Investment, Shareholder Monitoring and
The Economics of Corporate Securities Fraud

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Abstract: In this study, I investigate the economic determinants of firms' propensity to commit securities fraud and the determinants of fraud detection. The analysis is based on a new hand-compiled fraud sample of private securities class action litigation suits filed between 1996 and 2003 involving allegations of accounting irregularities. I use econometric methods to account for the unobservability of undetected frauds, and disentangle the effects of cross-sectional variables into their effect on the probability of committing fraud and the effect on the probability of detecting fraud. I find the different types of investment have differential effects on firms' fraud incentives. Investment that introduces valuation imprecision negatively affects the probability of detection and positively affects the probability of fraud, but straightforward investment does not show this pattern. I further show that larger block ownership holdings and institutional holdings are associated with higher likelihood of detection and lower ex-ante propensity to commit fraud, which implies the important role of shareholder monitoring in combatting fraud. Finally, high growth potential, large external financing needs, and negative performance shocks seem to be important motivational factors for fraud. The paper also demonstrates the importance of disentangling the probability of committing fraud and the probability of detecting fraud, because cross-sectional variables can have opposing effects on these two probabilities, and therefore can be masked in their overall effect on the incidence of detected fraud.

Keywords: securities fraud, financial misreporting, fraud detection, investment, shareholder monitoring, corporate governance.

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In the past three years, a wave of high-profile corporate scandals has directed much public attention to the integrity of US public companies. As a result, corporate governance has become the resonant theme in corporate America. The governance crisis was followed by rapid and substantial legislative and regulatory changes that aim to restore investors' confidence in the capital markets. In order to well understand the governance failure and assess the potential effectiveness of the on-going governance reform, it is important to take a closer look into the economics of corporate securities fraud: What factors motivate fraud? What factors influence the probability of fraud detection? What governance mechanisms have been effective in discovering corporate fraudulent activities?

In this paper, I investigate the economic determinants of a firm's propensity to commit fraud and the likelihood of fraud detection. Following the approach in the economics of crime literature (see, e.g., Becker (1968)), we can view fraud as an economic activity, whose equilibrium supply depends on the expected benefit and cost from engaging in it. The expected cost is litigation risk: with some positive probability, fraud will be discovered, resulting in a penalty. Within this framework, I examine the effects of real investment, shareholder monitoring, and firm characteristics on firms' cost-benefit tradeoff of committing fraud.

The analysis is based on a new hand-compiled fraud data set. The data set consists of federal private securities class action lawsuits filed between 1996 and 2003 against US public companies involving allegations of accounting irregularities. I focus on accounting-related securities fraud, because this type of fraud has accounted for a large fraction of the total securities litigation activities since the second half of the 1990s. Existing studies mostly rely on the SEC's Accounting and Auditing Enforcement Releases (AAERs), or accounting restatements, to identify cases of fraudulent accounting. This paper is the first to study class action litigation involving accounting-related allegations. Private class action litigation has long been an important concomitant to the enforcement of securities laws (Cox and Thomas (2003)). The volume of class action lawsuits is also comparable to that of the SEC enforcement actions. More important, class action litigation can provide new insights for understanding market forces in securities litigation, because class action suits generally involve the interests of thousands of investors, and key plaintiff investors have a very important role in the litigation.

The next contribution of the paper is methodological. In assessing a firm's propensity to commit fraud, we face an identification problem because we only observe *detected fraud*. Non-litigated firms can be either honest firms or undetected fraudulent firms. This implies that the probability of a firm committing fraud and the probability of observing the firm as fraudulent can be very different. I am aware of only one study that attempts to control for this identification problem. Summers and Sweeney (1998) screen the litigation history of their control sample in the seven years after their sample period to mitigate the undetected fraud problem. My study utilizes statistical methods to control for this problem. In essence, I model the probability of detected fraud (what we observe) as the product of two latent probabilities: the probability of *committing* fraud and the probability of *detecting* fraud conditional on fraud occurrence. Then I use econometric methods to back out these two latent probabilities. Disentangling these components provides two advantages. First, it allows me to control for the unobservability of fraud committed but not detected. Second and more important, it allows me to examine the economics of each probability as well as their interactions.

Distinguishing the probability of fraud from the probability of detected fraud is not only important for understanding the economics of fraud, but also relevant from a regulatory point of view in setting policies relating to fraud. For example, board independence has been a focus in the current governance reform. Some studies have examined the relation between board independence and the likelihood of fraud, and found no significant relation between the two (see, e.g., Agrawal and Chadha (2004)). However, since those studies do not separate the probability of fraud from the probability of detected fraud, the interpretation is not clear, and two separate explanations may apply. One is that board independence does not matter. The other is that board independence increases the probability of detection and deters fraud ex ante (the deterrence effect), and thus exhibits no significant relation with the probability of detected fraud.

Using the above methodology, I examine the link between real investment and the incidence of fraud. There has been surprisingly little exploration on the relation between corporate fraud and investment. However, this is an important issue, because we have observed inefficient investments and serious value destructions in many fraudulent firms (e.g., Enron, Nortel, eToy). Hence, there could be large real economic cost associated with fraud. Wang (2004) theorizes that fraud can induce overinvestment incentives for two reasons. First, fraud can create (or sustain) market overvaluation and affect the external financing cost of the investment. Second, after committing fraud, the firm has incentive to strategically use investment to mask fraud and decrease its litigation risk. Making investment will help disguise fraud if the investment can introduce valuation imprecision and create inference problems for outside investors. I find evidence supporting this theory. In particular, I find that the alleged fraudulent firms on average have larger investment expenditures than a random sample of non-convicted firms, both before and around the commencement of fraud. Moreover, different types of investment appear to have differential effects on fraud detection and firms' propensity to commit fraud. Investment in R&D has a strong negative effect on the probability of detection, and this lower ex-post detection risk translates into higher ex-ante fraud incentives. Increasing R&D expenditures by 10% tends to decrease the probability of detection by 1.8% and increase the probability of fraud by 8.9%. Net investing cash flow exhibits a similar but weaker pattern. Capital expenditures and cash-based acquisitions do not significantly influence either the likelihood of detection or firms' propensity to commit fraud. Stock-based acquisitions, however, increases the probability of fraud, but not the detection likelihood. The empirical results imply that investment is associated with both firms' ex-ante benefit from fraud (e.g., the financing of the investment) and their ex-post litigation risk.

I also investigate the effect of shareholder monitoring on firms' fraud incentives. The nature and extent of shareholder monitoring has changed dramatically in the US during the past two decades, largely because of the institutionalization of shareholders. Many researchers have argued, and provided evidence, that institutional investors, who also tend to be large shareholders, can exert more effective monitoring on corporations (e.g., see Holderness (2003) for a review). The newly-passed Sarbanes-Oxley Act also attempts to strengthen shareholder monitoring through enhanced financial disclosure and insider trading regulation. Analyzing the monitoring role of large shareholders and institutional owners in the context of corporate fraud, particularly in class action litigation, can shed new light on the efficiency of such monitoring. I find that the presence of large shareholders and institutional owners increases the likelihood of fraud detection and discourages firms' ex ant incentive to commit fraud. Increasing block ownership by 10% increases the probability of detection by 1%, and decreases the probability of fraud by 3.8%. Institutional ownership has a similar effect. The results provide support for the efficiency view of large shareholder and institutional monitoring.

Lastly, I examine how firm characteristics influence a firm's cost-benefit tradeoff of engaging in fraud. I find that high growth potential and large external financing need are two important motivational factors for fraud. Alleged fraudulent firms on average grow much faster than comparison firms and have larger portion of the growth supported by external capital. A 10%

increase in externally financed growth increases the probability of fraud by 5.6%. I also find that the fraud sample on average outperformed the comparison sample before the commencement of fraud (in terms of higher return on assets). There is, however, some indirect evidence that the fraudulent firms experienced negative profitability shocks in the year when fraud began, which probably motivated the fraud. The performance deterioration, although temporarily concealed by fraud, tends to reveal itself and eventually leads to the discovery of fraud. For the fraud sample, the average return on assets one year after the commencement of fraud was 7% lower than what could be expected based on previous two years' (reported) performance, while the comparison sample did not have such discrepancy. The unexpected disappointing performance substantially increases a fraudulent firm's risk of being detected. A 10% unexpected decrease in profitability increases the probability of detection by about 2%.

Most existing studies on corporate fraud have largely focused on the benefit side of the tradeoff. The earnings management literature provides some evidence that managers tend to manage earnings prior to some major external financing activities, or to avoid violations of debt covenants, or to increase performance-related compensation (see Healy and Wahlen (1999) for a review). Several recent studies in finance examine the relation between executives' equity-based compensation and the likelihood of fraud, and find that larger equity incentives (particularly the incentives from stock options) are associated with higher likelihood of financial misreporting (see, e.g., Johnson, Ryan and Tian (2003), Peng and Röell (2003), Burns and Kedia (2003), Efendi, Srivastava and Swanson (2004)). On the cost side of the tradeoff, a few papers have examined the penalty after detection, but not detection risk. Agrawal, Jaffe and Karpoff (1999) study CEO turnover in litigated firms and find no significant difference in turnover between the fraud sample and the control sample. Dechow, Sloan, and Sweeney (1996) show that the revelation of fraud leads to persistent increase in fraudulent firms' cost of capital. Baucus and Baucus (1997) find that firms convicted for illegal corporate behavior suffer from prolonged poor performance. Griffin, Grundfest and Perino (2003) document negative abnormal returns upon the revelation of fraud.

