

ABSTRACT

Title of dissertation: Securities Fraud: An Economic Analysis

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This thesis develops an economic analysis of securities fraud. The thesis consists of a theory essay and an empirical essay. In the theory essay, I analyze a firm's propensity to commit securities fraud and the real consequences of fraud. I show that fraud can lead to investment distortions. I characterize the nature of the distortions, and show that it results from fraud-induced market mispricing and management's ability to influence the firm's litigation risk through investment. The theory also characterizes the equilibrium supply of fraud. I demonstrate the linkages between a firm's fraud propensity and the structure of its assets in place and growth options, and analyze the effect of corporate governance on fraud. The theory provides testable implications on cross-sectional determinants of firms' fraud propensities and the relation between fraud and investment.

In the empirical essay, I test my main model predictions, using a new hand-compiled fraud data set. 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 that the level, type, and financing of investment all matter in determining the probability of fraud and the likelihood of detection. I also examine the monitoring roles of large shareholders, institutional owners, independent auditors, and corporate boards. I find that large block or institutional holdings tend to discourage fraud by increasing the detection likelihood. The roles of independent auditors and corporate board are weaker. Finally, insider equity incentives, growth potential, external financing needs and profitability all influence a firm's propensity to commit fraud. The paper also demonstrates the importance of separating fraud commitment and fraud detection, because cross-sectional variables

can have opposing effects on these two components, and therefore can be masked in their overall effect on the incidence of detected fraud.

Securities Fraud : An Economic Analysis

by

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This dissertation is dedicated to my grandmother and grandfather.

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Chapter 1

Introduction

In recent years, a string of high profile corporate scandals like those of Global Crossing, Enron, Tyco, and Worldcom has brought securities fraud and corporate governance to the forefront of public attention and policy debate. The magnitude of the alleged securities fraud is stunning. According to Stanford Securities Class Action Clearinghouse and Cornerstone Research, 224 securities lawsuits in 2002 in the United States were associated with a total \$206 billion loss of market capitalization in the defendant firms.¹ The governance crisis was followed by rapid and substantial legislative and regulatory changes that aimed to restore investor confidence in the capital markets. The movement was so fast that 9 months after the Enron debacle, President Bush signed the Sarbanes-Oxley bill into law.

Securities fraud is a very serious issue. It undermines a core value in capital markets, the integrity of public companies, which is essential to investor confidence in those markets and the efficient allocation of capital. Furthermore, we also observe inefficient investments and serious value destructions in many fraudulent firms (e.g., Enron, Nortel, eToys), which implies that there could be large real economic cost associated with fraud. The governance crisis and the on-going governance reform call for careful economic reflections on what have happened, because the exact nature, significance, and consequences of securities fraud and the economics underlying the legislative and regulatory changes are still incompletely understood.

This thesis develops an economic framework to characterize the determinants and consequences of securities fraud. I define securities fraud as deliberate and material misrepresentation of corporate performance, and thus use fraud and misreporting interchangeably. The thesis consists of a theoretical model of fraud and empirical analysis.

¹Cornerstone Research, "Securities Class Action Case Filings 2002: A Year in Review."

1.1 Theory of Fraud

The theory part of the thesis builds on Gary Becker's (1968) economic analysis of crime. Following Becker's approach, one can view fraudulent behavior as an economic activity, whose equilibrium supply depends on a rational calculation of the expected benefits and costs from engaging in it. Different firms have different propensities to commit fraud because they face different cost-benefit tradeoffs. In this paper, the benefit from fraud is that financial misreporting can create (or sustain) short-term market overvaluation of the firm. The cost of fraud is litigation risk. With some positive probability, fraudulent activities will be uncovered, resulting in a fraud penalty (which includes both explicit monetary fines and other implicit costs, such as loss of reputation). Within this framework, the firm's propensity for fraud, the magnitude of fraud, and the firm's investment incentives are analyzed.

The theory demonstrates an interesting link between a firm's financial disclosure incentive and its real investment decision. First, financial misreporting can affect the short-term market valuation of the firm and allow the firm to invest using cheap outside capital. Second, after committing fraud, the firm has incentive to cover things up. Such incentive can motivate the firm to strategically use investment to mask fraud and reduce its litigation risk. The basic intuition is that stochastic cash flows from a new investment can decrease the precision of the firm's total cash flow and create inference problems for the market. In sum, investment can affect both the firm's ex ante benefit from committing fraud and its ex post probability of being detected. The model predicts that fraudulent firms tend to overinvest in the sense that they would undertake some negative NPV projects that destroy shareholder value. In particular, fraud can induce a preference for risky (in terms of high return volatility) or uncorrelated projects (uncorrelated with the cash flow from existing assets), because these types of investment can better disguise fraud than others. The investment distortion can lead to serious value destructions in the firm, which is the real economic cost of fraud. Furthermore, the cost of inefficiency is borne by not only shareholders of fraudulent firms but also those of honest firms, because ex ante the market cannot perfectly distinguish between the two types of firms.

The theory further characterizes the firm's equilibrium disclosure strategy. The model shows that the firm will honestly reveal performance if its performance is very good or if it is desperately bad. The former case is associated with low benefit from fraud, and the latter is associated with high litigation risk. The firm's propensity to commit fraud and the magnitude of fraud depend on the nature of the firm's assets and growth opportunities. The model predicts that fraudulent firms tend to have high growth potential but experience negative profitability shocks. Growth potential can positively influence the firm's payoff from fraud and negatively influence its litigation risk. In addition, litigation events tend to cluster in certain industries during some specific time period, because firms' cost-benefit tradeoffs of fraud are correlated within an industry.

The theory also generates implications about the role of corporate governance in the context of corporate fraud. The model shows that good corporate governance can increase the likelihood of fraud detection and thus deter fraud ex ante. However, corporate governance may also fail to prevent fraud if it is just about aligning the interest of the management with that of incumbent shareholders. This is because even when such alignment is perfect, fraud can still emerge in equilibrium.

Finally, the theory demonstrates the effect of the endogenous detection risk on the cross-sectional variations in firms' fraud propensities. While the penalty for fraud (at least the explicit liability provisions) is largely determined by securities laws and thus is exogenous to the firm, the probability of detection can be influenced by the firm's endogenous actions (e.g., investment, disclosure) as well as firm-specific attributes. This endogeneity implies that the detection risk is more important in determining cross-sectional variations in firms' fraud propensities than are penalty provisions. Therefore, without increasing the probability of detection, enhanced liability standards alone may achieve only limited deterrence, because firms can undo some effects of tightened penalty by adjusting their probabilities of getting caught. More important, fraudulent firms' incentive to decrease their likelihood of being detected can be a potential source of value destruction. Therefore, there is a real danger associated with over-regulation.

1.2 Empirical Investigation of Fraud

I then empirically test some of my key model predictions. Specifically, I examine the effects of real investment, corporate monitoring, and firm characteristics on a firm's cost-benefit tradeoff of committing fraud. The analysis is based on a new hand-compiled fraud data set, which consists of private securities class action lawsuits filed between 1996 and 2003 against US public companies with allegations of accounting irregularities.

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*. A non-litigated firm can be either an honest firm or an undetected fraudulent firm. This implies that the probability of a firm committing fraud and the probability of observing the firm as fraudulent can be very different. This 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 fraud commitment and fraud detection provides two advantages. First, it allows me to control for the unobservability of frauds committed but not detected. Second and more important, it allows me to examine the economics of each probability as well as their interactions.²

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. This is, however, an important issue. We have observed inefficient investments and serious value destructions in many fraudulent firms (e.g., Enron, Nortel, eToy). Hence, there can 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 decrease the external financing cost of investment. Second, after committing fraud, the firm has incentive to strategically use investment to mask fraud and decrease its litigation

²In a concurrent paper, Li (2004) uses a simultaneous model with partial observability to analyze the role of the SEC in detecting fraud.

risk. I find evidence that supports this theory. First, I find that the alleged fraudulent firms on average have larger investment expenditures than a random sample of non-convicted firms and a sample of size and age matched comparison firms. Second, different types of investment appear to have differential effects on the probability of fraud detection. Risky investment (e.g., investment in R&D) and uncorrelated investment (e.g., diversifying acquisition) tend to decrease the probability of detection, while straightforward investment (e.g., capital expenditures) and correlated investment (e.g., focused acquisition) do not. Lastly, different investments also influence a firm's propensity to commit fraud differently. This is either because of the way the investments are financed (e.g., stock-based vs. cash-based acquisitions) or because of the differential litigation risk they induce. Overall, the empirical results imply that investment is associated with both a firm's ex-ante benefit from committing fraud and its ex-post litigation risk, and thus is an important determinant of the firm's fraud incentives.

Corporate securities fraud also provides a new and interesting angle to examine the roles of different corporate monitors in determining firms' incentives and behavior. Effective monitoring should increase the probability of uncovering fraudulent corporate activities and discourage fraud ex ante. I investigate four types of corporate monitors: large shareholders, institutional owners, independent auditors, and board of directors. I find that the presence of block equity holders and large institutional ownership are associated with high probability of fraud detection and low probability of fraud. For example, increasing block ownership by 10% on average tends to increase the probability of detection by 1% and decrease the probability of fraud by 4%. This supports the view of enhancing shareholder monitoring in combatting corporate fraud. The roles of independent auditors and corporate boards seem to be much weaker. I find no evidence that auditors' opinions increase the likelihood of fraud detection. There is some weak evidence that reputable independent auditors and large corporate boards are related to higher likelihood of fraud detection.

The role of insider equity incentives has received a great amount of public attention following the recent wave of corporate scandals. Several studies have documented that large executive pay for performance sensitivity is associated with high probability of corporate fraudulent reporting

(see, e.g., Johnson, Ryan and Tian (2003), Peng and Röell (2004), and Burns and Kedia (2004)). In this paper, since I separate the probability of fraud from the probability of detected fraud, I am able to more directly examine the effect of insider equity incentive on a firm's propensity to commit fraud. Interestingly, I find a concave relation between the two. When insider equity incentive is small, the probability of fraud increases as the equity incentive increases. When insider equity incentive becomes large, the positive relation weakens and eventually reverses. Overall, this result seems to support the predictions of the agency theory. However, it also implies that equity incentive can be a double-edged sword when it is used to align managerial and shareholder interests in dispersedly-owned firms.

Finally, 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. There is also indirect evidence that fraudulent firms generally experience negative profitability shocks in the year when fraud begin.

Most existing studies on corporate fraud have focused on the benefit side of the tradeoff. The literature on earnings management and corporate fraud has provided evidence that managers misreport corporate performance in order to facilitate external financing activities, to avoid violations of debt covenants, or to increase performance-related compensation (see, Healy and Wahlen (1999) for a review). On the cost side of the tradeoff, a few papers have examined the consequences following the revelation of fraud. For example, Dechow, Sloan, and Sweeney (1996) show that the revelation of fraud leads to persistent increase in the firm's cost of capital. Baucus and Baucus (1997) find that firms convicted for illegal corporate behavior suffer from prolonged poor operating performance. Gande and Lewis (2005) document significant negative abnormal returns upon the filing of securities lawsuits. The only paper I know that studies the probability of fraud detection is Li (2004). Li emphasizes the strategic role of the SEC in detecting corporate fraud, and documents that a larger SEC budget increases the probability of fraud detection and deters fraud. My paper

further demonstrates the importance of understanding firm-level economic determinants of fraud detection and how the detection risk influences its ex-ante propensity to commit fraud. I show that the probability of detection depends on firms' investment decisions, the strength of corporate 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 latent probabilities, and thus can be masked in their overall effect on the incidence of detected fraud. For example, this paper shows that large institutional ownership is associated with high probability of fraud detection and low probability of fraud. The effect on detection tends to dominate and thus we observe a positive relation between institutional ownership and the compound probability (incidence of detected fraud). This may lead us to draw incorrect inferences. 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 that deal with fraud.

1.3 Thesis Structure

The thesis is structured as follows. Chapter 2 introduces the basic institutional knowledge about securities fraud and securities class action litigation. Chapter 3 reviews the related literature. Chapter 4 develops an analytical model to characterize the economic determinants of corporate fraud propensity and the real consequences of fraud. Chapter 5 empirically investigate firms' fraud incentives and fraud detection. Finally, Chapter 6 concludes.

Chapter 2

Securities Fraud & Securities Litigation

The purpose of this chapter is to provide some general knowledge about securities fraud, securities laws and regulations, and securities litigation. The structure of this chapter is as follows. Section 2.1 presents a definition of securities fraud, and describes the major anti-fraud laws and regulations that govern the securities industry. Section 2.2 describes the common types of fraud allegations in the private securities class action litigation between 1996 and 2002.

2.1 Securities Fraud

A thorough understanding of the nature, significance and consequences of securities fraud requires a proper definition of securities fraud. Fraud, in general, as defined in Webster's Universal College Dictionary, is deceit or trickery perpetrated for profit or to gain some unfair or dishonest advantage. I define securities fraud as follows based on the description of the SEC and the Securities Exchange Act of 1934. Securities fraud refers to the use of any manipulative and deceptive devices, *in connection with the purchase or sale of any security*, that are in contravention of such rules and regulations as the Commission may prescribe as necessary or appropriate in the public interest or for the protection of investors. The term "security" means any note, stock, treasury stock, bond, debenture, derivative securities, certificate of interest, or in general, any instrument commonly known as a security.

Section 10(b) of the Securities Exchange Act of 1934 and the rules promulgated thereunder (especially Rule 10(b)-5) build the major substance of the broad anti-fraud provisions that make it unlawful for anyone to engage in fraud or misrepresentation in connection with the purchase or sale of a security. Violations of these provisions include employment of any devices, schemes or artifice to defraud, misrepresentation and/or omission of material information, or engaging in any act, practice or course of business which operates or would operate as a fraud or deceit upon

any person, in connection with the purchase or sale of any security. The essence of the above regulations is to prohibit *deliberate and material information misrepresentation* in any form of public communications between the firm and its investors, and between the firm and its regulators.

There are two major types of securities litigation: the SEC's enforcement actions and the private class action litigation. According to Securities Class Action Clearinghouse (SCAC) established by the Stanford Law School, a 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 period of time (the class period). The complaint generally contains allegations that the company and/or certain of its officers and directors violated one or more of the federal or state securities laws. A suit is filed as a class action because the members of the class are so numerous that joinder of all members is impracticable.

2.2 Common Types of Alleged Securities Fraud

Table 1 lists the types of commonly alleged securities fraud in class action lawsuits between 1996 and 2002 and the frequency distribution. The litigation information is retrieved from SCAC. I identify the specific nature of fraud allegations based on information extracted from the case complaints and/or press releases. In each year there was a small number of cases that did not provide enough information for us to determine the nature of the allegations. Therefore, the information provided in this section is based on the identifiable filings.

1. Financial statement fraud, which refers to the deliberate and material misstatement of financial statements issued by publicly traded companies to mislead the financial statements users (Rezaee [2002]).
2. Misrepresentation or concealment of material facts (excluding misreporting in the financial statements). Material facts are the ones that, if made available, would cause the information receivers to change their judgment or decision. This category of securities fraud includes a public firm issuing false information and/or omit important information in security registration statements/prospectus (section 11, 12(a) of the Securities Act of 1933), in proxy

statements (section 14 of the Exchange Act of 1934) and other important public documents, as well as false and misleading oral communications at press releases and conference calls. Many allegations in this category also frequently involves affirmative fraud, i.e., the release of false forward-looking statements to the investing public. An example of affirmative fraud is that a public firm issue glowing but misleading projections about the firm's future business prospects and competitive position.

3. Illegal insider trading. According to the SEC's definition, 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, non-public information about the security. Insider trading violations may also include "tipping" such information, securities trading by the person "tipped", and securities trading by those who misappropriate such information. "Insiders" generally include officers, directors, and individuals who hold more than 10 percent of the company's stock (regardless of whether they work for the company).
4. Investment bank fraud. This category of fraud refers to the unfair dealings in investment banking activities. Most commonly alleged investment bank frauds include unfair IPO allocations and misleading analyst reports.
5. Breach of fiduciary duty. This category generally involves violations of section 14 of the Exchange Act. Section 14 prohibits any information misrepresentation in the proxy statements, particularly information related to tender offers, management buyouts, and other merger/acquisition activities. Most of the cases in this category alleged that the management or controlling shareholders expropriated minority shareholders in merger/acquisition activities, and misled minority shareholders to tender or exchange their shares at unfairly low prices.
6. Stock price manipulation, which refers to deliberate buying or selling of a security, or deliberate intervention of other people's buying or selling of a security, in order to control the price of the security.

Table 2.1: **Commonly Alleged Securities Fraud**

This table presents the types of commonly alleged securities fraud in 1268 private securities class action lawsuits between 1996 and 2002. Pure investment bank fraud cases (i.e., cases that allege unfair IPO allocations by securities underwriters and untrue securities analyst reports) are excluded. “Other information misrepresentation/omission” means material non-accounting related information misreporting or omission.

Nature of Fraud	# of Filings	% of Total
Number of observations	1268	
Accounting irregularity	596	47.08
Other information misrepresentation/omission	486	38.33
Illegal insider trading	337	26.58
Breach of fiduciary duty	49	3.90
Stock price manipulation	9	0.71

Chapter 3

Related Literature

This thesis is related to several strands of research: (1) the accounting literature on earnings management and financial disclosure; (2) the literature on agency theory; and (3) recent research on corporate fraud.

The economics of corporate misreporting is examined in the accounting disclosure literature. Dye (1988) analyzes two conditions under which earnings management may exist in equilibrium. First, the cost-minimizing contract that induces preferred action from the manager may not prevent earnings management, which leads to the internal demand for earnings management. Second, incumbent shareholders may attempt to alter the perceptions of prospective investors through managed earnings, which creates the external demand for earnings management.

In line with Dye's notion of internal demand for earnings management, Lacker and Weinberg (1989) show that the optimal risk sharing contract may not prevent the agent from falsifying the outcome. Goldman and Slezak (2003) show that the optimal equity compensation contract that induces the desired managerial effort may not prevent (and may even encourage) the agent from misreporting.

Several other papers together with my paper are consistent with Dye's notion of external demand for earnings management. Stein (1989) argues that capital market pressure can induce the management to inflate current profitability at the expense of forgoing future cash flows. Bebhuk and Bar-Gill (2002) present a model in which firms' needs for external financing and insiders' benefit from informed trading can motivate management to misreport corporate performance. Jensen (2004) argues that corporate fraud can result from a dramatic form of capital market pressure. When the market substantially overvalues a firm's equity, the firm may feel forced to defraud investors in order to defend such overvaluation, and this can lead to serious value destructions in the firm. I show that overvaluation can result from the firm's endogenous choice, and an important

source of value destruction is the fraud-induced investment distortions.

There has been a large body of empirical research on earnings management. Earnings management does not necessarily imply the existence of securities fraud. Earnings management reflects discretionary managerial judgment (or managerial flexibility) in corporate financial reporting.¹ However, both securities fraud and earnings management involve some information misrepresentation. A number of studies have examined different incentives for earnings management, including capital market needs, contracts written on accounting numbers and government regulations (see Healy and Wahlen (1999) for a review of empirical work on earnings management). The literature provides evidence that managers have incentives to manipulate earnings in an attempt to influence short-term stock price performance before major external financing activities or externally-financed investment (see, e.g., Teoh, Welch and Wong (1998a,b) on public equity offers; Erickson and Wang (1998) on stock-financed acquisitions). Efendi, Srivastava and Swanson (2004) find that the likelihood of an earnings restatement is significantly higher for firms that make one or more sizable acquisitions. Several studies have examined the relation between the structure of managerial compensation contracts and the likelihood of earnings management, and find that the pay-performance sensitivity induced by stock options seems to increase earnings management (see, e.g., Gao and Shrieves (2003)).

Research directly on corporate fraud has been sparse, but has started to attract academic interest after the explosion of corporate scandals and the recent legislation movement. Most of the recent studies focus on the effects of insider equity incentives on firms' incentives to misreport. Johnson, Ryan, and Tian (2003), Peng and Röell (2004), Burns and Kedia (2004), and Efendi, Srivastava and Swanson (2004) all find that large executive pay-for-performance sensitivity is positively associated with fraudulent reporting. These results seem to support the over-incentivization argument that insider equity incentive is a double-edged sword. It may induce managerial misreporting incentive rather than managerial effort in creating shareholder wealth. Alexander and Cohen (1999), however, documents a negative relation between insider ownership and the likelihood

¹Schipper [1989] defines earnings management as "purposeful intervention in the external reporting process, with the intent of obtaining some private gain to managers or shareholders".

of fraud and provide some support for the classic agency theory.

Several studies have examined the relation between the characteristics of the board and the probability of corporate fraudulent reporting. Beasley (1996) studies a sample of firms subject to SEC's AAERs and finds that board independence (proxied by the percentage of outside directors in the board) is significantly negatively related to the likelihood of financial statement fraud. Klein (2002) finds an inverse relation between board independence and abnormal accruals. Dechow, Sloan and Sweeney (1996) find that firms committing financial statement fraud are likely to have a board dominated by insiders and have a CEO who is also the chairman of the board or the founder of the company. Agrawal and Chadha (2004) examine the incidence of accounting restatements, and find that board independence is irrelevant, but the presence of independent directors with financial or accounting expertise on the audit committee is associated with significantly lower probability of accounting restatements.

The major contributions of my thesis to the literature are threefold. First, my thesis is the first paper that seriously analyzes the role of real investment in the context of corporate fraud. My theory model shows that investment influences both a firm's ex-post probability of fraud detection and its ex-ante propensity to commit fraud. Fraud can induce distorted investment incentives, which is the real economic cost of fraud. Second, I empirically examine the model predictions on the relation between fraud and corporate investment incentives, and find strong support for my theory. For example, I find that risky investment and uncorrelated investment have a strong negative effect on the probability of fraud detection, while straightforward investment and correlated investment do not. This implies that the type of investment matters in determining the firm's detection risk. I also find that acquisition expenditures influence the probability of fraud only if it is (at least partially) financed by stock, indicating that the financing of investment matters. The third contribution of my thesis is methodological. I introduce a new empirical methodology to analyze fraud. The existing literature has ignored the fact that we only observe detected fraud. That is, the outcome we observe depends on the outcome of two latent processes: fraud commitment and fraud detection. If we ignore this structure, we could draw incorrect inferences, because the same

variable can have opposing effects on the two latent processes and thus get masked in its overall effect on the outcome we observe. This study utilizes statistical methods to disentangling fraud commitment and fraud detection. This allows me to control for the unobservability of undetected frauds. More important, this allows me to examine the economics of each component as well as their interactions. My thesis provides new insights about corporate fraud incentives that cannot be obtained using the models in the existing literature.

