manage earnings must later either deal with the consequences of the accrual reversals or commit fraud to offset the reversals (Dechow, Sloan, & Sweeney, 1996; Beneish, 1997, 1999; Lee, Ingram, & Howard, 1999). Using income-increasing discretionary accruals over multiple years can also cause managers to run out of ways to manage earnings. Therefore, firms that manipulate financial statements over multiple years, for example to meet or beat analyst forecasts or to inflate revenue, become increasingly likely to use fraud rather than earnings management to manipulate financial statements.

Based on this link between earnings management and fraud, we address five research questions related to how previous earnings management impacts fraud in the current year. More specifically, we examine the relation between previous earnings management and (1) the likelihood that firms that meet or beat analyst forecasts are committing fraud and (2) the likelihood that firms with inflated revenue are committing fraud. Additionally, we examine (3) the relation between previous earnings management and the likelihood of fraud, assuming no evidence of inflated revenue and no evidence of financial statement manipulation to meet or beat analyst forecasts, (4) the relation between meeting or beating analyst forecasts and the likelihood of fraud when there is no evidence of previous earnings

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¹ Occupational fraud is divided into three categories: asset misappropriation, corruption, and financial statement fraud (ACFE, 2008).

² The ACFE (2008) report provides estimates of occupational fraud cost, mean cost per fraud category and number of cases. To derive the estimate for total cost of financial statement fraud, we assume that the relative differences in mean and number of cases are similar to the relative difference in median cost and number of cases included in the ACFE (2008) report.

management, and (5) the relation between inflated revenue and the likelihood of fraud when there is no evidence of previous earnings management.

Our results show that the likelihood of fraud is significantly higher for firms that have previously managed earnings even when there is no evidence of inflated revenue and when they do not meet or beat analyst forecasts. We further find that firms that meet or beat analyst forecasts or inflate reported revenue are more likely to be committing fraud, even when there is no evidence of previously managed earnings. The results also show that previous earnings management is associated with a higher likelihood that firms that meet or beat analyst forecasts are committing fraud and a higher likelihood that firms with inflated revenue are committing fraud. These findings contribute to the fraud detection literature and earnings management literature, and also contribute to practice by improving auditors' and regulators' ability to detect fraud.

In addition to contributing to prior research by examining the link between earnings management and fraud, we develop three new measures, *Aggregated Prior Discretionary Accruals*, *Meeting or Beating Analyst Forecasts*, and *Unexpected Revenue per Employee*, that can be used to detect fraud. These new measures represent refinements of prior research and thus provide relatively minor contributions compared to the examination of the link between earnings management and fraud. More specifically, our prior earnings management measure, *Aggregated Prior Discretionary Accruals*, is based on a previously conjectured, but only partially tested, relation. In addition, we investigate whether pressure to meet or beat analyst forecasts provides an incentive to commit fraud.³ Prior research has shown that pressure to meet or beat analyst forecasts provides an incentive to manage earnings, but not whether it provides an incentive to commit fraud or whether this relation can be used to detect fraud. We also develop a completely new measure, *Unexpected Revenue per Employee* that is designed to detect revenue fraud, i.e., inflated revenue. These three new measures are important as they can enhance practitioners' ability to detect fraud.

This paper is organized as follows. We define earnings management, fraud, and financial statement manipulation, review related fraud research, and develop our hypotheses in Section 2. We describe our sample selection criteria and research design in Section 3. We present empirical results in Section 4. Concluding remarks appear in Section 5.

2. Related research and hypothesis development

2.1. Earnings management, fraud, and financial statement manipulation definitions

We use Healy and Wahlen's (1999) definition⁴ of *earnings management*: "earnings management occurs when managers use

³ We recognize that incentives cannot be measured directly because they are unobservable. A positive association between the likelihood of fraud and meeting or beating analyst forecasts is consistent with the conjecture that meeting or beating analyst forecasts is an incentive for committing fraud. We, therefore, interpret this finding as evidence that supports this conjecture.

⁴ This definition of earnings management defines earnings management as the manipulation of earnings to *mislead* financial information users. Other definitions of earnings management conjecture that earnings management can also have positive effects (e.g., Guay, Kothari, & Watts, 1996). For example, management can manipulate financial information to improve the usefulness of financial information. We do not argue that one definition is more accurate than the other. We simply believe that they refer to slightly different concepts and that they have, unfortunately, been named the same thing. It is also important to note that earnings management is used to alter financial information in general, and not only earnings. Because earnings management is a commonly used term we use various forms of this term (e.g., earnings management, manage earnings, managing earnings, and management of earnings) when referring to financial statement management in general.

judgment in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company or to influence contractual outcomes that rely on reported accounting numbers" (p. 368). Fraud has the same objective as earnings management, but differs from earnings management in that fraud is *outside* of generally accepted accounting principles (GAAP), whereas, earnings management is *within* GAAP (Erickson, Hanlon, & Maydew, 2006). Using Healy and Wahlen's (1999) definition of earnings management, we define *financial statement fraud* as follows: financial statement fraud occurs when managers use accounting practices that do not conform to GAAP to "alter financial reports to either mislead some stakeholders about the underlying economic performance of the company or to influence contractual outcomes that rely on reported accounting numbers" (p. 368). Finally, given that firms can manipulate financial statements using accounting practices that are within GAAP or outside of GAAP, we define *financial statement manipulation* as occurring when managers commit financial statement fraud or manage earnings (or both).

2.2. The relation between earnings management and fraud

When firms inflate reported financial information by managing earnings, they generate income-increasing accruals that reverse over time (Healy, 1985). Firms with income-increasing accruals in prior years must, therefore, either deal with the consequences of the accrual reversals or commit fraud to offset the reversals (Dechow et al., 1996; Beneish, 1997, 1999; Lee et al., 1999). Prior year income-increasing discretionary accruals might also cause firms to run out of ways to manage earnings (Beneish, 1997, 1999).⁵ When confronted with earnings reversals and decreased earnings management flexibility, managers might resort to fraudulent activities to achieve objectives that were previously accomplished by managing earnings. We, therefore, expect a positive relation between prior discretionary accruals and fraud, and refer to this relation as the earnings management reversal and constraint hypothesis.

Prior literature has partially examined the earnings management reversal and constraint hypothesis. Beneish (1997) finds a positive relation between the likelihood of fraud in year t_0 , the first fraud year, and a dummy variable measuring whether the firm had positive accruals in both year t_{-1} , the year prior to the first fraud year, and year t_0 . Lee et al. (1999) subsequently document a positive relation between the likelihood of fraud and total accruals summed over a three-year period prior to the fraud being *discovered* by the SEC. However, the SEC fraud discovery date lags the first fraud occurrence by an average of 28 months (Beneish, 1999). Therefore, total accruals in Lee et al. (1999) measures total accruals summed over years t_{-1} , t_0 and t_{+1} . More specifically, by ending the 36-month measurement period 28 months after the first fraud occurrence, their measure includes, on average, 8 months (including the month in which the fraud first occurred) prior to the first fraud occurrence to 28 months after. More recently, Jones, Krishnan, and Melendrez (2008) document a positive relation between discretionary accruals in year t_{-1} and fraud, while Dechow, Ge, Larson, and Sloan (2011) conclude, but do not statistically test, that accruals reverse subsequent to t_0 . Finally, although they examine total accruals, rather than discretionary accruals, Dechow et al. (1996) document a significant positive relation

⁵ For example, managers make judgments regarding the amount of accounts receivables that are uncollectible. A manager can inflate earnings by understating the allowance for uncollectible accounts and the associated bad debt expense. If the allowance does not cover the amount of receivables written-off, the balance will need to be increased in a future period, thereby increasing future bad debt expense and decreasing future earnings. Further, there is a limit to how far bad debt expense (zero) can be lowered the following year, thereby limiting how much bad debt expense can be used to management earnings.

between total accruals in year t_0 and the likelihood of fraud in year t_0 , while Beneish (1999) reports a positive relation between total accruals in year t_{-1} and fraud in year t_0 .

While prior research provides support for the earnings management reversal and constraint hypothesis, the only studies (e.g. Beneish, 1999 and Jones et al., 2008) that, to our knowledge, have examined *prior* discretionary accruals examined whether firms had positive discretionary accruals in both year t_{-1} and year t_0 , and discretionary accruals in only t_{-1} , respectively. However, the flexibility to manage earnings should be lower and the pressure to commit fraud due to accrual reversals should be higher for firms that have used income-increasing accruals over multiple years rather than just one year and the more they have increased income using discretionary accruals during this period. Further, the earnings management reversal and constraint hypothesis does not predict whether firms will continue managing earnings in t_0 .⁶ Dechow et al. (1996) present graphical evidence (see Fig. 1 for a similar analysis using this study's data) that fraud firms have greater discretionary accruals to assets in the three years prior to the first fraud year than do non-fraud firms. Thus, the graph in Dechow et al. (1996) indicates that an appropriate time period to measure income-increasing discretionary accruals is three years prior to the first fraud year.

Firms commit fraud for a variety of reasons, which include discretionary accruals reversals and earnings management constraints. Given the shared objective of altering financial reports by fraud and earnings management, prior fraud research examines whether the same incentives that motivate earnings management also motivate fraud⁷ and focuses on incentives related to debt covenants and bonus compensation plans. We next discuss this research and introduce the idea that capital market expectations associated with analyst forecasts, which have been investigated as incentives in earnings management research but not in fraud research, also provide incentives to commit fraud.

2.3. Fraud motivated by capital market incentives

In the earnings management literature, the debt covenant hypothesis predicts that when firms are close to violating debt covenants, managers will use income-increasing discretionary accruals to avoid violating the covenants (Dichev and Skinner, 2002). Beneish (1999) and Dechow et al. (1996) propose a positive relation between demand for external financing and fraud, and between incentives related to avoiding debt covenant violations and fraud. Results are mixed, however, with Dechow et al. (1996) finding support for the hypothesized relations and Beneish (1999) finding no support.

The bonus plan hypothesis in the earnings management literature predicts that if bonuses are (not) increasing in earnings, then managers will use income-increasing (income-decreasing) discretionary accruals to increase their current (future) bonuses (Healy,

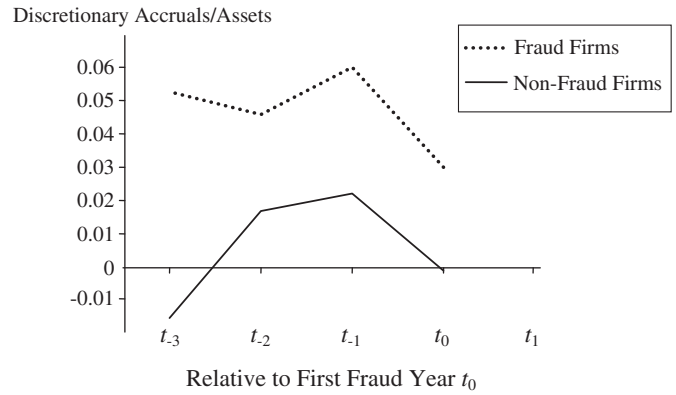


Fig. 1. Discretionary Accruals of Fraud and Non-Fraud Firms.

1985). In a fraud context, Dechow et al. (1996) and Beneish (1999) posit that managers have greater incentives to commit fraud when they can benefit from the fraud either through insider trading or through their compensation agreements. Unlike Dechow et al. (1996), Beneish (1999) obtains significant results for insider trading. In a similar study, Summers and Sweeney (1998) examine insider sales and purchases and find partial support for insider trading. Neither Dechow et al. (1996) nor Beneish (1999) find support for the hypothesis that the existence of a bonus plan increases the likelihood of fraud.