This paper demonstrates the importance of understanding what determines firms' risk of being detected and how this risk influences their ex-ante propensity to commit fraud. I show that the probability of detection depends on firms' endogenous investment decisions, the strength of shareholder monitoring, and firm-specific attributes. The cross-sectional variations in the detection risk help to explain the variations in firms' fraud propensities. I also demonstrate the importance of disentangling the probability of committing fraud from the probability of detecting fraud. Cross-sectional variables can have opposing effects on the two probabilities, and thus can be masked in their overall effect on the incidence of detected fraud.

This paper is structured as follows. Section 1 describes the accounting fraud sample and presents some stylized facts about accounting-related class action lawsuits from 1996 to 2003. Section 2 discusses the related literature, the empirical methodology, and the hypotheses. Section 3 reports the results from univariate comparisons between the fraud sample and the comparison sample. Section 4 reports the multivariate analysis on the determinants of firms' propensity to commit fraud and the likelihood of fraud detection. Section 5 concludes.

1 Fraud Sample

The fraud sample in this study is based on Securities Class Action Clearinghouse (SCAC) established by Stanford Law School. This clearinghouse provides a comprehensive database of federal private securities class action lawsuits filed since 1996 in the United States. A private securities class action is a case brought pursuant to Federal Rule of Civil Procedure 23 on behalf of a group of persons who purchased the securities of a particular company during a specified time (the class period). A suit is filed as a class action because the members of the class are so numerous that joinder of all members is impracticable.

I went through the details of all the available case documents associated with each lawsuit (e.g., case complaints, press releases, court decisions, etc.) to identify the nature of fraud allegations. As a result, I singled out 680 lawsuits filed against 656 US public companies during 1996 to 2003 involving allegations of accounting irregularities. For firms that had multiple securities lawsuits, I only use the earliest one in the analysis. The following sections provides detailed descriptive information about the fraud sample.

1.1 Time Trends & Firm Characteristics

Table 1 describes the evolution of class action litigation over time. Panel A shows that a large portion of the litigation activities was centered on accounting-related fraud since 1996. Accounting fraud has on average accounted for roughly 47% of all the class action lawsuits over the past 8 years. The number of accounting frauds further climbed at the beginning of this century, and peaked in 2002, where it represented 56% of all the class action filings. Interestingly, the intensity substantially decreased to about 40% in 2003, which may have resulted from tightened securities regulation and increased market vigilance.

Panel B shows the distribution of the year in which fraud began. The distribution, however, does not necessarily indicate any year effect on the incidence of fraud. Given the average class period is about one year, frauds uncovered during 1996 to 2003 are not likely to start in early 1990s, and some frauds that began between 2001 and 2003 are not yet discovered.

Panel C shows the distribution of the class periods associated with the 680 lawsuits under study. Every class action litigation lawsuit specifies a class period. The beginning of a class period shows the earliest time a fraud affects the market, based on the evidence collected by securities attorneys. A class period generally ends at the time of some major events that precipitate the litigation. The length of class periods provides some information about the duration of fraud. The class period on average lasted a little more than one year, but varied substantially across lawsuits. Some frauds affected the market for more than five years, while some got discovered within one quarter.

Panel C also shows that firms in the fraud sample were largely young public companies. The median age was only 3.43 years, and more than 60% of the sample firms were less than 5 years old. The majority of the alleged fraudulent firms were listed on NASDAQ or NYSE when fraud began. NASDAQ firms, however, accounted for about 64% of the whole sample.

1.2 Industry Distribution

Table 2 presents the industry distribution of fraud. I classify the alleged fraudulent firms into 24 industry categories. The primary classification is based on two-digit SIC codes, but in some instances, I use three-digit SIC codes, as this is more informative about the types of companies that engaged in fraud. Table 2 shows evidence of significant industry patterns in securities fraud litigation. First, technology firms are disproportionately more involved in accounting-related securities litigation. In particular, firms in software and programming alone accounted for 17.53% of all accounting fraud cases in the past 8 years. Electronic parts, computer manufacturing, and telecommunications companies represent another 19.36% of the litigation activities. Second, the service sector and particularly the financial service and the business service industries also show a high concentration of accounting fraud events. In total, the technology (including bio-technology firms) and service sectors account for 66.77% of all securities lawsuits studied in this paper.

1.3 The Nature of Fraud

Table 3 lists some specific accounting items that are most often manipulated, based on the relevant case documents in 560 class action lawsuits. Allegations of improper revenue recognition are most common, accounting for 67.5% of all the accounting fraud allegations. Operational expenses are also likely to be manipulated by managers to reach desired earnings targets. 17.3% of the accounting fraud cases alleged that the fraudulent companies had understated their operational expenditures. As for the balance sheet items, misstatements of assets are more frequently observed than misstatements of liabilities and equity in the balance sheet. Among the different types of assets, accounts receivable and inventory seem to be frequently misstated. This observation is consistent with the findings in Chan et al. (2001) that changes in inventory and accounts receivables are closely related to the earnings quality and thus can help to predict future stock returns. Finally, understatement of reserves and allowances is also often observed in alleged financial misreporting cases, accounting for about 9% of all the lawsuits.

2 Empirical Methodology and Hypothesis Development

A firm's propensity to commit fraud depends on its expected benefit and cost of engaging in fraud. The expected cost of fraud has two components: the probability of detection and the penalty upon detection. I focus on the detection likelihood. Wang (2004) argues that while the penalty (at least the explicit liability provision) is largely determined by securities laws and thus exogenous to the firm, the probability of detection depends on the firm's endogenous actions (e.g., investment, disclosure) as well as firm-specific attributes. This implies that the detection risk is a more important determinant of the cross-sectional variations in fraud propensities than are penalty provisions. Therefore, a factor will positively influence a firm's fraud propensity if it can increase the firm's benefit from committing fraud, or if it can decrease the firm's expected probability of getting caught, or both.

The structure of this section is as follows. Section 2.1 presents the econometric model. Sections 2.2 and 2.3 discuss factors that can potentially affect a firm's detection risk and its benefit from fraud, respectively. Section 2.5 summaries the model specification.

2.1 An Empirical Model of Fraud

In implementing comparisons between the fraud sample and any sample of non-convicted firms, we face an identification problem because we can only observe *detected* fraud. That is, we only observe the joint outcome of fraud occurrence and fraud detection. Firms that have not been sued in securities litigation could be either innocent firms or undetected fraudulent firms (see Figure 1 for an illustration). This implies that the probability of detected fraud (what we observe) is different from the probability of fraud (what we are interested to estimate but cannot observe), unless detection is perfect.

To address this identification problem, I use a bivariate probit model with partial observability as discussed in Poirier (1980).[1] Let F_i^* denote firm i's potential to commit fraud, and D_i^* denote the firm's potential of getting caught given that fraud has been committed. Then consider the following reduced form model:

$$F_i^* = x_{F,i}\beta_F + u_i; \tag{1}$$

$$D_i^* = x_{D,i}\beta_D + v_i, \tag{2}$$

where $x_{F,i}$ contains variables that help explain firm i's potential to commit fraud, and $x_{D,i}$ contains variables that help explain the firm's detection risk. u_i and v_i are zero-mean disturbance terms, and their variances have been normalized to equal unity. The correlation between is u_i and v_i is ρ. Now I define the following binary variables.

Fraud occurrence: $F_i = 1$ if $F_i^* > 0$, and $F_i = 0$ if otherwise;

Fraud detection: $D_i = 1$ if $D_i^* > 0$, and $D_i = 0$ if otherwise.

We, however, do not directly observe the realization of F_i or D_i. What we observe is whether

$$Z_i = F_i D_i$$

equals one or zero. $Z_i = 1$ if firm i has committed fraud and has been detected, and $Z_i = 0$ if firm i has not committed fraud or has committed fraud but has not been detected. Let Φ denote the bivariate standard normal cumulative distribution function. The empirical model for Z_i is[2]

$$P(Z_i = 1) = P(F_i D_i = 1) \tag{3}$$

[1]See Abowd and Farber (1982) and Chidambaran and Prabhala (2003) for some applications of this model.

[2]I assume that $P(D_i = 1|F_i = 0) = 0$, i.e., the probability of wrong lawsuits is zero. In my sample, the number of lawsuits that were later dismissed by the court is less than 3% of all the lawsuits filed.

$$
\begin{aligned}
&= P(F_i = 1)P(D_i = 1|F_i = 1) \\
&= P(F_i^* > 0, D_i^* > 0) \\
&= \Phi(x_{F,i}\beta_F, x_{D,i}\beta_D, \rho); \\
P(Z_i = 0) &= 1 - P(Z_i = 1) \qquad (4) \\
&= 1 - \Phi(x_{F,i}\beta_F, x_{D,i}\beta_D, \rho).
\end{aligned}
$$

Therefore, the log-likelihood function for the model is

$$L(\beta_F, \beta_D, \rho) = \sum_{i=1,\dots,n} \{z_i ln[\Phi(x_{F,i}\beta_F, x_{D,i}\beta_D, \rho) + (1 - z_i)ln[1 - \Phi(x_{F,i}\beta_F, x_{D,i}\beta_D, \rho)]\}. \qquad (5)$$

As discussed in Poirier (1980), the conditions for full identification of the model parameters are (1) $x_{F,i}$ and $x_{D,i}$ do not contain exactly the same variables; and (2) the explanatory variables exhibit substantial variations in the sample.

