Corporate Fraud and Costly Monitoring: An Empirical Analysis of a Simultaneous System with Partial Observability

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Abstract

It is well recognized that the SEC plays a critical role in corporate fraud detection and that much fraud remains undetected. Nevertheless, previous empirical literature on corporate fraud has completely ignored the monitoring role of the SEC in fraud and the problem of incomplete detection. This paper addresses these two issues by introducing an empirical framework that models the interdependence between corporate fraud and the SEC's monitoring and takes into account the incomplete detection problem. I estimate this empirical model using a sample of firms accused of corporate fraud by the SEC. First and foremost, I find that the magnitudes of the effects of stock-based incentives, corporate governance, and external financing needs on the probability of fraud are more than double those documented by models used in previous studies. The differences in the effects are both statistically and economically significant. Second, I find that a firm's fraud is more likely to be detected if there is a larger SEC budget, more insider trading, worse auditor's opinion, and higher total market value of detected fraudulent firms in the same industry in prior years. Third, I find that SEC detection deters fraud, and an increased probability of fraud leads to an increased probability of detection. Fourth, I find that the marginal shareholder benefits associated with fraud reduction greatly exceed the marginal costs of SEC law enforcement. Finally, the empirical model in this paper has a number of potential applications.

1 Introduction

A series of recent high-profile corporate fraud scandals like Enron and Worldcom have drawn the attention of the public, regulators, and academics. There has been a growing literature examining corporate fraud.[1] However, all the previous empirical literature on corporate fraud has ignored two important issues. First, it has ignored the monitoring role of the SEC (U.S. Securities and Exchange Commission) in firms' fraudulent behavior. It is well known that a firm's fraud decision and the SEC's detection decision are interdependent and that the SEC plays a critical role in corporate fraud monitoring.[2] Therefore, ignoring the role of the SEC causes a significant bias in previous studies of corporate fraud. Second, much fraud remains undetected and this problem of incomplete detection has been overlooked in previous corporate fraud studies. These studies only look at detected fraud, while fraud includes not only detected fraud but also undetected fraud. As a result, previous studies understate the true extent of fraud. This in turn introduces further bias.

In this paper, I address the above two issues by introducing an empirical framework that models the interdependence between corporate fraud and the SEC's monitoring and takes into account the incomplete detection problem. In this empirical framework, I study three questions.

The first question I study is the roles of stock-based incentives, corporate governance, and external financing needs in the occurrence of corporate fraud, in the presence of the interdependence between fraud and its monitor and incomplete detection. It has become evident lately that stock-based executive compensation is a double-edged sword. It can give managers incentives to maximize shareholder value, but at the same time it may provide perverse incentives. Since stocks and stock options only pay off big when stock prices increase, managers who receive stock compensation and option grants may have incentives to boost stock prices fraudulently. Contemporary papers

[1] The New Palgrave defines fraud as follows: An agent is said to have committed fraud when he misrepresents the information he has at his disposal so as to persuade another individual (principal) to choose a course of action he would not have chosen had he been properly informed. In this paper, corporate fraud is defined as the fraudulent misrepresentation of firms' material information by management.

[2] External auditors are also important monitors of corporate fraud. However, given that external auditors' independence is questioned extensively, the SEC is arguably the most important monitor.

such as Johnson, Ryan, and Tian (2003), Erickson, Hanlon, and Maydew (2003), and Burns and Kedia (2004) empirically document a positive association between equity-based compensation and detected corporate fraud. In addition, weaker corporate governance is associated with a higher likelihood of fraud. Beasley (1996), Dechow, Sloan, and Sweeney (1996), and Agrawal and Chadha (2005) find that the probability of detected corporate fraud is lower in companies whose boards are more independent or whose boards or audit committees have an independent director with financial expertise. Moreover, a firm's need for external financing may be a motive to commit fraud. A firm might fraudulently misrepresent its financial positions to improve the terms upon which it would be able to raise capital. Both Dechow, Sloan, and Sweeney (1996) and Erickson, Hanlon, and Maydew (2003) show that firms accused of fraud have greater external financing needs.

In a model that does not consider the monitoring role of the SEC, the effects of stock-based incentives, corporate governance, and external financing needs on the probability of fraud are biased downward. This bias results from the fact that the model ignores the negative impact of the likelihood of detection on fraud. This downward bias is eliminated in the model considering the interdependence. In addition, the model that does not consider the incomplete detection problem introduces further bias, which is discussed later in this section. It is important to remove the above bias because this downward bias causes the understatement of the economic loss due to fraud. By removing the bias, we can more accurately estimate the economic loss due to fraud caused by, for example, stock-based compensation, and thus can better address questions like the right amount of stock-based compensation granted to managers.