While prior fraud research examines fraud incentives related to compensation and debt, prior fraud research has not examined fraud incentives related to capital market expectations. In the earnings management literature, one capital market expectation hypothesis predicts that managers have incentives to manipulate financial statements to meet or beat analyst forecasts when these forecasts would not otherwise have been met or exceeded (Burgstahler and Eames, 2006). We extend fraud research by examining whether this capital market expectation incentive, which has been empirically linked to earnings management but not to fraud, also pertains to fraud. Managers can manipulate financial statements to meet or beat analyst forecasts by managing earnings or by committing fraud. While prior research has not examined the relation between analyst forecasts and fraud, Dechow et al. (2011) show that fraud firms have unusually strong stock price performance prior to committing fraud, and indicate that this may put pressure on the firm to commit fraud to avoid disappointing investors and sacrificing their high stock prices. Further, SEC Accounting and Auditing Enforcement Releases (AAER herein) provide anecdotal evidence of specific cases in which fraud was committed to meet or beat analyst forecasts. Thus, there are reasons to believe that managers may fraudulently manipulate financial statements to meet or beat analyst forecasts.

Combining these two ideas, i.e., the impact of prior earnings management on fraud and that analyst forecasts provide incentives for firms to commit fraud, we conjecture that firms that manipulate financial statements to meet or beat analyst forecasts are more likely to do so by committing fraud when they have previously managed earnings. Such firms face earnings reversals and are constrained in their ability to manage earnings further. Thus, while we expect a positive relation between meeting or beating analyst forecasts and fraud in general, we also expect that this relation is more positive when the firm has managed earnings in prior years. This discussion leads to our first hypothesis:

Hypothesis 1. Firms that meet or beat analyst forecasts are more likely to be committing fraud the more they have managed earnings in prior years.

⁶ If anything the earnings management reversal and constraint hypothesis would predict a reversal of accruals and less use of income increasing discretionary accruals due to earnings management constraints in t_0 . Thus, we argue that the measure used in (Beneish, 1999) is not congruent with the earnings management reversal and constraint hypothesis. Nevertheless, this measure might still be useful as it is possible that positive accruals in year t_0 are a proxy for the effect of the fraud.

⁷ Incentives/pressure is one of the three factors of the fraud triangle (Albrecht, Romney, & Cherrington, 1982; Loebbecke, Eining, & Willingham, 1989). The other two are opportunity (ability to carry out the fraud) and rationalization (rationalization of the fraud being acceptable). In this paper we examine fraud incentives, which we argue are similar to earnings management incentives as both fraud and earnings management have the shared objective of altering financial reports. We do not claim that earnings management and fraud also share similar opportunity and rationalization antecedents.

2.4. Fraud in the revenue account

One common objective for manipulating financial statements is to inflate reported revenue. In order to inflate revenue, firms can either manage earnings or commit fraud. Firms that have managed earnings in prior years are, as discussed earlier, constrained in their ability to manage earnings. These firms are, therefore, more likely than firms that have not managed earnings in prior years, to inflate revenue by committing fraud. We next discuss measures used to detect inflated revenue and then formally state a hypothesis related to the interaction between prior earnings management and inflated reported revenue.

Prior fraud research identifies the revenue account as the primary target for fraud (Beneish, 1997). Given that revenue account manipulation is common, unusual levels of or changes in revenue might be indicative of revenue fraud. However, considering that revenue varies from year to year and among firms for reasons other than fraud, unadjusted revenue is a noisy measure of fraud. To detect revenue fraud, SAS No. 99 emphasizes the need to analyze and identify unusual relations involving revenue (AICPA, 2002), for example between revenue and production capacity. As firms use resources to generate sales, the relation between sales and resources should be more stable over time than unadjusted revenue. Thus, some of the noise associated with using unadjusted revenue to detect fraud can be removed by deflating revenue by the resources used to produce the revenue, such as assets (capital productivity) and employees (labor productivity). Unusual levels or changes in the productivity measure would then signal the possibility of fraud.

Prior research includes sales in various ratios that were not designed for the purpose of detecting revenue fraud and were, therefore, also not designed taking the SAS No. 99 (AICPA, 2002) recommendations into account. Nevertheless, results from these studies are largely consistent with fraud firms manipulating the revenue account. Erickson et al. (2006) document a positive relation between sales growth and fraud. Brazel, Jones, and Zimbelman (2009) find a negative relation between sales growth and fraud, and a positive relation between sales growth minus growth measured using a non-financial measure and fraud. Collectively, these results indicate that firms that increase revenue fraudulently are more likely to have abnormally high growth rates and that firms with low actual growth rates are more likely to commit fraud.

Chen and Sennetti (2005) and Fanning and Cogger (1998) document a positive relation between gross profit margin and fraud, which is evidence of inflated sales (or manipulated cost of goods sold). Chen and Sennetti (2005) also find that fraud firms have lower ratios of research and development expenditures to sales, and sales and marketing expenditures to sales than non-fraud firms do. Lower values for these ratios are consistent with reducing discretionary spending (or manipulating revenue).⁸ Consistent with the idea of deflating revenue by a resource used to generate revenue, both Fanning and Cogger (1998) and Kaminski, Wetzel, and Guan (2004) find that sales to assets is a significant predictor of fraud. However, Fanning and Cogger (1998) find a negative relation between sales to assets and fraud, while Kaminski et al. (2004) find a positive relation. Fanning and Cogger (1998) interpret the negative relation as evidence that firms in financial distress are more likely to commit fraud. Thus, while the sales to assets measure does leverage the idea of using a productivity measure to detect revenue fraud, this measure does not appear to be useful for detecting revenue fraud. This might be due to the preponderance of changes in assets that do not directly impact revenue. Additionally, and more importantly, the double-entry

basis of accounting information systems reduces the utility of this measure in detecting fraud even further.⁹

Based on the recommendations made by AICPA (2002), we extend this research by developing a measure, *Unexpected Revenue per Employee*, specifically for detecting revenue fraud. This measure leverages the relation between production input and production output (revenue) without suffering from the double-entry effect discussed earlier. To accomplish this we use labor productivity, which measures the amount of output per employee. Like capital productivity, labor productivity reduces the noise associated with sales by scaling sales by the input used to generate the sales. However, unlike capital productivity, the denominator in labor productivity is not affected by double-entry accounting. Therefore, labor productivity should be a less noisy predictor of revenue fraud than sales to assets. By documenting a positive relation between fraud and the difference between the change in revenue and the change in the number of employees, Brazel et al. (2009) provide additional support for the use of the number of employees as the denominator.¹⁰ Based on this discussion, we measure *Unexpected Revenue per Employee* as the percentage change in firm revenue per employee from year $t-1$ to year t_0 , minus the percentage change in industry revenue per employee from year $t-1$ to year t_0 .

As eluded to at the beginning of this sub-section, we argue that there is an interaction between prior earnings management and inflated reported revenue. More specifically, firms that artificially increase revenue will, ceteris paribus, have relatively high unexpected revenue per employee. The artificially high revenue, as indicated by unexpected revenue per employee, can be due to earnings management or fraud. However, firms that have managed earnings in prior years are constrained in their ability to manage earnings and these firms are, therefore, more likely to exhibit artificially high revenue due to fraud. Thus, while we expect a positive relation between unexpected revenue per employee and fraud in general, we also expect that this relation is stronger when firms have managed earnings in prior years. This discussion leads to our second hypothesis:

Hypothesis 2. Firms that inflate revenue are more likely to be committing fraud the more they have managed earnings in prior years.

2.5. Direct effects of prior earnings management, meeting or beating analyst forecasts and inflated reported revenue

The first two hypotheses are based on the idea that firms that have managed earnings in prior years are more likely to commit fraud if they also have incentives to meet or beat analyst forecasts or to inflate revenue. Nevertheless, even when earnings have not been managed in prior years, firms might commit fraud to meet or beat analyst forecasts or to inflate revenue. For example, if actual earnings or revenue are significantly less than desired earnings or revenue levels, then it might be difficult to manage earnings enough to achieve the

⁹ For example, fictitious revenue will increase both the numerator (sales) and the denominator (assets) in capital productivity. The direction and magnitude of changes in capital productivity resulting from revenue fraud depends on the level of a firm's actual capital productivity and profit margins. As an illustration, consider firm A and firm B that both fraudulently increase sales by \$10 million, which in turn increases assets by \$5 million. Further assume that: (1) both firms have \$100 million in assets before manipulating sales; (2) firm A has pre-manipulation sales of \$50 million; and (3) firm B has pre-manipulation sales of \$250 million. Under these assumptions, sales to asset increases from 0.5 (50/100) to 0.57 ($[\$50 + 10]/[\$100 + 5]$) for firm A and decreases from 2.5 (250/100) to 2.48 ($[\$250 + 10]/[\$100 + 5]$) for firm B. Thus, because revenue fraud increases both the numerator and the denominator of capital productivity, the ability of capital productivity to predict revenue manipulation is compromised.

¹⁰ Their study examines the efficacy of nonfinancial measures, including the number of employees, in predicting fraud. They argue that nonfinancial measures that are strongly correlated to actual performance and at the same time relatively difficult to manipulate, like the number of employees, can be used to assess the reasonableness of performance changes.

⁸ Other related studies examine ratios that include sales and find no evidence of revenue manipulation. For example, Summers and Sweeney (1998) find a positive relation between change in inventory to sales and fraud, which they interpret to be evidence of fraudulent inventory manipulation. Note that a fraudulent increase in sales would reduce the ratio of inventory to sales in the fraud year.

desired levels and firms might instead commit fraud. Thus, we also hypothesize the following main effects for meeting or beating analyst forecasts and inflated reported earnings on fraud:

Hypothesis 3. Firms that have not managed earnings in prior years are more likely to be committing fraud if they meet or beat analyst forecasts.

Hypothesis 4. Firms that have not managed earnings in prior years are more likely to be committing fraud the more they inflate revenue.

Firms manipulate financial statements for reasons other than to meet or beat analyst forecasts and to inflate revenue. For example, firms also manipulate financial statements to avoid violating debt covenants or to increase stock prices, and they also target accounts such as fixed assets and expenses instead of revenue. These firms can, as discussed earlier, either manage earnings or commit fraud to manipulate financial statements. Given the reversing and constraining effect of prior earnings management, we expect that firms are more likely commit fraud to manipulate financial statements when they have managed earnings in the prior years. Thus, assuming that firms manipulate financial statements for reasons other than to meet or beat analyst forecasts or to inflate revenue, we expect that prior earnings management increases the likelihood that they commit fraud to manipulate financial statements even when they do not inflate revenue and do not meet or beat analyst forecasts. Based on this discussion we hypothesize:

Hypothesis 5. Firms that do not meet or beat analyst forecasts and do not inflate revenue are more likely to be committing fraud the more they have managed earnings in prior years.