The partial observability model implies that the appropriate comparison sample should be a random sample of non-litigated firms. I therefore use all the firms in the COMPUSTAT database that have not been subject to securities litigation between 1996 and 2003. For the entire sample of fraudulent and comparison firms, I obtain financial information from COMPUSTAT, ownership information from CDA Spectrum database, and merger/acquisition information from SDC database.

Note that a simple probit model, which has been utilized in many existing fraud studies, would be that for i=1,...,n,

$$P(D_i = 1|F_i = 1) = 1;$$

$$P(Z_i = 1) = P(F_i = 1).$$

Therefore, as long as detection is not perfect, the coefficient estimates from the simple probit model will be different from those from the bivariate probit model.

2.2 Fraud Detection Risk

The probability of fraud detection essentially determines how risky it is for a firm to engage in fraud. If a factor can significantly influence such probability ex post and if its effect can be anticipated at the time the firm makes the fraud decision, then this factor should influence the firm's ex-ante propensity to commit fraud (in the opposite direction). Therefore, I start with the determinants of the fraud detection likelihood (i.e., x_D), and then move to the determinants of fraud propensity (i.e., x_F) in Section 2.3.

To facilitate my analysis, I use the following fiscal year counting. For the fraud sample, I label the fiscal year in which fraud begins as fiscal year 0. Then the fiscal year prior to year 0 is year -1, and the one after is year 1. Since the comparison sample consists of all the non-litigated firms, all the comparison firms enter each relevant fiscal year. For example, fiscal year -1 spans from 1991 to 2002 for the fraud sample. Then all the observations of the comparison firms in year 1991 to year 2002 are used in the analysis.

2.2.1 Investment Intensity

Wang (2004) argues that fraudulent firms tend to overinvest. The overinvestment incentive is twofold. First, fraud can create short-term market overvaluation of the firm and thus decrease the external financing cost of the investment. Second, new investment may decrease the precision of the firm's cash flows and create inference problems for the market, and thus may be used strategically by the management to influence the firm's litigation risk. Wang's argument has three testable implications. First, fraudulent firms should have larger investment expenditures than comparable honest firms. Second, we should expect a negative relation between investment and the probability of fraud detection. Third, the type of investment that creates the most valuation imprecision should have the strongest negative effect on the detection likelihood.

To test the above implications, I investigate three types of investment: investment in research & development (R&D), capital expenditures, and mergers/acquisitions. These investments can substantially differ in their effects on a firm's valuation precision. Investment outcome of R&D projects are generally subject to large degree of uncertainty and it is difficult for the market to fully understand and correctly value its impact on the firm value. Capital expenditures tend to be more straightforward. COMPUSTAT defines capital expenditures as the the funds used for additions to the company's property, plant and equipment. Mergers and acquisitions, in theory, should fall in the middle, because the investment is to acquire an existing asset rather than to create something new. The synergy between the newly acquired and the existing assets, however, may not be correctly understood by the market and even the acquiring firm. I also examine firms' net investing cash flows, which generally includes capital expenditures and acquisition cash flows but not R&D expenditures. All the investment expenditures are deflated by the book value of total assets, and are measured as of the end of year 0. The reason for using year 0 information is that the investment was made around the time when fraud was committed, and therefore could have been used strategically by the management to disguise fraud.

2.2.2 Shareholder Monitoring

A firm's ownership structure can be very crucial in determining both the firm's benefit from fraud and its detection risk. This is because ownership structure is crucially related to the incentive structure within the firm, including the incentive of the management to defraud outside investors and the incentive of shareholders to monitor the management and detect fraud.

The monitoring role of large shareholders has received a great amount of attention in the finance and economics literature. Shleifer and Vishny (1997) argue that concentrated ownership is a key element of a good corporate governance system because large shareholders have high incentive and power to impose effective monitoring over the management. Empirical studies have provided some support for this theory. For example, Bethel, Liebeskind and Opler (1998) find that company performance improves after an activist investor purchases a block of shares. Bertrand and Mullainathan (2001) find that the presence of a large shareholder on the board is associated with tighter control over executive compensation. In the context of corporate fraud, it is also intuitive that large shareholders should go against fraudulent reporting, because they cannot cash out in a short time to catch the windfall from fraud, and they will likely suffer a lot from the severe consequences of fraud. Therefore, we should expect a positive relation between block ownership holding and the likelihood of fraud detection.

Monitoring by institutional shareholders has attracted growing public and academic interest as institutional ownership skyrocketed over the past two decades in the United States. Some institutional investors (e.g., some pension funds) hold substantial stakes in the companies they invest in, while others tend to diversify. For large institutional investors, we expect them to be active in fraud detection for the reasons discussed in the preceding paragraph. William Lerach, a partner in Milberg Weiss Bershad Hynes & Lerach LLP and a leader in representing investors in securities class action suits, has pointed out that some large pension funds have actively participated in securities litigation and have successfully established corporate governance enhancements in class action settlements.[3]

[3]Keynote address by William S. Lerach in council of institutional investors spring 2001 meeting.

The role of dispersed institutional holding in fraud detection, however, is less clear. On one hand, atomic institutional investors are subject to the free rider problem, and are also likely to concern more about liquidity than control. Therefore, dispersed institutional owners may not only be passive in corporate governance, but may even press managers to behave myopically. For example, momentum institutional investors have been accused by some economists and securities lawyers as responsible for the massive increase in corporate fraud because they push corporate managers to fixate on short term earnings. On the other hand, a large institutional investor base may increase the likelihood of external detection of fraud, as more investors observe and draw inferences from the firm's cash flows and update their beliefs about the probability of misreporting. A large institutional interest in a company generally also attracts analyst coverage of the company. Wang (2004) argues that this detection mechanism can be very effective and can well complement internal governance in combatting corporate misreporting. Therefore, I expect institutional equity holdings to have a positive effect on fraud detection.

Insider ownership can also influence the probability of detection. All of the lawsuits in my sample named key corporate officers and directors as individual defendants, which implies that the insiders were involved in fraud. Then they should have an incentive to suppress internal fraud detection forces. Insiders with large ownership are more likely to dominate and can more effectively quell the discovery of fraud. Therefore, we expect a negative relation between insider ownership and the probability of fraud detection.

Block ownership is the total percentage ownership of shareholders who own at least 5% of a firm's outstanding equity. Institutional ownership is the total ownership of all institutional investors of a firm. Insider ownership is the percentage ownership of officers and directors. The ownership is measured at the average level during years [-1,0].

2.2.3 Unexpected Performance Shock

Wang (2004) argues that fraud can be partially self-revealing. If the manager inflates the earnings and misleads the market to have a high expectation on the firm's future cash flows, then if later the cash flow realization turns out to be comparably bad (which the manager cannot fully control), outside investors would rationally think that they probably have been fooled and would start an investigation. Therefore, unexpected bad performance after the commencement of fraud will increase the probability of fraud detection.

To proxy for such unexpected performance shock (unexpected at the time of the fraud decision), I use the regression residual term from the following simple prediction model.

$$ROA_{i,1} = \beta_0 + \beta_1 ROA_{i,0} + \beta_2 ROA_{i,-1} + \epsilon_i. \quad (6)$$

ROA is the return on asset, which is defined as the ratio of operating income after depreciation over the previous year's total assets. ROA in year 1 is used as the dependent variable because the average length of the class period is about one year. ϵ_i (the residual ROA) will be low if firm i's performance in year 1 is bad compared to the (reported) performance in the previous two years. The realizations of this variable cannot be fully expected in year 0 when the management makes the fraud decision. Therefore, although this variable may significantly influence the firm's detection risk, its effect is ex-post and thus should not affect the firm's ex-ante fraud decision.[4]

2.3 Propensity to Commit Fraud

The equilibrium supply of fraud depends on the expected benefit and cost of engaging in fraud. Therefore, x_F should include factors that can affect either the benefit from fraud, or the litigation risk, or both. The previous section discusses some potential determinants of the detection risk. Now I turn to factors that can potentially influence a firm's benefit from committing fraud.

2.3.1 Profitability and Growth Potential

Wang (2004) and Bebchuk and Bar-Gill (2003) predict that firms that have growth potential but experience negative profitability shocks have high propensity to commit fraud. The intuition is that for such firms misreporting short-term firm performance can allow them to raise external capital and exercise their growth options on sweet terms.

In this study, I use ROA as the profitability measure. I use two proxies for growth potential, the annual asset growth rate and the book-to-market ratio, which equals assets over (assets - equity + market value of equity).[5] All the profitability and growth variables are measured at the average level in years [-2,-1]. Using pre-fraud information can help mitigate the effect of fraud on firms' reported profitability and growth.