The second issue that I study involves the factors that contribute to SEC detection. I examine the roles of the SEC budget, firms' insider trading, auditor's opinion, and total market value of fraudulent firms in the same industry detected in prior years. Since the SEC may be more effective in detecting fraud if it has more resources, the SEC budget is included as a variable affecting the probability of detection. In addition, abnormally high insider trading of managers and an adverse audit opinion both catch the SEC's attention and thus raise the probability of the firm's being detected by the SEC. Finally, if a larger fraction of companies in a specific industry have been caught committing fraud in prior years, the SEC may devote more investigative resources to this industry and thus increase the probability of detecting fraud in this industry. No empirical research has examined factors affecting the SEC's detection probability in conjunction with studying corporate fraudulent behavior.

The third question I study is the interdependence between corporate fraud and the SEC's monitoring activity. By looking at the interdependence, I am able to study how the behavior of the SEC affects the firm's decision and vice versa. No empirical paper on corporate fraud has looked at this interdependence.

To study the above three questions, I set up a simultaneous probit model with three equations. The first equation models a firm's fraud decision. In the fraud equation, the probability of corporate fraud depends on the firm's perceived probability of SEC detection, executive compensation, corporate governance, external financing needs, and some control variables. The second equation models the SEC's detection perceived by the firm ex ante. In this equation, the perceived probability of SEC detection depends on the firm's fraud probability, its insider trading activity, and the total market value of detected fraudulent firms in the same industry in prior years. The third equation models actual ex post SEC detection. In this equation, the actual probability of SEC detection depends on the firm's fraud probability, the SEC's budget, the firm's insider trading activity, the external auditor's opinion, and the total market value of detected fraudulent firms in the same industry in prior years.

The simultaneous probit model that I use differs from the standard simultaneous probit model because it accounts for the partial observability problem. Partial observability comes from the incomplete detection of fraud. In the real world, we can only observe detected fraud, that is, we can only partially observe fraud occurrence. This partial observability problem is important because the model without considering it has bias. Take my model as an example. In my model, there is an equation modeling a firm's fraud decision. This fraud equation has the occurrence of fraud as the dependent variable and other variables like executive compensation as the independent variables. As we know, fraud consists of detected fraud and undetected fraud. If we only consider detected fraud, we will understate the true extent of fraud and thus the dependent variable, fraud. The understatement of the dependent variable will in turn cause the underestimation of the effects of the independent variables such as executive compensation.

When fraud is not detected in a firm, there are two possibilities. One possibility is that the firm does not commit fraud. The other is that the firm has committed fraud but has not been detected. To solve the partial observability problem, one needs to separate these two groups of firms. The basic intuition of the solution to this partial observability problem is as follows. Suppose there are two groups of firms: group one consists of detected fraudulent firms and group two consists of all remaining firms. To split the second group into two subgroups, no fraud and undetected fraud, I use a set of firm characteristics A to fit the likelihood of fraud and a different set of firm characteristics B to fit the likelihood of detection. By doing this, we can find a subset of the second group that has similar characteristics A but different characteristics B than those of the first group. This subset is likely to consist of firms that have committed fraud but have not been detected. And the remaining firms in the second group are firms that do not commit fraud. To actually estimate this model with partial observability, I use the maximum likelihood method developed by Poirier(1980) and Feinstein(1989, 1990).

This paper is the first empirical paper ever to apply and estimate a model with both simultaneity and partial observability. Previous literature has either examined the interdependence between two parties using a simultaneous model or estimated a partially observable model without simultaneity. Feinstein(1990) theoretically discusses the identification and estimation issues of a model with both simultaneity and partial observability. However, there has been no empirical application of this methodology in the literature.

I estimate the empirical model using the sample of firms accused of corporate fraud by the SEC, the main findings and contributions being summarized as follows. First and foremost, this paper represents the first attempt to take into account the deterrent effect of the SEC and address the incomplete detection problem. The results indicate that the magnitudes of the effects of stock-based incentives, corporate governance, and external financing needs on the probability of fraud are about two and a half times as large as those in a model without simultaneity or partial observability, that is, as in the type of model used in previous studies. The differences in the effects are both statistically and economically significant. The shareholder loss due to fraud is understated by 60% if the model in previous studies is used. Second, this is the first study to identify the factors that affect SEC detection. The results indicate that a firm is more likely to be detected in fraud if there is a higher SEC budget, more insider trading, worse auditor's opinion, and higher total market value of fraudulent firms in the same industry detected in prior years. Third, this paper is the first to empirically study the interdependence between fraud and the SEC's monitoring. I find that SEC detection deters fraud, and the probability of a firm's being detected is higher if this firm is more likely to commit fraud. Fourth, this paper conducts a cost-benefit analysis of the SEC and finds the marginal shareholder benefit greatly exceeds the marginal cost of SEC law enforcement. An increase of $100 million in the annual SEC budget is associated with an increase of $6 billion in shareholder value. To my knowledge, this is the first paper to undertake such an analysis. Fifth, as far as I know, this paper employs the largest sample of firms accused of fraud by the SEC. Finally, my paper makes a methodological contribution. It is the first one to empirically estimate a model with both simultaneity and partial observability. This methodology can be applied to other issues such as tax evasion, accounting audits, insurance fraud, regulation, crime, etc.