Chapter 4

A Model of Securities Fraud

This chapter develops an economic framework of securities fraud. I analyze the interaction between the firm's financial disclosure and its real investment decision. I also characterize the firm's equilibrium disclosure strategy, probability of committing fraud and the magnitude of fraud. The chapter is structured as follows. Section 4.1 introduces the model framework and assumptions. Section 4.2 characterizes the firm's cost-benefit tradeoff of committing fraud. Section 4.3 examines the firm's investment incentives in the presence of fraud. Section 4.4 derives the firm's equilibrium disclosure strategy. Section 4.5 discusses model implications and possible extensions.

4.1 Model Framework

4.1.1 The Firm

Consider a typical public firm whose market value consists of both its assets in place and growth opportunities. The asset value is normally distributed, $\tilde{A} \sim N(\bar{A}, \sigma_A^2)$.¹ The growth opportunity takes the form of a possible new investment project in the future whose value is also normally distributed, $\tilde{G} \sim N(\bar{G}, \sigma_G^2)$. The market knows the distributions of \tilde{A} and \tilde{G} , but does not observe the realizations of each component. The market value of the firm is the expected discounted value of future cash flows. For simplicity, I assume that investors are risk neutral, and the discount rate is zero. Therefore, the firm value is simply $E(V) = \bar{A} + \bar{G}$.

The firm is operated by a manager who owns a fraction $0 < \alpha < 1$ of the firm. I assume that the manager holds restricted stock and thus is not allowed to trade any of his own equity shares. This simplifying assumption allows abstraction from the incentive and signalling effects of insider trading, and it also implies that the manager maximizes the wealth of long-term shareholders.²

¹I can always choose reasonable values for \tilde{A} and σ_A such that negative asset values have almost zero probabilities.

²I assume that there is no opportunity for perquisite consumption. This type of agency problem is not the focus

The accounting and auditing literature has provided evidence that both capital market activities (see the citations in the introduction) and profits from informed trading (e.g., Summers and Sweeney (1998)) can motivate fraudulent reporting. According to my study of private securities class action litigation against US public companies between 1996 and 2002, about 68% of the securities lawsuits involved misreporting surrounding major capital market activities (external financing or externally-financed investment), and about 29% of the cases involved allegations of illegal insider trading and insider personal gains. This paper focuses on fraud and firm investment, and thus analyzes the former scenario. The model shows that even when the manager's interest is perfectly aligned with that of existing shareholders, fraud can still exist in equilibrium. Adding managerial agency problem could, of course, further exacerbate the manager's fraud incentives.

4.1.2 Time Line and Assumptions

There are four periods in this model, $t = 0, 1, 2, 3$. The sequence of events is described below (also see Figure 1 at the end of the chapter for an outline).

Time 0: Institutional Arrangements At time 0, the institutional arrangement of the firm is established. The strength of the firm's internal corporate governance is indicated by $p \in [0, 1]$. Higher p represents better governance and also higher likelihood of internal detection of fraud.³

Time 1: Disclosure of Earnings At time 1, the manager privately observes the realization of the intermediate earnings generated by the firm's assets.⁴ The earnings realization is drawn from the following process.

$$\tilde{e} = q\tilde{A} + \tilde{u}. \quad (4.1)$$

q indicates the average productivity of the firm's assets in place, of which the market is aware. \tilde{u} is a white noise term, $\tilde{u} \sim N(0, \sigma_u^2)$. Equation (4.1) shows that the realized intermediate earnings (e) contain useful information about the value of the firm's assets. Let the signal-to-noise ratio be

of this paper.

³Section 4.5 will discuss the possibility of endogenizing this parameter.

⁴The intermediate information does not have to be earnings. It can be any valuable piece of accounting information, or even more general information about the firm's overall financial condition, operational condition, or business prospects.

$\delta \equiv \frac{q\sigma_A^2}{q^2\sigma_A^2 + \sigma_u^2}$. Then the expected value of the assets conditional on the earnings realization e is $E(\tilde{A}|e) = \bar{A} + \delta(e - \bar{e})$.

After observing the intermediate earnings, the manager makes a disclosure decision,

$$y(e) = e + \eta. \quad (4.2)$$

η represents the amount of distortion in the reported earnings. $\eta = 0$ means that the manager chooses to truthfully reveal the earnings realization. $\eta > 0$ implies that the manager inflates earnings. η is assumed to be nonnegative. That is, this paper focuses on *overreporting* of earnings. It is possible that managers may intentionally understate earnings (e.g., the case of Freddie Mac). Empirical studies on earnings management as well as SEC accounting and auditing enforcement actions, however, indicate that accounting overstatement is much more frequently observed than understatement (see, e.g., Feroz, Park, and Pastena (1991); Rezaee (2002)), and thus it is a more interesting subject for research.

Once the earnings disclosure is made, the market prices the firm's equity based on the *reported* earnings $y(e)$, but the market does not have to take the earnings announcement at face value. Investors are generally aware of the possibility of misreporting. The market's prior belief about the firm's likelihood of misreporting is $\pi_0 \in [0, 1]$, and the expected amount of misreporting is $\bar{\eta}$. Then the time 1 market value of the firm's assets is $V_1 = E_{\pi_0}[\tilde{A}|y(e)]$, where the expectation incorporates the market's prior belief about fraud.

Time 2: Investment Decision In this period, a new investment opportunity arrives with probability λ , requires an initial outlay of $\$I$, and will generate a gross return \tilde{R} , $\tilde{R} \sim N(\bar{R}, \sigma_R^2)$. For simplicity, I set $\bar{R} = 1$, which allows me to parameterize the profitability of the new investment in a straightforward way. Once the new investment opportunity arrives, the manager observes the gross return as r , the realization of \tilde{R} . The market does not observe this but knows the return distribution (i.e., the mean and variance of \tilde{R}).

The manager makes an investment decision: whether to take the new project or not. If he decides to take it, the firm needs to raise $\$I$ as the initial capital. I assume that new equity shares are issued. I will discuss the robustness of the model results with respect to this assumption in

section 4.2.2.

Time 3: Liquidation At time 3, the firm has a liquidating cash flow \tilde{V} . If the firm invests at time 2,

$$\tilde{V} = \tilde{A} + I\tilde{R} = \frac{1}{q}\tilde{e} + I\tilde{R} - \frac{1}{q}\tilde{u}. \quad (4.3)$$

If the firm does not invest,

$$\tilde{V} = \tilde{A} = \frac{1}{q}\tilde{e} - \frac{1}{q}\tilde{u}. \quad (4.4)$$

The market is able to observe this final cash flow and can use this information to update its belief about the probability of fraud at time 1. How the market interprets a particular final cash flow realization depends on the market's expectation about \tilde{V} . The following table lists four distributions of \tilde{V} : the perceived distribution (conditional on $y(e)$), the true distribution (conditional on e), the distribution given that the firm invests (I), and the one given not (N).

	Investment (I)	No Investment (N)
True	$E(\tilde{V} I, e) = E(\tilde{A} + I\tilde{R} I, e)$ $Var(\tilde{V} I, e) = Var(\tilde{V} I)$	$E(\tilde{V} N, e) = E(\tilde{A} e)$ $Var(\tilde{V} N, e) = Var(\tilde{V} N)$
Perceived	$E(\tilde{V} I, y) = E(\tilde{A} + I\tilde{R} I, y)$ $Var(\tilde{V} I, y) = Var(\tilde{V} I)$	$E(\tilde{V} N, y) = E(\tilde{A} y)$ $Var(\tilde{V} N, y) = Var(\tilde{V} N)$

$Var(\tilde{V}|I) = \sigma_e^2/q^2 + (I\sigma_R)^2 + 2\rho I\sigma_R\sigma_e/q + \sigma_u^2/q^2$, where ρ is the correlation between \tilde{e} and \tilde{R} . $Var(\tilde{V}|N) = \sigma_e^2/q^2 + \sigma_u^2/q^2$. We can see that misreporting only distorts the expected value of the firm's final cash flow, not the variance of it.

4.2 Cost and Benefit of Fraud

This section characterizes the cost-benefit tradeoff of committing fraud. The litigation cost of fraud is derived in section 4.2.1. The benefit from fraud and the manager's optimization problem are presented in section 4.2.2.

4.2.1 Litigation Cost of Fraud

At time 3, after the realization of the final cash flow, the market may unearth the manager's misreporting at time 1 with some probability. If fraud is detected, the firm will be subject to a fraud penalty. The expected litigation cost, which is the product of the detection likelihood and the penalty after detection, is the cost of committing fraud.

Probability of Fraud Detection

This model considers two fraud detection mechanisms: detection through cash flow and detection through internal corporate governance.⁵ At time 3, after observing the firm's final cash flow, the uninformed outsiders rationally choose an investigation strategy that maximizes their payoff from litigation.⁶ More specifically, the market chooses a threshold \underline{v} such that it will investigate the manager's time 1 disclosure whenever the final cash flow realization V falls below this threshold. I assume that any misreporting, if it exists, will be discovered upon investigation (i.e., the conditional probability of fraud detection upon investigation is 1). Thus, I will use the probability of fraud investigation and the probability of fraud detection interchangeably. I call the region $\{V : V \leq \underline{v}\}$ the *cash flow detection region*. If this region is not reached (i.e., $V > \underline{v}$), no external investigation will be triggered, but detection of fraud is still possible. In this situation, the probability of fraud detection solely depends on the firm's quality of corporate governance (p). That is, p indicates the likelihood of an internal investigation of fraud when the cash flow realization does not automatically reveal fraud. In sum, the likelihood of detection conditional on $V \leq \underline{v}$ is 1, and the likelihood conditional on $V > \underline{v}$ is p . Then the effective probability of fraud detection is

$$P = Prob.(V > \underline{v}) \times p + Prob.(V \leq \underline{v}) \times 1. \quad (4.5)$$

Probability of Cash Flow Detection At time 3, if the market investigates the firm, the

⁵Of course, there are other detection forces, such as regulators (SEC) and independent auditors. This paper focuses on the role of capital markets and internal corporate governance in discovering fraud.

⁶Here the outsiders can be the firm's outside (and uninformed) investors or the regulators such as the SEC. Therefore, the role of outsiders represents general capital market monitoring.

expected payoff from the effort is $fE(\eta|V) - C$, where $C > 0$ is the investigation cost. Therefore, the market will examine the firm's disclosure practice if and only if $fE(\eta|V) - C \geq 0$, or

$$E(\eta|V) = y - E(e|V) \geq \frac{C}{f}. \quad (4.6)$$

Define $\delta_V = \frac{\text{cov}(e,V)}{\text{Var}(V)}$. Then under the perceived cash flow distribution (the one based on $y(e)$), we have

$$E(e|V) = \bar{e} + \delta_V[V - E(V|y)]. \quad (4.7)$$

When we substitute this expression into equation (4.6), we can see that an external investigation will be triggered if and only if

$$V \leq \underline{v} = E(V|y) - \frac{\bar{e} + C/f - y}{\delta_V}. \quad (4.8)$$

This condition implies that when the final cash flow realization is sufficiently below the market expectation, outside investors will rationally think they have been misled and will start an investigation. Define

$$v_c = \frac{\underline{v} - E(V|y)}{\sqrt{\text{Var}(V)}},$$

and let Φ denote the standard normal cumulative distribution function. Then the firm's probability of facing an outside investigation under the perceived distribution is⁷

$$\text{Prob.}[V \leq \underline{v}|y] = \Phi(v_c). \quad (4.9)$$

Yet, the firm's *true* probability of having an external investigation is not simply $\Phi(v_c)$. Let $\nu = \frac{1}{\sqrt{\text{Var}(V)}}$ be the precision of the firm's final cash flow. Then, under the true cash flow distribution (the one based on e), we have

$$\text{Prob.}[V \leq \underline{v}|e] = \Phi(v_c + K), \quad (4.10)$$

where $K = [E(V|y) - E(V|e)]\nu$. We can see that when K is positive, the firm's actual probability of cash flow detection is strictly greater than $\Phi(v_c)$. In other words, the more the manager can

⁷Since $\Phi(v_c)$ is not necessarily zero, even an honest firm may face an outside investigation. However, if the firm has not misreported, the investigation will not lead to discovery of fraud. Thus the honest firm will not be punished even if it may face an outside investigation.

raise the market's expectation about V by false disclosure ($E(V|y) > E(V|e)$), the more likely is an outside investigation of fraud (see Figure 2 at the end of the chapter for an illustration). This implies that the benefit and cost of fraud are endogenously related to each other, and there exists an optimal size of fraud.

In sum, the essential point underlying the cash flow detection mechanism is that the final cash flow realization V is a function of the true earnings realization e , not the reported earnings $y(e)$ (see equations (4.3) and (4.4)). Therefore, investors can update their belief about the probability of misreporting after observing V , whose realization the fraudulent manager cannot fully control. This implies that fraud can be partially self-revealing, which is supported by securities litigation in the United States. Table 2 at the end of the paper lists the corporate events or entities that precipitated the federal private securities class action lawsuits filed in 1996 and 1997 in the United States. Among the 187 lawsuits, at least 132 cases (or 70.6% of the total) were filed after some unexpectedly disappointing earnings realizations.

Expected Probability of Fraud Detection At time 1, when the manager makes the disclosure decision $y(e)$, what matters is his expected fraud detection likelihood P . Essentially, P tells the manager how risky it is to commit fraud.

Let Φ_I (Φ_N) be the probability of cash flow detection if the firm invests (does not invest).

$$\Phi_I = \Phi(v_{c,I} + K_I), \quad (4.11)$$

$$\Phi_N = \Phi(v_{c,N} + K_N), \quad (4.12)$$

$$v_{c,I} = -\frac{\bar{e} + C/f - y}{\delta_{V,I}} \nu_I, \quad (4.13)$$

$$v_{c,N} = -\frac{\bar{e} + C/f - y}{\delta_{V,N}} \nu_N, \quad (4.14)$$

$$K_I = [E(V|y) - E(V|e)] \nu_I, \quad (4.15)$$

$$K_N = [E(V|y) - E(V|e)] \nu_N, \quad (4.16)$$

where $\nu_I = \frac{1}{\sqrt{\text{Var}(V|I)}}$ and $\nu_N = \frac{1}{\sqrt{\text{Var}(V|N)}}$. Now let P_I (P_N) denote the effective probability of fraud detection, given that the firm invests (does not invest) at time 2. Then according to equation

(4.5). We have

$$P_I = (1 - \Phi_I)p + \Phi_I, \quad (4.17)$$

$$P_N = (1 - \Phi_N)p + \Phi_N. \quad (4.18)$$

These two equations imply that the probability of fraud detection within the firm depends on firm-specific attributes, such as the quality of corporate governance and the nature of cash flows. More important, Φ_I and Φ_N depend on the manager's disclosure strategy ($y(e)$) and the market's response ($E[V|y(e)]$). This implies that the likelihood of detection and thus the litigation cost are endogenous to the manager's decision making.

At time 1, the manager's expected probability of fraud detection (P) is simply a weighted average of P_I and P_N . Let x be the probability that the firm will undertake a newly arrived investment project (x will be endogenously determined in section 4.3). Then λx is the probability that the firm will exercise a growth option at time 2. Then we have

$$P = \lambda x P_I + (1 - \lambda x) P_N. \quad (4.19)$$

Fraud Penalty

Once fraud is discovered, the firm is subject to a legal fine of $f\eta$. That is, the fraud penalty is assumed to be proportional to the amount of distortion in the earnings announcement. The fine is paid out of the company's final cash flow V . Monetary settlement is a prevailing means of fraud punishment. Of course, there are other negative consequences of fraud such as the negative price response to securities litigation (Griffin, Grundfest and Perino (2003)), loss of the firm's reputation, persistent increase in the cost of capital (Dechow, Sloan, and Sweeney (1996)), and long-run poor firm performance (Baucus and Baucus (1997)). I incorporate all the explicit and implicit fraud consequences in the marginal fraud penalty parameter f and measure them in terms of money.

In order to understand the nature of securities fraud and the role of securities litigation (or fraud detection), it is important to know who bears the litigation cost of fraud (i.e., who pays the fine and who receives the compensation). Let us consider a typical private securities class action

litigation. The plaintiff (or class members) is a group of the firm's outside security holders (e.g., equity holders, debt holders) who purchase the firm's public securities during some specific time period (class period). Once the lawsuit is settled, the defendant firm (or its existing shareholders) pays the settlement to the plaintiff investors. In this model, the class period would start at time 1 if the manager makes false disclosure and end at time 3 if the fraud is uncovered. The class members would be the new (and uninformed) shareholders who finance the firm's new project at time 2.

4.2.2 Fraud Incentives

If a new investment opportunity arrives at time 2 and the firm takes it, the market value of the firm based on its earnings disclosure and investment decision is $E(V|I, y)$, while the true value of the firm is $E(V|I, e)$. The difference between $E(V|I, y)$ and $E(V|I, e)$ results from the misreporting of earnings at time 1.

In order to undertake the new investment, the firm needs to raise $\$I$ by issuing a fraction

$$\beta(y) = \frac{I}{E(V|I, y)}$$

of new equity. β is the percentage ownership of the new shareholders. The expected value to existing shareholders at time 3 is thus $(1 - \beta)E(V|I, e)$. The value of β indicates the cost of external financing. A high β means that the incumbent shareholders need to sacrifice a large fraction of the final cash flows in order to raise $\$I$, or a high cost of external capital. We can see that β is a function of the reported earnings $y(e)$. If $E(V|I, y)$ increases in $y(e)$, then β decreases in $y(e)$. This implies that a potential benefit of committing fraud is that financial misreporting may create (or sustain) short-term market overvaluation of the firm's equity and thus reduce the firm's cost of external financing.⁸ Of course, there may exist other motives for fraud, such as incentive

⁸I assume that the firm has to finance the new project by raising new equity. Since the benefit of fraud derives from the effect of financial misreporting on the short-term market valuation of the firm's outside security, the insight of the model will not change if the firm can use debt financing. In the debt context, there is still an external financing cost, which is the interest rate the firm pays.

compensation and insider trading profit. This paper, however, focuses on firms' financing and investment incentives in the presence of fraud.

Misreporting also comes with a cost: the expected litigation liability. Both the fraud penalty and the probability of detection are functions of $\eta = y(e) - e$. The cost-benefit tradeoff leads to the following maximization problem for the manager at time 1.

$$\max_{\eta \geq 0} \Pi = \lambda x [1 - \beta(y)] E(V|I, e) + (1 - \lambda x) E(V|N, e) - P(\eta) f \eta, \quad (4.20)$$

where $P(\eta) = \lambda x P_I + (1 - \lambda x) P_N$. The expected value to long-term shareholders is their expected final cash flow net of the litigation cost. The solution to this problem, η^* , is the optimal amount of misreporting.

4.3 Securities Fraud and Investment Incentives

In order to solve the manager's optimization problem in equation (4.20), I need to derive the manager's investment incentive x in the presence of fraud. Recall that x is the probability that the manager will undertake a newly arrived investment project at time 2. Section 4.3.1 derives the firm's investment incentive at time 2, given its disclosure strategy at time 1. Section 4.3.2 presents a numerical illustration.

4.3.1 Investment Distortions

Suppose that a new investment opportunity does arrive at time 2. The manager privately observes the gross return to the new project as r . If the firm issues new equity and invests, the market value of the firm's equity will be

$$E(V|I, y) = E(\tilde{A}|I, y) + IE(\tilde{R}|I). \quad (4.21)$$

The true value of the firm is, however, $E(\tilde{A}|e) + Ir$. In order to invest, the firm needs to issue a fraction $\beta = I/E(V|I, y)$ of new equity. The firm also faces the potential litigation liability $P_I f \eta$, if $\eta \neq 0$. Then the expected final payoff to the existing shareholders is $(1 - \beta)[E(\tilde{A}|e) + Ir] - P_I f \eta$ if the firm invests, or $E(\tilde{A}|e) - P_N f \eta$ if the firm does not issue and invest. Therefore, for the firm

to issue and invest, we need

$$(1 - \beta)[E(\tilde{A}|e) + Ir] - P_I f \eta > E(\tilde{A}|e) - P_N f \eta. \quad (4.22)$$

A cutoff investment profitability r_c can be derived such that the above condition is satisfied when $r > r_c$. In other words, the firm will invest if and only if the return to the new investment exceeds some threshold level r_c . $r_c = 1$ means that the firm will strictly follow the positive NPV rule when making new investment. $r_c > 1$ implies that the firm tends to underinvest in the sense that it will pass up some positive NPV projects. $r_c < 1$ implies that the firm tends to overinvest in the sense that it will undertake some negative NPV projects. Therefore, the manager's investment incentive is reflected in his choice of the cutoff profitability to new investments. The model results about the manager's investment decision are presented in the following propositions. Detailed proofs are provided in the appendix.

Proposition 1 *Financial misreporting can affect the firm's investment incentives. Specifically, the firm's cutoff profitability to new investments (r_c^*) depends on its magnitude of fraud (η). $r_c^*(\eta)$ is the solution to the following equation.*

$$r_c = \frac{E(\tilde{A}|e)}{E(\tilde{A}|I, y) + I\sigma_R m(z_c)} - \frac{(P_N - P_I)f\eta}{(1 - \beta)I}, \quad (4.23)$$

where

$$z_c = (r_c - \bar{R})/\sigma_R,$$

and

$$m(z_c) = \phi(z_c)/[1 - \Phi(z_c)].$$

Given the manager's misreporting strategy η at time 1, the probability that the firm will undertake a newly arrived investment opportunity at time 2 is

$$x = Prob.[r > r_c^*(\eta)] = 1 - \Phi[z_c^*(\eta)]. \quad (4.24)$$

The lower the cutoff investment profitability, the more likely is the firm to exercise its growth option at time 2.

Proposition 2 *Making a new investment can decrease the firm's probability of being investigated at time 3 if the firm can boost its market value by overstating its earnings, and either the correlation between the cash flow from the new investment and that from the existing assets is in a neighborhood around zero or the cash flow from the new investment is volatile enough and the correlation is in some certain range. Specifically, $P_I < P_N$ if $E[V|y(e)] > E[V|e]$ when $\eta > 0$ and one of the following conditions is satisfied:*

(1) $\rho \in [-\epsilon, \epsilon]$, where ϵ is an arbitrary small positive number;

(2) $\max(-1, -\frac{\sigma_e}{qI\sigma_R}) < \rho < \bar{\rho} \leq 1$, and $I\sigma_R > \overline{I\sigma_R}$.