[4]It is true that this variable is not completely exogenous. The direction of causality, however, is not ambiguous. It is intuitive that bad operating performance eventually reveals fraud. Detection of fraud may result in immediate plunge in stock returns and may affect the long-run performance of the fraudulent firm, but it is hard to believe that the revelation of fraud leads to immediate bad operating performance.

[5]Negative equity observations are not used in the computation.

2.3.2 External Financing Needs

The combination of low asset profitability and high growth implies large reliance of a firm on the external capital markets. Stein (1989) argues that the lack of financial slack can expose the manager to capital market pressure and can motivate the manager to inflate short-term performance at the cost of forfeiting long-term value. The earnings management literature has provided evidence that managers tend to overreport earnings prior to major external financing activities such as public equity offerings (see, e.g., Teoh, Welch and Wong (1998a,b)) and stock-based acquisitions (Erickson and Wang (1998)). I construct two variables to proxy for a firm's external financing needs. The first variable, externally financed growth rate, is constructed based on Demirgüç-Kunt and Maksimovic (1998) to proxy for a firms' *projected* need for outside capital. Specifically, the externally-financed growth rate is a firm's asset growth rate in excess of the maximum growth rate that can be supported by the firm's internally available capital (ROA/(1-ROA)).[6] The second variable, EF, is constructed following Richardson and Sloan (2003) to measure a firm's net external financing cash flows. Specifically,

$$EF_t = \frac{\Delta CE_t + \Delta PE_t + \Delta DEBT_t}{ASSETS_t},$$

where ΔCE_t and ΔPE_t are the changes in the book value of common equity and preferred equity in year t, respectively. $\Delta DEBT_t$ is the change in the book value of total debt in year t. $ASSETS_t$ is the book value of assets.[7] This variable can be viewed as a measure of a firm's *realized* external financing need. Since the second variable is an outcome-based measure, I focus on the first variable in order to reduce endogeneity, and use the second measure only as a robustness check. The external financing variables are measured at the average level in years [-2,-1].

2.3.3 Financial Distress

A another factor that is closely related to financial slack and external financing need is the degree of financial distress. Maksimovic and Titman (1991) theorize that financial difficulties can affect a firm's incentive to honor its implicit contracts and in other ways maintain a favorable reputation. In their model, both financial shortfalls and overall debt overhang can induce the distressed firm to increase current cash flow at the cost of losing reputation and long-term profitability. Several

[6]See Demirgüç-Kunt and Maksimovic (1998) for assumptions and justifications for this measure. According to the discussion in that paper, ROA here is the ratio of income before extraordinary items over assets.

[7]See Richardson and Sloan (2003) for a discussion of some possible limitations of this measure.

accounting studies find some evidence that avoidance of penalties associated with the violations of debt covenants is a motivation to manage earnings (Sweeney (1994), DeFond and Jiambalvo (1994), and Dechow et al. (1996)). These studies imply that financial distress can increase firms' incentives to misreport. I use the ratios of long-term debt and short-term debt to total assets to proxy for the degree of financial distress.

2.3.4 Insider Ownership

The relation between insiders' equity incentives and the incidence of corporate fraud has been in the center of the current debate and reform on corporate governance. There are two forces associated with insiders' equity stake. On one hand, the classic agency theory implies that higher percentage insider ownership can better align insiders' incentives to that of the shareholders. Since fraud is outright contravention of shareholders' interest, high insider ownership should be associated with low fraud propensity. The agency view is supported by the work of Alexander and Cohen (1999). They examine public firms convicted of federal crimes in 1984-1990, and find that crime occurs less frequently among firms in which management has a larger ownership stake. On the other hand, large equity incentives can be a double-edged sword, because the positive relation between firm performance and insiders' compensation (or wealth) can induce distorted managerial reporting incentives (see, e.g., Goldman and Slezak (2003)). The second force seems to be supported by the findings in some recent empirical work such as Johnson, Ryan and Tian (2003), Peng and Röell (2003), and Burns and Kedia (2003). These papers find that high pay-for-performance ratio (as a result of large equity-based compensation) is related to high probability of fraud or earnings manipulation, indicating over-incentivization of the management.

In this study, I use insider ownership to proxy for insiders' equity incentives. Given the dramatic increase in the use of stock options in managers' compensation, the percentage stock ownership will not capture the full impact of managers' equity incentives. However, companies generally include in the calculation of insider ownership the shares of stock options that are already vested or will be vested within 60 days as of the proxy statement filing date. The equity incentive from vested (or to be vested) stock options is likely to matter more than that from unvested options in the context of fraudulent reporting, since fraud may be detected before any long-term options become exercisable.

2.4 Control Variables

Some previous studies on financial statement fraud find that firms tend to commit fraud at a very early stage of their business cycle. Beasley, Carcello and Hermanson (1990) document that firms that have engaged in financial statement fraud are generally small. The National Commission on Fraudulent Financial Reporting (AICPA 1987, 29) states that young public firms may face greater pressure to dress up firm appearance and thus have higher likelihood of engaging in fraud. Table 2 also shows clear industry patterns in securities litigation. Technology firms (software & programming, computer and electronic parts, biotech), service firms (financial services, business services, utility, and telecommunication services) and the trade industries (whole sales and retails) appear to have disproportionately high fraud concentration. This implies that these industries tend to have either large benefit from fraud, or high detection risk, or both. Furthermore, firm size, age and industry segments are likely to be correlated with the firm's profitability, growth potential, external financing need and ownership structure. Therefore, I control for firm size (log of total assets), age, and firms' membership in the technology, service and trade sectors. Age is defined as the number of years between a firm's IPO date and the end of fiscal year -1.[8] [9]

2.5 Summary of Model Specification

The following table summarizes the model specification discussed in above sections. The first column X_F shows the factors that may explain a firm's propensity to commit fraud. The third column X_D describes the factors that may explain the probability of fraud detection. The second and fourth columns indicate the predicted direction of influence. The last three variables are control variables, and thus no predictions are attached to them.

[8] Note that age is defined slightly differently from what is reported in Table 1 Panel D, because the comparison firms do not have class periods.

[9] I do not control for year effects for two reasons. First, the data is not in the form of a panel and I thus cannot make any predictions about the effect of a year on the fraud likelihood. Second, since the fraud sample is constructed based on lawsuits filed during 1996 to 2003, year 0 will naturally be concentrated in later years (see Table 1 Panel C), which makes any year effect difficult to interpret.

X_F	β_F	X_D	β_D
Growth Potential	+		
External Financing Need	+		
Financial Distress	+		
Profitability	-	Profitability (ex-post)	-
Investment	+	Investment	-
Insider Ownership	+/-	Insider Ownership	-
Block Ownership	-	Block Ownership	+
Institutional Ownership	-	Institutional Ownership	-
Firm Size		Firm Size	
Age		Age	
Tech/Service/Trade		Tech/Service/Trade	

3 Descriptive Information & Univariate Analysis

This section presents univariate comparisons between the fraud sample and the comparison sample. The explanatory variables are grouped into five categories: (1) firm size and age; (2) profitability and growth; (3) external financing needs; (4) investment intensity; and (5) ownership structure. Table 4 reports the median and mean of each variable for both samples and the non-parametric Wilcoxon z-statistics for testing differences between the two samples.

The fraud sample on average appears to be larger but younger than the comparison sample. Studies that examine firms subject to the SEC's Accounting and Auditing Enforcement generally find that those firms tend to be small (see, e.g., Beasley, Carcello and Hermanson (1999)). Firms that are subject to private class action litigation can be larger because class action lawsuits tend to target firms with "deeper pockets" (Cox and Thomas (2003)).

The fraud sample seemed to outperform the comparison sample in the two years before the commencement of fraud, but underperformed the comparison sample in year 1. A possible explanation for this result is that fraudulent firms experienced some negative performance shock in year 0 but they covered up the problems by false financial disclosure. Then fraud got uncovered in year 1, and the concealed bad performance was revealed.

Table 4 also shows that fraudulent firms tend to have significantly higher growth rate and lower book-to-market ratio than the comparison firms. The median asset growth rate is 45% for the fraud sample, and only 10% for the comparison sample. The median book-to-market ratio for the fraud sample is 0.51, much lower than that of the control sample (0.76). High growth and low internal profitability naturally leads to large need for outside capital. According to the argument in Demirgüç-Kunt and Maksimovic (1998), on average only 13% of the growth in the fraudulent firms could be supported by internal funds, resulting in a high projected externally financed growth. The fraudulent firms also raised more external capital even before the commencement of fraud. The median ratio of net external financing cash flow to total assets is 21% for the fraud sample, and only 4% for the comparison sample. The financial distress variables, however, do not turn out to be significantly different between the two samples.

The difference in growth opportunities across the two samples is further reflected by the statistics on investment expenditures. We can see that the fraud sample on average invested more than the comparison sample did both before and around the commencement of fraud. For instance, in fiscal year 0 the median ratio of net investing cash flow to total assets is 11% for the fraud sample, and 6% for the comparison sample. This provides some support for the overinvestment prediction in Wang (2004).