The rest of the paper proceeds as follows. The next section sets up the empirical model. Section 3 describes the data and variable measurements. Results, implications, and robustness tests are given in Section 4. And the last section concludes.

2 An Empirical Model of Corporate Fraud and Monitoring

2.1 Model Setup

A system of three equations with binary dependent variables is set up to model the interdependence between an individual firm and the SEC:

Fraud:

$$Prob(Y_1 = 1) = \Phi(\gamma_1 Prob(Y_2 = 1|Y_1 = 1)_{ex\ ante} + \beta_1 X + c_1) \tag{1}$$

SEC's detection perceived by the firm ex ante:

$$Prob(Y_2 = 1|Y_1 = 1)_{ex\ ante} = \Phi(\gamma_2 Prob(Y_1 = 1) + \beta_2 EW + c_2) \tag{2}$$

SEC's actual ex post detection:

$$Prob(Y_2 = 1|Y_1 = 1)_{ex\ post} = \Phi(\gamma_2 Prob(Y_1 = 1) + \beta_2 W + c_3) \tag{3}$$

where

$$Y_1 = \begin{cases} 1 & \text{fraud} \\ 0 & \text{no fraud} \end{cases} \tag{4}$$

$$Y_2 = \begin{cases} 1 & \text{detection} \\ 0 & \text{no detection} \end{cases} \tag{5}$$

Equation (1) models a firm's fraud. In this equation, Y_1 denotes a firm's fraud decision. It equals one if a firm commits fraud and zero otherwise. So $Prob(Y_1 = 1)$ is the probability that a firm commits fraud. Y_2 denotes the SEC's detection decision. It equals one if the SEC detects a fraud and zero otherwise. $Prob(Y_2 = 1|Y_1 = 1)_{ex\ ante}$ is the probability that a firm is caught by the SEC if it commits fraud perceived by the firm when it decides whether to commit fraud or not. X is a set of independent variables affecting the probability of fraud. These variables include stock-based executive compensation, corporate governance, external financing needs, and some control variables. Φ is the cumulative distribution function of the standard normal distribution. c_1 is a constant term.

Equation (2) models the SEC's detection perceived by the firm ex ante, $Prob(Y_2 = 1|Y_1 = 1)_{ex\ ante}$. In this equation, EW is a set of independent variables affecting the perceived detection probability. These variables include the forecast values of the following variables: the firm's insider trading activity, total market value of detected fraudulent firms in the same industry, the firm's external auditor's opinion regarding its financial statements, and the SEC's budget. c_2 is a constant term.[3]

Equation (3) models the SEC's actual ex post detection probability if the firm commits fraud, $Prob(Y_2 = 1|Y_1 = 1)_{ex\ post}$.[4] W is a set of independent variables affecting the actual probability of detection. These variables include the actual values of the following variables: the firm's insider trading activity, total market value of detected fraudulent firms in the same industry, the firm's external auditor's opinion regarding its financial statements, and the SEC's budget. c_3 is a constant term.

In this model, three issues need to be addressed. First, I model the interaction between a firm's probability of fraud ($Prob(Y_1 = 1)$) and the SEC's probability of detection ($Prob(Y_2 = 1|Y_1 = 1)$ rather than that between the firm's fraud action (Y_1) and the SEC's detection action (Y_2). The reason is the following. The model is an incomplete information one in the sense that the firm has its own private information that is unobservable to the SEC and econometricians, and the SEC has its own private information that is unobservable to the firm and econometricians. This incomplete information setting requires modeling the interaction between probabilities, which corresponds to the Bayesian equilibrium in the incomplete information model.[5]

[3] EW does not directly enter the fraud equation (1) for the following reason. The model is a structural one and only variables directly affecting the probability of fraud enter the fraud equation directly. EW indirectly affects the likelihood of fraud through the perceived detection and thus does not enter the fraud equation directly. By the same token, X does not enter the detection equations directly.

[4] This model assumes no false detection and does not model $Prob(Y_2 = 1|Y_1 = 0)$. I argue this is a reasonable assumption because the SEC won't accuse a firm of fraud unless the SEC is very positive about it. Further, false detection is not supported by my data.