3. Research design

3.1. Variable construction

To test our hypotheses, we require a measure of aggregated prior discretionary accruals that captures the pressure of earnings reversals and earnings management limitations. Per the earnings management reversal and constraint hypothesis, and based on the graph provided in Dechow et al. (1996), we argue that the pressure of accruals reversal is greater and that earnings management flexibility is reduced¹¹ the more earnings were managed in prior years. Thus, we define *Aggregated Prior Discretionary Accruals*_{*j,t*} as the total amount of discretionary accruals in the three years prior to the first fraud year deflated by assets at the beginning of each year:

$$\text{Aggregated Prior Discretionary Accruals}_{j,t} = \sum_{t-3}^{t-1} DA_{j,t} / A_{j,t-1}, \quad (1)$$

where discretionary accruals $DA_{j,t}$ is calculated as the difference between total accruals $TA_{j,t}$ and estimated accruals, typically referred to as nondiscretionary accruals, $N\hat{D}A_{j,t}$

$$DA_{j,t} / A_{j,t-1} = TA_{j,t} / A_{j,t-1} - N\hat{D}A_{j,t} / A_{j,t-1}, \quad (2)$$

where total accruals, $TA_{j,t}$, is defined as income before extraordinary items minus cash flow from operations. Nondiscretionary accruals,

$N\hat{D}A_{j,t}$, for firm j in year t_0 is estimated using the extended version of the modified Jones model (Jones, 1991; Dechow, Sloan, & Sweeney, 1995) proposed in Kasznik (1999). To derive $N\hat{D}A_{j,t}$, we estimate the regression parameters in model (3) for firm j using all firms in J , where J is the two-digit SIC code industry of j . These estimates are then used to calculate estimated $N\hat{D}A_{j,t}$ for firm j using model (4):

$$TA_{j,t} / A_{j,t-1} = \alpha_0 / A_{j,t-1} + \alpha_1 (\Delta REV_{j,t} - \Delta REC_{j,t}) / A_{j,t-1} + \alpha_2 PPE_{j,t} / A_{j,t-1} + \alpha_3 \Delta CFO_{j,t} / A_{j,t-1}, \quad (3)$$

$$N\hat{D}A_{j,t} / A_{j,t-1} = \hat{\alpha}_{0,j} / A_{j,t-1} + \hat{\alpha}_{1,j} (\Delta REV_{j,t} - \Delta REC_{j,t}) / A_{j,t-1} + \hat{\alpha}_{2,j} PPE_{j,t} / A_{j,t-1} + \hat{\alpha}_{3,j} \Delta CFO_{j,t} / A_{j,t-1}, \quad (4)$$

where $\Delta REV_{j,t}$ is the change in revenue, $\Delta REC_{j,t}$ is the change in receivables and $\Delta CFO_{j,t}$ is the change in cash flow from operations of firm j from year $t-1$ to year t_0 ; $PPE_{j,t}$ is firm j 's gross property, plant and equipment at time t_0 ; and all values are deflated by $A_{j,t-1}$, firm j 's assets at time $t-1$.

To test hypotheses 1, 3, and 5, we define *Meeting or Beating Analyst Forecasts*_{*j,t*} as a dummy variable that measures whether or not analyst forecasts were met or exceeded¹²:

$$\text{Meeting or Beating Analyst Forecasts}_{j,t} = \begin{cases} 1, & \text{if } (EPS_{j,t} - AF_{j,t}) \geq 0 \\ 0, & \text{if } (EPS_{j,t} - AF_{j,t}) < 0 \end{cases}, \quad (5)$$

where for firm j , $EPS_{j,t}$ is actual I/B/E/S adjusted earnings per share¹³ in year t_0 ; and $AF_{j,t}$ is the first one year ahead analyst consensus forecast of earnings per share for firm j in year t_0 based on mean I/B/E/S earnings forecasts.¹⁴

To test hypotheses 2, 4 and 5, we develop *Unexpected Revenue per Employee* to identify unusual relations between revenue and a key

¹² When financial statements are manipulated using earnings management, managers are likely to manage earnings to just meet analyst forecasts (Burgstahler & Eames, 2006). While there are incremental benefits associated with exceeding forecasts, managers prefer to just meet analyst forecasts because the costs of earnings management also increase when forecasts are exceeded (Burgstahler & Eames, 2006). One such cost relates to future earnings being negatively impacted by current earnings management due to future discretionary accrual reversals. As in the case of earnings management, both the incremental benefits from meeting or exceeding analyst forecasts and expected costs associated with fraud are increasing in the magnitude of the fraud. However, financial statements manipulated using fraud, unlike financial statements manipulated using earnings management, might not reverse in future periods. For example, if company A sells a product or service to company B and B sells the same product or service back to A, both companies artificially inflate revenue (and expenses), and these transactions are not undone in future periods unless they are detected. Further, the degree to which financial statements can be manipulated using earnings management is more limited than when using fraud. Thus, even if firms have incentives to greatly exceed earnings forecasts, they might only have the ability to greatly exceed analyst forecasts through fraud. Additionally, the more earnings are managed, the less reasonable the discretionary accrual decision appears, and firms, therefore, have an additional reason to attempt to limit the amount of the manipulation. On the contrary, fraud firms might not perceive a significant difference between committing fraud to meet or to greatly exceed analyst forecasts, i.e., when compared to the risk of committing fraud just to meet forecasts, the incremental risk associated with greatly exceeding rather than just meeting analyst forecasts might be considered negligible. Therefore, it is difficult to predict whether firms prefer to fraudulently manipulate financial statements to meet or to exceed forecasts. Some firms that commit fraud in response to analyst forecasts might meet or just beat analyst forecasts, while others might decide that the additional benefits outweigh the additional costs of greatly exceeding analyst forecasts. Since the exact nature of the utility that managers derive from meeting or beating analyst forecasts when committing fraud is unknown, we define meeting or beating analyst forecasts as a dummy variable, *Meeting or Beating Analyst Forecasts*, that equals one if analyst forecasts are met or exceeded rather than attempting to define a cut-off as in earnings management research (Burgstahler & Eames, 2006). We examine the usage of a threshold in sensitivity tests reported in Section 4.2.6.

¹³ Payne and Thomas (2003) show that adjusted I/B/E/S EPS figures contain potential rounding errors for firm years with stock splits. We examine the sensitivity of our results to these rounding errors by excluding all firms with stock splits in the fraud year. The results from this sensitivity analysis are reported in Section 4.2.7.

¹⁴ See Section 4.2.6 for a discussion about this choice and for results using the last analyst consensus forecasts.

¹¹ Note that firms with strong performance are less likely to resort to fraudulent activities to offset earnings reversals because their strong performance offsets the reversals. The opposite is true for firms with poor performance. However, on average, firms facing accrual reversals are more likely to commit fraud than firms that are not facing accrual reversals. Although the posited relation could be refined by considering firm performance, we do not hypothesize an interaction between performance and accrual reversals as firms that commit fraud also report better performance. That is, while firms with low performance are more likely to commit fraud when faced with accrual reversals, firms that commit fraud are also more likely to report better performance.

input, the number of employees. We define *Unexpected Revenue per Employee*_{*j,t*} as the difference in percentage change in revenue per employee, between firm *j* and firm *j*'s industry *J*:

$$\text{Unexpected Revenue per Employee}_{j,t} = \% \Delta RE_{j,t} - \% \Delta RE_{J,t}, \quad (6)$$

where revenue per employee, *RE*, defined as total revenue to total number of employees, is measured for firm *j* and for firm *j*'s industry *J* in year *t*₀ and year *t*₋₁.

3.2. Control variables

Confirmatory fraud research typically relies on matching non-fraud firms to fraud firms based on size and year of fraud, and includes measured variables, to control for potential omitted variable bias. However, the use of control variables is not standard. For example, Beneish (1999) and Summers and Sweeney (1998) include additional control variables, while Dechow et al. (1996) and Beasley, Carcello, Hermanson, and Lapides (2000) do not. Further, control variables have not been used consistently and are instead typically selected to fit the research hypotheses. Following prior research, we thus rely on variables that, given our hypotheses, are likely to be omitted variables.

We select control variables primarily from Fanning and Cogger (1998), who examine a relatively comprehensive set of 62 potential predictors covering a wide number of types of fraud predictors ranging from corporate governance to financial ratios.¹⁵ Using stepwise logistic regression, they derive a model with eight significant fraud predictors: percent of inside directors (*Percent inside Directors*); whether the auditor was a Big 4 auditor (*Auditor*); whether the Chief Financial Officer changed in the last three years (*CFO Change*); whether LIFO was used (*LIFO*); debt to equity (*Debt to Equity*); sales to assets (*Sales to Assets*); whether accounts receivable was greater than 110% of last year's accounts receivable (*AR Growth*); and whether the gross margin percentage was greater than 110% of last year's (*Gross Margin Growth*). To these eight significant predictors, we add five controls that are not examined by Fanning and Cogger (1998): *Sales Growth* (Beneish, 1999; Erickson et al., 2006), *Current Discretionary Accruals* (Beneish, 1999), *Return on Assets* (Brazel et al., 2009; Erickson et al., 2006), *Total Assets*, and *Total Sales*.

We include *Percent inside Directors*, which measures the percentage of executive directors on the board of directors, and *CFO Change*, a dummy variable equal to one if the chief financial officer of the firm has changed during the three years leading up to the first fraud year and zero otherwise, to control for the possibility that both *Aggregated Prior Discretionary Accruals* and *Fraud* are related to ineffective corporate governance. Based on the empirical results in Fanning and Cogger (1998), we expect a negative relation between *CFO Change* and *Fraud*¹⁶ and a positive relation between *Percent inside Directors* and *Fraud*.¹⁷ Like *CFO Change* and *Percent inside Directors*, the next control variable, *Auditor*, is included to provide a measure that could conceptually explain the hypothesized relation between *Aggregated*

Prior Discretionary Accruals and *Fraud* given that audit quality is negatively related to both earnings management and fraud. *Auditor* is a dummy variable equal to one if the firm's auditor is a Big 4 auditor or one of their predecessors and zero otherwise. Big 4 auditing firms are believed to provide higher quality audits, which are expected to increase the effectiveness of the monitoring function provided by the auditors and thereby decrease the likelihood of fraud. Thus, we expect *Auditor* to be negatively related to *Fraud* (Fanning and Cogger, 1998).

We include *Sales to Asset* (capital productivity) to examine our claim that *Unexpected Revenue per Employee* is a better predictor of revenue fraud than *Sales to Assets*. Given that low *Sales to Assets* is an indicator of financial distress (Fanning and Cogger, 1998), we predict a negative relation between *Sales to Assets* and fraud. The inclusion of *Sales to Assets* also allows us to examine whether *Sales to Assets* and *Unexpected Revenue per Employee* capture different aspects of productivity that can lead to fraud — *Sales to Assets* capturing low productivity and financial distress that drive fraud and *Unexpected Revenue per Employee* capturing productivity that is artificially high as a result of revenue fraud.

Note that the matching procedure implemented in our study controls for firm size and firm age, and indirectly for firm growth (Beneish, 1999). Nevertheless, we include five variables to control for firm growth and firm size. *AR Growth* is measured as a dummy variable equal to one if accounts receivable exceeds 110% of the previous year's value and zero otherwise. Given that accounts receivable often increase as a result of fraud, we expect a positive relation between *AR Growth* and *Fraud*. Note that this effect is also captured by *Current Discretionary Accruals* and might, as such, be a redundant control variable. *Gross Margin Growth* is a dummy variable that is one if the gross margin percent exceeds 110% of the previous year's value and zero otherwise. Assuming that the gross margin improves as a result of fraud, we predict a positive relation between *Gross Margin Growth* and *Fraud*. Following Beneish (1999) and Erickson et al. (2006), we measure *Sales Growth* as the percentage change in revenue from *t*₋₂ to *t*₋₁ and use it to capture revenue growth rather than revenue manipulation.¹⁸ *AR Growth*, *Gross Margin Growth*, and *Sales Growth* are included to control for the possibility that actual growth explains the positive relations between *Unexpected Revenue per Employee* and *Fraud*, and between *Meeting or Beating Analyst Forecasts* and *Fraud*. In addition, we expect that these three variables are positively related to *Fraud* because small, rapidly growing firms are more likely to be investigated by the SEC (Beneish, 1999) than firms growing slowly. To control for firm size, we include *Total Assets* and *Total Sales* and posit a negative relation between both variables and the likelihood of fraud.

We also include *Current Discretionary Accruals*, *Debt to Equity*, *Return on Assets*, and *LIFO* as control variables. *Current Discretionary Accruals* are the discretionary accruals in the first fraud year, *t*₀, calculated using the extended version of the modified Jones model (Jones, 1991; Dechow et al., 1995) proposed in Kasznik (1999). As an indication of management's attitude towards fraud, we expect *Current Discretionary Accruals* to be positively related to fraud. Attitude (henceforth management character) is difficult to measure and as in prior fraud research, we must assume that management character is not an omitted variable. However, *Current Discretionary Accruals* might proxy for management character given that management character is positively related to management's use of discretionary accruals.¹⁹ Based on the assumption that a manager's attitude towards earnings management is an indication of the manager's attitude towards fraud, we include *Current Discretionary Accruals* to control for the possibility that management character, and more specifically a poor set of ethical values, explains both *Aggregated Prior Discretionary*

¹⁵ By selecting variables from Fanning and Cogger (1998), who, based on prior research and practice, empirically compared a large set of variables covering different aspects of fraud, we reduce the risk of (1) selecting control variables that are not significant predictors of fraud given other variables, but appear to be significant predictors when these other variables are omitted, (2) selecting control variables that are not as strong predictors of fraud as other similar variables, and (3) excluding control variables that are significant predictors of fraud given other variables, but appear to be insignificant predictors when these other variables are not included.