Proposition 3 *If the firm can boost its market value by overstating its earnings, then the firm has an incentive to overinvest. That is, if $E[V|y(e)] > E[V|e]$ when $\eta > 0$, then $r_c^* < 1$. The larger the magnitude of fraud, the lower is the fraudulent firm's threshold return to new investments,*

$$\frac{\partial r_c^*}{\partial \eta} < 0. \quad (4.25)$$

The essential message in these propositions is that financial misreporting can influence the firm's investment incentives in two ways. First, misreporting can influence the short-term firm value and thus the firm's short-term external financing cost. This effect is reflected in the first term on the right-hand side of equation (4.23). If a low-earnings firm overstates its earnings ($y(e) > e$) to pool with a high-earnings firm, and if the market cannot fully see through this, then we have $E(\tilde{A}|y) > E(\tilde{A}|e)$ for the low-earnings and dishonest firm. This implies that the market on average will overvalue the equity of the fraudulent firm. This overvaluation lowers the firm's external financing cost and thus gives the firm a larger incentive to raise money and invest, resulting in overinvestment. The high-earnings firm, however, will suffer from some market undervaluation due to the cross-subsidization between the good firm and the fraudulent firm. The good firm cannot finance the new investment on reasonable terms and therefore has less incentive to issue and invest. This is consistent with the underinvestment argument in Myers and Majluf (1984). In sum, the fraud-induced market mispricing implies that a fraudulent firm tends to overinvest, and a good and honest firm tends to underinvest.

Second, financial misreporting can also affect the firm's investment decision through the influence of investment on the firm's litigation risk. The second term on the right-hand side of equation (4.23) represents the change in the expected litigation cost per investment dollar if the firm invests rather than not. If this change is negative, then the reduction in litigation risk will push the fraudulent firm's profitability threshold r_c^* further down below 1. This means that the potential negative effect of making a new investment on the firm's litigation risk will exacerbate the investment distortion. Given any $\eta > 0$, Proposition 2 states that $P_I < P_N$ if the investment is uncorrelated with the firm's existing assets or if the investment is risky enough. The basic intuition is as follows. The market observes the combined cash flow from the firm's assets in place and from the new investment, and draw inference about the magnitude of misreporting on the asset value based on the total cash flow. On one hand, given the level of cash flow volatility of the new investment, the inference problem will be most difficult for the market when the cash flow correlation between the new investment and the existing assets is low around zero. On the other hand, given the level of correlation, high cash flow volatility from the new investment will decrease the valuation precision of the firm's total cash flow and make it harder for the outsiders to see through fraud. Therefore, the incentive to disguise fraud will induce the fraudulent manager to overinvest in risky (high cash flow volatility) and uncorrelated projects. In the following analysis, I will focus on the case in which $P_I < P_N$.

In sum, the key insight in Propositions 1 to 3 is that securities fraud can lead to real value losses. The distorted investment incentive can arise both from the fraud-induced market misvaluation of the firm's assets ($E[A|y(e)] \neq E[A|e]$) and from the effect of investment on the firm's litigation risk ($P_I \neq P_N$). Securities fraud can lead to underinvestment by good and honest firms and overinvestment by fraudulent firms.

4.3.2 A Numerical Illustration

This section presents a numerical example to illustrate the relationship between fraud and the firm's investment incentives. Two levels of earnings realization are considered: e_L and e_H ,

$e_L < e_H$. Based on the firm's true earnings realization (e) and its reported earnings (y), I label the firm as one of the following three types.

LH firm: low earnings ($e = e_L$) are honestly revealed ($y = e_L$);

HH firm: high earnings ($e = e_H$) are honestly revealed ($y = e_H$);

LD firm: low earnings ($e = e_L$) are reported as high earnings ($y = e_H$).

Table 3 presents each type of firm's cutoff return to new investments r_c^* and probability of making a new investment x (in parentheses). The numerical example reveals the following patterns with respect to the firm's investment incentives in the presence of securities fraud.

- (1) The HH firm tends to underinvest ($r_c^* > 1$), and the LD firm tends to overinvest ($r_c^* < 1$).

Put differently, the LD firm is more likely to exercise its growth option than the HH firm and the LH firm. These distortions emerge in all three panels.

- (2) Holding other parameters constant, an increase in the magnitude of misreporting (η) worsens both the underinvestment problem of the HH firm and the overinvestment problem of the LD firm (as shown in panel A). This clearly demonstrates the investment distortion spillover between fraudulent and honest firms.

- (3) Holding other parameters constant, an increase in the volatility of the investment return ($I\sigma_R$) helps to mitigate the underinvestment problem of the HH firm but exacerbates the overinvestment problem of the LD firm (as shown in panel B). This is because higher investment volatility is associated with higher value of the firm's growth option, which to some extent lessens the market undervaluation of the HH firm but worsens the overvaluation of the LD firm.⁹ Furthermore, according to Proposition 2, large $I\sigma_R$ also strengthens the negative effect of investment on the firm's litigation risk, which motivates the fraudulent firm to overinvest.

- (4) Holding other parameters constant, larger asset volatility (σ_A) exacerbates both the underinvestment problem of the HH firm and the overinvestment problem of the LD firm (as shown

⁹The market's expected NPV of the new project is $I[E(\tilde{R}|I) - 1] = I\sigma_R m(z_c)$. Since $m(z_c) > 0$, a large $I\sigma_R$ scales up the market value of the new project.

in panel C). The intuition is that high volatility of the asset value implies less valuation precision of the firm's cash flows, which can not only worsen the misvaluation of the firm's assets in place but also decrease the litigation risk of the fraudulent firm.

- (5) Even the LH firm tends to overinvest slightly, but this distortion has nothing to do with securities fraud. It arises solely from the effect of asymmetric information about the investment return, as shown in Myers and Majluf (1984).¹⁰ What is important is the difference between the r_c^* of the LH firm and of the LD firm, because this difference measures the effect of misreporting on the investment incentive of a low-earnings firm.

In sum, the numerical illustrations demonstrate that financial misreporting can distort investment decisions in both fraudulent and honest firms. The degree of distortion depends on the magnitude of fraud as well as the characteristics of the firm's assets and growth options.

4.4 Disclosure Strategy

Section 4.3 shows that the manager's investment incentive (r_c^* or x) can be influenced by financial misreporting (η). Now I move back to time 1 and examine the manager's disclosure strategy $y(e)$, taking into consideration her investment incentives at time 2.

At time 1, the manager privately observes the earnings (e) generated from the firm's assets and makes an earnings announcement $y(e) = e + \eta(e)$. That is, given any earnings realization e , the manager optimally chooses the amount of misstatement η such that the expected value to long-term shareholders at time 3 is maximized. The manager's objective function is specified in equation (4.20) in section 4.2.2. Now I substitute equation (4.24) into (4.20) and rewrite the manager's maximization problem as follows.

$$\max_{\eta \geq 0} \Pi = \lambda[1 - \Phi(z_c^*)][1 - \beta(y)]E(V|I, e) + \{1 - \lambda[1 - \Phi(z_c^*)]\}E(V|N, e) - P(\eta)f\eta, \quad (4.26)$$

¹⁰For the LH firm, $r_c^* = 1$ if and only if $E(\tilde{R}|I) = 1$, that is, the market believes new investments are on average zero NPV projects. If the market has bullish expectations and believes new projects on average have strictly positive NPV ($E(\tilde{R}|I) > 1$), then the LH firm will have an incentive to overinvest.

where $z_c^* \equiv [r_c^*(\eta) - \bar{R}]/\sigma_R$. In sum, misreporting affects the manager's objective function in three ways. First, it can directly affect the short-term market valuation of the firm $V_2(I, y)$ and thus its external financing cost $\beta(y)$. Second, it can indirectly influence the long-term performance of the firm V through the endogenous investment decision $r_c^*(\eta)$. Third, misreporting brings a potential litigation liability $P(\eta)f\eta$. The optimal strategy balances the benefit of misreporting and the cost of it.

Section 4.4.1 describes a perfect Bayesian equilibrium disclosure strategy $y^*(e) = e + \eta^*(e)$. Section 5.3.2 analyzes some important properties of the firm's fraud propensity and the fraud magnitude.

4.4.1 Equilibrium Misreporting

I adopt the perfect Bayesian equilibrium concept to study the manager's equilibrium misreporting strategy. A perfect Bayesian equilibrium has two requirements. First, the market forms expectations on the firm value $[E(V|y)]$ using Bayes's rule whenever possible. Second, given the market's beliefs, the manager's disclosure strategy $y(e)$ maximizes her objective function in (4.27).

Proposition 4 *An equilibrium disclosure strategy involves partitioning the earnings space into fraud region(s) and nonfraud region(s). Specifically, there are three cutoff earnings realizations $-\infty < e_l < e_c < e_h < +\infty$, and the manager's earnings disclosure strategy is as follows.*

$$y^*(e) = e, \text{ if } e \geq e_c,$$

$$y^*(e) = e + \eta_1^*(e) > e_c, \text{ if } e_l \leq e < e_c,$$

$$y^*(e) = e, \text{ if } e < e_l.$$

Let e' denote the earnings value the market infers from $y(e)$. Then the market value of the firm's assets in place after the earnings announcement is

$$V_1(y) = E(\tilde{A}|e', e' = y), \text{ if } y > e_h,$$

$$V_1(y) = (1 - \pi_1)E(\tilde{A}|e', e' = y) + \pi_1 E[\tilde{A}|e', e' = y_1^{-1}(e)], \text{ if } e_c \leq y \leq e_h,$$

$$V_1(y) = E[\tilde{A}|e', e' = y_2^{-1}(e)], \text{ if } e_l \leq y < e_c,$$

$$V_1(y) = E(\tilde{A}|e', e' = y), \text{ if } y < e_l,$$

where $\pi_1 \equiv \text{Prob.}(\text{misreporting} | e_c \leq y \leq e_h)$, $y_1^{-1}(e) = y(e) - \bar{\eta}_1(e)$, and $y_2^{-1}(e) = y(e) - \bar{\eta}_2(e)$. $\bar{\eta}_1$ and $\bar{\eta}_2$ are the market's expected amount of misreporting when $e_c \leq y \leq e_h$ and when $e_l \leq y < e_c$, respectively.

Detailed proof of this proposition is provided in the appendix. Here I discuss the implications. Proposition 4 implies that the manager will honestly reveal intermediate earnings when the true earnings realization is very good or desperately bad. The manager has an incentive to overstate earnings when the earnings realization is mediocre or fairly disappointing. The intuition is as follows. When the firm is in good shape ($e > e_c$), the manager does not need to overreport earnings at the cost of incurring future litigation liability. When the firm is in a shaky condition ($e_l \leq e < e_c$) but faces some possible future growth opportunities, the manager will rationally want to take the chance and dress up short-term firm appearance so that the future growth options can be exercised on favorable terms (i.e., a lower external financing cost). When intermediate earnings happen to be stunningly bad ($e < e_l$), however, moderate overreporting of earnings will not change the picture much. In this case, in order to mimic a high-earnings firm, the low-earnings firm has to engage in substantial overstatement of earnings, which implies a large potential litigation cost. When the expected cost of fraud exceeds the benefit, the manager and the shareholders are better off by honestly revealing the earnings.

Proposition 4 shows that outside investors will rationally discount the firm's earnings announcement if $e_l \leq y \leq e_h$. When $e_c \leq y \leq e_h$, the fraudulent firm pools with high-earnings firms. The market value of the firm's assets reflects a weighted average of the two types. When $e_l \leq y < e_c$, the market fully discounts the reported earnings because the firm has an incentive to overreport when its true earnings realization is in this region. Proposition 4 implies, however, that $e_l \leq y < e_c$ will not be observed in equilibrium. So $V_1(y) = E[\tilde{A} | e', e' = y_2^{-1}(e)]$ if $e_l \leq y < e_c$ is an off-equilibrium specification.

4.4.2 Fraud Propensity

Given any cutoff value e_c and e_l , the firm's probability of misreporting is simply

$$Prob.(fraud) = Prob.(e_l \leq e < e_c).$$

The combination of a high e_c and a low e_l implies a high fraud propensity. Different firms can have different cutoff values and thus different likelihoods of misreporting. The fraud region as well as the magnitude of misreporting depend on the structural parameters in the model. The following proposition presents some comparative-static results for η^* and $Prob.(fraud)$ with respect to some important benefit and cost parameters. Proof is provided in the appendix.

Proposition 5 *The firm's fraud propensity and the magnitude of fraud are related to its profitability, growth potential, and quality of corporate governance. Specifically,*

- (1) $\partial\eta_1^*/\partial e < 0$;
- (2) If $P_I < P_N$, then $\partial\eta_1^*/\partial\lambda > 0$, and $\partial Prob.(fraud)/\partial\lambda > 0$;
- (3) $\partial\eta_1^*/\partial p < 0$, $\partial Prob.(fraud)/\partial p < 0$;

The first result states that in the fraud region, the magnitude of misreporting increases as earnings realization decreases. This is because a low-earnings firm has high marginal benefit from misreporting, $\frac{\partial^2\beta}{\partial\eta\partial e} < 0$.

The second result shows that if exercising a growth opportunity can decrease the probability of fraud detection, then both the firm's fraud propensity and the amount of misreporting increase in its growth potential (λ). In this model, growth can affect both the benefit and cost of engaging in fraud. First, for a rapidly growing but cash-poor firm, misreporting business prospects and conditions can create a short-term benefit by enabling the firm to raise external capital on favorable terms to support its growth. Second, growth can decrease the firm's litigation risk, if it can decrease the valuation precision of the firm's cash flows, $\frac{\partial P}{\partial\lambda} = -x(P_N - P_I) < 0$.

The last result relates the firm's fraud propensity to the quality of corporate governance. Good corporate governance implies more effective monitoring of management and thus a better

chance that any fraudulent activities within the firm will be discovered, $\frac{\partial P}{\partial p} > 0$.¹¹

4.5 Model Implications and Discussion

The cost-benefit analysis of securities fraud provides testable implications for (1) the relation between fraud and investment incentives and (2) the economic determinants of the cross-sectional differences in firms' fraud propensities.

Fraud and Inefficient Investment This theory predicts that fraudulent firms tend to overinvest. Yet, the investment can be inefficient and can lead to serious value destructions. The telecommunications industry is a good illustration. Sidak (2003) offers evidence that the prevailing financial misrepresentations in this industry during the past 7 years (particularly by WorldCom) have led to excessive investment and overbuilding. The Eastern Management Group estimates that a significant percentage of the \$90 billion invested in that industry was misallocated because of fraudulent growth projections.¹² Moeller, Schlingemann, and Stulz (2004) document that in the recent merger wave (1998-2001), acquiring firms lost a total of \$240 billion surrounding the announcement of acquisitions, and the acquisitions resulted in a net synergy loss of \$134 billion (compared to a net synergy gain of \$11.5 billion in the 1980s). This implies that the market did not see those investments as value-increasing. Interestingly, Wang (2004b) shows that this period appeared to be fraud-prevailing. Jensen (2004) also provides some good examples of bad investments and value destruction in fraudulent firms such as Nortel Networks and eToy.

The theory argues that part of the overinvestment incentives arise from the negative effect of investment on the firm's detection risk. The model predicts that the type of investment that produces the most valuation imprecision will have the strongest effect on detection likelihood.

The theory also implies there is investment distortion spillover between fraudulent and honest firms. Overinvestment by fraudulent firms can crowd out investment by good and honest

¹¹This study mainly focuses on the monitoring role of corporate governance, and does not incorporate the broader functions of governance such as designing executive compensation structures.

¹²Eastern Management Group, *supra* note 42, at 2 (quoting Joelle Tessler, "WorldCom Spine UUNET is Critical Part of Internet," *San Jose Mercury News*, September 1, 2002).

firms. This implies that fraud-induced real value losses are borne not only by shareholders of fraudulent firms but also by those of firms that have no intention to misreport.

Fraud Propensity and Firm Attributes The theory shows that firm characteristics can influence the firm's likelihood of engaging in fraud. Specifically, fraudulent firms tend to be those who have good growth prospects and large external financing needs, but experience negative profitability shocks. Growth itself is not a bad thing, but this model shows that it can have a significant effect on the manager's fraud incentives (both on the benefit and cost of fraud). The model predictions are consistent with many findings in the accounting literature on earnings management and corporate fraud. Loebbecke, Eining, and Willingham (1989) study a small sample of managerial frauds and conclude that the most significant "red flags" for fraud are rapid company growth and poor accounting performance. The National Commission on Fraudulent Financial Reporting (1987) states that young public companies have a proportionately greater risk of financial statement fraud. Young firms generally have higher growth potential than mature firms.

Litigation Across Industries The model predicts an industry effect in the cross-sectional distribution of securities fraud. That is, there will be "litigation clustering" in certain industries during a specific time period. This is because both firms' benefit from fraud (such as asset profitability and growth potential) and litigation risk are correlated within an industry, which implies that firms' fraud propensities will be influenced by industry factors.

Effect of Increasing Disclosure The model shows that increasing the informativeness of the earnings has an ambiguous effect on the firm's likelihood of committing fraud. This implies that imposing heavy disclosure requirements on public firms may not produce the expected effects. The reason is that increased disclosure could give the market an illusion of increased transparency, which could actually decrease market vigilance.

Fraud Detection Likelihood This theory shows that while the fraud penalty (f) is largely determined by securities laws and regulations, fraud detection likelihood (P) is substantially influenced by the firm's endogenous actions as well as firm-specific attributes. This implies that the probability of detection is more important than the penalty in determining cross-sectional

differences in firms' fraud propensities. The policy implication is that raising litigation liability standards alone will achieve only limited deterrence, because firms may adjust P to offset some effect of increased f on their expected litigation cost. More important, the theory shows that firms may even destroy value in order to decrease their detection risk, which can be an unintended consequence of imposing heavy penalty. Inefficient investment is one example. Leuz, Triantis and Wang (2004) provide possibly another. They document that since the passage of Sarbanes-Oxley Act there has been a dramatic surge in the number of public firms that voluntarily deregistered their common stock and ceased to file regular reports with the SEC (they call this "going dark" transactions). They also document substantial negative abnormal returns and loss of liquidity associated with deregistration and continued drop in the firms' market capitalization after deregistration. Their findings imply that insiders of those companies may have sacrificed shareholders' interest in order to hide from market scrutiny.

Internal Corporate Governance and Extensions This paper shows that even when the manager's interest is perfectly aligned with that of shareholders, fraudulent behavior can still emerge, because incumbent shareholders may find it advantageous to defraud prospective investors. Good corporate governance will not completely prevent fraud if it is under the control of existing shareholders. In fact, Table 2 shows that the likelihood of fraud detection is much lower from within the firm than from outside. Therefore, enhancing other detection forces such as capital market vigilance, responsibility of "gatekeepers" (e.g., auditors and lawyers) and securities regulation is necessary in combating corporate fraud.

In the present model, the quality of internal corporate governance p is exogenously determined, and I focus on detection by capital markets. A more general model can allow shareholders of the company to choose the level of p , and allow the market to incorporate this information into its belief about the likelihood of fraud ($\pi_0 = g(p)$, $g'(p) < 0$). Therefore, a higher p corresponds to a higher ex ante benefit from fraud because it leads to a lower π_0 and thus a smaller discount of the firm's earnings report (the signalling effect). As illustrated by Figure 2, however, a larger difference between $E(V|y)$ and $E(V|e)$ also implies a higher likelihood of cash flow detection. This

means that a higher p will increase the likelihood of both internal and external fraud detection (the litigation effect). The optimal quality of internal corporate governance p^* balances the signalling effect with the litigation effect. Since in this paper the manager represents the interests of incumbent long-term shareholders, the extension is equivalent to having a model in which the manager chooses η and p at the same time (i.e., time 0 and time 1 are combined). The manager's optimization problem can be as follows.

$$\max_{\eta \geq 0, 0 \leq p \leq 1} \Pi = E(V|N, e) + \lambda[1 - \Phi(z_c^*)][\beta_0 - \beta(y, p)]E(V|I, e) - P(\eta, p)f\eta - h(p), \quad (4.27)$$

where $h(p)$ is the cost of building the quality of internal corporate governance. p^* depends on the functional form of $g(p)$ and $h(p)$. For example, if the market is not sensitive to corporate governance (at least for some range of p realizations), then the firm will choose a p as low as possible, regardless of its fraud propensity. If the market values good corporate governance but it is very costly to build up the quality, then the firm may still lean towards a low p . If the market values good governance and the cost of establishing good governance is reasonable, then the choice of p will depend on the firm's ex ante fraud incentives.

Table 4.1: **Fraud Discovery (1996-1997)**

This table lists the various corporate events or entities that precipitated the 187 federal securities class action lawsuits during 1996 and 1997. The litigation information is retrieved from Stanford Securities Class Action Clearinghouse. Information about the triggering events of each lawsuit is extracted from the relevant case documents (i.e., the case complaints, the press releases, and the court decisions). The first column of the table lists the event or entity that precipitated or initiated the securities lawsuits. The triggering events can overlap in some lawsuits.

Precipitator	1996	1997	Total	% of Total
Number of observation	93	94	187	
Devastating news announcement	63	69	132	70.59
Regulators (mostly SEC)	6	6	12	6.42
Independent auditors	10	7	17	9.09
Business journal articles	7	5	12	6.42
Board/internal investigation	7	4	11	5.88
Securities analysts	1	3	4	2.14
Shareholder/Investor	3	4	7	3.74
Stock Exchanges/credit rating services	0	1	1	0.53
Management turnover	2	1	3	1.60

Table 4.2: **A Numerical Illustration of Investment Incentives**

I assume the following parameter values. The value of the firm's assets in place is normally distributed with expectation $\bar{A} = 100$ and volatility $\sigma_A = 30$. The average return on assets is $q = 0.16$. The earnings noise u is normally distributed with zero mean and volatility $\sigma_u = 4$. The expected earnings is $\bar{e} = q\bar{A} = 16$, and volatility is $\sigma_e = \sqrt{q^2\sigma_A^2 + \sigma_u^2} = 6.25$. The size of the new investment is $I = 25$. The volatility of investment return is $I\sigma_R = 25 * 0.3 = 7.5$. The correlation coefficient between \tilde{R} and \tilde{e} is $\rho = 0.3$. The market's prior belief about the probability of misreporting is $\pi_0 = 0.5$. The marginal fraud penalty is $f = 1.5$. The institutional efficiency is $p = 0.3$. The cost of investigation is $C = E(f\eta) = f\eta$. In panel A, I set $e_L = \bar{e} - \sigma_e = 9.75$. I consider two levels of e_H . First, $e_H = \bar{e} = 16$, which means that $\eta = 6.25$. Second, $e_H = \bar{e} + \sigma_e = 22.25$, which means that $\eta = 12.5$. In panels B-C, $\eta = 12.5$.