[5] To model the interaction between actions, it must be assumed that each party knows the information to the other party perfectly, which is not the case in reality. Further, there does not exist any equilibrium if the interaction between actions is modeled. If a firm commits fraud, then the monitor will choose to detect the firm. But if the monitor chooses to detect, the firm will choose not to commit fraud. If the firm chooses not to commit fraud, the monitor will not detect the firm and then the firm will choose to commit fraud......Therefore, no equilibrium exists if

Second, it is necessary to differentiate the actual (ex post) detection probability from the perceived (ex ante) detection probability. Fraud detection usually happens several years after fraud occurrence, so the probability of detection perceived by a firm when it decides whether to commit fraud or not is different from the probability of detection realized later on. In equation (1), I use the perceived ex ante detection probability instead of the actual ex post detection probability because it is the perceived ex ante detection probability that affects a firm's fraud decision. In equation (3), it is necessary to model the actual ex post detection probability because it is the actual ex post detection instead of the perceived ex ante detection that generates the detected fraud data we observe. The difference between the ex ante detection probability equation (2) and the ex post detection probability equation (3) is the difference between the forecast values of W and the realized values of W. This difference is the ex post surprise to the firm. When the model is actually estimated, the forecast values of external auditor's opinion and the SEC's budget do not appear in equation (2). The reasons are the following. First, the sample fraud period is between 1992 and 1999 and during this period, there is little variation in the SEC budget (Figure 2). Thus the budget predicted by the firm ex ante would be constant. Second, the firm could predict external auditors' good opinions but not adverse opinions because it is very difficult to predict adverse opinions. Therefore, the predicted auditors' opinions would be mostly good and constant.[6]

Third, I constrain the coefficients of all the variables in the perceived detection equation (2) to be the same as the corresponding ones in the actual detection equation (3). I impose these constraints because it can be reasonably assumed that a firm can rationally expect the magnitudes of these variables' effects on detection ex ante.

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we model the interaction between actions.

[6]I perform a robustness test using different forecast methods in which firms forecast SEC budget using the first order autoregressive (AR(1)) model and forecast auditors' opinions perfectly. The results keep essentially the same.

2.2 Identification Issue

The empirical model presented in the last section has a partial observability problem because neither of the dependent variables, $Prob(Y_1 = 1)$(fraud) and $Prob(Y_2 = 1|Y_1 = 1)_{ex\ post}$(detection), is observable and only their product, detected fraud, is observable from the data. This partial observability raises a model identification issue. The model in this paper decomposes a single datum, detected fraud, into two components: fraud and detection. The identification issue arises because initially we don't know whether we can conduct this decomposition uniquely. According to Feinstein (1990) and Poirier (1980), identification requires that the independent variables in the fraud equation and the independent variables in the ex post detection equation vary differently. So if there is at least one variable in either equation that is not in the other, the model can be identified.[7] The model presented in the last section can be identified because two variables, auditor's opinion and SEC's budget, enter the actual detection equation only.

2.3 Estimation Approach

The model is estimated using the maximum likelihood method proposed by Poirier (1980) and Feinstein (1990). This method is explained as follows.

To simplify notations, I let $F = Prob(Y_1 = 1) = \Phi(\gamma_1 G_0 + \beta_1 X + c_1)$, $G_0 = Prob(Y_2 = 1|Y_1 = 1)_{ex\ ante} = \Phi(\gamma_2 F + \beta_2 EW + c_2)$, and $G = Prob(Y_2 = 1|Y_1 = 1)_{ex\ post} = \Phi(\gamma_2 F + \beta_2 W + c_3)$. Then the joint probability of detected fraud ($Prob(Y1 = 1\ \&\ Y2 = 1)$) is simply FG, which represents the probability of fraud ($Prob(Y1 = 1)$) multiplied by the ex post probability of detection given that there is fraud ($Prob(Y2 = 1|Y1 = 1)_{ex\ post}$). The probability of undetected fraud or no fraud is 1-FG, which equals the sum of the probability of undetected fraud, F(1-G), and the probability of no fraud, 1-F. The probability of detected fraud is FG instead of FG_0 because it is the actual ex post detection probability, G, instead of the perceived ex ante detection probability, G0, that generates the detected fraud data we observe.

[7] See Feinstein (1990) for detailed discussions about and formal proofs of conditions for identification.

The log-likelihood function can be written as follows:

$$\begin{aligned} logL &= \sum_{Y_1Y_2=1} log(Prob(Y_1=1,Y_2=1)) + \sum_{Y_1Y_2=0} log(1-Prob(Y_1=1,Y_2=1)) \\ &= \sum_{Y_1Y_2=1} log(Pr(Y_1=1)Pr(Y_2=1|Y_1=1)) + \sum_{Y_1Y_2=0} log(1-Pr(Y_1=1)Pr(Y_2=1|Y_1=1)) \\ &= \sum_{Y_1Y_2=1} log(FG) + \sum_{Y_1Y_2=0} log(1-FG) \qquad (6) \end{aligned}$$

This log-likelihood function is maximized to obtain the parameter estimates. Heteroskedasticity-robust standard errors of parameter estimates b equal the square roots of the diagonal elements of the following asymptotic variance:

$$AVAR = [\sum_i A_i]^{-1}[\sum_i S_i S_i'][\sum_i A_i]^{-1} \qquad (7)$$

where S_i, the score function, is equal to $\frac{dlogL_i}{db}$, and A_i is equal to $-E[H_i]$, the expectation of negative Hessian.[8]