¹⁶ Although Fanning and Cogger (1998) predicted a positive relation based on the idea that some chief financial officers who commit fraud will leave their firms to avoid getting caught or are fired because of fraud suspicion, they found a negative relation but do not provide an explanation for this finding. A possible explanation for the negative relation is that chief financial officers who commit fraud are less likely to leave as by leaving they relinquish control over evidence of the fraud and expose themselves to scrutiny by the incoming chief financial officer.

¹⁷ Note that Fanning and Cogger (1998) examine 31 variables related to corporate governance and find that only *CFO Change*, *Auditor*, and *Percent inside Directors* are significant predictors of fraud.

¹⁸ Note that because of our matched design, we follow Beneish (1999) and examine the same sales growth time period for both fraud and non-fraud firms. This approach differs slightly from the one used by Erickson et al. (2006) who measure sales growth percent from *t*₋₂ to *t*₋₁ for fraud companies and from *t*₋₁ to *t*₀ for non-fraud firms.

¹⁹ Current discretionary accruals might also proxy for other firm characteristics, for example, low earnings quality.

Accruals and Fraud. Further, assuming that some fraud might have commenced earlier than reported and that abnormal discretionary accruals might measure fraud (in addition to earnings management), *Current Discretionary Accruals* is included to control for the possibility that *Aggregated Prior Discretionary Accruals* measures fraud rather than earnings management. We predict a positive relation between *Debt to Equity* and fraud because higher debt to equity levels put more pressure on management to comply with debt covenants. Assuming that firms with poor performance perceive pressure to artificially improve financial results, we expect a negative relation between *Return on Assets* and fraud.²⁰ *LIFO* is a dummy variable, which equals one if the last-in-first-out inventory method is used and zero otherwise. Given that prices were generally rising during the sample period and assuming that firms that commit fraud are more interested in inflating earnings than minimizing taxable income, we predict a negative relation between *LIFO* and *Fraud* (Fanning and Cogger, 1998).

3.3. Model for hypotheses testing

To evaluate the five hypotheses, we use Model 7. More specifically, **H1** and **H2** predict that β_4 and β_5 , respectively, are positive and significant, while **H3**, **H4**, and **H5** predict that β_1 , β_2 , and β_3 , respectively, are positive and significant:

$$\begin{aligned} \text{Fraud} = & \beta_0 + \beta_1 \text{Aggregated Prior Discretionary Accruals} \\ & + \beta_2 \text{Meeting or Beating Analyst Forecasts} \\ & + \beta_3 \text{Unexpected Revenue per Employee} \\ & + \beta_4 \text{Aggregated Prior Discretionary Accruals} \\ & * \text{Meeting or Beating Analyst Forecasts} \\ & + \beta_5 \text{Aggregated Prior Discretionary Accruals} \\ & * \text{Unexpected Revenue per Employee} \\ & + \beta_n \text{control variables} + \varepsilon \end{aligned} \quad (7)$$

where *Fraud* is a dependent dichotomous variable, equal to 1 if the firm was investigated by the SEC for fraud and 0 otherwise, *Aggregated Prior Discretionary Accruals* are the total of discretionary accruals in years $t-1$, $t-2$ and $t-3$, *Meeting or Beating Analyst Forecasts* is a dummy variable, equal to 1 if analyst forecasts were met or exceeded and 0 otherwise, and *Unexpected Revenue per Employee* is the difference between a firm and its industry in the percentage change in revenue per employee from year $t-1$ to t_0 . We also include the thirteen previously described control variables: *Percent inside Directors*, *Auditor*, *CFO Change*, *Sales to Assets*, *AR Growth*, *Gross Margin Growth*, *Sales Growth*, *Current Discretionary Accruals*, *LIFO*, *Debt to Equity*, *Return on Assets*, *Total Assets*, and *Total Sales*.

3.4. Sample selection

We identify our initial sample of firms that commit fraud by performing a keyword search and reading SEC fraud investigations reported in AAER from Oct. 18, 1999 through Sep. 30, 2005.²¹ We search for AAERs that include explicit reference to Section 10(b) and Rule 10b-5, or descriptions of fraud.²² As shown in **Table 1**, this search yields an initial fraud sample of 745 observations. We exclude 35 observations associated with financial firms because regulations

governing financial firms are substantially different from those governing other types of firms. We eliminate 116 observations that are not related to annual 10-K reporting because they do not pertain to our research questions. We also exclude 9 observations for foreign corporations and 10 observations for not-for-profit organizations. We next remove observations that lack data required for our empirical tests, including 78 observations of fraud related to registration statements (10-KSB or IPO) and 13 observations that do not specify the first fraud year in the SEC release. After eliminating 287 duplicates, 197 observations remain.²³ An additional 75 fraud firms²⁴ from Beasley (1996) were added to the initial sample, for a total of 272 fraud firms. Finally, we eliminate 218 firms due to missing data and obtain a final sample of 54 fraud firms. This sample attrition is similar to those documented in prior fraud research with similar data requirements (e.g., Beneish, 1997; Feroz, Kwon, Pastena, & Park, 2000; Erickson et al., 2006).²⁵

Table 2 presents the industry distribution of firms in our fraud sample by one-digit SIC groups. Compared to the population of firms in Compustat, the sample firms occur in higher proportion in three industry groups: Manufacturing (35.2% of fraud sample versus 26.6% of population), Personal and Business Services (24.1 versus 17.6%), and Wholesale and Retail (16.67 versus 9.4%). This industry distribution is similar to those documented in prior fraud research (e.g., Beneish, 1997).

To examine the determinants of fraud, we use a matched sample design, where each firm that commits fraud is matched by fiscal reporting year, industry, age, and size to a control firm that does not commit fraud. Based on the previously discussed finding that fraud firms are clustered by industry, we identify our initial control sample by first matching on industry. For each fraud firm, we select all firms with the same two-digit SIC code in the year of the fraud. We then eliminate potential control firms that are not in the same age group as the matched fraud firm. Three age groups (over ten years, five through ten years, and four years) were created so that several firms would be available for selection when matching on size. The minimum firm age is four years because our empirical tests require Compustat data for the fraud year and the four years prior to the first fraud year. The decision to match on firm age before firm size is based on Beneish's (1999) finding that matches based on age reduce the potential for omitted variable problems.²⁶ Finally, from the remaining potential control firms, we identify the firm closest in size, as measured by total assets in the year of the fraud, and include it in our final sample of 54 control firms.

For the 108 firms in our matched sample, we obtain financial statement data for the first year of the fraud and each of the four years

²³ The SEC typically publishes multiple AAERs for a single firm, where the different AAERs single out different parties involved with the fraud (various internal parties, external auditors, outside parties assisting in the fraud, etc.).

²⁴ These 75 fraud observations were kindly provided by Mark Beasley. Beasley (1996) collected the data from 348 AAERs released between 1982 and 1991 (67 observations) and from the Wall Street Journal Index caption of 'Crime – White Collar Crime' between 1980 and 1991 (8 observations).

²⁵ We lost 74 of the 75 fraud observations provided by Beasley (1996), primarily due to I/B/E/S data requirements. Of the final sample of 54 fraud firms, 53 are from AAERs covering a period of 5 years and 9 months. For comparison, Beneish (1997) obtained a final sample of 49 fraud firms based on AAERs issued from 1987 to 1993 (7 years), Feroz et al. (2000) obtained a final sample of 42 fraud firms based on AAERs issued from April 1982 through August 14 1991 (9 years and 4.5 months), and Erickson et al. (2006) obtained a final sample of 50 fraud firms based on AAERs issued from January 1, 1996 through November 19, 2003 (7 years and almost 11 months).

²⁶ The SEC typically targets young growth firms for investigation, and, therefore, an omitted variable problem can be introduced when comparing such firms to other firms of similar size that are not young growth firms (Beneish, 1999). For example, a young growth firm could have both high *Unexpected Revenue per Employee* and increased fraud likelihood. By matching based on age and size, Beneish (1999) found that differences in age, growth and ownership structure between fraud and non-fraud firms were better controlled than when matched on only size. Because young firms are more likely to be growth firms, the pair-wise matching should, at least partially, control for growth as well as age (Beneish, 1999). In addition to matching, we include *AR Growth*, *Gross Margin Growth*, and *Sales Growth* to control more directly for growth because not all high (low) growth firms are young (old).

²⁰ Artificially improved financial results could improve *Return on Assets* and, therefore, this ratio could also provide evidence of earnings manipulation. However, including *Current Discretionary Accruals* and *Sales to Assets* in our model should control for this effect.

²¹ When the data were collected for this study, the earliest AAER available online at the SEC was dated Oct. 18, 1999 and the most recent AAER was dated Sep. 30, 2005.

²² Our search criteria are based on those used by Beasley (1996). Section 10(b) of the Securities Exchange Act of 1934 permits the SEC to make rules and regulations to protect the public and investors from fraud in connection with the purchase or sale of any security. Rule 10b-5 prohibits committing fraud and making materially misleading statements, including omission of material facts, in connection with the purchase or sale of any security.

Table 1
Sample selection.

	Number of observations
<i>Fraud sample</i>	
Firm investigated by the SEC for fraudulent financial reporting from Oct. 18, 1999 through Sep. 30, 2005	745
Less: financial companies	(35)
Less: not annual (10-K) fraud	(116)
Less: foreign companies	(9)
Less: not-for-profit organizations	(10)
Less: registration, 10-KSB and IPO related fraud	(78)
Less: fraud year missing	(13)
Less: duplicates	(287)
Remaining fraud observations	197
Add: fraud firms from Beasley (1996)	75
Less: not in I/B/E/S for first fraud year ^a	(123)
Less: not in CompactD for first fraud year or three prior years ^b	(74)
Less: not in Compustat for first fraud year or four prior years ^c	(21)
Final fraud sample	54
<i>Non-fraud (control) sample</i>	
Firms in the same two-digit SIC industry as fraud firm in the year the fraud was committed (firms included are counted once for each year matched to one or more fraud firms)	12,423
Less: Firms with missing data in fraud year or in four years prior to the fraud	(2,705)
Less: Firms not most similar in age and size to the fraud firms	(9,664)
Final control sample	54

^a I/B/E/S data is somewhat sparse in the early 1990s and earlier. Given that the sample obtained from Beasley (1996) contains fraud firms that committed fraud in 1990 or earlier, 54 of these firms were eliminated due to lacking I/B/E/S data.

^b We were only able to obtain CompactD data going back to 1988. Of the remaining 21 Beasley (1996) fraud firms, 18 were eliminated due to lacking CompactD data.

^c The *Aggregate Prior Discretionary Accruals* measure sums discretionary accruals for the three years leading up to the fraud year. Each discretionary accruals estimate is obtained using both current and previous year's data. Thus, to obtain three years of prior discretionary accruals requires four years of data.

prior to the first fraud year from Compustat. One-year-ahead analyst earnings per share forecasts and actual earnings per share in the fraud year are collected from I/B/E/S and matched to financial statement data from Compustat. Finally, we extract data for certain control variables, *CFO Change* and *Percent inside Directors*, from Compact D/SEC and proxy statements.