Panel A: Fraud Magnitude and Investment Bias

	$\eta = 6.25$	$\eta = 12.5$
<i>LD</i>	0.83 (71%)	0.73 (81%)
<i>LH</i>	0.94 (58%)	0.94 (58%)
<i>HH</i>	1.05 (43%)	1.14 (33%)

Panel B: Investment Volatility and Investment Bias

$I\sigma_R$	2.5	7.5	12.5	17.5
<i>LD</i>	0.76 (79%)	0.73 (81%)	0.71 (83%)	0.69 (85%)
<i>LH</i>	0.98 (53%)	0.94 (58%)	0.91 (62%)	0.89 (65%)
<i>HH</i>	1.19 (26%)	1.14 (33%)	1.09 (38%)	1.06 (42%)

Panel C: Asset Volatility and Investment Bias

	$\sigma_A = 30$	$\sigma_A = 40$
<i>HH</i>	1.14 (31%)	1.17 (28%)
<i>LD</i>	0.74 (81%)	0.69 (85%)
<i>LH</i>	0.94 (58%)	0.94 (58%)

Chapter 5

An Empirical Investigation of Securities Fraud

This chapter empirically investigates the economic determinants of firms' fraud propensity and the fraud detection likelihood. More specifically, I address the following research questions:

1. How does investment influence the firm's fraud incentives and their detection risk?
2. What are the roles of different corporate monitors in the context of fraud? What type of corporate monitor has been effective in discovering corporate fraudulent activities?
3. What is the role of insider equity incentives in determining the firm's propensity to commit fraud?
4. How are firm characteristics related to the firm's likelihood of engaging fraud and the firms' likelihood of getting caught?

The structure of this chapter is as follows. Section 5.1 describes the accounting fraud sample and presents some stylized facts about accounting-related class action lawsuits from 1996 to 2003. Section 5.2 presents the empirical model of fraud. Section 5.3 discusses the related literature and develops the empirical hypotheses. Section 5.4 reports the results from univariate comparisons between the fraud sample and the comparison sample. Section 5.5 reports the multivariate analysis on the determinants of firms' propensity to commit fraud and the likelihood of fraud detection. Section 5.6 presents robust checks on the model results regarding the possibility of false detection, the timing of fraud, and different model specifications.

5.1 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 (class members) who purchased the securities of a particular company during a specified time (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 684 lawsuits filed against 660 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.

Existing studies mostly rely on the SEC's Accounting and Auditing Enforcement Releases (AAERs) to identify accounting frauds. Several recent studies use accounting restatements to proxy for fraudulent financial reporting (Agrawal and Chadha (2004), Burn and Kedia (2004), Efendi, Srivastava and Swanson (2004)). 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's 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 play an important role in the litigation.

My class action sample does overlap with the SEC's AAER sample and the accounting restatement sample that have been used in the existing studies. Among the 660 fraudulent firms in my sample, 207 firms were subject to parallel SEC's AAERs, and 334 firms had accounting restatements according to the General Accounting Office's October 2003 report.¹ In Section 5.6, I will use these two subsamples to check the robustness of my results across different proxies of

¹The General Accounting Office's October 2003 report lists all the accounting restatements between January 1997 and June 2003. My sample period is from January 1996 to December 2003. Therefore, there can potentially be more than 334 restatements in my sample.

securities fraud.

The following sections provides detailed descriptive information about the fraud sample.

5.1.1 Time Trends and Firm Characteristics

Table 1 describes the evolution of class action litigation over time. Panel A shows that accounting-related frauds have on average accounted for about 47% of the total litigation activities (excluding litigation against investment banks) over the past 8 years. The number of accounting frauds peaked in 2002, where it represented 56.13% of all the securities class action filings. Interestingly, accounting-related litigation substantially decreased in 2003 (only 40% of all lawsuits), which may have resulted from tightened securities regulation and increased market vigilance.

Panel B shows the distribution of the class periods associated with the 660 lawsuits. Every class action lawsuit specifies a class period. The beginning of a class period shows the earliest time a fraud affects the market, based on the judgment of securities attorneys. A class period generally ends at the time of some major events that precipitate the litigation. The length of the class period provides some information about the duration of fraud. The average length of the class period is a little more than one year, but there is substantial variation. Some frauds affected the market for more than five years, while some less than a quarter.

Panel B also shows that firms in the fraud sample were largely young public companies. The median age was only 3.45 years, and more than 60% of the sample firms were less than 5 years old. About 64% of the alleged fraudulent firms were listed on NASDAQ when fraud began.

Panel C shows the distribution of the fiscal year in which fraud began. I label the beginning fiscal year of fraud as year 0. I determine year 0 based on the beginning of the class periods and the firms' fiscal year end. The beginning of a class period indicates the earliest time fraud affected the market, but does not necessarily indicate the beginning of fraud. In general, an accounting fraud starts to affect the market when a fraudulent financial report is released to the public. Given that there is about one month's lag for quarterly reports and a two-to-three-month lag for annual reports, year 0 can be the same fiscal year in which the class period starts, or the previous fiscal

year. Figure 1 illustrates the two scenarios. If a firm was subject to both private litigation and the SEC's enforcement action, I cross check the beginning year with that specified by the SEC. The information about the SEC's enforcement actions is retrieved from the SEC's litigation archive.

5.1.2 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 17.42% of all accounting fraud cases in the past 8 years. Electronic parts, computer manufacturing, and telecommunications companies represent another 19% of the litigation activities. Second, the service sector and particularly the financial services and the business services industries also show a high litigation concentration. In total, the technology (including bio-technology firms) and service sectors account for 67% of all securities lawsuits studied in this paper.

5.1.3 The Nature of Fraud

Table 3 lists some specific accounting items that are often manipulated, based on the relevant case documents in 563 class action lawsuits.² Allegations of improper revenue recognition are most common, accounting for 67.44% of all the accounting fraud allegations. Operational expenses are also likely to be manipulated by managers to reach desired earnings targets (17.26% of the 563 cases). As for the balance sheet items, misstatements of assets are more frequently observed than misstatements of liabilities and equity. 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. (2005) that changes in inventory and accounts receivables are closely related to

²I am only able to clearly identify the specific accounting items in 563 out of 660 cases.

the earnings quality and thus can help to predict future stock returns. Finally, understatement of reserves and allowances is also fairly often, accounting for about 9% of the 563 lawsuits.

5.2 Empirical Methodology

5.2.1 A Model with Partial Observability of Fraud

In implementing comparisons between the fraud sample and any sample of non-convicted firms, we face an identification problem because we only observe *detected* fraud. That is, we only observe frauds that have been committed and subsequently detected. Firms that have not been sued in securities litigation are either innocent firms or undetected fraudulent firms (see Figure 2 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) and Feinstein (1990). In essence, this technique models the observed outcome (detected fraud) as a function of the joint realizations of two latent processes. Let F_i^* denote firm i 's potential to commit fraud, and D_i^* denote the firm's potential of getting caught *conditional on fraud being committed*. Then consider the following reduced form model:

$$F_i^* = x_{F,i}\beta_F + u_i; \quad (5.1)$$

$$D_i^* = x_{D,i}\beta_D + v_i, \quad (5.2)$$

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 follows a bivariate normal distribution. Their variances have been normalized to equal unity. The correlation between 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 realizations of F_i and D_i . What we observe is

$$Z_i = F_i D_i$$

$Z_i = 1$ 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

$$\begin{aligned} P(Z_i = 1) &= P(F_i D_i = 1) & (5.3) \\ &= P(F_i = 1, D_i = 1) \\ &= P(F_i^* > 0, D_i^* > 0) \\ &= \Phi(x_{F,i}\beta_F, x_{D,i}\beta_D, \rho); \end{aligned}$$

$$\begin{aligned} P(Z_i = 0) &= P(F_i D_i = 0) & (5.4) \\ &= P(F_i = 0, D_i = 0) + P(F_i = 1, D_i = 0) \\ &= 1 - \Phi(x_{F,i}\beta_F, x_{D,i}\beta_D, \rho). \end{aligned}$$

An implicit assumption in the model is that false detection of fraud is not allowed for ($P(F_i = 0, D_i = 1) = 0$), because the process of D_i^* is only defined conditional on $F_i = 1$. Extension of the above model to statistically control for false detection is possible, but it tends to complicate the estimation.³ I will come back to the issue of false detection in Section 5.6.

Although I define D_i^* conditional on $F_i = 1$, the correlation between the two disturbance terms ρ may not necessarily be zero. As discussed in Feinstein (1990), a non-zero correlation may arise for a number of reasons, particularly when the potential fraud-doer and the detection force possess information about one another.

³Let $D'_i = 1$ indicate false detection. Then

$$P(Z_i = 1) = P(F_i = 1, D_i = 1) + P(F_i = 0, D'_i = 1);$$

$$P(Z_i = 0) = P(F_i = 0, D_i = 0) + P(F_i = 1, D_i = 0) - P(F_i = 0, D'_i = 1).$$

In a well-functioning legal environment, $P(D'_i = 1)$ should be very small, much smaller than $P(D_i = 1)$. Then assuming $P(D'_i = 1) = 0$ will not substantially bias the model estimation.

5.2.2 Model Identification and Estimation

The partial observability of fraud raises a model identification issue. This is because we only observe the joint outcome of two latent processes, and the decomposition between the two latent components may not be unique. According to 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 above model can be estimated using the maximum-likelihood method. The log-likelihood function for the model is

$$\begin{aligned} L(\beta_F, \beta_D, \rho) &= \sum_{z_i=1} \log[P(z_i = 1)] + \sum_{z_i=0} \log[P(z_i = 0)] \\ &= \sum_{i=1, \dots, n} \{z_i \ln[\Phi(x_{F,i}\beta_F, x_{D,i}\beta_D, \rho)] + (1 - z_i) \ln[1 - \Phi(x_{F,i}\beta_F, x_{D,i}\beta_D, \rho)]\}. \end{aligned} \quad (5.5)$$

I use the filing of class action lawsuits to proxy for detected fraud (i.e., $Z = 1$). The partial observability model implies that the appropriate comparison sample ($Z = 0$) 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 any private securities litigation (accounting-related or not) or the SEC's AAERs between 1996 and 2003.

5.2.3 Comparison with Straight Probit Model

A straight probit model, which has been used in many existing studies on fraud, is as follows. For firms $i=1, \dots, n$,

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

$$P(Z_i = 1) = P(F_i = 1) = \Phi(x_{F,i}\beta_F).$$

The log likelihood function associated with this model is

$$L(\beta_F) = \sum_{i=1, \dots, n} \{z_i \ln[\Phi(x_{F,i}\beta_F)] + (1 - z_i) \ln[1 - \Phi(x_{F,i}\beta_F)]\}. \quad (5.6)$$

We can see that as long as detection is not perfect (i.e., $P(D_i = 1) \leq 1$), the straight probit model will systematically understate the true probability of fraud.

An inference problem could also arise when (5.6) is estimated instead of (5.5). For example, we want to examine the marginal effect of an explanatory variable x_i on the probability of fraud $P(F_i = 1)$. Let us take partial derivative of x_i on both sides of equation (5.3).

$$\frac{\partial P(Z_i = 1)}{\partial x_i} = \frac{\partial P(F_i = 1)}{\partial x_i} P(D_i = 1|F_i = 1) + \frac{\partial P(D_i = 1|F_i = 1)}{\partial x_i} P(F_i = 1). \quad (5.7)$$

If this variable has opposite effects on $P(F_i = 1)$ and $P(D_i = 1|F_i = 1)$, then $\frac{\partial P(F_i=1)}{\partial x_i}$ and $\frac{\partial P(Z_i=1)}{\partial x_i}$ can even have different signs, not to mention that the magnitude will be different. This may lead us to draw incorrect inference about the role of x_i . Section 5.5.6 provides concrete examples of the discussions here.

5.3 Hypothesis Development and Model Specification

Following the framework of fraud in Wang (2004), a firm's propensity to commit fraud depends on its expected benefit and cost from engaging in fraud. The expected cost of fraud is the litigation risk: with some positive probability, fraudulent activities will be uncovered, resulting in a penalty. 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 firms' fraud propensities than are penalty provisions. Therefore, I focus on the likelihood of detection for the cost side of the tradeoff. 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. Sections 5.3.1 and 5.3.2 discuss factors that can potentially affect a firm's detection risk and its benefit from fraud, respectively. Section ?? discusses the control variables. Section 5.3.4 summaries the model specification.

5.3.1 Probability of Fraud Detection

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 and if its effect can be anticipated at the time the firm makes the fraud decision, then this factor will 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 5.3.2.

Investment

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 investment. Second, after committing fraud, the fraudulent firm has incentive to cover things up. This incentive can motivate the management to strategically use investment to disguise fraud. Wang shows that investment with high uncertainty and/or low correlation with current activities can mask fraud better than others, because these types of investment can decrease the precision of the firm's cash flows and create inference problems for the market.

Wang's argument has the following three testable implications: (1). Fraudulent firms have larger investment expenditures than comparable honest firms; (2). Different types of investment have differential effects on a firm's probability of being detected and the probability of fraud. Risky investments and uncorrelated investments have stronger negative effects on the detection likelihood than other types of investments; (3). Financing of the investment influences a firm's probability of committing fraud. Externally-financed investment will motivate fraud better than internally-financed investment.

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 is generally highly uncertain. 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 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. However, the true value of the acquired assets and the synergy between the acquired and the existing assets may not be correctly understood by the market or even the acquirer.

I further distinguish between cash-based acquisitions and stock-based acquisitions. The earnings management literature has provide evidence that stock-based acquisitions are associated with higher incentive of earnings management (e.g., Erickson and Wang (1998)). In this study, I examine the effect of stock-based acquisitions on both the probability of fraud and the probability of fraud detection. I also distinguish between focused acquisitions and diversifying acquisitions. I define focused acquisitions as acquisitions within the same two-digit SIC codes. According to Wang (2004), focused acquisitions should be associated with higher probability of detection than diversifying ones are.

Corporate Monitoring

Effective monitoring over the management should increase the likelihood of fraud detection and deter fraud ex ante. In this study, I examine the roles of four types of corporate monitors in the context of corporate securities fraud: large shareholders, institutional owners, independent auditors, and board of directors.

Monitoring by Shareholders: A firm's ownership structure is important in determining both the firm's benefit from committing fraud and its detection risk. This is because the 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. There has been quite some empirical evidence on the role of large shareholders in corporate governance (see a recent survey by Holderness (2003)). 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 period of time to catch the windfall from fraud, and they will likely suffer a lot from the severe consequences of fraud. Therefore, I expect a positive relation between block ownership holding and the likelihood of fraud detection.

Large shareholders are often institutional investors. Monitoring by institutional shareholders has attracted growing public and academic interest, as institutional ownership skyrocketed over the past two decades in the United States. The Private Securities Litigation Reform Act (PSLRA), which was passed in December 1995, explicitly encourages more active participation of institutional investors in securities litigation by requiring each class action lawsuit to specify a lead plaintiff. William Lerach, a partner in Milberg Weiss Bershad Hynes & Lerach LLP and a leader in representing investors in securities class action suits, points out that some large pension funds have actively participated in securities litigation and have successfully established corporate governance enhancements in class action settlements.⁴ Therefore, I expect institutional equity holdings to have a positive effect on fraud detection.

Monitoring by Independent Auditors: Independent auditors are probably the most important corporate “gatekeepers”. They pledge their reputational capital and provide protections to dispersed investors by verifying and assessing the quality of firms’ disclosures. In the late 1990s, however, such protections seemingly failed. The most notorious example is Arthur Andersen’s role in the

⁴Keynote address by William S. Lerach in council of institutional investors spring 2001 meeting.

Enron scandal and its subsequent criminal indictment. The increasing importance of non-audit services in auditing firms' total revenue has also led to widespread market concern about auditor independence. Frankel, Johnson, and Nelson (2002) find that auditor independence is negatively associated with the probability of earnings management. Anup and Chadha (2004) find a negative but insignificant relation between auditor independence and the probability of accounting restatements. Bajaj, Gunny and Sarin (2003) examine a sample of class action lawsuits that involve allegations of accounting irregularities, and find no significant difference in auditors' compensation (audit vs. non-audit fees) between the fraud sample and the comparison sample. However, for firms with large market reaction to the alleged fraud, their auditors have significantly higher non-audit income.

In this study, I directly examine whether higher auditor reputational capital leads to higher likelihood of fraud detection. First, I examine whether firms whose independent auditor is one of the five largest accounting firms (Arthur Andersen, PricewaterhouseCoopers, Deloitte & Touche, Ernst & Young, KPMG) have a higher probability of fraud detection. Second, I examine the role of auditor opinion in fraud detection. If the independent auditors exert due diligence in certifying disclosures, then I expect that adverse auditor opinions to increase fraud detection.

Monitoring by Board of Directors: The monitoring role of the board of directors is an important component of corporate governance. The board is presumed to monitor the management on behalf of shareholders, because diffuse ownership makes direct shareholder control difficult. The economics and finance literature on the board starts with the assumption that the board's monitoring effectiveness is a function of the board's independence from the management. Two characteristics of the board, size and composition, are related to board independence. Empirical research in this area finds that board size and composition affect the observable board actions such as the board's decision on CEO turnover, executive compensation, and merger/acquisitions (see surveys by John and Senbet (1998) and Hermalin and Weisbach (2003)).

The recent wave of high-profile corporate scandals has brought the effectiveness of board monitoring to the center of securities legislation and governance reform. The newly-passed Sarbanes-

Oxley Act (SOX) and the NYSE and NASDAQ's new corporate governance guidance mandate a number of changes that are aimed to improve board monitoring. For example, SOX requires that the audit committee consist entirely of independent directors and the audit committee hire the outside auditor. Both SEC and the national stock exchanges strongly recommend overall board independence. Several studies have examined the relation between the characteristics of the board and the probability of corporate fraudulent reporting. Beasley (1996) studies a sample of firms subject to SEC's AAERs and finds that board independence (proxied by the percentage of outside directors in the board) is significantly negatively related to the likelihood of financial statement fraud. Klein (2002) finds an inverse relation between board independence and abnormal accruals. Dechow, Sloan and Sweeney (1996) find that firms committing financial statement fraud are likely to have a board dominated by insiders and have a CEO who is also the chairman of the board or the founder of the company. Agrawal and Chadha (2004) examine the incidence of accounting restatements, and find that board independence is irrelevant, but the presence of independent directors with financial or accounting expertise on the audit committee is associated with significantly lower probability of accounting restatements.

In this study, I examine the effect of board independence on the likelihood of fraud detection. Following the literature, I use board size and the percentage of outside directors to proxy for board independence. "Grey" directors who are not employees of a firm but have some business relation with the firm are not counted as outside directors.

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 will rationally think that they probably have been fooled and will start an investigation. Therefore, unexpected bad performance (unexpected by the market) after the commencement of fraud will increase the probability of fraud detection.

To proxy for such unexpected performance shock, I use the regression residual term from the following simple prediction model.

$$ROA_{i,1} = \beta_0 + \beta_1 ROA_{i,0} + \beta_2 ROA_{i,-1} + \epsilon_i. \quad (5.8)$$

$ROA_{i,t}$ is firm i 's return on asset in year t , which is defined as the ratio of operating income after depreciation over the average total assets from year $t-1$ to year t . $ROA_{i,1}$ 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 with 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.⁵

5.3.2 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.

⁵There are two caveats associated with this variable. First, 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. Second, the management could have better information about future abnormal bad performances than the market does. Therefore, expectation of the residual ROA may impose some ex ante deterrence. However, a reasonable counter argument is that the managers commit fraud because they believe that the current bad performance is only temporary and things should go back to normal later. I will discuss the robustness of the results regarding this variable in Section 5.6.

Profitability and Growth Potential

Wang (2004) and Bebchuk and Bar-Gill (2002) predict that firms that have high 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.

A problem emerges when we test the above prediction. We cannot directly observe the negative profitability shocks because they are covered by fraud. A possible solution is to use the ex-post restated financial data rather than the originally reported data. However, to my knowledge, the restatement data in COMPUSTAT is not as comprehensive and complete as the original data. Therefore, I try to infer the existence of profitability shocks by comparing the profitability before the commencement of fraud and that at the revelation of fraud. The difference between the two profitability levels can imply hidden performance changes when fraud is alive. I use return on asset *ROA* as the profitability measure. I use two proxies for growth potential, the annual asset growth rate and the book-to-market ratio.

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 values. 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)). 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 actual net external financing cash flows. Specifically,

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

where ΔCE_t , ΔPE_t , and $\Delta DEBT_t$ are the changes in the book value of common equity, preferred equity, and total debt in year t , respectively. $ASSETS_t$ 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.

Financial Distress

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 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.

Insider Equity Incentives

The relation between insiders' equity incentives and the incidence of corporate fraud has been at 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

⁶See 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.

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

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 (2004), and Burns and Kedia (2004). 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 examine the role of insider percentage stock ownership and executive equity compensation in the context of accounting fraud. Executive equity compensation is measured as the value of restricted stock and stock options (using the Black-Scholes model) over an executive's total compensation. I then compute the sum and average of the ratios across the five top executive officers in the firm.

5.3.3 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 (1999) 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. There are also clear industry patterns in securities litigation (see Table 2). 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 firms' profitability, growth potential, external financing need and ownership structure. Therefore, I control for firm size (log of total assets), age (as a public company), and firms' membership in the technology, service and trade sectors.

5.3.4 Summary of Model Specification

Factors	Variables	β_F	β_D
Growth Potential	Asset Growth, Book-to-Market	+	
External Financing Need	Ext. Fin. Growth, Ext. Fin. C.F.	+	
Financial Distress	Leverage, ST Debt	+	
Profitability	ROA	-	
Profitability (ex post)	Residual ROA		-
Insider Equity Incentive	Insider Own, Equity Compensation	+/-	
Investment	R&D, Capital Exp., Acquisition	+	-
Shareholder Monitoring	Block Own, Institution Own	-	+
Board Monitoring	Board Size, Outside Director	-	+
Independent Auditor	Big Five, Auditor Opinion	-	+
Control Variables	Firm Size, Age, Industry		

5.4 Descriptive Information and 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; and (5) corporate monitoring. Table 4 Panel A 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. All the financial

information is retrieved from COMPUSTAT database. Information on stock-based acquisition and acquisition volume is from SDC Platinum database. Ownership information is from CDA Spectrum. Information on executive equity compensation is from ExecuComp database. Information on board of directors is from EdgarPro database.

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 year 0. The determination of year 0 is discussed in Section 5.1.1. 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 labelled as information from year -1 and are used in the analysis.

In this study, all the variables on profitability, growth, and external financing needs are measured at the average level from year -2 to year -1. Using pre-fraud information helps to mitigate the effect of fraud on those measures. Information on investment is from year 0. The reason is that those investments were made around the time when fraud was committed, and therefore could have been used strategically by the management to disguise fraud. Corporate monitoring variables are measured at the average level from year -1 to year 0. Year 0 information is incorporated to strengthen the deterrence effect of monitoring on firms' decision to commit fraud.

The fraud sample on average appears to be larger but younger than the comparison sample. Studies on SEC's AAERs generally find that alleged firms are 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 seems to have outperformed the comparison sample in the two years before the commencement of fraud, and underperformed the comparison sample in year 1. This is consistent with the argument in Section 5.3.2. Fraudulent firms experienced some negative performance shock in year 0 but chose to cover up the problems by false financial disclosure. Then fraud got uncovered in year 1, and the concealed bad performance was revealed.