Finally, a technical point needs to be made. The evaluation of the log-likelihood function (6) requires solving for F and G in terms of parameters to be estimated. Specifically, F needs to be solved from the equation $F = \Phi(\gamma_1 G_0 + \beta_1 X + c_1) = \Phi(\gamma_1\Phi(\gamma_2 F + \beta_2 EW + c_2) + \beta_1 X + c_1)$ and G to be solved from the equation $G = \Phi(\gamma_2 F + \beta_2 W + c_3)$. The existence and uniqueness of the solutions F and G are required to ensure that the likelihood function is properly defined. Appendix A proves that the sufficient and necessary condition for the existence and uniqueness of the solution is $\gamma_1\gamma_2 < 2\pi$. I expect γ_1 to be less than or equal to zero since increased enforcement deters fraud and γ_2 to be greater than or equal to zero since the monitor may shift more resources to detection and thus increase the detection probability when fraud is more likely.[9] This gives $\gamma_1\gamma_2 \leq 0$, which satisfies the existence and uniqueness condition of the solutions.

[8]Since the probability of detection given fraud is explicitly modeled, the correlation between random errors of equations (1) and (3) does not affect the log-likelihood function or standard errors. If the unconditional probability of detection instead of the conditional one is modeled, the joint probability Prob(Y1=1,Y2=1) will depend on the joint distribution of Y1 and Y2 and thus the correlation between Y1 and Y2.

[9]Some might argue that γ_2 should be less than or equal to zero. This is true only if we study firms at an aggregate level. When the overall prob(fraud) goes up, the overall prob(detection if fraud) may actually go down because the monitor cannot immediately adjust its budget in response to more fraud. However, in this paper, I examine prob(fraud) and prob(detection if fraud) at an individual firm level. Therefore, γ_2 should be greater than or equal to zero.

2.4 Comparison with the Approach in Previous Research

To make a comparison, I also estimate the single equation model without simultaneity or partial observability used in previous studies. The single equation model can be written as:

$$Prob(Z = 1) = \Phi(\delta X + d) \tag{8}$$

where Z is a binary variable that equals one if a firm commits fraud and is then detected and zero otherwise. Therefore, Z is equal to $Y_1 \times Y_2$. Let $P = Prob(Z = 1)$. Then the log-likelihood function of the single equation model is:

$$logL = \sum_{Y_1 Y_2 = 1} log(P) + \sum_{Y_1 Y_2 = 0} log(1 - P) \tag{9}$$

The single equation model differs from the model proposed in this paper in two ways. First, comparing with the fraud equation (1), the single equation model does not consider the perceived detection probability $Prob(Y_2 = 1|Y_1 = 1)_{ex\ ante}$ and thus ignores the deterrent effect of SEC detection on fraud. Second, the single equation approach assumes complete detection and treats the probability of **detected fraud**, $Prob(Z = 1)$, as the probability of **fraud**. In contrast, my approach allows incomplete detection by explicitly modeling the ex ante and ex post probabilities of detection, G0 and G.

3 Data and Variables

3.1 Data

3.1.1 Sample Selection

In this paper, corporate fraud is defined as the fraudulent misrepresentation of firms' material information by management. The data on corporate fraud come from the SEC enforcement releases. Table I summarizes the sample selection procedure. I select the releases dated between January 1st, 1992 and May 31st, 2003 that specify violation of the antifraud rule 10b-5 "Employment of Manipulative and Deceptive Devices".[10] From these releases, I obtain 849 unique fraud events,

[10] Rule 10b-5 of Securities Exchange Act of 1934 states that "It shall be unlawful for any person, directly or indirectly, by the use of any means or instrumentality of interstate commerce, or of the mails, or of any facility of

among which 396 unique fraud events are from Accounting and Auditing Enforcement Releases (AAERs) and 453 from non-AAERs. Then I impose the following screening conditions upon these events.

First, I remove 139 cases which are not against firm top management because top management are the most important corporate fraud decision makers. These removed cases are against broker-dealers, external auditors, lower-level firm managers, etc. Second, I drop 84 cases in which fraudulent behavior is related to non-stock securities such as promissory notes, limited partnerships, bonds, etc. because this paper looks at stock-based incentives. Third, I exclude 38 cases where there is no manipulation of information because I am only interested in the cases where manipulation of information occurred.[11]

The exclusion of the above 261 cases gives 588 unique fraud events, among which 255 are overstatement of earnings, 81 are other kinds of misrepresentations in financial statements, and 252 are false press releases.[12] All these 588 events are about misrepresenting material information by firm top managers and thus fall into my fraud sample. A further requirement of having valid Compustat, executive compensation (from both ExecuComp and proxy statements), and corporate governance (from proxy statements) data removes additional 456 events and gives 132 unique fraud events. All these 132 fraud events started between 1992 and 2002 and correspond to 130 unique firms.[13]

Table II presents all the 130 firms accused of fraud grouped by the initial year of fraud. On average, about 14 frauds occurred each year from 1992 to 1999 but less fraud occurred between

any national securities exchange, a. to employ any device, scheme, or artifice to defraud, b. to make any untrue statement of a material fact or to omit to state a material fact necessary in order to make the statements made, in the light of the circumstances under which they were made, not misleading, or c. to engage 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."