3.5. Descriptive statistics

Table 3 contains univariate tests of differences in firm characteristics for fraud firms and their matched control firms. *Age*, *Sales* and *Assets* are not significantly different across the two samples, confirming that the matching procedure controls effectively for these factors. Fraud firms are, however, more likely to have high *AR Growth* and *Sales Growth*; 63% of the fraud firms versus 46% of control firms have high *AR growth* ($p = 0.041$) and the average *Sales Growth* of fraud firms is 53% compared to 16% for control firms ($p = 0.001$). We, therefore, include the variables *Sales Growth*, *AR Growth*, and *Gross Margin Growth* to control for differences in growth between fraud and non-fraud firms. With the exception of *Debt to Equity*, there is no significant difference between fraud and control firms in average values of the remaining control variables. It is noteworthy that 96% of both the fraud and non-fraud sample has a big 4 auditor. The marginally significant difference for *Debt to Equity* ($p = 0.089$) indicates that fraud firms have higher debt to equity ratios than control firms do (1.44 versus 0.59). Turning to the test variables, *Aggregated Prior Discretionary Accruals*, *Meeting or Beating Analyst Forecasts*, and *Unexpected Revenue per Employee* are all significant ($p = 0.041$, $p = 0.009$

Table 2
Industry distribution of fraud firms.^a

2-digit SIC code	Industry description ^b	Number of firms	Sample (%)	Population (%) ^c
10–19	Mining and construction	0	0.00	6.83
20–29	Commodity production	6	11.11	15.79
30–39	Manufacturing	19	35.19	26.56
40–49	Transportation and utilities	2	3.70	11.93
50–59	Wholesale and retail	9	16.67	9.38
60–69	Financial services (excl. 60–63)	0	0.00	5.71
70–79	Personal and business services	13	24.07	17.63
80–89	Health and other services	4	7.41	4.35
99	Nonclassifiable establishments	1	1.85	1.83
		54	100.00	100.00

^a Table adapted from Beneish (1997).

^b Industry names are from the Standard Industrial Classification Manual (1987).

^c Industry distribution of all firm years in Compustat from 1998 to 2005 (the range of fraud years for 53 of the 54 observations in the sample).

and $p = 0.048$, respectively) and in the predicted direction. More specifically, fraud firms have higher *Aggregated Prior Discretionary Accruals* (0.15) and *Unexpected Revenue per Employee* (4%) than control firms (0.02 and -7%, respectively) and are more likely than controls firms to meet or beat analyst forecasts (52 versus 30%).

Before moving to the multivariate analysis where multicollinearity is a potential concern, we present Pearson and Spearman correlation coefficients for our variables. Consistent with univariate results, Table 4 reveals positive significant correlations between *Fraud* and *Meeting or Beating Analyst Forecasts* ($r = 0.23$) and *Sales Growth* ($r = 0.29$); and marginally significant correlations between *Fraud* and *Aggregated Prior Discretionary Accruals* ($r = 0.17$), *Unexpected Revenue per Employee* ($r = 0.16$) and *AR Growth* ($r = 0.17$). Firms are seemingly more likely to commit fraud if they have high *Aggregated Prior Discretionary Accruals*, *Unexpected Revenue per Employee*, *Sales Growth*, or *AR Growth*, or meet or beat analyst forecasts. We also observe significant correlations between *Aggregated Prior Discretionary Accruals* and *Current Discretionary Accruals* ($r = 0.34$), *LIFO* and both *Debt to Equity* and *Sales to Assets* ($r = 0.25$ and $r = 0.23$, respectively), *Total Sales* and *Total Assets* ($r = 0.91$), and *Auditor* and three other variables, *CFO Change*, *Total Assets* and *Total Sales* ($r = -0.24$, $r = 0.27$ and $r = 0.23$, respectively). These correlations indicate that: firms that have managed earnings in the past are also more likely to currently be managing earnings, firms that use the LIFO inventory method also tend to have high debt to equity and sales to assets ratios; firms that have high sales also tend to have a lot of assets; and firms that do not have a Big 4 audit firm, tend to be smaller and have a relatively high turnover of CFOs.

The positive correlation between *Aggregate Prior Discretionary Accruals* and *Current Discretionary Accruals* is particularly interesting. While the earnings management reversal and constraint hypothesis was partially developed based on the idea that there should be a negative relation between prior earnings management and earnings management in the year a firm commits fraud, it is possible that *Aggregate Prior Discretionary Accruals* is positively related to *Current Discretionary Accruals* as *Aggregate Prior Discretionary Accruals* predicts fraud and *Current Discretionary Accruals* is an indicator of fraud (Lee et al., 1999). It is also possible that both measures provide an indication of poor management values, aggressive reporting practices, etc. The inclusion of *Current Discretionary Accruals* as a control variable is thus important to control for the possibility that *Aggregate Prior Discretionary Accruals* simply captures early fraud tendencies (as discussed earlier, assuming that some fraud might have commenced earlier than reported, *Current Discretionary Accruals* is included to control for the possibility that *Aggregated Prior Discretionary Accruals* measures fraud rather than earnings management) and poor management character. However, this variable cannot be used to provide a direct test of discretionary accrual reversals as it is possible that it measures earnings manipulation in general (including fraud), rather than just earnings management.

Table 3
Univariate tests of differences between fraud and matched control samples.

Variables ^a	Fraud sample (n = 54)			Control sample (n = 54)			Prediction ^b	Difference p-value ^c
	Mean	St dev	Median	Mean	St dev	Median		
Aggregated Prior Discretionary Accruals	0.15	0.51	0.07	0.02	0.23	0.03	F > C	0.041
Meeting or Beating Analyst Forecasts	0.52	0.50	1.00	0.30	0.46	0.00	F > C	0.009
Unexpected Revenue per Employee	0.04	0.38	0.00	-0.07	0.26	-0.02	F > C	0.048
Percent inside Directors	0.34	0.18	0.30	0.32	0.19	0.25	F > C	0.254
Auditor	0.96	0.19	1.00	0.96	0.19	1.00	F < C	1.000
CFO Change	0.15	0.36	0.00	0.07	0.26	0.00	F < C	0.221
LIFO	0.06	0.23	0.00	0.07	0.26	0.00	F < C	0.350
Debt to Equity	1.44	1.35	1.08	0.59	4.38	0.77	F > C	0.089
Sales to Assets	1.16	0.64	1.09	1.24	0.76	1.16	F < C	0.270
AR Growth	0.63	0.49	1.00	0.46	0.50	0.00	F > C	0.041
Gross Margin Growth	0.09	0.29	0.00	0.07	0.26	0.00	F > C	0.364
Sales Growth	0.53	0.84	0.32	0.16	0.23	0.12	F > C	0.001
Return on Assets	0.02	0.14	0.03	0.03	0.14	0.05	F < C	0.389
Current Discretionary Accruals	0.00	0.20	0.01	0.00	0.13	0.00	F > C	0.448
Assets	3254	6993	386	2595	5802	361	F < C	0.703
Sales	2996	6893	507	2679	6847	394	F < C	0.595
Firm Age	15.3	10.1	13.0	11.1	5.76	11.5	F > C	0.347

^a Numbers in parentheses that appear in variable descriptions below refer to the Compustat number for the variable identified: *Aggregated Prior Discretionary Accruals_{it}* is the total amount of discretionary accruals deflated by assets in the beginning of the year in the three years leading up to the fraud year. Discretionary accruals in year *t* is estimated using the extended version of the modified Jones model (Jones, 1991; Dechow et al., 1995; Kasznik, 1999). Discretionary accruals *DA_{it}* is calculated as estimated nondiscretionary accruals minus total accruals. Total accruals are income before extraordinary items (#18) minus cash flow from operations (#308). To obtain nondiscretionary accruals, *NDA_{it}*, for firm *j* in year *t* regression parameters are first estimated in cross section for all firms in the same major industry group *J* (two-digit sic): $TA_{jt} = \alpha_0/A_{jt-1} + \alpha_1(\Delta REV_{jt} - \Delta REC_{jt}) + \alpha_2PPE_{jt} + \alpha_3\Delta CFO_{jt}$. These parameter estimates are then used to derive estimated nondiscretionary accruals: $\hat{NDA}_{jt} = \hat{\alpha}_{0,j} + \hat{\alpha}_{1,j}(\Delta REV_{jt} - \Delta REC_{jt}) + \hat{\alpha}_{2,j}PPE_{jt} + \hat{\alpha}_{3,j}\Delta CFO_{jt}$, where ΔREV_{jt} is the change in revenue (#12), ΔREC_{jt} is the change in receivables (#2) and ΔCFO_{jt} is the change in cash flow from operations from time *t*-1 to *t*; and *PPE_{it}* is gross property, plant and equipment (#8) at time *t*. All values are deflated by *A_{jt-1}*, firm *j*'s assets (#6) at time *t*-1. *Meeting or Beating Analyst Forecasts* is a dummy variable, equal to 1 if analyst forecasts were met or exceeded and 0 otherwise (1/B/E/S). *Unexpected Revenue per Employee* for firm *j* in industry *J* is the difference between the percentage change in revenue per employee, $RE = \text{total sales} \#12 / \text{number of employees} \#29$, of *j* and the percentage change in revenue per employee of *J*: $Unexpected Revenue per Employee = (RE_{jt} - RE_{jt-1})/RE_{jt-1} - (RE_{jt} - RE_{jt-1})/RE_{jt-1}$. *Percent inside Directors* is the percentage of executive directors on the board of directors. *Auditor* is a dummy variable equal to 1 if auditor was a Big 4 audit firm (#149) and 0 otherwise. *CFO Change* is a dummy variable equal to 1 if CFO has changed in the three years leading up to the first fraud year and 0 otherwise. *LIFO* is a dummy variable equal to 1 if the last-in-first-out inventory method (#59) is used and 0 otherwise. *Debt to Equity* = (current liabilities (#5) + long term debt (#9)) / assets. *Sales to Assets* = net sales / assets. *AR Growth* is a dummy variable equal to 1 if accounts receivable exceed 110% of the previous year's value and 0 otherwise. *Gross Margin Growth* is a dummy variable equal to 1 if the gross margin percent exceeds 110% of the previous year's value and 0 otherwise. *Sales Growth* = (sales_{t-1} - sales_{t-2}) / sales_{t-2}. *Return on Assets* = net income / assets. *Current Discretionary Accruals* are the discretionary accruals in year *t*, see definition for *Aggregated Prior Discretionary Accruals*. *Assets* is total assets of firm *j*. *Sales* is total sales of firm *j*. *Firm Age* is the number of years between *t*₀ and the first year data are reported for the company in Compustat.

^b F is the statistic for the fraud firms and C is the statistic for the control sample.

^c Difference p-value is based on pair-wise Student's t comparison between fraud and control sample for continuous Variables, Pearson ^χ2 for dichotomous variables. One-tailed tests reported for estimates in the direction predicted; other tests are two-tailed.

4. Results of empirical tests

4.1. Test of hypotheses

We next discuss the multivariate analyses. To test our hypotheses, we estimate Model 7 with logistic regression where the dependent variable equals 1 for the fraud firms and 0 for the matched control firms.²⁷ Based on descriptive data (in Tables 3 and 4), which indicate that outliers and multicollinearity in our data are potential concerns, we perform additional diagnostic tests.²⁸ Using Pearson residuals, we find four observations in Model 7 that are potential outliers (have Pearson residuals above 2) and truncate continuous measures at plus or minus two standard deviations.²⁹ Further diagnostics tests reveal that multicollinearity is not an issue in Model 7.³⁰

²⁷ Before estimating the model, we confirm that our data satisfy the primary assumptions for logistic regression.

²⁸ For example, the median value of *Assets* for fraud (control) firms is \$386 (\$361) as compared to a mean of \$3254 (\$2595).

²⁹ We also examine the hypotheses after deleting the outliers from the sample. The results from the sensitivity tests are stronger than the reported results. More specifically, the *Unexpected Revenue per Employee* main effect, which is marginally significant in the main results, becomes significant. Thus, when deleting the outliers all hypothesized relations are significant (p < 0.001, p = 0.002, p = 0.005, p < 0.001, and p = 0.008, for H1, H2, H3, H4, and H5, respectively). We include the outliers in all other analyses because the outliers appear to be part of the population we are interested in and because this is a more conservative approach. Thus, including outliers biases against finding support for our hypothesis.