Table 4 Panel A 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 46% for the fraud sample, and only 9% for the comparison sample. 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 need for outside capital. 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 19% for the fraud sample, and only 4% for the comparison sample. The fraud sample, however, does not seem to be more burdened by debt than the comparison sample.

The difference in growth opportunities across the two samples is further reflected in investment expenditures. The fraud sample on average invested more than the comparison sample did in the year when fraud occurred. For instance, the median ratio of net investing cash outflow to total assets is 11% for the fraud sample, and 6% for the comparison sample. However, the univariate comparisons do not control for factors that may influence the size of investment. We know that different industries have different investment patterns, and young firms tend to invest more than mature firms do. Firm size is also a potential determinant of investment size. Since all the investment variables have been normalized by the book value of assets, the size effect is already taken into account. Therefore, in order to have a more direct test of the overinvestment prediction in Wang (2004), I construct a control sample that is matched with the fraud sample in terms of industry distribution (two-digit SIC codes) and firm age at the end of year -1. Table 4 Panel B shows that the fraud sample on average had a much higher investment intensity than the control sample did both before and after the commencement of fraud. Except for capital expenditures, the differences across the two samples are statistically significant, and particularly so for merger/acquisition-related expenditures.

Finally, Table 4 Panel A shows that the fraud sample on average has more concentrated ownership, more institutional holdings, more large insider equity incentives. The fraud sample also

tends to have a smaller board and lower percentage of independent directors.

5.5 Multivariate Analysis

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

5.5.1 Firm Characteristics and Fraud

Table 5 reports the effects of profitability, growth and external financing need on a firm's fraud incentives. We can see that ROA is positively associated with the likelihood of fraud. This result may seem counterintuitive at first glance. However, it is actually 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 deterioration in profitability has already started. The concealed performance deterioration, if it continues, will eventually lead to the revelation of fraud. The average marginal effect of residual ROA on $P(D|F)$ across all the models is -0.26, which means that a 10% unexpected decrease in ROA in year 1 is associated with an average 2.6% increase in the probability of detection. 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 leads to the discovery of fraud.

Table 5 also shows that a firm's growth potential and external financing need are important motivational factors for fraud. Models 1 and 2 indicate that higher asset growth rate and lower book-to-market ratio are related to higher probability of fraud. Model 3 implies that fraudulent firms are likely to have a growth rate higher than what can be supported by their internal funds. The average marginal effect of externally financed growth on $P(F)$ across models is 0.64, which means that increasing the externally financed growth by 10% tends to increase a firm's probability

of misreporting by 6.4%. Models 4-6 further show that fraudulent firms on average 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.

5.5.2 Investment and Fraud

Table 6 reports the relation between firms' investment expenditures and their fraud incentives. Several interesting results emerge. First, I find that different types of investment have differential effects on the likelihood of fraud detection. Investment in R&D has the strongest negative effect on the probability of fraud detection. The relation is statistically and economically significant. The average marginal effect of R&D expenditures on $P(D|F)$ across models is -0.17, which means that a 10% higher R&D expenditures is on average associated with a 1.7% lower probability of detection. Note that a firm's total litigation cost is the probability of detection times the penalty upon detection. Suppose that the penalty can be completely measured in terms of money, then a 1.7% decrease in the detection likelihood can correspond to a substantial reduction in the dollar value of litigation cost.

The effect of net investing cash flow on the probability of detection is also significantly negative but much weaker than that of R&D expenditures. The average marginal effect of net investing cash flow on $P(D|F)$ is -0.05. Straightforward investment like capital expenditures does not seem to influence the likelihood of detection. Neither do acquisition expenditures. I further examine some different measures of merger/acquisition intensity. Model 10 shows that larger the number of acquisitions in year 0, higher the probability of detection. A possible explanation for this result is that the regulators and the market may pay more attention to firms that are active in mergers/acquisitions. Furthermore, Model 11 shows that more focused acquisitions (acquisitions within the same two-digit SIC codes), higher the probability of detection. It is consistent with

the argument in Wang (2004) that investments that have high correlation with a firm's current business can increase the firm's litigation risk.

Second, different types of investment also have differential effects on firms' propensity to commit fraud. The differences can stem from two sources: either different investments affect firms' benefit from fraud differently, or they affect firms' risk of being detected differently. Let us compare cash-based acquisitions and stock-based acquisitions. Table 6 shows that these two types of acquisitions have different effects on $P(F)$, but not on $P(D|F)$. Stock-based acquisitions have a significant positive relation with $P(F)$, while cash-based acquisitions do not. This implies that the financing of the investment influences firms' benefit from committing fraud, but not the detection risk. Then let us compare R&D expenditures and capital expenditures. In all models, R&D expenditures are significantly positively associated with $P(F)$, while capital expenditures do not influence $P(F)$. If these two types of investment are not generally financed differently, then their differential effects on $P(F)$ should largely arise from their differential effects on $P(D|F)$. Holding other factors constant, firms that invest more in R&D tend to have lower litigation risk. Low litigation risk can encourage fraud.

5.5.3 Equity Ownership and Fraud

Table 7 presents the roles of insider equity incentives and shareholder monitoring in determining a firm's fraud incentives. First, insider percentage stock ownership has a significant concave relation with the probability of fraud. That is, when insider ownership is small, the probability of fraud increases as insider ownership increases. When insider ownership is large, however, the probability of fraud decreases as insider ownership increases. 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. Therefore, I construct an executive equity compensation variable, which is the total value of an executive's restricted stock and stock options over her total compensation and sum over all the key executives in the company.⁸ Model 14 shows that

⁸For insider equity incentives, I have also examined various specifications of executive equity compensation other than the one reported in Model 14. For example, I compute the average ratio rather than the sum across executives

executive equity compensation exhibits a similar but slightly weaker concave shape.

The concavity implies that insider equity ownership (or equity compensation) can be a double-edged sword when it is used to align the interest of the managers to that of the outside shareholders. When insiders hold small stakes in the firm, the agency problem due to separation of ownership and control can be severe. However, steep equity incentive scheme may not solve the problem, because it can induce insiders to misreport rather than to work harder for the interest of outside shareholders. Interestingly, equity incentive seems to work well only when insiders already have substantial equity stakes in the firm.⁹

Second, I find that the presence of large shareholders and institutional shareholders increases fraud detection and discourages fraud. The marginal effects of institutional ownership on $P(D|F)$ and $P(F)$ are 0.14 and -0.27, respectively. This means that a 10% increase in institutional share holdings is associated with an average 1.4% increase in the probability of fraud detection, and an average 2.7% decrease the probability of fraud.¹⁰ Block ownership has a similar effect. In general, however, block ownership has a slightly stronger effect on $P(F)$, while institutional ownership has a slightly stronger effect on $P(D|F)$. These results imply that the strength of shareholder monitoring influences firms' propensity to commit fraud through their impact on the likelihood of fraud detection, and provide support for enhancing shareholder monitoring in the on-going corporate governance reform.

in a company. I use the value of exercised stock options rather than the Black-Scholes value of all stock option holdings. I also examine equity ownership and equity compensation of CEO. Overall, the results are qualitatively consistent across different specifications.

⁹I separately examine the subsample of firms that have 20% or higher insider ownership. I find a significant negative relation between insider ownership and the probability of fraud. This result is not reported in the tables.

¹⁰There is a caveat regarding the interpretation of the result. The Private Securities Litigation Reform Act (PSLRA) that was passed in December 1995 requires that every class action lawsuit appoint a lead plaintiff. PSLRA encourages large institutional investors to be lead plaintiffs. Therefore, class action suits could be more likely to go through for firms that have large institutional investors. This may lead to the positive relation between institutional ownership and $P(D|F)$.

5.5.4 Auditor, Board and Fraud

Table 8 presents the effects of independent auditors and corporate boards on corporate fraud incentives. The auditor being one of the five largest accounting firms appears to be related to higher likelihood of fraud detection.¹¹ The deterrence effect, however, is not statistically significant. Auditor opinions seem to have no influence on detection. The reason is that auditor opinions do not exhibit much variation at all. For the fraud sample, 79% of the auditor opinions in the year when fraud occurred were unqualified opinions, and the rest 21% were unqualified opinions with some explanations. The uniformly unqualified auditor opinions themselves show the problem: Why do independent auditors seldom disagree with their clients regarding the quality of disclosure? Are they truly independent?

On monitoring by the board of directors, models 16-17 show that board size and the percentage of outside directors are positively associated with the probability of detection and negatively associated with the probability of fraud. However, the relations are not statistically significant. This could be due to the power issue. Unfortunately, I do not have board data for a large number of firms in my sample (see Table 4).

5.5.5 Summary of Results

In sum, Tables 5-8 present the multivariate analysis on the effects of firm characteristics, investment, and corporate monitoring on a firm's probability of committing fraud and the probability of fraud detection. I find 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 fraud detection.

Second, I find that 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. Therefore,

¹¹I take out Arthur Andersen and find similar result on the big four accounting firms. I also examine Arthur Andersen separately, and find no significant result. Since these results are similar to what is reported in Table 8 Model 15, they are not reported.

it is an important determinant of firms' incentives to defraud investors. Investments with high degree of uncertainty and/or low correlation with existing assets tend to negatively influence the likelihood of fraud detection. These results, together with the evidence of overinvestment in Panel B of Table 4, imply that fraud can be associated with investment distortions and thus real economic costs.

Finally, different types of corporate monitors also appear to have different effects on fraud propensity and fraud detection. The presence of block equity holders and high institutional holdings is associated with high probability of fraud detection and low probability of fraud. There is weak evidence that reputable independent auditors and large corporate boards increase the likelihood of fraud detection.

5.5.6 Comparison with Simple Probit Models

Existing studies on fraud have used straight probit models to assess the effect of a factor on a firm's probability of committing fraud. As discussed in Section 5.2.3, the straight probit model equates the probability of detected fraud to the probability of fraud. Therefore, it can not only underestimate the probability of fraud, but also lead to incorrect inferences. Table 9 compares the results from the straight probit model and the bivariate probit model, and demonstrates the problems associated with the straight probit model. Using the full sample of comparison firms as in the previous models (i.e., using multiple years' data for every comparison firm) leads to very low marginal effects of all the variables in the straight probit model. Therefore, in order to better illustrate the differences between the straight probit and the bivariate probit models, I randomly choose one year for every comparison firm. That is, each comparison firm only enters the regression once in Table 9.

First, let us look at the results on R&D expenditures. The straight probit model shows no significant effect of R&D expenditures on $P(F)$, while the bivariate probit model shows a strong positive effect. The reason is that investment in R&D has opposing effects on $P(F)$ and $P(D|F)$. The two forces roughly offset each other, resulting in no effect on the probability of detected fraud

$P(Z)$. Second, the marginal effects of net investing cash flows on $P(F)$ have consistent signs across the two models, but substantially differ in magnitude (0.10 in probit and 0.43 in bivariate probit). The straight probit model underestimates the marginal effect of this variable. Third, the two models show opposing effects of institutional ownership on $P(F)$. The straight probit model reports a positive effect, while the bivariate probit model reports a negative one. Again, the reason is that institutional ownership has opposite effects on $P(F)$ and $P(D|F)$, and for this variable the positive effect on detection dominates.

The comparisons in Table 9 clearly show that disentangling the effect of a factor on the probability of detecting fraud and its effect on the probability of committing fraud is important for us to draw sensible conclusions.

5.6 Robustness Checks

5.6.1 Frivolous Lawsuits

In this study, I use the filing of securities class action lawsuits to proxy for detected fraud. However, the filing of a lawsuit does not necessarily indicate that the alleged firm is fraudulent, because allegations could be frivolous or mistaken. Therefore, the fraud sample could be subject to biases due to possible false detections.

Many studies in the legal literature have argued that The Private Securities Litigation Reform Act (PSLRA), which was passed in December 1995, makes it more difficult for shareholders to sue a public company (see., e.g., Choi (2004)). My sample consists of litigation suits since 1996 (post PSLRA). Therefore, the probability of frivolous lawsuits in my sample should be lower than it was before PSLRA.

In order to further mitigate the bias of false detection in the estimation, I separately examine the following three subsamples. The first subsample has 334 firms that announced accounting restatements surrounding the securities lawsuits. The accounting restatement information is from General Accounting Office (GAO)'s October 2003 report. Since I study accounting-related fraud, the fact that the alleged firms restated their financial reports provides support to the allegations.

The second subsample contains 207 firms that were subject to parallel SEC's AAERs. Information on AAERs is retrieved from SEC's web site. If frivolous lawsuits could result from the profit-orientation of private securities lawyers, then having parallel SEC's litigation increases the credibility of the lawsuits, because SEC is not profit-oriented. Several papers in the legal literature (see, e.g., Johson, Nelson and Pritchard (2002), Choi (2004)) have viewed suits that result in dismissal or a low value settlement (\$2 million or less) as "nuisance". Therefore, in the last subsample, I exclude 27 cases that were either later dismissed by the court or had a settlement less than \$2 million. The dismissal and settlement information is retrieved from the Securities Class Action Clearinghouse (SCAC).

Table 10 shows that the main model results hold qualitatively across all three subsamples. This implies that the possible existence of false detection does not drive the results.

5.6.2 Timing of Fraud

The beginning of a firm's fraudulent scheme is generally a little fuzzy due to the difficulty of tracing evidence far back in time. For accounting-related frauds, identifying the timing of fraud can be even more difficult because the border line between aggressive accounting and securities fraud is not always a clear cut.

In this study, I determine the beginning fiscal year of fraud (year 0) based on the specification of class periods and firms' fiscal year ending months. For firms that are subject to both private class action litigation and SEC's AAERS, I also cross check the timing of fraud using the information in SEC's litigation filings. To further examine the validity of the year 0 specifications, I compare firms' ROA based on the originally reported accounting data with ROA based on the restated data from COMPUSTAT. Figure 5 plots the median historic and restated ROA for both the fraud and comparison samples from year -2 to year 2. We can see that for the fraud sample, the historic ROA and the restated ROA are consistent with each other in years -2 and -1, start to diverge in year 0, and then re-converge in year 2. This implies that the determination of year 0 is on average valid.

5.6.3 Industry and Business Cycle effects

So far, this paper has focused on firm-level economic determinants of fraud. Several papers have argued that industry and market environment also influences firms' fraud incentives. Wang (2004) predicts that fraudulent events tend to cluster in certain industries during certain time period, because both the benefit from fraud and the litigation risk are correlated among firms in the same industry. Gande and Lewis (2005) empirically document the industry spillover effect in securities litigation. That is, the filing of lawsuits on one firm significantly negatively affects the stock performances of other firms in the same industry. I have controlled for industry distribution in the analysis. Here I further control for the industry securities litigation environment. I use the logarithm of the total market value of fraudulent firms in an industry in year -1 to proxy for industry litigation intensity. A high total market value can result from either a large number of frauds or the existence of some mega cases.

Poval, Singh and Winton (2004) argue that firms' fraud incentives are influenced by business-cycle factors. Their model shows that corporate fraud incentives are low when the economic condition is very good (investors are highly optimistic) or when it is very bad (investors are highly skeptical). The fraud incentives are high when the economic condition is switching from good to bad. In order to understand the effect of market-wide determinants on the probability of fraud, I construct a business cycle variable that equals -1 if the year in which fraud begins is between 1992 and 1994 or between 2001 and 2002 (bust), equals 0 if year 0 is between 1995 and 1997 or in 2003, and equals 1 if year 0 is between 1998 and 2000 (boom).

Table 11 shows that the main model results remain unchanged after incorporating the industry and business cycle effects. In addition, both industry litigation intensity and business cycle variables tend to be positively related to $P(D|F)$ and negatively related to $P(F)$. The likelihood of fraud detection is high in industries with high litigation intensity. Good economic conditions are also related to higher ex post detection risk. This is actually intuitive. First, if a fraud begins in a very good year, this implies that the fraudulent firm has some negative idiosyncratic shocks. Second, very good economic conditions may not continue. The problems

concealed by fraud are likely to be revealed as the overall condition weakens, which leads to the discovery of fraud.¹²

5.6.4 Different Model Specifications

The model specification described in Section 5.3.4 is mainly from the firm's viewpoint. Companies rationally compare the expected benefit and litigation risk of engaging in fraud. The explanatory variables in the $P(F)$ equation consist of variables that either influence firms' benefit from committing fraud or influence their litigation risk. We can extend the model into a strategic two-party game: The firm calculates its risk of being detected when it makes the fraud decision. The detection forces also anticipate the firm's likelihood of committing fraud when allocating their resources. For example, the market may be more vigilant with firms with high externally financed growth if those firms tend to have high propensity to commit fraud. This implies that the externally financed growth can be positively associated with the probability of fraud detection. Therefore, in Table 11 Specification 3, if a factor affects a firm's benefit from committing fraud and its effect can be anticipated ex ante by the detection forces, then this factor is in both the fraud commitment and fraud detection equations. The results show that although high externally financed growth is an important motivational factor for fraud, it does not appear to significantly influence firms' probability of being detected. A possible explanation for this is that growth itself is not necessarily a bad thing, and therefore does not necessarily trigger investor vigilance.

As discussed in Section 5.3.1, the residual ROA variable is not completely exogenous. This variable, however, appears in all the models. In Table 11 Specification 4, I take out this variable and examine whether the results on other variables still hold. The main results are qualitatively unchanged. The statistical significance of variables is consistent with previous models. However, the marginal effects of variables in the $P(F)$ equation are lower.

¹²I also use the return to a market portfolio to proxy for overall business conditions. The results are consistent with those reported in Table 11. High market return in the beginning year of fraud is associated with high probability of fraud detection.

Table 5.1: **Allegations of Accounting Fraud : 1996 – 2003**

Panel A: Litigation Filings by Calender Year

The fraud sample consists of 684 class action lawsuits against 660 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	107	88	119	71	684
Total # of lawsuits	100	163	232	195	206	168	212	177	1454
% of total	45.00	42.94	44.40	36.92	51.94	52.38	56.13	40.11	47.04

Panel B: Class Periods, Age, and Stock Exchange

The information on class periods is retrieved from the class action lawsuits. Age is defined as the number of years between a firm’s IPO date and the beginning of its class period. A firm’s stock exchange is identified as of the beginning of the class period.

Class Period (days)		Age (years)		Stock Exchange	
# of obs.	660	# of obs.	652	# of obs.	660
mean	471	mean	8.16	NYSE	30.3%
median	354	median	3.45	AMEX	3.7%
maximum	2040	age<5 years	61.2%	NASDAQ	64.0%
minimum	13	age>10 years	22.66%	Other	2.0%

Panel C: Accounting Fraud by the Beginning Fiscal Year

The beginning fiscal year of a fraud is identified based on the specification of the class period and the firm’s fiscal year ending month.

Fiscal year	1992	1993	1994	1995	1996	1997
# of cases	1	8	15	47	86	107
Fiscal year	1998	1999	2000	2001	2002	2003
# of cases	97	117	108	57	16	1

Table 5.2: **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 3-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 database.

Industry	Fraud Events	% of Sample	% of Total
Agriculture (100-900)	1	0.15	1.18
Mining (1000-1400)	10	1.52	0.74
Construction (1520-1731)	1	0.15	0.78
Food & Tobacco (2000-2111)	11	1.67	2.59
Fabrics & Textile Products (2200-2390)	12	1.82	3.79
Wood & Furniture (2400-2590)	2	0.30	1.06
Paper & Printing (2600-2790)	3	0.45	0.72
Chemicals (2800-2821, 2840-2990)	4	0.61	0.82
Pharmaceutical (2833-2836)	22	3.33	2.81
Materials & Related Products (3011-3490)	18	2.73	1.89
Industry Manuf. (3510-3569, 3578-3590, 3711-3873)	49	7.42	2.44
Computer-related Hardware (3570-3577)	33	5.00	6.82
Electronics (3600-3695)	64	9.70	5.13
Miscellaneous Manuf. (3910-3990)	2	0.30	0.91
Transportation (4011-4731)	11	1.67	2.24
Telecommunications (4812-4899)	31	4.70	3.65
Utilities (4900-4991)	29	4.39	4.37
Wholesales (5000-5190)	31	4.70	3.64
Retails (5200-5990)	36	5.45	2.70
Financial Services (6021-6799)	73	11.06	1.51
Services (7000-7361, 7380-7997, 8111-8744)	66	10.00	3.72
Software & Programming (7370-7377)	115	17.42	6.13
Healthcare Services (8000-8093)	36	5.45	9.57
Others (8880-9995)	0	0.00	0.00
Total	660	100	2.96

Table 5.3: **Table 3: Nature of Accounting Fraud**

This table presents the nature of the alleged financial misrepresentations in 563 securities lawsuits studied in this paper. I am only able to identify the exact nature of the misrepresentation in 563 cases based on the information in relevant case documents (e.g., case complaints, press releases and court decisions). I categorize these 563 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	563	
Improper revenue recognition	380	67.50
Understatement of expenses	97	17.26
Non-recurring items	4	0.71
Overstatement of account receivables	53	9.43
Overstatement of inventory	38	6.76
Overstatement of intangibles	13	2.31
Overstatement of investment	9	1.60
Overstatement of other assets	72	12.81
Understatement of reserves/allowances	49	8.72
Understatement of liability	20	3.56
Other	24	4.27

Table 5.4: **Univariate Comparisons of Firm Characteristics**

For each variable, the median, the mean (in the brackets) and the z -statistics for Wilcoxon tests are reported. ** and * indicate significance at 1 and 5% levels, respectively. “ROA”=(operating income after depreciation)/assets. “Res. ROA” is the residual from regression: $ROA_1 = \alpha_0 + \alpha_1 ROA_0 + \alpha_2 ROA_{-1} + \epsilon$. “B-M”=(assets)/(assets-equity+market value). “EF. Growth”=“Asset Growth” - $\frac{ROA_2}{1-ROA_2}$, where ROA_2 =(income before extraordinary items)/assets. “EF. C.F.”=(Δ common stock+ Δ preferred stock+ Δ debt)/assets. “Leverage”=(LT debt)/assets. “ST Debt”= (debt in current liabilities)/debt. “Bank/Debt”=(bank loan)/debt. “Invest. C.F.”= -(net investing cash flow)/assets. “Focused Acquis” is the percentage of acquisitions in which the target firm is within the same two-digit SIC codes as the acquirer. “Insider” is the percentage ownership of officers and directors. “Block” is the total percentage ownership of the shareholders who own at least 5% of the firm’s equity. “Institution” is the percentage ownership of financial institutions. “Big Five”=1 if the independent auditor is one of the biggest five accounting firms, and 0 if otherwise. “Opinion” goes from 1 (best) to 5 (worst). “B-Independ.” is the fraction of independent directors. “Equity Comp.” is executives’ value of stock and stock option over total compensation.