[11]The cases I exclude are those in which managers traded based on inside information but did not misrepresent firm information. One example is that a person knew in advance the merger of two companies and used this information to gain by trading stocks of the merged companies.

[12]One example of false press releases is that a firm issued a press release announcing that it had developed and was offering for sale a new product while the product actually did not exist.

[13]Two of the 130 firms committed two counts of fraud during different periods. For these two firms, I use the data associated with their first count of fraud in the final sample.

2000 and 2003. The reason could be that it usually takes the SEC several years to detect fraud and thus some fraud that happened between 2000 and 2003 may have not been detected by May 2003, the time when the sample collection ends. To avoid the potential bias caused by the abnormally small amount of fraud that happened in those years, I remove 16 firms whose first year of fraud are later than 1999 from those 130 firms. This leaves 114 firms whose initial years of fraud are between 1992 and 1999. These 114 firms are all the firms that have been accused by the SEC of committing fraud (i.e., fraudulent misinformation) during this period and have valid data.

Finally, the full sample in this study is composed of the above 114 firms accused of fraud, and 1507 unique firms on ExecuComp not accused of fraud and with valid data. I perform all the empirical tests based on this full sample.

3.1.2 Sample Description

Industry Distribution of Sample Firms Table III shows the distributions of sample firms by industry. Panel A provides the distribution by SIC division and Panel B provides the distribution by two digit SIC. As we can see from Panel A, detected fraud concentrates in two industries: 47% in the manufacturing industry and 28% in the services industry. In Panel B, business service and electronic, computer equipments industries have the most detected fraud. Interestingly, these industries belong to the so-called new economy firms. According to Ittner, Lamber, and Larcker (2003) and Murphy (2003), compared with old economy firms, new economy firms have smaller size, higher growth option, more research and development investments, and more stock option grants. It might be the characteristics of these new economy firms that are correlated with more fraud detections. As can be seen from the summary statistics of variables in the fraud equation (Table V), firms accused of fraud do have such characteristics. They are smaller, have higher market-to-book, and grant more stock options.

Time Distribution of Sample Firms The time line of fraud and detection is presented in Figure 1. Fraud starts at T0 and lasts till T1. The SEC starts investigation at Ti and brings an enforcement action against the firm at T2. The time from T0 to T1 is fraud period and the time from Ti to T2 is investigation period.

Table IV presents the number, percentage, total market value, and total market value as a percent of U.S. stock market capitalization of all the 114 unique firms detected in fraud by the initial year of fraud (T0), the initial year of SEC investigation (Ti), and the year of SEC enforcement (T2). Panel A shows the distributions by the initial year of fraud. On average, about 14 firms committed fraud each year from 1992 to 1999, with the late 1990's seeing slightly more fraud than the early 1990's. The total market value and the total market value scaled by the U.S. market capitalization of detected fraud are much larger in the late 1990's than the early 1990's. Panel B and C show the distributions by the year of investigation and the year of enforcement. There is an increase in the number and magnitude of fraud detections in the years from 2000 to 2003. This increase appears to be consistent with the increase in the SEC's budget shown in Figure 2, which was almost flat in the 1990's and started to increase quickly from 2000.[14]

Figure 3 shows the distributions of fraud period (T1-T0+1), number of years between the first year of fraud and the first year of investigation (Ti-T0), number of years between the first year of fraud and SEC enforcement (T2-T0), and investigation period (T2-Ti+1) for the 114 detected frauds in the final sample. On average, a fraud lasts two years, with 35%-40% of frauds lasting two years, 25% three years, and 15%-20% one year. Less than 20% of frauds last for more than three years. The number of years between the first year of fraud and the first year of investigation is two years on average and one to three years for most firms. The number of years between the first year of fraud and SEC enforcement is four on average and three to six for more than 80% of detected frauds. The investigation period is three years on average and two to four years for 70% of detected frauds.

[14] I also perform the same analysis on 310 fraud events out of 588 fraud events. In these 310 frauds, companies committed fraud between 1984 and 2002 and have valid data in Compustat. I find the pattern is about the same as those in Table IV.