³⁰ The highest Variance Inflation Factors (VIF) is 2.04 when only including one of the firm size proxies, i.e., deleting *Assets* from the model while retaining *Sales* or vice versa.

Table 5 presents the results from estimating Model 7 with a total of 108 observations. After including control variables, the interaction between *Aggregated Prior Discretionary Accruals* and *Meeting or Beating Analyst Forecasts* is positive and significant (p = 0.008). The results thus provide evidence that earnings management in prior years is associated with a higher likelihood that firms that meet or beat analyst forecasts are committing fraud, as predicted in H1. The significant (p = 0.048) positive interaction between *Aggregated Prior Discretionary Accruals* and *Unexpected Revenue per Employee* provides evidence that earnings management in prior years is also associated with a greater likelihood that firms with inflated revenue are committing fraud, as predicted in H2. Further, the main effects for *Aggregated Prior Discretionary Accruals* and *Meeting or Beating Analyst Forecasts* are positive and significant (p = 0.018 and p = 0.002, respectively), while the main effect for *Unexpected Revenue per Employee* is in the expected direction and marginally significant (p = 0.074).³¹ Thus, we also find support for H3 and H4, and some support for H5. The significant main effects provide evidence that (1) previous earnings management is associated with higher likelihood of fraud in the current year even for firms that do not meet or beat analyst forecasts and do not inflate revenue, (2) firms that meet or beat analyst forecasts are more likely to be committing fraud even when they have not managed earnings in prior years, and (3) firms that inflate revenue are more likely to be committing fraud even when they have not managed earnings in prior years.

Interpreted collectively, these results indicate that (1) *Aggregated Prior Discretionary Accruals* are positively related with *Fraud* for firms that do not meet analyst forecasts and do not inflate revenue, and this

relation is stronger for firms that meet or beat analyst forecasts or inflate revenue; (2) firms that meet or beat analyst forecasts are more likely to be committing fraud even when they have not previously managed earnings, and this relation is stronger for firms that have previously managed earnings; and (3) firms that choose to artificially increase revenue are more likely to be committing fraud even when they have not previously managed earnings, and this relation is stronger for firms that have previously managed earnings.

Moving to our control variables, Table 5 reveals insignificant coefficient estimates for *Percent inside Directors*, *Auditor*, *CFO Change*, *LIFO*, *Debt to Equity*, *Sales to Assets*, *Gross Margin Growth*, *Current Discretionary Accruals*, *Total Assets*, and *Total Sales*, a marginally significant ($p=0.058$) coefficient estimate for *Return on Assets*, and significant coefficient estimates for *AR Growth* and *Sales Growth* ($p=0.038$ and $p<0.001$, respectively). Both *AR Growth* and *Sales Growth* have positive coefficient estimates while *Return on Assets* has a negative coefficient estimate. The results for the control variables indicate that, as predicted, growth firms and poorly performing firms are more likely to commit fraud.

4.2. Sensitivity tests

We next examine the robustness of the reported results and the appropriateness of variable design choices.

4.2.1. Real activities manipulation

Prior research (Roychowdhury, 2006) shows that in addition to using discretionary accruals to manipulate financial statements, some managers use real activities manipulation.³² Real activities manipulation could conceptually be positively related to both *Aggregated Prior Discretionary Accruals* and *Fraud* if real activities manipulation is captured by discretionary accruals and this manipulation is subsequently detected or leads to fraud. Thus, we examine whether real activities manipulation is an omitted variable for *Aggregated Prior Discretionary Accruals*.³³ We add two real activities manipulation measures to Model 7, *Abnormal Production Costs* and *Abnormal Discretionary Expenditures* (Roychowdhury, 2006), each summed over the three years leading up to the first fraud year.³⁴ We also include interactions between the two real activity measures and *Meeting or Beating Analyst Forecasts* and *Unexpected Revenue per Employee*, and add these four interactions to Model 7.

Based on the premise that managers who manipulate financial statements using real activities will reduce discretionary expenditures, we expect a negative relation between *Abnormal Discretionary Expenditures* in prior years and *Fraud*.³⁵ The results (not tabulated) show a marginally significant main effect for *Abnormal Discretionary Expenditures*

³² For example, reducing discretionary expenditures, such as research and development, increases current earnings.

³³ This analysis also provides insight regarding whether the earnings reversal hypothesis pertains to real activities manipulation.

³⁴ Production costs are the sum of cost of goods sold and change in inventory. *Abnormal Production Costs* is the residual from a regression model estimating normal production costs using current sales, change in sales between t_0 and t_{-1} , and change in sales between t_{-1} and t_{-2} . All variables are deflated by beginning of the period assets. *Discretionary Expenditures* are the sum of advertising expenses, R&D expenses, and selling, general and administrative expense. *Abnormal Discretionary Expenditures* is the residual from a regression model estimating normal discretionary expenditures using sales in t_{-1} . All variables are deflated by t_{-1} assets. Refer to Roychowdhury (2006) for details regarding how to compute these measures.

³⁵ To clarify, managers will over time run out of ways to manipulate financial statements using real activities manipulation similar to when they manipulate financial statements using discretionary accruals. For example, if discretionary expenditures, such as research and development, are reduced to increase earnings, then further reductions will eventually become difficult as there are limits to how much these real activities can be manipulated. Further, by manipulating earnings using real activities manipulation, the firm does not operate at an optimal level, and the firm becomes less likely to perform well in subsequent years. The deterioration in performance will pressure management to increase earnings, and as the flexibility to manipulate financial statements using real activities manipulation decreases due to earlier manipulation, it becomes more likely that the manager will commit fraud to increase earnings. Thus, we predict a negative relation between *Abnormal Discretionary Expenditures* and *Fraud*.

Table 4 Pearson and Spearman correlation^a coefficients (n = 108).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 ^b	1																
2	0.17*	1															
3	0.23**	0.02	1														
4	0.16*	-0.01	-0.08	1													
5	0.06	-0.01	-0.01	0.00	1												
6	0.00	-0.04	0.06	-0.12	0.01	1											
7	0.12	-0.13	-0.05	0.07	0.04	-0.24**	1										
8	-0.04	-0.05	-0.07	-0.11	-0.07	0.05	0.03	1									
9	0.13	0.02	0.07	0.00	-0.06	0.00	0.02	0.12	1								
10	-0.06	0.06	0.04	0.05	-0.02	-0.03	0.01	0.33**	-0.06	1							
11	0.17*	-0.07	0.15	-0.05	0.01	-0.08	-0.03	0.09	-0.13	0.01	1						
12	0.03	0.17*	-0.05	-0.05	-0.07	0.06	0.11	0.06	-0.07	0.05	-0.06	1					
13	0.25***	0.08	-0.01	0.18*	0.00	0.01	0.06	0.02	0.10	0.00	0.11	-0.09	1				
14	0.01	0.34***	-0.02	-0.01	-0.03	0.01	0.02	0.05	0.09	0.03	-0.03	0.15	0.02	1			
15	-0.03	-0.02	0.09	0.14	-0.12	0.07	-0.01	0.02	-0.04	0.18*	0.18*	0.01	-0.05	0.58***	1		
16	0.05	-0.06	0.17*	-0.06	-0.16	0.09	-0.11	-0.02	0.18*	-0.15	0.08	-0.06	-0.09	0.07	0.15*	1	
17	0.02	-0.05	0.09	-0.07	-0.16	0.08	-0.10	0.09	0.14	0.07	0.12	0.03	-0.06	0.01	0.19	0.91***	1

* Significant at the 0.10 level.

** Significant at the 0.05 level.

*** Significant at the 0.01 level.

^a Pearson (Spearman) correlations are below (above) the diagonal.

^b 1 = Fraud; 2 = Aggregated Prior Discretionary Accruals; 3 = Meeting or Beating Analyst Forecasts; 4 = Unexpected Revenue per Employee; 5 = Percent Inside Directors; 6 = Auditor; 7 = CFO Change; 8 = LIFO; 9 = Debt to Equity; 10 = Sales to Assets; 11 = AR Growth; 12 = Gross Margin Growth; 13 = Sales Growth; 14 = Current Discretionary Accruals; 15 = Return on Assets; 16 = Total Assets; and 17 = Total Sales. Variable definitions are in Table 3.

Table 5
Hypotheses tests – logistic regression results.^a

Variable ^b	Prediction	Estimate	Standard error	prob > χ^2
Intercept	(?)	−0.838	1.428	0.557
<i>Tests for Hypotheses</i>				
Aggregated Prior Discretionary Accruals	(+)	2.789	1.458	0.018
Meeting or Beating Analyst Forecasts	(+)	0.806	0.304	0.002
Unexpected Revenue per Employee	(+)	1.619	1.158	0.074
Aggregated Prior Discretionary Accruals*	(+)			
Meeting or Beating Analyst Forecasts		3.129	1.467	0.008
Aggregated Prior Discretionary Accruals*	(+)			
Unexpected Revenue per Employee		10.708	7.209	0.048
<i>Control Variables</i>				
Percent inside Directors	(+)	1.414	1.724	0.206
Auditor	(−)	0.075	0.715	0.916
CFO Change	(−)	0.562	0.446	0.194
LIFO	(−)	−0.609	0.605	0.153
Debt to Equity	(+)	0.119	0.157	0.220
Sales to Assets	(−)	−0.131	0.564	0.408
AR Growth	(+)	0.480	0.276	0.038
Gross Margin Growth	(+)	0.409	0.494	0.203
Sales Growth	(+)	3.275	1.097	0.000
Current Discretionary Accruals	(+)	2.309	3.260	0.237
Return on Assets	(−)	−4.497	2.941	0.058
Total Assets	(−)	0.000	0.000	0.477
Total Sales	(−)	0.000	0.000	0.813
Pseudo R ²			0.299	
χ^2 -test of model fit			44.73 (p = 0.0005)	
N			108	

^a Effect Likelihood Ratio Tests, one-tailed tests reported for estimates in the direction of the prediction, all other two-tailed.

^b Dependent variable is fraud likelihood, which equals 1 for firms that commit fraud and 0 for control firms. All other variable definitions appear in Table 3.

tures ($p=0.065$) and insignificant interactions between *Abnormal Discretionary Expenditures* and *Meeting or Beating Analyst Forecasts* and between *Abnormal Discretionary Expenditures* and *Unexpected Revenue per Employee* ($p=0.223$ and $p=0.547$, respectively). One plausible explanation for the surprising positive relation is that abnormally high discretionary expenditures in prior years indicate inefficient use of resources in prior years. The inefficient use of resources then leads to poor performance in subsequent years, and this poor performance puts pressure on management to manipulate financial statements. The relation between *Abnormal Production Costs* and *Fraud* is insignificant ($p=0.215$), as are the interactions between *Abnormal Production Costs* and *Meeting or Beating Analyst Forecasts* and between *Abnormal Production Costs* and *Unexpected Revenue per Employee* ($p=0.150$ and $p=0.106$, respectively). Turning to the impact of real activity manipulation on the relation between *Aggregated Prior Discretionary Accruals* and *Fraud*, we find, after controlling for real activities manipulation, a positive and significant ($p=0.016$) *Aggregated Prior Discretionary Accruals* main effect, a positive and significant ($p=0.004$) interaction between *Aggregated Prior Discretionary Accruals* and *Meeting or Beating Analyst Forecasts*, and a positive and marginally significant ($p=0.096$) interaction between *Aggregated Prior Discretionary Accruals* and *Unexpected Revenue per Employee*. Thus, it does not appear that real activities manipulation is an omitted variable that is an antecedent to both *Aggregated Prior Discretionary Accruals* and *Fraud*.