Finally, Table 4 shows that the fraud sample tends to have more concentrated ownership than the comparison sample. Both the median block holdings and median institutional holdings are much larger in the fraud sample than in the comparison sample (30.79% vs. 25.74%, and 37.06% vs. 18.99%). There is, however, no significant difference in insider ownership (10.95% vs. 9.22%).

In sum, the univariate analysis yield the following results. Compared with the comparison sample, the fraud sample tends to grow much faster, invest more, heavily rely on external capital markets, and have concentrated ownership.

4 Multivariate Analysis

This section presents evidence from multivariate tests to simultaneously assess the effect of firm characteristics, investment, and shareholder monitoring on a firm's propensity to commit fraud and the probability of fraud detection.

4.1 Firm Characteristics and Fraud

Table 5 reports the effects of profitability, growth and external financing need on a firm's fraud incentives. Higher ROA seems to increase the likelihood of fraud. This result may seem counter-intuitive at first glance. However, it can be intuitive because it is difficult for a (known) troubled firm to sell a good earnings report. A firm will have incentive to fool the market and may easily succeed when the market believes that the firm is profitable based on previous years' performance, while negative shocks or deterioration in profitability has already started. However, the concealed performance deterioration, if it continues, actually increases the likelihood of fraud detection. The average marginal effect of residual ROA on $P(D|F)$ across models is -0.20, which means that a 10% unexpected decrease in ROA in year 1 tends to increase the probability of detection by 2%. This result supports the argument in Wang (2004) that fraud is, to some extent, self-revealing. The more the manager is able to raise the market's expectation by fraudulent reporting, the more likely the market will later see inconsistency between firm performance and what it has been guided to expect. The inconsistency will drive fraud detection.

Table 5 also shows that a firm's growth potential and external financing need appear to be important motivational factors for fraud. Models 1 and 2 indicate that higher asset growth and lower book-to-market ratio are positively related to a firm's probability of committing fraud. Model 3 further shows that fraudulent firms are likely to have a growth rate higher than what can be supported by internal funds. The average marginal effect of externally financed growth on $P(F)$ across models is 0.56, which means that increasing the externally financed growth by 10% increases a firm's probability of misreporting by 5.6%. Models 4-6 indicate that fraudulent firms are able to raise more external capital, but they do not appear to be more burdened by debt. This implies that fraudulent firms may pursue more equity financing than debt financing.

Overall, results in Table 5 imply that rapidly growing firms with insufficient internal capital are likely to misreport their financial performance, because fraud enables them to exercise their growth options on favorable terms.

4.2 Investment & Fraud

Table 6 reports the relation between firms' investment expenditures and their fraud incentives. I find that different types of investment have differential effects on a firm's ex-post detection risk and ex-ante propensity to commit fraud. Investment in R&D has a strong negative effect on the probability of fraud detection. This effect is statistically and economically significant. The average marginal effect of R&D expenditures on $P(D|F)$ is -0.18, which means that a 10% increase in R&D expenditures tends to decrease the detection risk by 1.8%. Note that a firm's total litigation cost is the probability of detection times the penalty upon detection. Therefore, the effect of R&D expenditures on the probability of detection will be levered by the size of the penalty. Suppose that the penalty can be completely measured in terms of money, then a 1.8% decrease in the detection likelihood can correspond to a substantial reduction in the dollar value of litigation cost. The lower litigation cost translates into higher propensity to commit fraud. The average marginal effect of R&D expenditures on $P(F)$ is 0.89, which means that a 10% increase in R&D expenditures tends to increase a firm's probability of fraud by about 9%.

The effect of net investing cash flow on firms' fraud incentives is similar to but weaker than that of R&D expenditures. Its average marginal effect on $P(D|F)$ is -0.07, and is 0.48 on $P(F)$. Capital expenditures and cash-based acquisitions do not have much effect on either the detection likelihood or the fraud propensity. Stock-based acquisitions, however, tend to increase the probability of fraud, but still does not influence fraud detection. This implies that the financing of the investment can motivate fraud by affecting a firm's benefit from committing fraud.

Overall, the results support the implications in Wang (2004)'s model. First, investment can influence both firms' ex-ante benefit from committing fraud (e.g., through the financing of the investment) and their ex-post detection risk, and therefore is an important determinant of firms' incentives to defraud investors. Second, risky investments (in terms of lower valuation precision) can mask fraud better than straightforward ones, which implies that fraudulent firms may be motivated to pursue more risk than what is optimal.

4.3 Shareholder Monitoring

Table 7 presents the effect of shareholder monitoring on a firm's fraud incentives. I find that the presence of large shareholders and institutional shareholders increases fraud detection and discourages fraud. The marginal effects of block ownership on $P(D|F)$ and $P(F)$ are 0.1 and -0.38, respectively. This means that a 10% increase in block ownership tends to increase the probability of fraud detection by 1%, and decrease the probability of fraud by 3.8%. The marginal effect of institutional ownership has a similar magnitude (0.1 and -0.30). In addition, the number of institutional shareholders is also positively related to $P(D|F)$, which implies that a broad institutional investor base can increase fraud detection. These results show that the strength of shareholder monitoring significantly influences firms' propensity to commit fraud, and provide support for enhancing shareholder monitoring in the on-going corporate governance reform.

I find that insider ownership seems to negatively influence the probability of detection and positively influence the probability of fraud. The effects, however, are not consistently significant across models.[10] I also partition the insider ownership distribution into three regions: less than 5%, between 5% and 25%, and greater than 25%.[11] No significant relation between insider ownership and fraud propensity emerges in any region.

Dye (1988) and Wang (2004) show that fraud can emerge in equilibrium if a firm's incumbent shareholders can benefit at the cost of potential new investors. In other words, fraud may result from two types of agency problems, the conflict of interest between existing shareholders and new shareholders, and the conflict between the management and existing shareholders. In the former case, managerial ownership may not play a big role in determining the managers' fraud incentives, while in the latter case it should, as predicted by the agency theory. In order to distinguish these two scenarios, I examine a subsample of lawsuits involving allegations of both accounting irregularities and illegal insider trading. Illegal insider trading refers generally to buying or selling a security, in breach of a fiduciary duty or other relationship of trust and confidence, while in possession of material, nonpublic information about the security. Among the 656 lawsuits, 161 cases involved illegal insider trading. These cases clearly indicate misaligned managerial incentives. The effects of insider ownership become much stronger in this subsample, but are still not statistically significant at 5% level.

Several studies have found that large executive equity incentives are associated with high probability of fraud or accounting restatements (see references in Section 2.3). The significant positive relation in those studies, however, seems to be driven almost exclusively by stock options. For example, Peng and Röell (2003) study executive compensation in firms subject to securities class action lawsuits and find that straight stock ownership does not affect the likelihood of securities litigation, but stock option holdings (vested as well as unvested) and new option grants are positively associated with the probability of litigation. Then all the results seem to indicate that it is excessive option grants that can have unintended consequences for long-term shareholder value.

[10] Log transformation of ownership yields similar results and are not reported.

[11] Other cutoff points, such as 10% and 40%, yield similar results and are not reported.

4.4 Summary of Results

In sum, Tables 5-7 show that fraudulent firms are likely to be high-growth firms that have large needs for external capital but experience negative shocks in profitability. Performance deterioration, although temporarily concealed by fraud, tends to reveal itself and increase the probability of detecting fraud. Investment around the commencement of fraud appears to decrease the detection likelihood and increase firms' ex-ante fraud incentives. Large shareholders and institutional owners seem to increase the probability of fraud detection and their presence tends to deter fraudulent reporting. There is some weak evidence that large insider ownership tends to suppress fraud detection and encourage fraud. There are no persistent and significant effects associated with the control variables.

4.5 Comparison with Simple Probit Models

Existing studies on fraud have used (univariate) probit models to assess the effect of a factor on a firm's probability of committing fraud. As discussed in Section 2.1, the simple probit model ignores the fact that the probability of detected fraud does not equal the probability of fraud. Table 8 reports the simple probit regression results for several key models, and clearly demonstrates the problems we face when interpreting the regression results.

First, all the simple probit models show no significant effect of R&D expenditures on firms' fraud incentives. This is in sharp contrast with the results from the bivariate probit models. The reason is that investment in R&D has opposing effects on $P(D = 1|F = 1)$ and $P(F = 1)$. Therefore, its effect on $P(Z = 1) = P(F = 1)P(D = 1|F = 1)$ is not clear. Second, the simple probit models show that block ownership and institutional ownership are positively related to the $P(Z = 1)$. This may lead us to conclude that the presence of large shareholders and institutional shareholders increases a firm's fraud incentives, which is again opposite to what we would conclude using bivariate probit models. The positive relation in a simple probit model actually results from the positive effect of block and institutional holdings on the detection likelihood. Holding other factors constant, firms with large block ownership and institutional ownership are more likely to get caught if commit fraud, and thus are more likely to be observed in the fraud sample.

The comparison between the results from simple probit models and those from bivariate probit models clear show that disentangling the effect of a factor on the probability of detecting fraud and its effect on the probability of committing fraud is very important for us to draw sensible conclusions.