	Fraud Sample	# of obs.	Nonfraud Sample	# of obs.	Wilcoxon z
Assets(\$10 ⁶)	192 (5515)	631	136 (3538)	68202	5.44**
Market Value(\$10 ⁶)	496 (5102)	535	93 (1764)	56493	15.64**
Sales(\$10 ⁶)	157 (2057)	627	90 (1520)	65696	6.44**
Age	2.89 (7.64)	630	6.25 (8.73)	63338	-9.00**
ROA	0.08 (-0.00)	616	0.05 (-0.06)	66634	8.03**
Res. ROA [1]	-0.01 (-0.07)	545	0.02 (-0.00)	49764	-10.22**
Asset Growth	0.46 (1.09)	563	0.09 (0.36)	61470	20.03**
B-M	0.50 (0.53)	521	0.77 (0.74)	53270	-14.90**
EF. Growth	0.41 (1.08)	562	0.07 (0.39)	59819	17.94**
EF. CF.	0.19 (0.23)	551	0.04 (0.03)	59893	19.05**
Leverage	0.10 (0.17)	626	0.11 (0.18)	66873	0.45
ST Debt	0.27 (0.36)	561	0.24 (0.35)	59676	1.12
R&D	0.00 (0.05)	632	0.00 (0.05)	64389	5.04**
Invest. C.F.	0.11 (0.14)	611	0.06 (0.08)	59165	9.92**
Capital Exp.	0.04 (0.06)	614	0.04 (0.06)	56480	2.06*
Acquis.(cf.)	0.00 (0.04)	579	0.00 (0.02)	54566	15.91**
Acquis.(cf.+stock)	0.01 (0.11)	587	0.00 (0.03)	55785	17.37**
# of Acquis.	0.00 (0.79)	631	0.00 (0.14)	65047	24.07**
Focused Acquis.	0.00 (0.22)	631	0.00 (0.05)	65047	21.72**
Insider	0.15 (0.21)	599	0.09 (0.18)	37526	5.58**
Block	0.35 (0.38)	602	0.26 (0.32)	37569	6.88**
Institution	0.36 (0.39)	572	0.19 (0.26)	37506	11.38**
Big Five	1.00 (0.81)	631	1.00 (0.71)	68202	5.06**
Opinion	1.00 (1.21)	533	1.00 (1.29)	56210	-3.91**
B-Size	2.67 (3.59)	273	4.33 (4.75)	2312	-10.05**
B-Independ.	0.25 (0.29)	273	0.29 (0.34)	2617	-6.30**
Equity Comp.	2.31 (2.31)	223	1.42 (1.52)	12178	9.78**

Table 5.5: **Investment: Fraud Sample vs. Industry-Age Matched Sample**

The control sample is matched with the fraud sample based on two-digit SIC codes and firm ages (the number of years since IPO date).

	Fraud Sample	# of obs.	Control Sample	# of obs.	Wilcoxon z
Age [-1]	2.89 (7.64)	630	2.90 (7.00)	630	0.13
R&D [-2,-1]	0.00 (0.07)	627	0.00 (0.06)	573	2.14*
R&D [0]	0.00 (0.05)	630	0.00 (0.05)	571	2.11*
R&D [1]	0.00 (0.06)	577	0.00 (0.06)	565	2.77**
Capital Exp. [-2,-1]	0.05 (0.06)	608	0.05 (0.06)	552	0.87
Capital Exp. [0]	0.04 (0.06)	614	0.04 (0.06)	548	1.03
Capital Exp. [1]	0.04 (0.06)	560	0.04 (0.06)	545	1.57
Acquis(cf.) [-2,-1]	0.00 (0.03)	589	0.00 (0.02)	544	3.78**
Acquis(cf.) [0]	0.00 (0.04)	579	0.00 (0.02)	536	6.47**
Acquis(cf.) [1]	0.00 (0.03)	553	0.00 (0.02)	523	4.65**
Acquis.(cf.+stock) [-2,-1]	0.01 (0.09)	595	0.00 (0.04)	550	6.53**
Acquis.(cf.+stock) [0]	0.01 (0.11)	587	0.00 (0.05)	542	9.00**
Acquis.(cf.+stock) [1]	0.00 (0.07)	544	0.00 (0.04)	509	5.10**
Invest. C.F. [-2,-1]	0.11 (0.14)	604	0.09 (0.10)	547	3.81**
Invest. C.F. [0]	0.11 (0.14)	611	0.07 (0.10)	537	4.84**
Invest. C.F. [1]	0.07 (0.09)	553	0.07 (0.07)	511	1.67

Table 5.6: **Profitability, Growth, & Fraud**

This table reports the relation between firms' profitability, growth potential, external financing need and their propensity to commit accounting fraud. Probit coefficient estimates/marginal effects and their t -statistics (in parentheses), the Wald Chi-squared statistics and the degree of freedom (in parentheses) are reported. **, * indicate significance at 1 and 5% levels, respectively. ρ is correlation between u and v in equations (1) and (2).

	Model 1		Model 2		Model 3	
	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$
ROA	1.09/0.40 (3.61)**		1.11/0.10 (3.85)**		2.16/0.71 (4.81)**	
Asset Growth	1.81/0.67 (5.27)**					
B-M			-2.03/-0.19 (-10.24)**			
EF. Growth					1.88/0.62 (4.87)**	
Res. ROA	-	-1.16/-0.10 (-6.07)**	-	-5.72/-0.72 (-8.04)**	-	-1.13/-0.09 (-5.16)**
Log(Assets)	-0.03/-0.01 (-0.44)	0.07/0.01 (1.80)	0.27/0.02 (7.97)**	-0.14/-0.02 (-3.87)**	-0.03/-0.01 (-0.41)	0.06/0.01 (1.77)
Age	0.01/0.01 (2.57)*	-0.00/-0.00 (-1.12)	-0.01/-0.00 (-3.35)**	0.02/0.00 (3.38)**	0.01/0.00 (2.49)*	-0.00/-0.00 (-0.98)
Tech.	0.19/0.07 (0.56)	0.25/0.02 (1.76)	-0.28/-0.02 (-2.12)*	0.58/0.09 (5.05)**	0.03/0.01 (0.08)	0.30/0.03 (2.23)*
Service	-0.36/-0.13 (-0.97)	0.24/0.02 (1.46)	-0.16/-0.01 (-1.02)	0.53/0.08 (4.34)**	-0.41/-0.14 (-1.12)	0.26/0.02 (1.62)
Trade	-0.57/-0.22 (-1.40)	0.51/0.06 (2.48)*	0.37/0.04 (2.02)*	0.21/0.03 (1.68)	-0.63/-0.23 (-1.59)	0.51/0.06 (2.63)**
Constant	0.02 (0.02)	-2.26 (-18.97)**	-1.43 (-6.63)**	-1.25 (-4.15)**	0.25 (0.32)	-2.27 (-19.48)**
ρ (p-value)		-0.49 (0.06)		-0.33 (0.05)		-0.56 (0.06)
Log Likelihood		-2431.56		-2201.25		-2415.48
$\chi^2(d.f.)$		112.43 (13)		425.41 (13)		107.44 (13)
# of obs.		50137		45354		49019

Table 5.7: External Financing & Fraud

	Model 4		Model 5		Model 6	
	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$
ROA	0.39/0.07 (2.14)*		1.08/0.39 (3.35)**		1.18/0.45 (3.94)**	
Asset Growth	0.06/0.01 (1.99)*		1.80/0.66 (5.20)**		1.80/0.69 (5.45)**	
EF. C.F.	2.63/0.46 (6.83)**					
Leverage			0.08/0.02 (0.35)			
ST Debt					0.07/0.03 (0.21)	
Res. ROA	-	-3.60/-0.71 (-8.75)**	-	-1.17/-0.10 (-5.70)**	-	-1.29/-0.11 (-6.53)**
Log(Assets)	0.30/0.05 (9.15)**	-0.18/-0.04 (-5.58)**	-0.03/-0.01 (-0.47)	0.07/0.01 (1.82)	-0.03/-0.01 (-0.33)	0.07/0.01 (1.56)
Age	-0.02/-0.00 (-4.03)**	0.02/0.00 (4.45)**	0.01/0.01 (2.59)**	-0.00/-0.00 (-1.11)	0.01/0.01 (2.24)*	-0.00/-0.00 (-0.95)
Tech.	-0.00/-0.00 (-0.02)	0.43/0.10 (3.12)**	0.18/0.07 (0.55)	0.24/0.02 (1.75)	0.21/0.08 (0.58)	0.24/0.02 (1.62)
Service	-0.56/-0.09 (-2.64)**	0.60/0.13 (3.90)**	-0.34/-0.13 (-0.93)	0.24/0.02 (1.44)	-0.36/-0.14 (-0.87)	0.25/0.02 (1.34)
Trade	-0.49/-0.07 (-1.79)	0.72/0.19 (3.12)**	-0.56/-0.22 (-1.39)	0.50/0.06 (2.45)*	-0.57/-0.22 (-1.28)	0.51/0.06 (2.33)*
Constant	-2.51 (-9.67)**	-0.78 (-2.39)*	0.03 (0.04)	-2.25 (-18.75)**	-0.12 (-0.17)	-2.26 (-17.81)**
ρ (p-value)		-0.19 (0.32)		-0.50 (0.08)		-0.45 (0.07)
Log Likelihood		-2335.23		-2424.07		-2417.36
$\chi^2(d.f.)$		352.63 (14)		105.96 (14)		124.91 (14)
# of obs.		49146		49585		49677

Table 5.8: **Investment, Fraud Propensity & Detection**

This table reports the regression results on the relation between investment and fraud. Probit coefficient estimates/marginal effects and their t -statistics (in parentheses), the Wald Chi-squared statistics and the degree of freedom (in parentheses) are reported. **, * indicate significance at 1 and 5% levels, respectively. ρ is correlation between u and v in equations (1) and (2).

	Model 7		Model 8		Model 9	
	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$
ROA	1.74/0.29 (4.86)**		1.84/0.35 (4.97)**		12.71/0.80 (4.48)**	
EF. Growth	1.61/0.27 (3.43)**		1.64/0.31 (3.48)**		2.27/0.67 (4.38)**	
R&D	3.42/0.58 (4.70)**	-1.50/-0.13 (-5.06)**	3.71/0.71 (4.69)**	-1.56/-0.14 (-4.91)**	2.61/0.63 (3.24)**	-1.57/-0.16 (-3.48)**
Invest. CF.	0.99/0.17 (2.27)*	-0.32/-0.03 (-2.10)*				
Capital Exp.			-0.57/-0.11 (-0.48)	0.15/0.01 (0.26)	-0.97/-0.29 (-0.70)	0.26/0.02 (0.46)
Acquis.(cf.)			1.19/0.23 (0.49)	0.38/0.03 (0.52)		
Acquis.(cf.+stock)					2.43/1.06 (2.45)*	0.43/0.03 (1.61)
Res. ROA	-	-1.03/-0.09 (-7.71)**	-	-1.13/-0.10 (-7.42)**	-	-1.44/-0.10 (-4.93)**
Log(Asset)	0.00/0.00 (0.02)	0.04/0.00 (1.18)	-0.01/-0.00 (-0.20)	0.06/0.00 (1.64)	0.05/0.01 (0.58)	0.03/0.00 (1.02)
Age	0.01/0.00 (1.90)	-0.00/-0.00 (-0.75)	0.01/0.00 (2.10)*	-0.00/-0.00 (-0.81)	0.01/0.00 (1.23)	0.00/0.00 (0.24)
Tech	-0.32/-0.06 (-1.18)	0.40/0.04 (3.10)**	-0.24/-0.05 (-0.82)	0.37/0.04 (2.55)*	-0.19/-0.06 (-0.53)	0.37/0.03 (3.12)**
Service	-0.25/-0.04 (-0.86)	0.24/0.02 (1.67)	-0.23/-0.05 (-0.82)	0.24/0.02 (1.44)	-0.36/-0.11 (-1.08)	0.30/0.02 (2.29)*
Trade	-0.56/-0.12 (-1.68)	0.46/0.05 (2.58)**	-0.49/-0.12 (-1.44)	0.44/0.05 (2.31)*	-0.28/-0.09 (-0.71)	0.32/0.03 (1.89)
Constant	0.65 (1.18)	-2.06 (-15.07)**	0.69 (1.25)	-2.14 (-14.94)**	-0.19 (-0.17)	-2.23 (-15.21)**
ρ (p-value)		-0.80 (0.00)		-0.79 (0.00)		-0.54 (0.19)
Log Likelihood		-2300.92		-2187.11		-2099.20
$\chi^2(d.f.)$		134.03 (17)		129.77 (19)		114.44 (19)
# of obs.		43920		41482		41930

Table 5.9: Investment, Fraud Propensity & Detection (Continued)

	Model 10		Model 11	
	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$
ROA	1.75/0.25 (3.45)**		1.77/0.22 (3.87)**	
EF. Growth	1.80/0.25 (3.00)**		1.83/0.23 (2.90)**	
R&D	3.11/0.44 (2.69)**	-1.37/-0.10 (-3.14)**	3.34/0.42 (3.35)**	-1.42/-0.09 (-3.88)**
Invest. CF.	0.80/0.11 (1.66)	-0.31/-0.02 (-1.96)*	1.09/0.14 (2.29)*	-0.41/-0.03 (-2.46)*
# of Acquis	0.36/0.05 (1.63)	0.09/0.01 (4.60)**	0.34/0.04 (1.58)	0.07/0.01 (3.47)**
Focused Acquis			-0.73/-0.09 (-2.67)**	0.37/0.02 (3.80)**
Res. ROA	-	-1.04/-0.07 (-4.87)**	-	-1.02/-0.07 (-6.22)**
Log(Asset)	0.15/0.02 (1.62)	-0.03/-0.00 (-1.04)	0.17/0.02 (1.82)	-0.03/-0.00 (-1.28)
Age	-0.00/-0.00 (-0.45)	0.00/0.00 (0.80)	-0.00/-0.00 (-0.29)	0.00/0.00 (0.70)
Tech.	-0.64/-0.11 (-2.57)*	0.51/0.05 (5.27)**	-0.59/-0.09 (-2.20)*	0.49/0.04 (4.83)**
Service	-0.57/-0.09 (-1.79)	0.33/0.03 (2.99)**	-0.61/-0.09 (-1.84)	0.35/0.03 (3.16)**
Trade	-0.76/-0.16 (-2.11)*	0.50/0.05 (3.10)**	-0.98/-0.21 (-2.56)*	0.59/0.06 (3.44)**
Constant	0.21 (0.20)	-1.94 (-14.84)**	0.23 (0.28)	-1.96 (-16.00)**
ρ (p-value)		-0.75 (0.07)		-0.75 (0.02)
Log Likelihood		-2262.09		-2252.92
$\chi^2(d.f.)$		164.86 (19)		209.68 (21)
# of obs.		43920		43920

Table 5.10: Insider Equity Incentive, Corporate Monitoring & Fraud

	Model 12		Model 13		Model 14	
	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$
ROA	2.06/0.82 (5.05)**		2.11/0.81 (5.76)**		2.87/1.14 (3.80)**	
EF. Growth	1.63/0.65 (4.97)**		1.75/0.68 (6.90)**		2.09/0.84 (2.53)*	
R&D	3.32/1.32 (3.52)**	-2.11/-0.28 (-4.53)**	2.83/1.09 (2.83)**	-1.89/-0.25 (-3.96)**	1.77/0.71 (1.50)	-2.40/-0.20 (-2.46)*
Invest. CF.	1.70/0.67 (2.90)**	-0.54/-0.07 (-2.26)*	1.50/0.58 (2.50)*	-0.69/-0.09 (-2.82)**	1.63/0.65 (1.98)*	-1.08/-0.18 (-2.04)*
Insider	1.72/0.68 (2.90)**		1.81/0.70 (2.96)**			
(Insider) ²	-2.45/-0.97 (-3.00)**		-2.28/-0.88 (-2.68)**			
Equity Comp.					2.35/0.94 (2.45)*	
(Equity Comp.) ²					-2.17/-0.86 (-1.88)	
Block	-1.02/-0.40 (-2.40)*	0.84/0.11 (3.71)**				
Institution			-0.69/-0.27 (-2.03)*	1.08/0.14 (6.39)**	-0.68/-0.27 (-1.25)	0.35/0.06 (1.08)
Res. ROA	-	-1.98/-0.27 (-7.20)**	-	-2.06/-0.28 (-5.93)**	-	-3.42/-0.60 (-5.83)**
Log(Asset)	0.26/0.10 (3.81)**	-0.06/-0.01 (-1.71)	0.23/0.09 (4.07)**	-0.08/-0.01 (-2.86)**	0.11/0.05 (1.31)	-0.05/-0.01 (-1.02)
Age	-0.01/-0.00 (-1.17)	0.01/0.00 (1.66)	0.00/0.00 (0.04)	0.00/0.00 (0.71)	0.01/0.00 (1.49)	0.01/0.00 (2.86)**
Tech.	-0.29/-0.11 (-1.07)	0.60/0.10 (4.66)**	0.03/0.01 (0.10)	0.40/0.06 (2.66)**	0.21/0.08 (0.43)	0.43/0.09 (1.57)
Service	-0.59/-0.23 (-1.98)*	0.59/0.10 (4.06)**	-0.32/-0.12 (-0.99)	0.50/0.08 (2.98)**	-0.21/-0.08 (-0.40)	0.79/0.18 (2.75)**
Trade	-0.74/-0.27 (-2.33)*	0.65/0.12 (3.59)**	-0.76/-0.26 (-2.23)*	0.73/0.14 (3.44)**	-1.05/-0.38 (-1.79)	1.16/0.31 (2.48)*
Constant	-1.59 (-2.66)**	-1.75 (-8.73)**	-2.01 (-3.32)**	-1.54 (-8.94)**	-1.66 (-1.80)	-1.53 (-3.40)**
ρ (p-value)		-0.39 (0.05)		-0.36 (0.11)		-0.51 (0.02)
Log Likelihood		-1999.62		-1923.87		-765.64
$\chi^2(d.f.)$		256.28 (21)		236.42 (21)		115.10 (21)
# of obs.		29439		29330		8747

Table 5.11: Independent Auditor, Corporate Board & Fraud

	Model 15		Model 16		Model 17	
	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$
ROA	2.08/0.83 (5.00)**		1.72/0.63 (2.46)*		1.79/0.69 (2.56)*	
EF. Growth	1.63/0.65 (5.38)**		3.64/1.35 (4.89)**		3.60/1.38 (4.56)**	
R&D	3.33/1.33 (3.27)**	-2.04/-0.24 (-4.39)**	5.28/1.95 (3.05)**	-3.14/-1.24 (-2.58)**	5.21/2.00 (3.12)**	-3.01/-1.18 (-2.58)**
Invest. CF.	1.67/0.66 (2.84)**	-0.53/-0.06 (-2.25)*	1.42/0.52 (1.71)	-0.81/-0.32 (-1.46)	1.45/0.56 (1.71)	-0.78/-0.30 (-1.43)
Insider	1.61/0.64 (2.53)*		1.21/0.45 (1.03)		1.58/0.61 (1.33)	
(Insider) ²	-2.38/-0.95 (-2.69)**		1.45/0.54 (0.76)		0.96/0.37 (0.51)	
Block	-1.04/-0.41 (-2.26)*	0.79/0.09 (3.44)**	-0.26/-0.09 (-0.61)	0.26/0.10 (0.66)	-0.24/-0.09 (-0.58)	0.19/0.08 (0.50)
Big Five	-0.04/-0.01 (-0.16)	0.30/0.03 (1.94)				
Opinion		-0.01/-0.00 (-0.12)				
B-Size			-0.02/-0.01 (-0.35)	0.10/0.04 (1.91)		
B-Independ.					-0.78/-0.30 (-0.98)	0.36/0.14 (0.48)
Res. ROA	-	-1.94/-0.23 (-7.01)**	-	-2.28/-0.90 (-3.90)**	-	-2.16/-0.85 (-3.96)**
Log(Asset)	0.26/0.10 (3.79)**	-0.07/-0.01 (-2.19)*	0.09/0.03 (0.65)	-0.36/-0.14 (-5.61)**	0.08/0.03 (0.70)	-0.30/-0.12 (-5.82)**
Age	-0.01/-0.00 (-1.66)	0.01/0.00 (1.78)	0.01/0.00 (1.78)	0.00/0.00 (0.69)	0.01/0.00 (1.70)	0.00/0.00 (0.62)
Tech.	-0.22/-0.09 (-0.76)	0.53/0.08 (3.82)**	0.09/0.03 (0.21)	0.49/0.19 (1.92)	-0.02/-0.01 (-0.05)	0.51/0.20 (1.91)
Service	-0.43/-0.17 (-1.33)	0.47/0.07 (3.05)**	-0.32/-0.11 (-0.52)	1.43/0.51 (4.51)**	-0.50/-0.18 (-0.96)	1.52/0.54 (4.52)**
Trade	-0.69/-0.25 (-1.99)*	0.60/0.10 (3.07)**	-0.88/-0.27 (-1.28)	1.83/0.58 (3.02)**	-1.06/-0.33 (-1.78)	1.86/0.59 (3.06)**
Constant	-1.52 (-2.32)*	-1.97 (-8.18)**	-2.01 (-3.52)**	1.34 (2.70)**	-2.08 (-3.55)**	1.21 (2.68)**
ρ (p-value)		-0.38 (0.42)		-0.30 (0.56)		-0.38 (0.35)
Log Likelihood		-1833.71		-481.81		-482.16
$\chi^2(d.f.)$		229.88 (24)		109.18 (23)		105.99 (23)
# of obs.		29225		2186		2186

Table 5.12: **Bivariate Probit Model vs. Straight Probit Model**

This table compares the results from the following two statistical models:

Bivariate probit model: $P(Z_i = 1) = P(F_i = 1)P(D_i = 1)$;

Straight probit model: $P(Z_i = 1) = P(F_i = 1)$.

Both models are estimated using a random comparison sample without repetition. That is, every comparison firm only enters the estimation once. The probit coefficient estimates/marginal effects and their t-statistics (in parentheses), the Wald Chi-squared statistics and the degree of freedom (in parentheses) are reported. **, * indicate significance at 1 and 5% levels, respectively. ρ is correlation between u and v in equations (1) and (2).