3.2 Variables

Recall that the empirical model in this paper is composed of three equations: a fraud equation, in which the perceived detection probability and variables in X affect the probability of fraud; an ex ante perceived detection equation, in which the probability of fraud and variables in EW affect the perceived detection probability; and an ex post actual detection equation, in which the probability of fraud and variables in W affect the actual probability of detection.

3.2.1 Variables in the Fraud Equation

Variable Measurements X in the fraud equation includes stock-based executive compensation, corporate governance, external financing need, firm size, Z-score, debt-to-assets, and book-to-market.[15]

First, stock-based executive compensation provides incentives for managers to commit fraud. To measure this incentive, I use the pay performance sensitivity (PPS) averaged among the firm's top five executives. PPS is equal to PPS of stocks plus PPS of stock options. PPS of stocks is defined as the number of shares owned by an executive as a fraction of total shares outstanding. And PPS of stock options is defined as the number of shares in options granted to an executive multiplied by the Black-Scholes hedge ratio divided by total shares outstanding. The calculation of PPS follows Palia (2001), Yermack (1995), and Core and Guay (2002). To actually calculate PPS, I use unrestricted stocks and vested options instead of all the stocks and options owned by a manager. This gives a PPS measuring short-term stock-based incentives. This measurement of fraud incentives is more accurate than those using both restricted and unrestricted stocks and both vested and unvested options. The reason is that fraud is a relatively short-term event and in order

[15]Presumably, size of punishment also affects a firm's fraud decision. Punishment for fraud includes monetary penalty, reputation loss, and imprisonment. Monetary penalty includes disgorgement of illgotten gains and fines. The net penalty of disgorgement is zero. In most fraud cases, fines are negligible and can even be waived based on defendents' demonstrated inability to pay. Reputation loss can be captured by firm size because fraud detection usually results in more reputation loss for managers in larger firms. In addition, very few wrongdoers were imprisoned due to fraud. Further, there has been little change in punishment in my sample period, which is in the pre-Sarbanes-Oxley era. Therefore, the size of punishment can be assumed to be constant both cross-sectionally and in time series and will be absorbed into the intercept.

to gain from it, managers must be able to sell shares or exercise options in a short period.[16] Data required to calculate PPS are obtained from ExecuComp, proxy statements, and CRSP.

Second, corporate governance is proxied by the number of inside board directors as a fraction of board size ($FracInsideDir$). As in Core, Holthausen, and Larcker (1999), I define inside directors as directors who are current or former firm managers or their family members.[17] A higher fraction of inside directors indicates a less independent board and thus weaker corporate governance. Data on inside directors and board size are obtained from proxy statements.

Third, a firm's need for external financing may serve as a motive to commit fraud. Following Dechow, Sloan, and Sweeney (1996) and Erickson, Hanlon, and Maydew (2004), I define a firm's external financing needs at time t as an indicator variable $Financing_t = I(0 < C_t < 2)$. When $0 < C_t < 2$, $Financing_t$ equals 1, meaning the firm has external financing needs. C_t is equal to $\frac{\text{Current assets}_{t-1}}{\text{Average capital expenditures}_{t-3\ to\ t-1} - \text{Cash from operations}_t}$. When C_t is less than zero, the firm can generate enough cash from operations to cover its capital expenditure and thus has no need for external financing. When C_t is greater than zero, the firm has less cash from operation than its capital expenditure. In this case, the firm can use current assets to fund investments in excess of cash from operations for C_t years. I assume that the firm has external financing needs if $0 < C_t < 2$ and no such needs if $C_t \geq 2$. Therefore, a firm has external financing needs only when $0 < C_t < 2$. Data on current assets, cash from operations, and capital expenditure are obtained from Compustat.

Finally, firm size, Z-score, debt-to-assets, and book-to-market serve as control variables. I control for firm size using log(sales). I control for the degree of financial distress using Altman's Z-score (Altman (1968)). Following Graham, Lemmon, and Schallheim (1998), I use a modified version of Z-score: Z-score$= 1.2 \times \frac{working\ capital}{total\ assets} + 1.4 \times \frac{retained\ earnings}{total\ assets} + 3.3 \times \frac{EBIT}{total\ assets} + 1.0 \times$

[16] I also calculate PPS using both restricted and unrestricted stocks and both vested and unvested options. This PPS measure gives essentially the same results in the empirical tests.

[17] An alternative definition of inside directors is directors who are current managers of a firm. The empirical analysis based on this definition gives essentially the same results.

$\frac{sales}{total\ assets}$.[18] Lower Z-score reflects a higher degree of financial distress, which may be a motive for management fraud. I also control for firm leverage, measured as the ratio of total debt to total assets. According to Dechow, Sloan, and Sweeney (1996), because high leverage is associated with the existence and tightness of covenants, management may manipulate financial statements to meet certain debt covenants. Finally I use the book-to-market ratio to capture firm growth. Growth firms are harder to be monitored and thus may be correlated with higher likelihood of fraud. Data on these control variables are from Compustat.