4.2.2. Discretionary accruals measure

To assess the sensitivity of the results to our measure of prior discretionary accruals, we use an alternative cash flow statement based measure of discretionary accruals from Hribar and Collins (2002). This measure, *Cash Based Aggregated Prior Discretionary Accruals* calculates total accruals as net income minus cash flow from operations. We estimate discretionary accruals and nondiscretionary accruals following Eqs. (2)–(4) and then sum discretionary accruals over the three years prior to the first fraud year. Results for

logit estimates of Model 7 (not tabulated) provide additional support for the hypothesized interaction between *Cash Based Aggregated Prior Discretionary Accruals* and *Meeting or Beating Analyst Forecasts* ($p=0.014$) and for the *Cash Based Aggregated Prior Discretionary Accruals* main effect ($p=0.018$). The results also show marginal support for the hypothesized interaction between *Cash Based Aggregated Prior Discretionary Accruals* and *Unexpected Revenue per Employee* ($p=0.097$). Thus, our findings appear robust with respect to the discretionary accrual measurement method.

4.2.3. Alternative revenue fraud measure

We now examine an alternative measure for revenue fraud. The measure *Difference between Revenue Growth and Employee Growth* (*DiffEmp*), introduced in (Brazel et al., 2009), is similar to percentage change in revenue per employee, $\% \Delta RE$,³⁶ which is used to calculate *Unexpected Revenue per Employee*. However, the conceptual basis for each measure differs leading to differences in definitions and in which effect is actually measured. *DiffEmp*, defined as $\frac{rev_t - rev_{t-1}}{rev_t} - \frac{emp_t - emp_{t-1}}{emp_{t-1}}$, is based on the idea that nonfinancial measures that are highly correlated to performance and that are also difficult to manipulate can be used to evaluate the reasonableness of changes in firm performance. We based *Unexpected Revenue per Employee* on the premise that revenue manipulation is difficult to detect in the revenue account, as revenue varies for reasons other than fraud, and that some of this variation can be removed by deflating revenue by a production process input variable. The number of employees was selected as the deflator rather than assets because revenue fraud does not affect the number of employees. The primary computational difference between the two

³⁶ Recall that *Unexpected Revenue per Employee* is the difference between a firm's $\% \Delta RE$ and the $\% \Delta RE$ of the firm's industry, where $\% \Delta RE$ is the percentage increase in total revenue divided by total number of employees between $t-1$ and t_0 . *Diffemp* is, however, not adjusted for industry differences and as such we use $\% \Delta RE$ instead of *Unexpected Revenue per Employee* in this comparison. Refer to Section 4.2.4 for a comparison of $\% \Delta RE$ and *Unexpected Revenue per Employee*.

measures is how each adjusts revenue growth using employee growth. Note that both measures assume a relatively constant relation between the number of employees and revenue. The two measures, however, differ in how the difference between expected and actual revenue is measured. *Diffemp* is increasing in the absolute difference between expected revenue growth and actual revenue growth, whereas % Δ RE is increasing in the ratio of expected revenue growth to actual revenue growth.³⁷ Based on this discussion, we expect models that include % Δ RE will afford better fit and predictive ability than models that include *Diffemp* when the models do not control for real firm growth, and that their performance will be similar when the models control for real firm growth.

We next perform empirical tests in order to evaluate this claim. Using Model 7, first without controls for firm growth (removing *AR Growth*, *Gross Margin Growth* and *Sales Growth* from the model), and replacing *Unexpected Revenue per Employee* with % Δ RE, we find (results not tabulated) that the % Δ RE main effect and the interaction between % Δ RE and *Aggregated Prior Discretionary Accruals* are in the predicted direction and significant ($p = 0.004$ and $p = 0.031$, respectively). We then replace *Unexpected Revenue per Employee* with *Diffemp*, and find that the coefficient on the *Diffemp* main effect is in the predicted direction and significant ($p = 0.004$) and that the interaction between *Diffemp* and *Aggregated Prior Discretionary Accruals* is also in the expected direction, but insignificant ($p = 0.130$). In the last two tests, we use the same models but include the three growth control variables, and find the coefficients on the % Δ RE and *Diffemp* main effects ($p = 0.049$ and $p = 0.027$) are in the predicted direction. However, the interaction between *Diffemp* and *Aggregated Prior Discretionary* is insignificant ($p = 0.185$), while the interaction between % Δ RE and *Aggregated Prior Discretionary* is marginally significant ($p = 0.079$). These results appear to partially support the previous discussion by providing evidence that without a control for employee growth, % Δ RE is a better predictor of fraud than *Diffemp*. While not expected, the results also show that % Δ RE is a better predictor of fraud than *Diffemp* when controlling for employee growth.

We further substantiate the claim that % Δ RE is a better predictor of fraud than *Diffemp* when not controlling for firm growth by comparing the predictive ability of the % Δ RE model to the predictive ability of the *Diffemp* model when the growth control variables are excluded. Based on a matched-pairs t-test of the prediction errors³⁸ of the two models, the prediction errors of % Δ RE model appear to be lower than the prediction errors of the *Diffemp* model, but the mean difference is not statistically significant ($p = 0.161$). While not providing strong support for our earlier claim, these results provide

³⁷ For clarification, consider the following example in which company A grows at a rate of 10% (as indicated by the number of employees growing by a rate of 10%), company B grows at a rate of 100%, and both companies start with 110 employees (the actual number is irrelevant in these calculations). Thus, company A grows to 121 employees and company B grows to 220 employees. Further assume that both companies fraudulently increase revenue by 30% over what could be expected based on prior revenue, prior number of employees and current number of employees, and that both companies start with \$1320 in revenue (the actual number is irrelevant in these calculations), i.e., company A has revenue of \$1452 (1320×1.1) and reports revenue of \$1887.6 ($1320 \times 1.1 + 1320 \times 1.1 \times 30\%$) in year two, while company B has revenue of \$2640 (1320×2) and reports revenue of \$3432 ($1320 \times 2 + 1320 \times 2 \times 30\%$) in year two. Thus, in absolute terms, company B manipulated revenue more than company A did ($3432 - 2640 > 1887.6 - 1452$), but as a percentage of expected revenue there is no difference between the two firms. In this situation *Diffemp* equals 0.33 ($[(1887.6 - 1320)/1320 - [121 - 110]/110]$) for company A and 0.6 ($[(3432 - 1320)/1320 - [220 - 110]/110]$) for company B, while % Δ RE is 0.3 for both companies ($[(1887.6/121 - 1320/110)/(1320/110)]$ for company A, and $[3432/220 - 1320/110]/(1320/110)$ for company B). Assuming a constant percentage manipulation over expected revenue, *Diffemp* is, while % Δ RE is not, increasing in the percentage change in the number of employees.

³⁸ Prediction errors refer to the absolute value of the difference between fraud probability predictions and actual values of the dependent variable. For example, if the model estimates that the probability of fraud is 0.72 for a given observation and this observation is a fraud firm, then the prediction error is 0.28. If the observation is a non-fraud firm, then the prediction error is 0.72.

further indications that % Δ RE performs better than *Diffemp* when not controlling for firm growth.

4.2.4. Industry data availability and Unexpected Revenue per Employee

Unexpected Revenue per Employee uses current industry productivity data (recall that *Unexpected Revenue per Employee* is the difference between a firm's and its industry's percentage change in revenue per employee). The industry data may not be available to fraud model users, such as auditors and the SEC, in a timely manner. However, the most important element in the design of *Unexpected Revenue per Employee* is the relation between production input and output and not the comparison to industry levels. Thus, it is possible to maintain the most important element of *Unexpected Revenue per Employee* without needing current industry data by only using individual firms' percentage change in revenue per employee, i.e., % Δ RE = $(RE_{jt} - RE_{jt-1})/RE_{jt-1}$ where RE = total sales/number of employees. To evaluate whether % Δ RE can be used instead of *Unexpected Revenue per Employee*, we use Model 7 and replace the *Unexpected Revenue per Employee* main effect ($p = 0.074$) and *Aggregated Prior Discretionary Accruals* and *Unexpected Revenue per Employee* interaction ($p = 0.048$) with a % Δ RE main effect ($p = 0.049$) and *Aggregated Prior Discretionary Accruals* and % Δ RE interaction ($p = 0.079$). The test statistics for the variables of the two models are comparable. We next compare the predictive ability of the model using % Δ RE and the model using *Unexpected Revenue per Employee* and find no significant difference between the two models. More specifically, based on a matched-pairs t-test of the prediction errors of the two models, the prediction errors of the % Δ RE model are not significantly higher than the prediction errors of the *Unexpected Revenue per Employee* model (mean difference, $p = 0.479$).³⁹ Thus, when a more timely fraud proxy is needed, the % Δ RE can be used instead of *Unexpected Revenue per Employee*.

4.2.5. Alternative discretionary accruals aggregation period

To evaluate the appropriateness of measuring discretionary accruals over a period of three years, we examine the relation between fraud likelihood and two alternative measures: discretionary accruals aggregated over the two years prior to the first fraud year, *Aggregated Prior Discretionary Accruals2*, and discretionary accruals in the year prior to the first fraud year, *Aggregated Prior Discretionary Accruals1*.

Using Model 7 and adding *Aggregated Prior Discretionary Accruals2* while retaining *Aggregated Prior Discretionary Accruals* in the model,⁴⁰ we find (results not tabulated) that the coefficients on the *Aggregated Prior Discretionary Accruals2* main effect and the interactions between *Meeting or Beating Analyst Forecasts* and *Aggregated Prior Discretionary Accruals2* and between *Unexpected Revenue per Employee* and *Aggregated Prior Discretionary Accruals2* are insignificant ($p = 0.283$, $p = 0.122$, and $p = 0.634$, respectively). We further find that the *Aggregated Prior Discretionary Accruals* main effect and the interaction between *Aggregated Prior Discretionary Accruals* and *Meeting or Beating Analyst Forecasts* remains positive and significant ($p = 0.039$ and $p = 0.012$, respectively), while the *Aggregated Prior Discretionary Accruals* and *Unexpected Revenue per*

³⁹ Results from a one-tailed test of the % Δ RE model having higher average prediction errors than the *Unexpected Revenue per Employee* model (two-tailed test, $p = 0.958$).

⁴⁰ When all three *Aggregated Prior Discretionary Accruals* measures are included in the same model (Model 7 without the interactions but with the two additional *Aggregated Prior Discretionary Accruals* measures included), *Aggregated Prior Discretionary Accruals2* have a Variance Inflation Factor exceeding 5 (VIF = 5.35). When one of the two alternative *Aggregated Prior Discretionary Accruals* measures is included with *Aggregated Prior Discretionary Accruals*, i.e., *Aggregated Prior Discretionary Accruals2* (VIF = 3.68) with *Aggregated Prior Discretionary Accruals* (VIF = 3.66) and *Aggregated Prior Discretionary Accruals1* (VIF = 2.47) with *Aggregated Prior Discretionary Accruals* (VIF = 2.28), in two different models, all variables have Variance Inflation Factors less than 5. We, therefore, use two different models to compare the alternative aggregation periods.

Employee interaction is insignificant ($p=0.108$). Estimating the same model but replacing *Aggregated Prior Discretionary Accruals2* with *Aggregated Prior Discretionary Accruals1*, we find that the *Aggregated Prior Discretionary Accruals1* main effect and the interactions between *Aggregated Prior Discretionary Accruals1* and *Meeting or Beating Analyst Forecasts* and between *Aggregated Prior Discretionary Accruals1* and *Unexpected Revenue per Employee* are insignificant ($p=0.520$, $p=0.864$, and $p=0.660$, respectively), while the *Aggregated Prior Discretionary Accruals* main effect and the interactions between *Aggregated Prior Discretionary Accruals* and *Meeting or Beating Analyst Forecasts* and between *Aggregated Prior Discretionary Accruals* and *Unexpected Revenue per Employee* remain significant or marginally significant ($p=0.018$, $p=0.038$, and $p=0.068$, respectively). Thus, in addition to the graphical evidence in Fig. 1, the individual variable statistics from these sensitivity tests support the use of *Aggregated Prior Discretionary Accruals* over *Aggregated Prior Discretionary Accruals1* and *Aggregated Prior Discretionary Accruals2*.