	Probit		Bivariate Probit	
	$P(F)$	$P(F)$	$P(F)$	$P(D F)$
ROA	1.04/0.18 (4.16)**	2.34/0.65 (5.45)**		
EF. Growth	0.24/0.04 (6.97)**	2.65/0.74 (5.41)**		
R&D	-0.49/-0.08 (-1.17)	3.51/1.29 (3.42)**	-2.71/-0.97 (-4.72)**	
Invest. CF.	0.59/0.10 (2.59)**	1.46/0.43 (2.59)**	-0.80/-0.25 (-2.54)**	
Insider Own	1.56/0.27 (3.74)**	2.33/0.71 (2.44)*		
(Insider) ²	-1.74/-0.30 (-2.88)**	-2.74/-0.84 (-2.70)**		
Institution	0.98/0.17 (7.58)**	-0.61/-0.20 (-1.96)*	1.30/0.48 (5.82)**	
Res. ROA	-2.12/-0.36 (-8.09)**	-	-2.94/-0.85 (-6.31)**	
Log(Asset)	0.04/0.01 (2.18)*	0.28/0.07 (4.12)**	-0.11/-0.03 (-2.86)**	
Age	0.00/0.00 (1.13)	0.00/0.00 (0.26)	0.01/0.00 (2.03)*	
Tech.	0.53/0.11 (6.17)**	0.13/0.04 (0.44)	0.41/0.17 (2.13)*	
Service	0.43/0.08 (5.34)**	-0.17/-0.07 (-0.55)	0.50/0.17 (2.48)**	
Trade	0.27/0.05 (2.73)**	-0.53/-0.30 (-1.61)	0.66/0.37 (2.58)**	
Constant	-2.39 (-17.78)**	-2.26 (-4.32)**	-0.44 (-1.88)	
ρ (p-value)			-0.49 (0.03)	
Log Likelihood	-1100.36		-1007.66	
$\chi^2(d.f.)$	275.66 (13)		219.26 (21)	
# of obs.	3336		3336	

Table 5.13: **Frivolous Lawsuits**

This table presents robustness checks of the main results over three subsamples: (1) 334 out of 660 firms that announced accounting restatements before or after the lawsuits; (2) 207 out of 660 firms that were subject to both private class action litigation and the SEC's Accounting and Auditing Enforcement; (3) exclusion of 27 nuisance cases. A case is considered as a nuisance case if it is later dismissed by the court or if it leads to a less than two million dollar settlement. The probit coefficient estimates/marginal effects and their t-statistics (in parentheses), the Wald Chi-squared statistics and the degree of freedom (in parentheses) are reported. **, * indicate significance at 1 and 5% levels, respectively. ρ is correlation between u and v in equations (1) and (2).

	Restatements		SEC Enforcement		Non-Nuisance Suits	
	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$
ROA	2.55/0.66 (4.39)**		2.40/0.66 (3.62)**		1.99/0.77 (5.60)**	
EF. Growth	1.89/0.49 (5.48)**		1.45/0.40 (3.55)**		1.67/0.64 (6.84)**	
R&D	3.31/0.86 (3.33)**	-2.01/-0.14 (-3.83)**	3.18/0.87 (1.98)*	-2.25/-0.14 (-2.11)*	2.81/1.08 (2.49)**	-1.90/-0.25 (-3.49)**
Invest. C.F.	1.97/0.51 (2.78)**	-0.53/-0.04 (-1.96)*	2.00/0.55 (1.84)	-0.96/-0.06 (-2.00)*	1.31/0.51 (2.02)*	-0.68/-0.09 (-2.51)*
Insider	1.91/0.50 (2.09)*		1.83/0.50 (1.60)		1.78/0.69 (2.96)**	
(Insider) ²	-2.27/-0.59 (-1.82)		-2.58/-0.71 (-1.40)		-2.22/-0.85 (-2.62)**	
Institution	-0.63/-0.16 (-1.50)	1.11/0.08 (5.49)**	-0.88/-0.24 (-0.99)	1.21/0.08 (2.93)**	-0.73/-0.28 (-2.02)*	1.12/0.15 (6.38)**
Res. ROA	-	-2.47/-0.17 (-7.07)**	-	-2.31/-0.15 (-4.49)**	-	-2.05/-0.27 (-5.19)**
Log(Asset)	0.18/0.05 (1.83)	-0.05/-0.00 (-0.99)	0.09/0.03 (0.66)	-0.01/-0.00 (-0.09)	0.23/0.09 (4.06)**	-0.08/-0.01 (-2.79)**
Age	0.01/0.00 (0.97)	0.00/0.00 (0.20)	0.01/0.00 (1.38)	-0.00/-0.00 (-0.65)	0.00/0.00 (0.14)	0.00/0.00 (0.74)
Tech.	0.14/0.04 (0.37)	0.35/0.03 (1.75)	0.45/0.13 (1.01)	-0.01/-0.00 (-0.02)	0.05/0.02 (0.16)	0.39/0.06 (2.46)*
Service	-0.17/-0.4 (-0.38)	0.26/0.02 (1.15)	0.17/0.05 (0.17)	-0.15/-0.01 (-0.23)	-0.31/-0.12 (-0.95)	0.50/0.08 (2.72)**
Trade	-0.74/-0.14 (-1.65)	0.73/0.08 (2.82)**	-0.21/-0.05 (-0.26)	0.26/0.02 (0.48)	-0.76/-0.26 (-2.20)*	0.74/0.15 (3.28)**
Constant	-2.62 (-4.17)**	-2.06 (-9.04)**	-2.20 (-1.83)	-1.98 (-6.82)**	-1.96 (-3.15)**	-1.55 (-8.78)**
ρ (p-value)		0.02 (0.93)		-0.15 (0.72)		-0.37 (0.11)
Log Likelihood		-1141.10		-740.56		-1859.72
$\chi^2(d.f.)$		196.18 (21)		113.22 (21)		239.00 (21)
# of obs.		29117		29021		29312

Table 5.14: **Different Model Specifications**

This table presents robustness checks of the main results across different model specifications. “Ind. Lit” is the logarithm of the total market value of fraudulent firms in an industry in year -1. “Cycle”=-1 for years between 1992 and 1994 and between 2001 and 2002 (bust), =0 for years between 1995 and 1997, and =1 for years between 1998 and 2000 (boom).

	Specification 2		Specification 3		Specification 4	
	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$	$P(F)$	$P(D F)$
ROA	1.90/0.75 (4.93)**		1.61/0.64 (2.66)**		0.39/0.04 (1.97)*	
EF. Growth	1.56/0.62 (5.42)**		1.34/0.53 (2.52)*	-0.03/-0.00 (-0.67)	0.55/0.06 (2.27)*	
R&D	3.07/1.22 (2.98)**	-1.93/-0.23 (-3.79)**	2.78/1.10 (2.78)**	-1.97/-0.29 (-3.10)**	2.34/0.26 (3.69)**	-1.56/-0.20 (-4.20)**
Invest. C.F.	1.68/0.67 (2.92)**	-0.60/-0.07 (-2.49)*	1.58/0.63 (2.53)**	-0.66/-0.10 (-1.80)	1.02/0.11 (3.39)**	-0.65/-0.08 (-3.37)**
Insider	1.71/0.68 (2.88)**		2.45/0.97 (3.26)**	-0.59/-0.09 (-1.85)	0.44/0.05 (1.98)*	
(Insider) ²	-2.41/-0.96 (-2.95)**		-2.31/-0.91 (-2.91)**		-0.65/-0.07 (-1.93)	
Block	-1.00/-0.40 (-2.21)*	0.78/0.09 (3.24)**	-1.31/-0.52 (-2.65)**	1.04/0.15 (2.76)**	-0.75/-0.08 (-1.98)*	0.71/0.09 (2.26)*
Ind. Lit. (*10 ³)	-0.77/-0.31 (-0.99)	0.70/0.08 (1.75)	-1.00/-0.40 (-1.20)	0.90/0.13 (1.64)	-0.97/-0.11 (-2.02)*	0.89/0.12 (2.54)*
Cycle	-0.21/-0.08 (-1.73)	0.31/0.04 (5.70)**	-0.19/-0.07 (-1.19)	0.30/0.04 (4.34)**	-0.38/-0.04 (-6.05)**	0.38/0.05 (7.00)**
Res. ROA	-	-1.89/-0.23 (-6.43)**	-	-1.86/-0.28 (-5.88)**	-	-
Log(Asset)	0.26/0.10 (3.46)**	-0.05/-0.01 (-1.48)	0.28/0.11 (2.60)**	-0.08/-0.01 (-1.00)	0.04/0.00 (0.83)	0.00/0.00 (0.04)
Age	-0.01/-0.00 (-1.04)	0.01/0.00 (1.50)	-0.01/-0.00 (-0.70)	0.01/0.00 (0.91)	0.00/0.00 (0.16)	0.00/0.00 (0.06)
Tech	-0.24/-0.10 (-0.93)	0.52/0.08 (3.96)**	-0.24/-0.10 (-1.01)	0.52/0.09 (3.71)**	-0.43/-0.06 (-2.36)*	0.46/0.07 (3.28)**
Service	-0.54/-0.21 (-1.81)	0.52/0.08 (3.51)**	-0.54/-0.21 (-1.90)	0.53/0.10 (2.91)**	-0.50/-0.07 (-2.61)**	0.48/0.08 (3.24)**
Trade	-0.82/-0.31 (-2.51)*	0.67/0.12 (3.66)**	-0.84/-0.32 (-2.73)**	0.73/0.15 (3.45)**	-0.81/-0.14 (-3.49)**	0.72/0.14 (3.77)**
Constant	-1.21 (-1.79)	-1.92 (-9.05)**	-1.21 (-1.85)	-1.63 (-3.26)**	1.71 (5.18)**	-2.05 (-11.09)**
ρ (p-value)		-0.45 (0.04)		-0.55 (0.02)		-0.99 (0.00)
Log Likelihood		-1959.12		-1955.92		-2183.13
$\chi^2(d.f.)$		291.98 (25)		311.90 (27)		336.68 (24)
# of obs.		29439		29439		31696

Figure 3: Determination of the Beginning Fiscal Year of Fraud

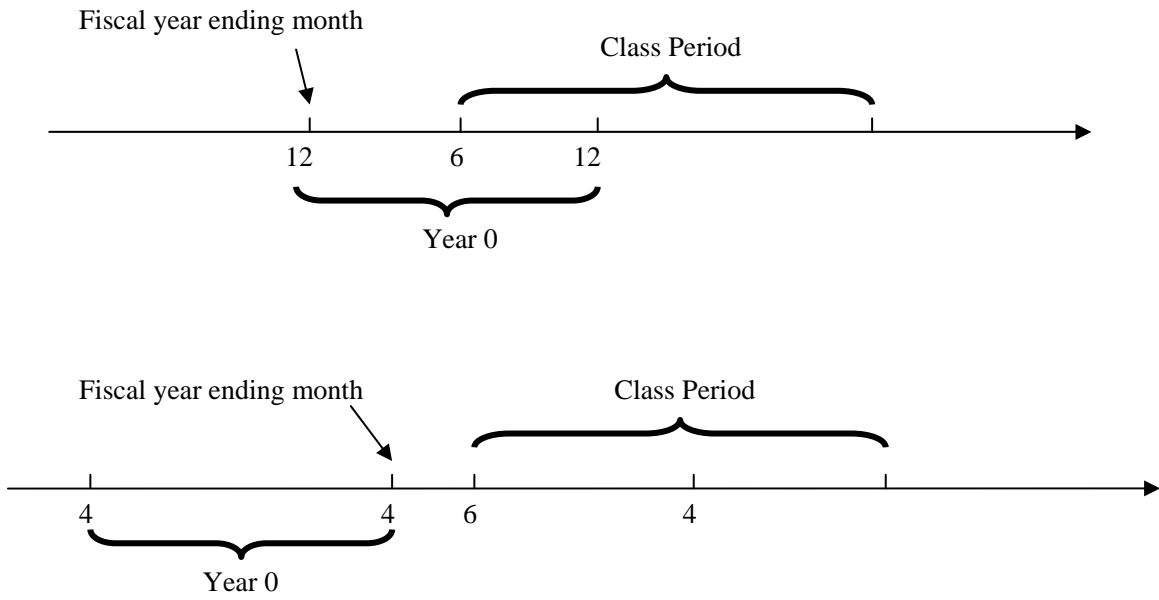


Figure 4: Identification Problem

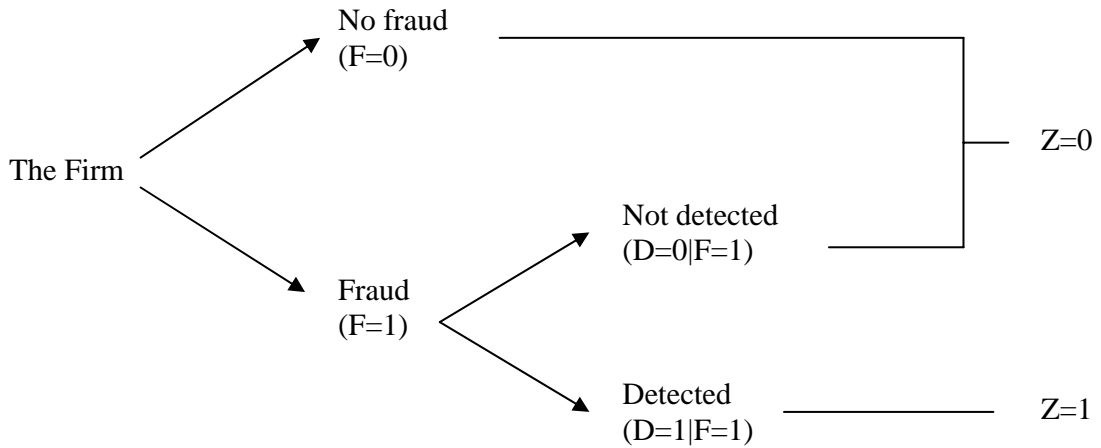
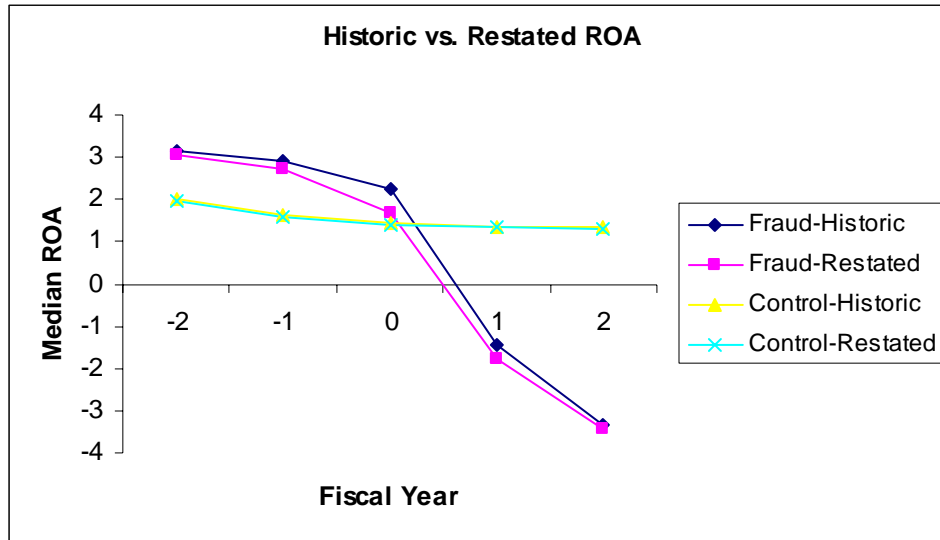


Figure 5: Timing of Fraud



Note: ROA is the ratio of net income over total assets. I use net income because the restated information on this variable is more complete than the one on other accounting measures such as income before extraordinary items and operating income. The purpose here is to compare the originally reported data with the restated data.

Chapter 6

Conclusion

This thesis analyzes corporate securities fraud and its consequences. The theory model shows that fraud can lead to investment distortions in both fraudulent firms and honest firms, which is the real economic cost of fraud. The investment distortion is twofold. On one hand, fraud can inflate short-term firm value and allow the firm to invest using cheap outside capital. On the other hand, once committed fraud, the firm has incentive to strategically use investment to mask fraud. The incentive to disguise fraud can not only induce the firm to overinvest, but also gives the firm a preference for risk and suboptimal diversification.

The theory model also characterizes the endogenous cost-benefit tradeoff of committing fraud and derives the firm's equilibrium disclosure strategy. The model shows that the cost and benefit of fraud are endogenously related, which results in the optimal size of fraud and the firm's equilibrium fraud propensity. In particular, the theory demonstrates the important role of the endogenous detection risk in determining the cross-sectional variations in firms' fraud incentives.

The model generates testable implications about the economic determinants of cross-sectional differences in fraud propensities and the relationship between fraud and corporate investment incentives. The theory predicts that fraudulent firms tend to have good growth prospects, but experience negative profitability shocks. Litigation events tend to cluster in certain industries during some specific time period. The theory also predicts that fraudulent firms tend to overinvest. Investment can negatively influence the firm's litigation risk. The type of investment that introduces the most valuation imprecision has the strongest effect on the likelihood of fraud detection. The investment, however, can be inefficient and can result in long-term underperformance of fraudulent firms.

I also empirically investigate the economic determinants of firms' propensity to commit accounting fraud and the probability of fraud detection, using a sample of public companies that

were subject to federal private securities class action litigation between 1996 and 2003. I use econometric methods to control for the unobservability of undetected frauds, and 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 separation of fraud commitment and fraud detection allows me to examine the economics of each probability as well as their interactions.

The results of this study show that investment, strength of corporate monitoring, insider equity incentives, and some firm characteristics significantly influence a firm's cost-benefit tradeoff of engaging in fraud. First, the level, type, and financing of investment types of investment all matter in determining a firm's ex-post probability of fraud detection and ex-ante propensity to commit fraud. Second, different types of corporate monitors have different effects on firms' fraud incentives. The presence of block equity holders and large institutional ownership tends to increase the likelihood of fraud detection and discourage fraud. The roles of independent auditors and board of directors appear to be weaker. Third, there is a concave relation between insider equity incentive and the probability of fraud. When insider equity incentive is small, increasing equity incentive can have the unintended effect of increasing the probability of fraud. When insider equity incentives is already large, such effect disappears. This implies that insider equity incentive can be a double-edged sword when it is used to align managerial and shareholder interests in dispersely-owned firms. Finally, high growth potential, large external financing need, and (hidden) negative profitability shocks seem to be important motivational factors for fraud.

This study 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 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.

Chapter 7

Appendix: Proofs of Propositions

Proof of Proposition 1

The market value of the firm at time 2 after the investment announcement is

$$\begin{aligned} V_2(I, y) &= E(V_3|I, y) = E(A|I, y) + IE(R|I), \\ E(R|I) &= E(R|R > r_c) = \bar{R} + I\sigma_R m(z_c), \\ z_c &= (r_c - \bar{R})/\sigma_R, \\ m(z_c) &= \frac{\phi(z_c)}{1 - \Phi(z_c)}. \end{aligned}$$

The investment condition is

$$(1 - \beta)[E(\tilde{A}|e) + Ir] - P_I f \eta > E(\tilde{A}|e) - P_N f \eta, \quad (7.1)$$

where $\beta = I/V_2(I, y)$. Solving for r , we get

$$r > \frac{E(\tilde{A}|e)}{E(\tilde{A}|I, y) + I\sigma_R m(z_c)} - \frac{(P_N - P_I)f\eta}{(1 - \beta)I}. \quad (7.2)$$

This leads to equation (4.23). The left-hand side of equation (4.23) monotonically increases in r_c , while the right-hand side monotonically decreases in r_c . Therefore, there exists a unique solution to equation (4.23), r_c^* .

Proof of Proposition 2

$P_I < P_N$ if and only if $\Phi_I < \Phi_N$, or equivalently $v_{c,I} + K_I < v_{c,N} + K_N$. $v_{c,I} + K_I$ is a function of $I\sigma_R$, while $v_{c,N} + K_N$ is not. Let $M = \bar{e} + C/f - y$, and $\rho_I = \text{cov}(e, V_3|I)/(\sigma_e \sqrt{\text{Var}(V_3|I)})$. Take the derivative of $v_{c,I} + K_I$ with respect to $I\sigma_R$.

$$\frac{\partial(v_{c,I} + K_I)}{\partial(I\sigma_R)} = \frac{\partial v_{c,I}}{\partial(I\sigma_R)} + \frac{\partial K_I}{\partial(I\sigma_R)} \quad (7.3)$$

$$= \frac{M}{\sigma_e \rho_I^2} \frac{\partial \rho_I}{\partial(I\sigma_R)} + [E(V_3|y) - E(V_3|e)] \frac{\partial \nu_I}{\partial(I\sigma_R)}. \quad (7.4)$$

If $\max(-1, -\frac{\sigma_e}{qI\sigma_R}) < \rho < \frac{\sqrt{\sigma_u^4 + (2q\sigma_e I\sigma_R)^2} - \sigma_u^2}{2q\sigma_e I\sigma_R} < 1$, then $\frac{\partial \nu_I}{\partial(I\sigma_R)} < 0$ and $\frac{\partial \rho_I}{\partial(I\sigma_R)} < 0$, and therefore $\frac{\partial(v_{c,I} + K_I)}{\partial(I\sigma_R)} < 0$. If $\frac{\sqrt{\sigma_u^4 + (2q\sigma_e I\sigma_R)^2} - \sigma_u^2}{2q\sigma_e I\sigma_R} \leq \rho \leq 1$, then $\frac{\partial \nu_I}{\partial(I\sigma_R)} > 0$ but $\frac{\partial \rho_I}{\partial(I\sigma_R)} < 0$. Therefore, there exists $\bar{\rho} \in [\frac{\sqrt{\sigma_u^4 + (2q\sigma_e I\sigma_R)^2} - \sigma_u^2}{2q\sigma_e I\sigma_R}, 1]$ such that when $\max(-1, -\frac{\sigma_e}{qI\sigma_R}) < \rho < \bar{\rho}$, $\frac{\partial(v_{c,I} + K_I)}{\partial(I\sigma_R)} < 0$. Since $v_{c,N} + K_N$ does not depend on $I\sigma_R$ and $v_{c,I} + K_I$ decreases with $I\sigma_R$, there exists a cutoff value $\overline{I\sigma_R}$, such that when $I\sigma_R \geq \overline{I\sigma_R}$, $v_{c,I} + K_I \leq v_{c,N} + K_N$.

Proof of Proposition 3

Note that $E(A|I, y) + I\sigma_R m(z_c) = V_2(I, y) - I$. Let us take derivative with respect to η on both sides of equation (4.23).

$$\begin{aligned} \frac{\partial r_c}{\partial \eta} &= -\frac{E(A|e)}{[V_2(I, y) - I]^2} \frac{\partial V_2(I, y)}{\partial \eta} - \frac{(P'_N - P'_I)f\eta + (P_N - P_I)f}{(1 - \beta)I} \\ &\quad - \frac{(P_N - P_I)f\eta(-\partial\beta/\partial\eta)}{(1 - \beta)^2 I}. \end{aligned} \quad (7.5)$$

$$P'_N - P'_I = \frac{\partial P_N}{\partial \eta} - \frac{\partial P_I}{\partial \eta} = (1 - p)(\phi_N \nu_N - \phi_I \nu_I) \frac{\partial V_2(I, y)}{\partial \eta},$$

where $\phi = \partial\Phi(s)/\partial s$.