5 Conclusion

This study investigates the economic determinants of firms' propensity to commit accounting fraud and the probability of fraud detection, using a unique fraud sample. I use econometric methods to control for frauds committed but not yet detected, and to disentangle the effect of a factor on a firm's probability of committing fraud and its effect on the firm's probability of being detected. The results of this study show that some firm characteristics, investment expenditures, and strength of shareholder monitoring can significantly influence a firm's cost-benefit tradeoff of engaging in fraud. Firms that have high growth potential and large external financing need but experience negative profitability shocks tend to have high fraud propensity. The fraud sample on average has larger investment expenditures than the comparison sample. Different types of investment have differential effects on firms' detection risk and their propensity to commit fraud. Investments that introduce valuation imprecision can disguise fraud better than straightforward investments. Finally, I find that monitoring by large shareholders and institutional owners seems to increase fraud detection and deter fraud.

This study also shows the importance of disentangling the probability of committing fraud and the probability of detecting fraud, because cross-sectional variables can have opposing effects on the two latent probabilities, and therefore can be masked in their overall effect on the incidence of detected fraud. Ignoring this structure can lead us to draw incorrect inferences about the determinants of corporate fraud.

REFERENCES

Agrawal, Anup, and Sahiba Chadha, 2004, "Corporate Governance and Accounting Scandals," *Journal of Law and Economics* Forthcoming.

Agrawal, Anup, Jeffrey F. Jaffe, and Jonathan M. Karpoff, 1999, "Management turnover and corporate governance changes following the revelation of fraud," *Journal of Law and Economics* April, 309-342.

Alexander, Cindy R., and Mark A. Cohen, 1999, "Why do corporations become criminals? Ownership, hidden actions, crime as an agency cost," *Journal of Corporate Finance* 5, 1-34.

Baucus, Melissa S., and David A. Baucus, 1997, "Paying the piper: An empirical examination of long-term financial consequences of illegal corporate behavior," *Academy of Management Journal* 40 (February), 129-151.

Beasley, Mark S., 1996, "An empirical analysis of the relation between the board of director composition and financial statement fraud," *The Accounting Review* 71, No. 4, 443-465.

Beasley, Mark S., Joseph V. Carcello, and Dana R. Hermanson, 1999, "Fraudulent financial reporting: 1989-1997," Research commissioned by the Treadway Commission.

Bebchuk, Lucian A., and Oren Bar-Gill, 2003, "Misreporting corporate performance," working paper, Harvard University.

Becker, Gary S., 1968, "Crime and punishment: An economic approach," *Journal of Political Economy* , 169-217.

Bertrand, M., and S. Mullainathan, 2001, "Are CEOs rewarded for luck? The ones without principals are," *Quarterly Journal of Economics* 116, 901-932.

Bethel, J., J. Liebeskind, and T. Opler, 1998, "Block share purchases and corporate performance," *Journal of Finance* 53, 605-635.

Burns, Natasha, and Simi Kedia, 2003, "Do executive stock options generate incentives for earnings management? Evidence from accounting restatements," working paper, Harvard University.

Chan, Konan, Louis K. C. Chan, Narasimhan Jegadeesh, and Josef Lakonishok, 2001, "Earnings quality and stock returns," NBER working paper.

Chidambaran N.K., and Nagpurnanand R. Prabhala, 2003, "Executive stock option repricing, internal governance mechanisms, and management turnover," *Journal of Financial Economics* 69, 153-189.

Coffee, John C. Jr., 1991, "Liquidity versus control: The institutional investor as corporate monitor," *Columbia Law Review* 91, No. 6, 1277-1367.

Cox, James D, and Randall S. Thomas, 2003, "SEC enforcement actions for financial fraud and private litigation: An empirical inquiry," *Duke Law Journal* forthcoming.

Dechow, Patricia M., Richard G. Sloan, and Awy P. Sweeney, 1996, "Causes and consequences of earnings manipulation An analysis of firms subject to enforcement actions by the SEC," *Contemporary Accounting Research* 13, No. 1, 1-36.

DeFond, M. and J. Jiambalva, 1994,"Debt Covenant Effects and the Manipulation of Accruals," *Journal of Accounting and Economics* 17, 145-176.

Demirgüç-Kunt, Asli and Vojislav Maksimovic, 1998, "Law, finance, and firm growth," *Journal of Finance* 53, 2107-2137.

Erickson, Merle. , and Shiing-wu Wang, 1999, "Earnings management by acquiring firms in stock for stock mergers," *Journal of Accounting and Economics* 18, 3-28.

Goldman, Eitan, and Steve L. Slezak, 2003, "The economics of fraudulent misreporting," working paper, University of North Carolina at Chapel Hill.

Griffin, Paul A., Joseph A. Grundfest, Michael A. Perino, 2003, "Stock price responses to securities fraud litigation: Market efficiency and the slow diffusion of costly information," working paper, Stanford Law School.

Healy, Paul M., and James M. Wahlen, 1999, "A review of the earnings management literature and its implications for standard setting," *Accounting Horizons* 13, No. 4, 365-383.

Holderness, Clifford G., 2003, "A survey of blockholders and corporate control," *Economic Policy Review* April, 51-64.

Johnson, Shane A., Harley E. Ryan, and Yisong S. Tian, 2003, "Executive compensation and corporate fraud," working paper, Louisiana State University.

Maksimovic, Vojislav, and Sheridan Titman, 1991, "Financial policy and reputation for product quality," *The Review of Financial Studies* 4, No. 1, 175-200.

Peng, Lin, and Ailsa Röell, 2003, Executive pay, earnings manipulation and shareholder litigation, working paper, Princeton University.

Poirier, Dale J., 1980, Partial observability in bivariate probit models, *Journal of Econometrics* 12, 209-217.

Pound, John, 1988, "Proxy contests and the efficiency of shareholder oversight," *Journal of Financial Economics* 20, 237-265.

Richardson, Scott A., and Richard G. Sloan, 2003, "External financing and future stock returns," working paper, University of Pennsylvania.

Shleifer, Andrei, and Robert W. Vishny, 1997, "A survey of corporate governance," *Journal of Finance* 52, No. 2, 737-783.

Singh, Ravi, 2004, "Incentive compensation and the quality of disclosure," working paper, Harvard Business School.

Summers, Scott L., and Sweeney, John T., 1998, "Fraudulently misstated financial statements and insider trading: An empirical analysis," *The Accounting Review* 73, No. 1, 131-146.

Sweeney, A.P., 1994,“Debt Covenant Violations and Manager’s Accounting Responses,” *Journal of Accounting and Economics* 17, 281-308.

Teoh, Siew Hong, Ivo Welch, and T. J. Wong, 1998a, Earnings management and the post-issue performance of seasoned equity offerings, *Journal of Financial Economics* 50, No. 1 63-99.

—, 1998b, Earnings management and the long-term market performance of initial public offerings, *Journal of Finance* 53, No. 6, 1935-1974.

Wang, Tracy Yue, 2004, “Securities fraud: An economic analysis,” working paper, University of Maryland.

Table 1: Allegations of Accounting Fraud : 1996 – 2003

Panel A: Litigation Filings by Calender Year

The fraud sample consists of 680 class action lawsuits against 656 US public companies. The total number of lawsuits each year does not include cases filed against private companies or cases against investment companies for pure fraudulent investment banking activities (such as unfair allocation of IPO shares and misleading analyst reports).

Year	1996	1997	1998	1999	2000	2001	2002	2003	1996-2003
Accounting fraud	45	70	103	80	106	87	118	70	680
Total # of lawsuits	100	163	232	195	206	168	212	177	1454
% of total	45.00	42.94	44.40	36.92	51.46	51.79	55.66	39.55	46.77

Panel B: Accounting Fraud by the Beginning Fiscal Year

Fiscal year	1992	1993	1994	1995	1996	1997
# of cases	1	5	16	48	78	115
Fiscal year	1998	1999	2000	2001	2002	2003
# of cases	96	117	105	58	15	2

Panel C: Class Periods, Age, and Stock Exchange

Every class action lawsuit specifies a class period. The beginning of a class period shows the earliest time fraud affects the market, based on the evidence collected by securities attorneys. A class period generally ends at the time of some major events that lead to subsequent litigation. Age is defined as the number of years between a firm's IPO date and its beginning of the class period. A firm's stock exchange is identified as of the beginning of class periods.

Class Period (days)		Age (years)		Stock Exchange	
# of obs.	656	# of obs.	648	# of obs.	656
mean	470	mean	8.05	NYSE	30.2%
median	353	median	3.43	AMEX	3.8%
maximum	2040	age<5 years	61.4%	NASDAQ	63.9%
minimum	13	age>10 years	22.3%	Other	2.1%

Table 2: Industry Distribution of Accounting Fraud

This table reports the distribution of accounting-fraud firms across industry segments. I classify firms into 24 industry segments based on 2-digit or 4-digit SIC codes, as detailed in the table. Percentage of total is computed based on the total number of public firms in each industry in the COMPUSTAT universe.