4.2.6. Alternative Analyst Forecast Period

We use the first forecast rather than the most current forecast because fraud can be an ongoing activity, occurring throughout the year. Further, the first analyst forecast sets early performance expectations that put pressure on management early in the reporting period. Nevertheless, it is likely that some firms commit fraud towards the end of the reporting period in response to last forecasts. We therefore evaluate the appropriateness of using first forecasts by examining two alternative forecast measures: the last consensus forecast, *Last Forecast*, and a combination of the first and the last forecasts, *Last and First Forecast Combination*. The *Last Forecast* measure is a dummy variable that equals 1 if the firm meets or just beats the last forecast, where just beats is defined as less than five cents above the last earnings per share forecast. The *Last and First Forecast Combination* is a dummy variable that equals 1 if the firm meets or beats the first forecast or meets or just beats the last forecast (again using a five cent threshold). These thresholds enable us to also evaluate the sensitivity of the results to the decision to not use thresholds, see footnote 12.

To evaluate the predictive ability of these two alternative measures, we use Model 7 and one of the two alternative analyst forecast measures together with the original *Meeting or Beating Analyst Forecasts* at a time.⁴¹ The results (not tabulated) for *Last Forecast* show an insignificant ($p=0.995$) interaction between *Aggregated Prior Discretionary Accruals* and *Last Forecast* and an insignificant ($p=0.362$) *Last Forecast* main effect, while the interaction between *Aggregated Prior Discretionary Accruals* and *Meeting or Beating Analyst Forecasts* and the *Meeting or Beating Analyst Forecasts* main effect remain significant ($p=0.041$ and $p=0.006$, respectively). The results for the *Last and First Forecast Combination* reveal both an insignificant interaction ($p=0.150$) and main effect (0.200), while the *Meeting or Beating Analyst Forecasts* main effect is marginally significant ($p=0.058$) and the *Meeting or Beating Analyst Forecasts* interaction is insignificant ($p=0.283$). Thus, for fraud detection, it appears that using the first forecast in the period is preferable to using the last forecast, but that it might be useful to combine the two into one measure that captures both firms that are pressured by analyst

⁴¹ When all three analyst forecast measures are included in the same model (Model 7 without the interactions but with *Last Forecast* and *Last and First Forecast Combination* included), *Last and First Forecast Combination* have a Variance Inflation Factor exceeding 5 (VIF = 5.29). When the two alternative analyst forecast measures are included with *Meeting or Beating Analyst Forecasts* one at a time, i.e., *Last Forecast* (VIF = 1.43) with *Meeting or Beating Analyst Forecasts* (VIF = 1.46) and *Last and First Forecast Combination* (VIF = 2.81) with *Meeting or Beating Analyst Forecasts* (VIF = 2.94), in two different models, all variables have Variance Inflation Factors less than 5. We, therefore, use two different models to compare the alternative analyst forecast measures.

forecasts throughout the year and firms that commit fraud close to year end to meet or just beat the latest forecasts.

To examine if there is a significant difference between using first forecasts, and last and first forecasts in combination, we compare the predictive ability of two models, one including the original *Meeting or Beating Analyst Forecasts* measure and one including the alternative *Meeting or Beating Analyst Forecasts* measure. Comparing prediction errors using matched-pairs t-tests, we find that while the average of the prediction errors are lower for the first forecast model (the model including *Meeting or Beating Analyst Forecast*), the difference between the two models is insignificant (mean difference, $p=0.278$). Thus, it appears that using the first forecast is appropriate and that there is no gain (and there might be a loss) in predictive ability and individual variable significance, from using last forecasts even when used in conjunction with first forecasts.

4.2.7. Impact of I/B/E/S EPS adjustments

Payne and Thomas (2003) show that adjusted I/B/E/S EPS figures contain potential rounding errors for firm years with stock splits. We, therefore, examine the sensitivity of our results to these rounding errors by excluding all firms with stock splits in the fraud year. After removing these firms, the *Meeting or Beating Analyst Forecast* main effect and the interaction between *Aggregate prior Discretionary Accruals* and *Meeting or Beating Analyst Forecast* remain positive and significant ($p=0.018$ and $p=0.015$, respectively). Thus, the results are not sensitive to adjusted I/B/E/S EPS rounding errors.

4.2.8. Utility of Aggregated Prior Discretionary Accruals, Meeting or Beating Analyst Forecasts and Unexpected Revenue per Employee

While one objective of this research is to develop new measures that can be used to detect fraud, we believe that our primary contribution is the analyses of the link between earnings management and fraud, which adds to the body of knowledge about fraud. Researchers and practitioners can use this more basic research contribution to develop additional fraud predictors and design better models. Nevertheless, one of our objectives is to make a more practical contribution that improves the ability of fraud models in detecting fraud. Although the statistical analyses, including the additional analyses, show that *Aggregated Prior Discretionary Accruals*, *Meeting or Beating Analyst Forecasts*, *Unexpected Revenue per Employee*, and their interactions, are significant predictors of fraud and thus indicate that these variables can provide utility in fraud detection, these analyses were performed using a balanced sample and did not evaluate the measures using a hold-out sample. To provide some initial insight into the utility of these variables we, therefore, compare the utility of a model (the full model) that includes the three proposed measures and the control variables to a model (the control model) that only includes the control variables. To make this comparison more realistic, we use a dataset with 298⁴² non-fraud firms and the original 54 fraud firms and evaluate the performance of the models using hold-out data. We run a 10-fold cross-validation, which uses all data for both model estimation and model evaluation.⁴³ This comparison reveals that the full model performs 8.2% better than the control models have Area

⁴² The ratio of 54 fraud firms to 298 non-fraud firms is based on estimates of the frequency of fraud and the relative cost of making various misclassifications: 0.6% of firms commit financial statement fraud (Bell & Carcello, 2000) and the relative cost of a false positive misclassification (classifying a non-fraud firm as a fraud firm) to a false negative misclassification (classifying a fraud firm as a non-fraud firm) is 1:30 (Bayley & Taylor, 2007). Based on these estimates and that our dataset contains 54 fraud firms, we include 298 $((1-0.006)*54/(0.006*30))$ non-fraud firms.

⁴³ In 10-fold cross validation, the dataset is divided into 10 subsets and the different subsets rotate, over 10 rounds, between being used for training or testing. In each round, one of the subsets is used for testing while the remaining nine subsets are used for training. For example, in the first round, subsets one through nine are used for training and subset 10 is used for testing, in round two, subsets one through eight and subset 10 are used for training and subset nine is used for testing, and so on (Witten & Frank, 2005).

under the Receiver Operating Characteristics Curve of 0.62 and 0.57, respectively).⁴⁴ Thus, it appears that in addition to contributing to fraud research in general, the proposed measures have the potential to directly improve fraud detection.

5. Concluding remarks

This research provides new evidence regarding the characteristics of firms that commit fraud. It contributes to the body of research that describes the antecedents of fraud, and therefore also facilitates fraud detection. More specifically, we examine the relation between previous earnings management and the propensity to commit fraud and in doing so develop three new measures: *Aggregated Prior Discretionary Accruals*, *Meeting or Beating Analyst Forecasts*, and *Unexpected Revenue per Employee*. The first new measure, *Aggregated Prior Discretionary Accruals*, sums discretionary accruals over the three years prior to the first fraud year to capture the pressure of earnings reversals and earnings management constraints. We find that firms that have previously managed earnings are more likely to commit fraud even when there is no evidence of earnings manipulation to meet or beat analyst forecasts or inflate revenue. We also perform more in depth analyses of the earnings management reversal and constraint hypothesis and find that measures of prior discretionary accruals summed over three years have more predictive ability than those summed over two years or one year.

The second measure, *Meeting or Beating Analyst Forecasts*, measures whether firms meet or beat analyst forecasts or fail to do so. We find that firms that meet or beat analyst forecasts are more likely to be committing fraud even when there is no evidence of prior earnings management. In addition to showing that evidence of a firm meeting or beating analyst forecasts can be used to detect fraud, this study contributes to earnings management research investigating capital market expectations, which typically assumes that distributional inconsistencies in reported earnings around analyst forecasts indicate that some firms manage earnings to meet analyst forecasts. Our results are consistent with capital market expectations providing an incentive for firms to manipulate financial statements and thus corroborate the findings of earnings management research.

We also develop a new productivity-based measure, *Unexpected Revenue per Employee*, designed to capture revenue fraud. The results indicate that this measure can facilitate fraud prediction. More specifically, we find some evidence that firms with inflated revenue are more likely to be committing fraud even when they have not managed earnings in prior years. It should, also, be noted this relation becomes stronger when outliers are deleted from the sample. It is possible that because this measure is designed specifically to capture revenue fraud, including firms that commit other types of fraud in the sample weakens the results. Future research might investigate additional measures designed to capture other types of fraud in conjunction with *Unexpected Revenue per Employee*.

More importantly, we contribute to the understanding of fraud antecedents by examining the link between earnings management and fraud and how prior earnings management interacts with other

fraud antecedents. In doing so we obtain results that are consistent with positive associations between capital market related fraud incentives and fraud and between inflated revenue and fraud that are increasing in prior years' earnings management. In other words, our results indicate that it is more likely that firms that have (1) incentives to commit fraud will commit fraud if they have managed earnings in prior years, and (2) inflated revenue have committed fraud if they have managed earnings in prior years.

In addition to contributing to fraud literature and earnings management literature, the improved understanding about the link between earnings management and fraud and the variables developed can be used to build better fraud prediction models. Better fraud models can be useful to auditors during client selection and continuation judgments, and audit planning. Regulatory bodies such as the SEC can also leverage these results to improve their effectiveness and efficiency when monitoring and selecting firms to investigate for potential fraud.

These results, however, have some limitations. Because the sample of fraud firms was identified using SEC AAER, results might not fully generalize to other types of fraud. That is, results might apply only to fraud firms investigated by the SEC. Other limitations provide opportunities for future research. We propose that total discretionary accruals increase the likelihood of fraud through two processes: previous earnings management puts pressure on management as the accruals reverse and constrains current earnings management flexibility. Our results document a positive relation between prior earnings management and fraud, but we do not provide any direct evidence of this being caused by earnings management reversals or earnings management constraints. Future research can explore these two dimensions further. Future research can also examine whether discretionary accruals growth, in addition to aggregate levels, in the years leading up to the first fraud year predicts fraud. It would also be interesting to examine whether prior earnings management strengthens the relations between other fraud antecedents and fraud. Future research can also examine fraud incentives related to capital market expectations other than *Meeting or Beating Analyst Forecasts*. For example, do firms commit fraud in order to avoid reporting small losses or small earnings growth declines? Further, it might be possible to improve *Unexpected Revenue per Employee* by adjusting the denominator to count only the number of employees that are actually involved in revenue generating activities. Future advances in financial reporting, such as XBRL, might provide additional data necessary to implement such adjustments.

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⁴⁴ To evaluate model performance in domains with class imbalance, e.g., the fraud domain that contains fewer fraud firms than non-fraud firms, and cost imbalance, e.g., the fraud domain in which the relative cost of making a false negative classification is much higher than the cost of making a false positive classification, Receiver Operating Characteristics (ROC) curves and the related measure, Area Under the ROC Curve (AUC), are typically used. ROC curves show the performance of classifiers in terms of true positive rate (i.e., the percentage of fraud firms accurately classified as fraud firms) on the y-axis and false positive rate on the x-axis (i.e., the percentage of non-fraud firms incorrectly classified as fraud firms) as the classification threshold (probability cut-off) is varied. ROC curves are used to visually compare classifiers, while AUC provides a single measure related to the ROC curve that can be used to make quantitative comparisons.

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