$\beta = \frac{I}{V_2(I, y)}$ is the fractional ownership of the new shareholders. $V_2(I, y)$ does not directly depend on η , since the market does not observe η . From the manager's point of view, however, what is important is how much $V_2(I, y)$ will be different from $V_2(I, e)$ if the manager reports one more unit of earnings above the true realization e . So let us define

$$\frac{\partial V_2(I, y)}{\partial \eta} = \lim_{(y-e) \rightarrow 0} \frac{V_2(I, y) - V_2(I, e)}{y - e}. \quad (7.6)$$

Then

$$\frac{\partial \beta}{\partial \eta} = \frac{I}{V_2(I, y)^2} \left(-\frac{\partial V_2(I, y)}{\partial \eta} \right). \quad (7.7)$$

If $y(e) \neq e$ does not generate any effect on the market valuation (i.e., $V_2(I, y) = V_2(I, e)$), then $\partial\beta/\partial\eta = 0$.

As long as misreporting can increase the market value of the firm's assets, i.e., $\frac{\partial V_2(I, y)}{\partial \eta} \geq 0$, then $\partial\beta/\partial\eta < 0$. Substitute these relations into (7.5), and we have $\frac{\partial r_c}{\partial \eta} < 0$.

Proof of Proposition 4

The first-order condition for the maximization problem (4.20) is

$$\frac{\partial \Pi}{\partial \eta} + g = 0; \quad (7.8)$$

$$g\eta = 0, \quad (7.9)$$

where g is the Lagrange multiplier for the nonnegativity constraint on η .

$$\begin{aligned} \frac{\partial \Pi}{\partial \eta} &= \lambda \left(-\frac{\phi_z}{\sigma_R} \frac{\partial r_c}{\partial \eta} \right) [(1 - \beta)E(V_3|I, e) - E(V_3|N, e)] \\ &+ \lambda [1 - \Phi(z_c)] \left[\left(-\frac{\partial \beta}{\partial \eta} \right) E(V_3|I, e) + (1 - \beta)Im'(z_c) \frac{\partial r_c}{\partial \eta} \right] \\ &- \left\{ \lambda \frac{\phi_z}{\sigma_R} \frac{\partial r_c}{\partial \eta} (P_N - P_I) + \lambda [1 - \Phi(z_c)] P_I' + (1 - \lambda [1 - \Phi(z_c)]) P_N' \right\} f\eta \\ &- Pf. \end{aligned} \quad (7.10)$$

The following steps present the derivations of the equilibrium strategy specified in Proposition 4.

Step 1: A Conjecture. Suppose that there exists a cutoff earnings realization e_c such that the manager will honestly reveal the earnings if the true earnings realization is above e_c , and the manager would like to overreport earnings if the true realization is below e_c . Mathematically,

$$y(e) = e \text{ or } \eta(e) = 0, \quad \text{if } e \geq e_c;$$

$$y(e) > e \text{ or } \eta(e) > 0, \quad \text{if } e < e_c.$$

Given the above conjecture about the manager's fraud incentives, the market's reaction to an earnings announcement can be as follows. When investors observe the announced earnings $y(e)$, they rationally infer $e' = y(e) - \bar{\eta}$, using their prior belief about the probability of misreporting π_0 . $\bar{\eta}$ is the market's expected amount of misreporting. The time 1 conditional probability of fraud is $\pi_1 = \text{Prob.}(\text{misreporting} | y \geq e_c)$. Therefore, whenever $y \geq e_c$, investors believe that

$$e' = y > e_c, \text{ with probability } (1 - \pi_1);$$

$$e' = y - \bar{\eta}_1 < e_c, \text{ with probability } \pi_1.$$

When investors observe $y < e_c$, they rationally discount the earnings announcement, and $e' = y - \bar{\eta}_2$. Then the market value of the firm's assets in place after the earnings announcement is

$$V_1(y \geq e_c) = (1 - \pi_1)E(\tilde{A}|e' = y) + \pi_1 E(\tilde{A}|e' = y - \bar{\eta}_1); \quad (7.11)$$

$$V_1(y < e_c) = E(\tilde{A}|e' = y - \bar{\eta}_2). \quad (7.12)$$

$\bar{\eta}_1$ and $\bar{\eta}_2$ are the market's expected amount of misreporting given $y \geq e_c$ and $y < e_c$, respectively. In equilibrium, they should be equal to the manager's optimal choice of misreporting in the two earnings announcement scenarios.

$\eta \geq 0$ and the structure of litigation cost of fraud naturally leads to a conjecture that $\eta(e)$ is monotonic in e in each different region specified above. This does not imply, however, that $y(e)$ is always monotonic in e (due to the pooling of the two types of firm). Then in each of the two scenarios (fraud or honest) there is a one-for-one mapping between e and $y(e)$. This implies that under each scenario, $e' = y(e) - \bar{\eta}$ is still normally distributed. Therefore, given the true realization of earnings e , when $y \geq e_c$,

$$\frac{\partial V_2(I, y)}{\partial \eta} = \delta(1 - \pi_1) > 0. \quad (7.13)$$

When $y < e_c$,

$$\frac{\partial V_2(I, y)}{\partial \eta} = 0. \quad (7.14)$$

Step 2: Deriving e_c . Let us plug equation (7.13) and (7.14) into (7.10) and differentiate with respect to η on both sides. Then use the following relationships:

$$\begin{aligned} \frac{\partial r_c}{\partial \eta} &< 0; \\ P'_N &= (1 - p)\delta(1 - \pi_1)\phi_N\nu_N > 0; \\ P''_N &= (1 - p)\delta(1 - \pi_1)\phi_N|v_{c,N} + K_N|\nu_N > 0; \\ P'_I &= (1 - p)\delta(1 - \pi_1)\phi_I\nu_I > 0; \\ P''_I &= (1 - p)\delta(1 - \pi_1)\phi_I|v_{c,I} + K_I|\nu_I > 0, \end{aligned}$$

we can find that

$$\frac{\partial^2 \Pi}{\partial \eta^2} < 0.$$

This means that the objective function is globally concave. There exists a unique maximizer $\eta^* = \eta_1^*$. The concavity and the nonnegative η constraint imply that

$$\begin{aligned} \frac{\partial \Pi}{\partial \eta} \Big|_{\eta=0} > 0 &\Rightarrow \eta_1^* > 0, \\ \frac{\partial \Pi}{\partial \eta} \Big|_{\eta=0} \leq 0 &\Rightarrow \eta_1^* = 0. \end{aligned}$$

I define the following notations. $\beta_0 = \beta(y = e) = I/V_2(I, e)$, $r_{c,0} = r_c(\eta = 0)$, $z_{c,0} = (r_{c,0} - \bar{R})/\sigma_R$, $\phi_0 = \phi(z_{c,0})$, $\Phi_0 = \Phi(z_{c,0})$, and $m_0 = m(z_{c,0})$. Then plug $\eta = 0$ into equation (7.10), and we have

$$\frac{\partial \Pi}{\partial \eta} \Big|_{\eta=0} = \lambda(1 - \Phi_0) \left\{ I m_0 \left(-\frac{\partial r_c}{\partial \eta} \Big|_{\eta=0} \right) [\beta_0 m_0 + (1 - \beta_0) z_{c,0}] + \beta_0 \delta (1 - \pi_1) \right\} - p f, \quad (7.15)$$

where

$$\frac{\partial r_c}{\partial \eta} \Big|_{\eta=0} = -\frac{E(A|e)\delta(1 - \pi_1)}{[V_2(I, e) - I]^2}.$$

The first term on the right-hand side of equation (7.15) decreases as e increases, while the second term does not depend on e . Therefore, we can find a cutoff e_c , such that $\frac{\partial \Pi}{\partial \eta} \Big|_{\eta=0} > 0$ if $e < e_c$, and $\frac{\partial \Pi}{\partial \eta} \Big|_{\eta=0} \leq 0$ if $e \geq e_c$. e_c is the solution to

$$\frac{\partial \Pi}{\partial \eta} \Big|_{\eta=0} = 0.$$

Step 3: Deriving e_h . To facilitate the analysis below, it is convenient to decompose $\frac{\partial \Pi}{\partial \eta}$ into a marginal benefit of fraud term and a marginal cost of fraud term. Let

$$\begin{aligned} MB &= \lambda \left(-\frac{\phi_z}{\sigma_R} \frac{\partial r_c}{\partial \eta} \right) [(1 - \beta) E(V_3|I, e) - E(V_3|N, e)] \\ &\quad + \lambda [1 - \Phi(z_c)] \left[\left(-\frac{\partial \beta}{\partial \eta} \right) E(V_3|I, e) + (1 - \beta) I \frac{\partial m(z_c)}{\partial z_c} \frac{\partial r_c}{\partial \eta} \right]; \\ MC &= \left\{ \lambda \frac{\phi_z}{\sigma_R} \frac{\partial r_c}{\partial \eta} (P_N - P_I) + \lambda [1 - \Phi(z_c)] \frac{\partial P_I}{\partial \eta} + (1 - \lambda [1 - \Phi(z_c)]) \frac{\partial P_N}{\partial \eta} \right\} f \eta \\ &\quad + P f. \end{aligned} \quad (7.16)$$

Then let us take the first and the second derivatives of both MB and MC with respect to e . We can find that

$$\begin{aligned} \frac{\partial MB}{\partial e} &< 0, & \frac{\partial^2 MB}{\partial e^2} &< 0; \\ \frac{\partial MC}{\partial e} &> 0, & \frac{\partial^2 MC}{\partial e^2} &> 0. \end{aligned}$$

The relations about the first derivatives mean that when the true earnings realization is low, the marginal benefit of fraud is relatively high, while the marginal cost of fraud is relatively low. This implies that

$$\frac{\partial \eta_1^*}{\partial e} < 0.$$

The relations about the second derivatives imply that

$$\frac{\partial^2 \eta_1^*}{\partial e^2} > 0.$$

Given that $\eta_1^*(e)$ is a decreasing and concave function of e , there exists

$$e_h \equiv \max_{e < e_c} [e + \eta_1^*(e)].$$

This means that if the firm overreports earnings, there is an upper limit for how large the announced earnings could be. Then if the market observes $y > e_h$, the market rationally believes that $y = e$.

Step 4: Deriving e_l . Similarly, given that $\eta_1^*(e)$ is a decreasing and concave function of e , there also exists a lower bound e_l such that when $e < e_l$, $y(e) = e + \eta_1^*(e) < e_c$, and when $e_l \leq e < e_c$, $y(e) = e + \eta_1^*(e) \geq e_c$. e_l is the solution to the following equation:

$$MB[\eta_1(e_l)] = MC[\eta_1(e_l)],$$

where $\eta_1(e_l) = e_c - e_l$.

When the firm announces $y < e_c$, however, the market reaction changes, because now the low-earnings firm is not pooled with the high-earnings firm. In other words, the benefit-cost tradeoff is different, which implies that the optimal amount of misreporting in this region should be different from η_1^* .

Let $\eta_2(e)$ be the manager's misreporting strategy when $e < e_l$. If $\eta_2(e)$ is a monotonic function of e , then $y(e) = e + \eta_2(e) < e_c$ is also a monotonic function of e . In other words, $y(e)$ is a sufficient statistic of e , and thus $E(A|y) = E(A|e)$. Substitute $E(A|y) = E(A|e)$ into equations (4.17), (4.18), (4.23), (7.16) and (7.17), and we get $\frac{\partial r_c}{\partial \eta} = 0$, $MB = 0$, and $MC = pf > 0$. Since the marginal benefit is less than the marginal cost regardless of η , the optimal amount of misreporting is $\eta_2^* = 0$. Put differently, if the manager chooses a monotonic disclosure strategy when $e < e_l$, then the optimal monotonic strategy is $y(e) = e$.

Step 5: Possibility of $\eta(e)$ as a nonmonotonic function of e . Let us also consider whether there exists an equilibrium in which $\eta_2(e)$ is a nonmonotonic function of e . Since $\eta \geq 0$ (which means $y(e) \geq e$), and the litigation cost is an increasing and monotonic function of η , I can make the following conjecture about $\eta_2(e)$. I can partition the earnings space $\{e : e < e_l\}$ into many intervals, $[e_1, e_l)$, $[e_2, e_1)$, $[e_3, e_2)$, In each earnings interval, $y(e)$ equals the upper bound of that interval. The lower bound of each interval is determined, such that the earnings realization at the

lower bound plus the optimal amount of misreporting equals the upper bound earnings value. Take the first interval $[e_1, e_l)$ for an example. If the true earnings realization is in this interval, then the manager announces $y(e) = e_l$. The market rationally infers that $e' = E(e|e_1 \leq e < e_l)$ and uses e' to price the firm's assets in place. It is easy to see that firms with $e' < e < e_l$ get worse off by reporting $y(e) = e_l$ than reporting $y(e) = e$, because the firm's asset value is underpriced by the market, and the firm faces potential litigation cost. Then these firms would rather honestly reveal their earnings, and the conjectured equilibrium collapses. This happens to any nonmonotonic $\eta_2(e)$.

Proof of Proposition 5

1. e Proof is shown in the proof of Proposition 4 (step 3).
2. λ

$$\begin{aligned} \frac{\partial MB}{\partial \lambda} &= \frac{\phi_z}{\sigma_R} \left(-\frac{\partial r_c}{\partial \eta} \right) [(1 - \beta)E(V_3|I, e) - E(V_3|N, e)] \\ &+ (1 - \Phi(z_c)) \left[\left(-\frac{\partial \beta}{\partial \eta} \right) E(V_3|I, e) + (1 - \beta)Im'(z_c) \frac{\partial r_c}{\partial \eta} \right] \\ &> 0; \end{aligned} \tag{7.18}$$

$$\frac{\partial MC}{\partial \lambda} = -\lambda [1 - \Phi(z_c)] (P_N - P_I) f \eta < 0. \tag{7.19}$$

Since the marginal benefit of fraud increases in λ and the marginal cost decreases in λ , $\eta_1^*(e)$ increases in λ for any given e . This also implies that $\frac{\partial e_l}{\partial \lambda} < 0$.

$$\begin{aligned} \frac{\partial MB|_{\eta=0}}{\partial \lambda} &= (1 - \Phi_0) \left\{ Im_0 \left(-\frac{\partial r_c}{\partial \eta} \Big|_{\eta=0} \right) [\beta_0(m_0 + (1 - \beta_0)z_{c,0}) + \beta_0\delta(1 - \pi_1)] \right\} \\ &> 0; \end{aligned} \tag{7.20}$$

$$\frac{\partial MC|_{\eta=0}}{\partial \lambda} = 0. \tag{7.21}$$

This implies that $\frac{\partial e_c}{\partial \lambda} > 0$.

BIBLIOGRAPHY

- [1] Agrawal, Anup, and Sahiba Chadha, 2004, "Corporate Governance and Accounting Scandals," *Journal of Law and Economics* Forthcoming.
- [2] 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.
- [3] 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.
- [4] American Institute of Certified Public Accountants, National Commission on Fraudulent Financial Reporting (AICPA), 1987, *Reporting of the National Commission on Fraudulent Financial Reporting*, New York, NY.
- [5] Bajaj, Mukesh, Katherine Gunny, and Atulya Sarin, 2003, "Auditor compensation and auditor failure: An empirical analysis," working paper, University of California-Berkeley.
- [6] 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.
- [7] 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.
- [8] Beasley, Mark S., Joseph V. Carcello, and Dana R. Hermanson, 1999, "Fraudulent financial reporting: 1989-1997," Research commissioned by the Treadway Commission.
- [9] Bebchuk, Lucian A., and Oren Bar-Gill, 2002, "Misreporting corporate performance," working paper, Harvard University.
- [10] Becker, Gary S., 1968, "Crime and punishment: An economic approach," *Journal of Political Economy* , 169-217.

- [11] Bertrand, M., and S. Mullainathan, 2001, "Are CEOs rewarded for luck? The ones without principals are," *Quarterly Journal of Economics* 116, 901-932.
- [12] Bethel, Jennifer, J. Liebeskind, and T. Opler, 1998, "Block share purchases and corporate performance," *Journal of Finance* 53, 605-635.
- [13] Burns, Natasha, and Simi Kedia, 2004, "Do executive stock options generate incentives for earnings management? Evidence from accounting restatements," working paper, Harvard University.
- [14] Chan, Konan, Louis K. C. Chan, Narasimhan Jegadeesh, and Josef Lakonishok, 2005, "Earnings quality and stock returns," *Journal of Business* Forthcoming.
- [15] Choi, Stephen J., 2004, "Do the merits matter less after the Private Securities Litigation Reform Act?" working paper, University of California-Berkeley.
- [16] Coffee, John C. Jr., 1991, "Liquidity versus control: The institutional investor as corporate monitor," *Columbia Law Review* 91, No. 6, 1277-1367.
- [17] Cox, James D, and Randall S. Thomas, 2003, "SEC enforcement heuristics: An empirical inquiry," *Duke Law Journal* 53, 737-780.
- [18] 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.
- [19] DeFond, M. and J. Jiambalva, 1994, "Debt Covenant Effects and the Manipulation of Accruals," *Journal of Accounting and Economics* 17, 145-176.
- [20] Demirgüç-Kunt, Asli and Vojislav Maksimovic, 1998, "Law, finance, and firm growth," *Journal of Finance* 53, 2107-2137.
- [21] Dye, Ronald A., 1988, "Earnings management in an overlapping generations model," *Journal of Accounting Research* 26, No. 2, 195-235.

- [22] Efendi, Jap, Anup Srivastava and Edward P. Swanson, 2004, "Why do corporate managers misstate financial statements? The role of option compensation, corporate governance, and other factors," working paper, Texas A&M University.
- [23] 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.
- [24] Feinstein, Jonathan S., 1990, "Detection Controlled Estimation," *Journal of Law and Economics* 33, No. 1, 233-276.
- [25] Feroz, Ehsan, Kyungjoo Park, and Victor Pastena, 1991, "The financial and market effects of the SEC's accounting and auditing enforcement releases," *Journal of Accounting Research* 29, 107-142.
- [26] Frankel, Richard M., Marilyn F. Johnson, and Karen K. Nelson, 2002, "The relation between auditors' fee for non-audit services and earnings management," *Accounting Review* 77 Supplement, 71-105.
- [27] Gande, Amar, and Craig M. Lewis, 2005, "Shareholder initiated class action lawsuits: Shareholder wealth effect and industry spillovers," working paper, Vanderbilt University.
- [28] Gao, Pengjie, and Ronald E. Shrieves, 2003, "Earnings management and executive compensation: A case of overdose of option and underdose of salary?" working paper, University of Tennessee.
- [29] oldman, Eitan, and Steve L. Slezak, 2003, "The economics of fraudulent misreporting," working paper, University of North Carolina at Chapel Hill.
- [30] 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.
- [31] Hermalin, Benjamin E., and Michael Weisbach, 2003, "Boards of directors as an endogenously determined institution: A survey of the economic literature," *Economic Policy Review* April, 7-26.

- [32] Holderness, Clifford G., 2003, "A survey of blockholders and corporate control," *Economic Policy Review* April, 51-64.
- [33] Jensen, Michael C., 2004, "Agency costs of overvalued equity," working paper, Harvard University.
- [34] John, Kose, and Lemma W. Senbet, 1998, "Corporate governance and board effectiveness," *Journal of Banking & Finance* 22, 371-403.
- [35] Johnson, Shane A., Harley E. Ryan, and Yisong S. Tian, 2003, "Executive compensation and corporate fraud," working paper, Louisiana State University.
- [36] Johnson, Marilyn F., Karen K. Nelson, and A.C. Pritchard, 2002, "Do the merits matter more? Class action under the Private Securities Litigation Reform Act," working paper, Michigan State University.
- [37] Lacker, Jeffrey M., and John A. Weinberg, 1989, "Optimal contracts under costly state falsification," *The Journal of Political Economy* 97, No. 6, 1345-1363.
- [38] Li, Si, 2004, "Corporate fraud and costly monitoring: An empirical analysis of a simultaneous system with partial observability," working paper, Duke University.
- [39] Klein, April, 2002, "Audit committee, board of director characteristics, and earnings management," *Journal of Accounting & Economics* 33, No. 3, 375-400.
- [40] Leuz, Christian, Alexander Triantis, and Tracy Yue Wang, 2004, "Why do firms go dark? Causes and economic consequences of voluntary SEC deregistrations," working paper, University of Maryland.
- [41] Loebbecke, James K., Martha M. Eining, and John J. Willingham, 1989, "Auditors' experience with material irregularities: Frequency, nature, and detectability," *Auditing: A Journal of Practice & Theory* 9, No. 1, 1-28.
- [42] Maksimovic, Vojislav, and Sheridan Titman, 1991, "Financial policy and reputation for product quality," *The Review of Financial Studies* 4, No. 1, 175-200.

- [43] Moeller, Sara, Frederik P. Schlingemann and Rene M. Stulz, 2004, "Wealth destruction on a massive scale? A study of acquiring-firm returns in the recent merger wave," *Journal of Finance* forthcoming.
- [44] Myers, Stewart C., and Nicholas S. Majluf, 1984, "Corporate financing and investment decisions when firms have information that investors do not have," *Journal of Financial Economics* 13, 187-221.
- [45] Peng, Lin, and Ailsa Röell, 2004, "Executive pay, earnings manipulation and shareholder litigation," working paper, Princeton University.
- [46] Poirier, Dale J., 1980, "Partial observability in bivariate probit models," *Journal of Econometrics* 12, 209-217.
- [47] Povel, Paul, Rajdeep Singh, and Andrew Winton, 2004, "Booms, busts, and fraud," working paper, University of Minnesota.
- [48] Richardson, Scott A., and Richard G. Sloan, 2003, "External financing and future stock returns," working paper, University of Pennsylvania.
- [49] Shleifer, Andrei, and Robert W. Vishny, 1997, "A survey of corporate governance," *Journal of Finance* 52, No. 2, 737-783.
- [50] Sidak, Gregory J., 2003, "The failure of good intentions: The WorldCom fraud and the collapse of American telecommunications after deregulation," *Yale Journal on Regulation* 20, 207-267.
- [51] Stein, Jeremy, 1989, "Efficient capital markets, inefficient firms: A model of myopic corporate behavior," *Quarterly Journal of Economics* 104, 655-669.
- [52] Sweeney, A.P., 1994, "Debt Covenant Violations and Manager's Accounting Responses," *Journal of Accounting and Economics* 17, 281-308.

- [53] 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.
- [54] Teoh, Siew Hong, Ivo Welch, and T. J. Wong, 1998b, "Earnings management and the long-term market performance of initial public offerings," *Journal of Finance* 53, No. 6, 1935-1974.