Industry	Fraud Events	% of Sample	% of Total
Agriculture (100-900)	1	0.15	1.18
Mining (1000-1400)	9	1.37	0.74
Construction (1520-1731)	2	0.30	0.78
Food & Tobacco (2000-2111)	11	1.68	2.59
Fabrics & Textile Products (2200-2390)	12	1.83	3.79
Wood & Furniture (2400-2590)	2	0.30	1.06
Paper & Printing (2600-2790)	3	0.46	0.72
Chemicals (2800-2821, 2840-2990)	4	0.61	0.82
Pharmaceutical (2833-2836)	21	3.20	2.81
Materials & Related Products (3011-3490)	18	2.74	1.89
Industry Manufacturing (3510-3569, 3578-3590, 3711-3873)	49	7.47	2.44
Computer-related Hardware (3570-3577)	33	5.03	6.82
Electronics (3600-3695)	63	9.60	5.13
Miscellaneous Manufacturing (3910-3990)	2	0.30	0.91
Transportation (4011-4731)	11	1.68	2.24
Telecommunications (4812-4899)	31	4.73	3.65
Utilities (4900-4991)	29	4.42	4.37
Wholesales (5000-5190)	30	4.57	3.64
Retails (5200-5990)	35	5.34	2.70
Financial Services (6021-6799)	73	11.13	1.51
Services (7000-7361, 7380-7997, 8111-8744)	66	10.06	3.72
Software & Programming (7370-7377)	115	17.53	6.13
Healthcare Services (8000-8093)	36	5.49	9.57
Others (8880-9995)	0	0.00	0.00
Total	656	100	2.95

Table 3: Nature of Accounting Fraud

This table reports the nature of the alleged financial misrepresentations in the securities lawsuits studied in this paper. I am only able to identify the nature of misrepresentation in 560 cases based on the information in relevant case documents (e.g., case complaints, press releases and court decisions). I categorize these 560 cases into 11 groups based on the accounting items that have been manipulated. I report the number of filings and the frequency of each category.

Allegations	# of Filings	% of Sample
# of identified cases	560	
Improper revenue recognition	378	67.50
Understatement of expenses	97	17.32
Non-recurring items	4	0.71
Overstatement of account receivables	53	9.46
Overstatement of inventory	38	6.79
Overstatement of intangibles	13	2.32
Overstatement of investment	9	1.61
Overstatement of other assets	72	12.86
Understatement of reserves/allowances	49	8.75
Understatement of liability	19	3.39
Other	24	4.29

Table 4: Univariate Comparisons of Firm Characteristics

This table reports the univariate comparisons between the fraud sample and the comparison sample. For the fraud sample, the fiscal year in which fraud begins is labelled as year 0. For the non-fraud sample, all the observations in the corresponding years shares the same labelling. All the financial variables (except some investment variables with square brackets of year specification) are measured ats the average level during fiscal years [-2,-1]. The summary statistics are reported after excluding 1% of extreme observations at both ends of the distribution. The ownership variables are measured at the average level during fiscal years [-1,0]. The median and mean (in the brackets)of each characteristic variable are reported. I also report the z-statistics for Wilcoxon tests that compare characteristics of the fraud sample with those of the comparison sample. ROA is operating income after depreciation over total assets. Residual ROA is the residual from regression: $ROA_1 = \alpha_0 + \alpha_1 ROA_0 + \alpha_2 ROA_{-1} + \epsilon$. Book-to-Market equals (total assets)/(total assets-equity+market value), and only positive equity observations are used in the computation. Externally financed asset growth is asset growth rate minus ROA/(1-ROA), where ROA is income before extraordinary items over total assets. Net external financing cash flow is (change in common stock+change in preferred stock+change in debt)/total assets. R&D expenditures, capital expenditures and acquisition expenditures (the cash portion) are deflated by total assets. Insider ownership is the percentage ownership of officers and directors. Block ownership is the total percentage ownership of the shareholders who own at least 5% of the firm's outstanding equity. Institutional ownership is the percentage ownership of financial institutions.

	Fraud Sample	# of obs.	Comparison Sample	# of obs.	Wilcoxon z
Firm Size & Age					
Assets ($\$10^6$)	197 (5441)	635	150 (4052)	70385	4.56**
Market Value ($\$10^6$)	470 (4528)	546	107 (1983)	64244	3.47**
Sales ($\$10^6$)	160 (2006)	631	102 (1701)	67956	5.47**
Age	3.04 (7.72)	640	5.66 (8.24)	67205	-6.28**
Profitability & Growth					
ROA	0.08 (0.00)	617	0.05 (0.06)	69426	7.82**
Residual ROA	-0.02 (-0.07)	528	0.01 (-0.00)	51142	-11.25**
Asset Growth	0.45 (1.02)	561	0.09 (0.36)	64104	19.72**
Book-to-Market	0.51 (0.53)	533	0.76 (0.73)	56129	-13.99**
External Financing Need					
Ext. Fin. Growth	0.39 (1.03)	562	0.07 (0.39)	64077	17.60**
Ext. Fin. C.F.	0.21 (0.24)	619	0.04 (0.02)	63688	21.60**
Leverage	0.11 (0.17)	631	0.11 (0.18)	70336	0.16
Short-term Debt	0.27 (0.36)	570	0.25 (0.35)	63458	0.74

(Table 4 continued)

	Fraud Sample	# of obs.	Control Sample	# of obs.	Wilcoxon z
Investment Intensity					
R&D [-2,-1]	0.00 (0.07)	633	0.00 (0.05)	70434	6.23**
R&D [0,0]	0.00 (0.05)	622	0.00 (0.05)	66380	5.62**
Investing C.F. [-2,-1]	0.11 (0.14)	614	0.07 (0.09)	63187	10.64**
Investing C.F. [0,0]	0.11 (0.14)	609	0.06 (0.08)	59064	9.98**
Capital Exp. [-2,-1]	0.05 (0.07)	624	0.04 (0.07)	64520	2.69**
Capital Exp. [0,0]	0.04 (0.06)	609	0.04 (0.06)	59587	2.95**
Acquisition (c.f.) [-2,-1]	0.00 (0.04)	619	0.00 (0.02)	63953	9.93**
Acquisition (c.f.) [0,0]	0.00 (0.04)	588	0.00 (0.02)	57420	14.91**
Acquisition (c.f.+stock) [-2,-1]	0.01 (0.07)	623	0.00 (0.03)	64060	11.44**
Acquisition (c.f.+stock) [0,0]	0.00 (0.05)	588	0.00 (0.01)	66410	21.27**
Ownership Structure					
Insider (%)	10.95 (18.24)	517	9.22 (17.52)	40758	1.37
Block (%)	30.79 (34.65)	518	25.74 (31.37)	40807	3.49**
Institution (%)	37.06 (39.21)	518	18.99 (26.71)	40663	10.38**

Table 5: Profitability, Growth, External Financing and Fraud

This table reports the relation between firms' profitability, growth potential, external financing need and their propensity to commit accounting fraud. Probit coefficient estimates and their t-statistics (in parentheses) are reported. **,* indicate significance at 1 and 5% levels, respectively. ρ is the correlation coefficient between the F^*-equation and the D^*-equation.

Panel A: Profitability and Growth

	Model 1		Model 2		Model 3	
	$P(F)$	$P(D\|F)$	$P(F)$	$P(D\|F)$	$P(F)$	$P(D\|F)$
ROA	1.26 (3.47)**		1.08 (3.77)**		2.31 (6.83)**	
Asset Growth	1.76 (5.43)**					
Book-to-Market			-2.05 (-10.02)**			
Ext. Fin. Growth					1.93 (5.03)**	
Residual ROA	-	-1.45 (-5.38)**	-	-5.64 (-7.38)**	-	-1.38 (-6.70)**
Log(Assets)	-0.02 (-0.24)	0.07 (1.26)	0.28 (7.64)**	-0.15 (-4.05)**	-0.03 (-0.33)	0.07 (1.64)
Age	0.01 (1.63)	-0.00 (-0.59)	-0.01 (-3.63)**	0.02 (4.00)**	0.01 (2.14)*	-0.00 (-0.65)
Technology	0.21 (0.57)	0.25 (1.48)	-0.27 (-2.00)*	0.55 (4.76)**	0.15 (0.45)	0.26 (1.80)
Service	-0.27 (-0.63)	0.24 (1.19)	-0.09 (-0.54)	0.52 (4.18)**	-0.28 (-0.77)	0.23 (1.39)
Trade	-0.61 (-1.33)	0.57 (2.34)*	0.29 (1.48)	0.25 (1.91)	-0.62 (-1.53)	0.54 (2.62)**
_Cons	-0.36 (-0.52)	-2.21 (-13.85)**	-1.43 (-6.74)**	-1.21 (-4.13)**	-0.26 (-0.39)	-2.24 (-16.59)**
Model Specification:						
$\chi^2(d.f.)$		134.05 (13)		414.49 (13)		127.00
# of obs.		43583		39319		43585

(Table 5 continued)

Panel B: External Financing

	Model 4		Model 5		Model 6	
	$P(F)$	$P(D\|F)$	$P(F)$	$P(D\|F)$	$P(F)$	$P(D\|F)$
ROA	0.29 (1.82)		1.28 (3.25)**		1.10 (2.96)**	
Asset Growth	0.05 (1.99)*		1.76 (5.48)**		1.81 (5.21)**	
Ext. Fin. C.F.	1.65 (5.79)**					
Leverage			-0.07 (-0.34)			
ST Debt					001 (0.06)	
Residual ROA	-	-2.89 (-7.08)**	-	-1.52 (-4.61)	-	-1.37 (-5.25)**
Log(Assets)	0.29 (9.35)**	-0.23 (-6.86)**	-0.01 (-0.13)	0.06 (1.07)	-0.01 (-0.05)	0.05 (1.00)
Age	-0.02 (-5.12)**	0.03 (6.26)**	0.01 (1.40)	-0.00 (-0.46)	0.01 (1.52)	-0.00 (-0.06)
Technology	-0.04 (-0.18)	0.39 (2.01)*	0.22 (0.56)	0.24 (1.38)	0.07 (0.18)	0.29 (1.75)
Service	-0.45 (-1.95)	0.59 (2.96)**	-0.27 (-0.60)	0.25 (1.14)	-0.30 (-0.70)	0.26 (1.32)
Trade	-0.53 (-1.74)	0.79 (2.65)**	-0.60 (-1.24)	0.56 (2.21)*	-0.65 (-1.38)	0.58 (2.37)*
_Cons.	-2.14 (-8.18)**	0.04 (0.08)	-0.49 (-0.64)	-2.19 (-12.50)**	-0.33 (-0.43)	-2.16 (-13.37)**
Model Specification:						
$\chi^2(d.f.)$		261.69 (14)		133.96 (14)		105.37 (14)
# of obs.		43187		43344		39208

Table 6: Investment, Fraud Propensity and Detection

This table reports the regression results on the effect of investment expenditures on a firm's probability of fraud detection and its fraud propensity. Probit coefficient estimates and their t-statistics (in parentheses) are reported. **,* indicate significance at 1 and 5% levels, respectively.

	Model 7		Model 8		Model 9	
	$P(F)$	$P(D\|F)$	$P(F)$	$P(D\|F)$	$P(F)$	$P(D\|F)$
ROA	1.77 (4.23)**		1.77 (4.33)**		1.65 (2.90)**	
Ext. Fin. Growth	1.67 (3.24)**		1.71 (3.23)**		1.54 (2.80)**	
R&D	3.34 (4.22)**	-1.43 (-4.39)**	3.53 (4.19)**	-1.44 (-4.35)**	2.63 (3.24)**	-1.19 (-3.48)**
Net Investing C.F.	1.10 (2.39)*	-0.42 (-2.72)**				
Capital Exp.			-1.01 (-0.77)	0.37 (0.55)	-0.85 (-0.72)	0.27 (0.44)
Acquisition (c.f.)			0.41 (0.19)	0.57 (0.75)		
Acquisition (c.f.+stock)					2.43 (2.45)*	0.02 (0.48)
Residual ROA	-	-1.11 (-6.30)**	-	-1.14 (-6.08)**	-	-1.06 (-4.42)**
Log(Asset)	0.00 (0.03)	0.05 (1.20)	-0.02 (-0.23)	0.06 (1.62)	0.002 (0.04)	0.04 (1.80)
Age	0.01 (1.72)	-0.00 (-0.42)	0.01 (1.71)	-0.00 (-0.41)	0.01 (1.82)	-0.001 (-0.38)
Technology	-0.24 (-0.89)	0.36 (2.71)**	-0.19 (-0.64)	0.33 (2.23)*	-0.32 (-1.45)	0.38 (3.80)**
Service	-0.20 (-0.69)	0.21 (1.46)	-0.18 (-0.54)	0.21 (1.25)	-0.25 (-1.18)	0.23 (2.09)*
Trade	-0.62 (-1.86)	0.50 (2.69)	-0.58 (-1.66)	0.50 (2.43)*	-0.45 (-1.59)	0.39 (2.46)*
_Cons	0.45 (0.73)	-2.00 (-13.90)**	0.62 (1.00)	-2.14 (-14.55)**	0.84 (1.05)	-2.11 (-14.75)**
Model Specification:						
$\chi^2(d.f.)$		115.79 (17)		113.92 (19)		90.43 (19)
# of obs.		39974		37799		38901

Table 7: Shareholder Monitoring and Fraud

This table reports the effect of shareholder monitoring on the firm's fraud propensity and fraud detection likelihood. Insider ownership is the percentage ownership of officers and directors. Block ownership is the total percentage ownership of shareholders who own at least 5% of the firm. Institutional ownership is the total ownership of institutional owners. The table reports the probit coefficent estimates and their t-statistics (in the parentheses), the Wald Chi-squared statistics and the degree of freedom (in parentheses). **, * indicate significance at 1 and 5% levels, respectively.

	Model 10		Model 11		Model 12	
	$P(F)$	$P(D\|F)$	$P(F)$	$P(D\|F)$	$P(F)$	$P(D\|F)$
ROA	1.99 (2.79)**		1.77 (4.42)**		2.08 (5.28)**	
Ext. Fin. Growth	1.62 (1.99)*		1.87 (3.39)**		1.74 (5.79)**	
R&D	2.57 (3.12)**	-1.74 (-3.78)**	4.08 (4.41)**	-2.23 (-4.83)**	2.49 (1.97)*	-1.86 (-3.96)**
Investing C.F.	1.79 (2.53)*	-0.71 (-2.06)*	1.42 (2.65)**	-0.65 (-3.09)**	1.56 (2.84)**	-0.68 (-2.92)**
Insider	0.67 (1.38)	-0.63 (-2.27)*	0.31 (0.60)	-0.23 (-0.89)	0.34 (0.76)	-0.33 (-1.35)
Block	-0.99 (-1.85)	0.78 (2.57)**				
Institution			-0.84 (-2.36)*	0.90 (5.48)**		
# of Institution					-0.004 (-2.12)*	0.006 (4.95)**
Residual ROA	-	-2.13 (-6.87)**	-	-1.58 (-5.39)**	-	-2.00 (-5.34)**
Log(Asset)	0.23 (1.94)	-0.07 (-0.99)	0.18 (2.26)*	-0.07 (-1.88)	0.15 (1.23)	-0.11 (-2.35)*
Age	-0.01 (-0.39)	0.01 (1.25)	0.004 (0.67)	0.003 (0.72)	0.02 (2.80)**	-0.01 (-1.38)
Technology	-0.12 (-0.36)	0.42 (2.38)*	-0.16 (-0.50)	0.35 (2.07)*	0.55 (2.18)*	-0.02 (-0.09)
Service	-0.32 (-0.88)	0.42 (2.14)*	-0.13 (-0.38)	0.30 (1.65)	0.41 (1.50)	0.05 (0.25)
Trade	-0.62 (-1.69)	0.56 (2.62)**	-0.72 (-1.90)	0.58 (2.62)**	-0.24 (-0.67)	0.42 (1.87)
_Cons	-1.76 (-2.77)**	-1.52 (-4.13)**	-0.97 (-1.10)	-1.54 (-7.05)**	-2.46 (-3.91)**	-1.01 (-4.62)**
Model Specification:						
$\chi^2(d.f.)$		214.80 (21)		177.95 (21)		307.95 (21)
# of obs.		28538		28453		28547

Table 8: Simple Probit Models - An Comparison

This table reports results from simple probit models. Simple probit model means that we ignore the detection effect and $Pr(Z_i = 1) = \Phi(x_{F,i}\beta_F)$. The results in this table are used to compare with those from the bivariate probit models in tables 5-7. The probit coefficent estimates and their t-statistics (in the parentheses), the Wald Chi-squared statistics and the degree of freedom (in parentheses) are reported. **, * indicate significance at 1 and 5% levels, respectively.

	Probit 1	Probit 2	Probit 3
ROA	0.97 (4.67)**	1.02 (4.19)	0.91 (4.94)**
Ext. Fin. Growth	0.16 (13.26)**	0.19(11.77)	0.18 (11.67)**
R&D	0.09 (0.38)	-0.04 (-0.15)	-0.21 (-0.70)
Investing C.F.	0.50 (3.63)**	0.44 (2.69)**	0.37 (2.32)*
Log(Block)		0.04 (2.16)*	
Log(Institution)			0.11 (4.96)**
Residual ROA	-1.36 (-8.32)**	-1.61 (-7.99)**	-1.62 (-8.06)**
Log(Asset)	0.04 (5.30)**	0.05 (5.01)**	0.02 (1.52)
Age	-0.00 (-0.33)	0.00 (0.34)	0.00 (0.29)
Technology	0.38 (6.90)**	0.35 (5.83)**	0.34 (5.67)**
Service	0.19 (3.89)**	0.28 (5.00)**	0.31 (5.45)**
Trade	0.23 (3.59)**	0.19 (2.60)**	0.18 (2.49)*
_Cons	-2.86 (-37.65)**	-2.96 (-27.07)**	-3.02 (-29.64)**
Model Specification:			
$\chi^2(d.f.)$	401.93 (10)	329.70 (11)	324.44 (11)
# of obs.	39974	28571	28486

Figure 1: Identification Problem