For firms accused of fraud, I measure all the above variables as of time T0-1 (the year prior to fraud) instead of T0 (the first year of fraud). The reason is that the variables measured as of T0 may be misstated due to fraud. For firms not accused of fraud, I randomly select a year and use the data in that year to match the cross-sectional data of firms accused of fraud.[19] [20]

Summary Statistics Table V contains summary statistics and univariate comparisons of variables in the fraud equation. Firms accused of fraud have greater pay performance sensitivities, higher fraction of inside directors, more external financing needs, smaller size, higher degree of financial distress, and higher growth than firms not accused of fraud. The differences in means and medians of these variables are significant. Firms accused of fraud have slightly lower leverage ratios but the difference in means is not significant.

[18] Altman's Z-score$= 1.2 \times \frac{working\ capital}{total\ assets} + 1.4 \times \frac{retained\ earnings}{total\ assets} + 3.3 \times \frac{EBIT}{total\ assets} + 1.0 \times \frac{sales}{total\ assets} + 0.06 \times \frac{market\ value\ of\ equity}{book\ value\ of\ total\ debt}$. I use a modified version of Z-score which does not include the ratio of market value of equity to book value of total debt because a similar term, debt-to-assets, enters the regressions as a separate variable.

[19] 114 firms accused of fraud in the final sample are cross-sectional. I randomly select one year's data for each firm not accused of fraud to ensure the firms not accused of fraud are also cross-sectional. This in turn makes sure the probability of fraud and the probability of detection in the regressions represent probabilities in the period I am studying. Putting together cross-sectional firms accused of fraud and a panel of firms not accused of fraud would create a potential problem of comparing probabilities **in the period** I am studying for firms accused of fraud with probabilities **per year** for firms not accused of fraud in the regressions.

[20] To randomly select the years is reasonable because firms' characteristics do not change much within the sample period from 1992 to 1999, which is a relatively short period. To examine whether the random selection of years may affect the results of the paper, I perform robustness tests using different random samples.

3.2.2 Variables in the Detection Equations

Variable Measurements EW in the perceived detection equation includes insider trading of firm managers and total market value of fraudulent firms in the same industry detected prior to a firm's fraud.

A firm's insider trading activity may affect its perceived probability of being detected because abnormally high insider trading of managers will likely catch the SEC's attention and thus raise the detection likelihood.[21] I assume the firm can rationally expect this ex ante.[22]

To measure a firm's insider trading, I use the maximum of annual net insider sales during the fraud period (from T0 to T1) scaled by the firm's market value of equity. Annual net insider sales equals annual open market sales minus purchases by firm top management. I employ this measure because the insider trading during the fraud period is the most relevant to fraud and the maximum value of insider trading will most likely catch the SEC's attention.[23] Data on insider trading is from Thomson Financial's Insider Filing Data Feed Documentation.

Total market value of fraudulent firms in the same industry detected prior to a firm's fraud ($IndMveDetBeforeT0$) may affect the firm's perceived probability of being detected. This is because if a larger percentage of companies in a specific industry have been found committing fraud in prior years, the firm may expect that the SEC would devote more investigative resources to this industry and thus the detection probability may go up. To measure $IndMveDetBeforeT0$, I use total market value of all fraudulent firms in the industry detected in T0-1 (i.e., one year prior to fraud) scaled by the industry's total market value of that year. I look at fraud detected in T0-1 instead of other prior years because it is the most relevant. Market value data is obtained from

[21] According to United States General Accounting Office (2002) and McLucas (1997), the SEC does look at trading data. See Figure 6 for an illustration of the SEC's investigative and enforcement process.

[22] Some might argue that the insider trading variable should enter the fraud equation directly because more insider trading means more profits for managers and thus increases the likelihood of fraud. Indeed, more insider trading may be associated with higher likelihood of fraud. But this effect has mostly been captured by the stock-based incentives in the fraud equation.

[23] I also use a sum measure of insider trading by summing up all the annual insider trading during the fraud period and get similar results.

CRSP.

W in the actual detection equation includes a firm's insider trading activity, total market value of fraudulent firms in the same industry detected prior to a firm's detection, a firm's external auditor's opinion about its financial statements, and the SEC's budget.

First, a firm's insider trading activity may affect its actual probability of being detected because high insider trading may catch the SEC's attention and thus raise its probability of being caught. The measurement and data source of insider trading are the same as those in EW.

Second, total market value of fraudulent firms in the same industry detected prior to a firm's detection ($IndMveDetBeforeT2$) may affect the firm's actual probability of being detected. If more companies in this firm's industry have been found committing fraud in prior years, the SEC may shift more resources to this industry and thus raise the probability of detecting the firm. To measure this variable, I calculate total market value of all fraudulent firms in the firm's industry detected in T2-1 and that in T2-2 (i.e., one year and two years prior to the enforcement year), scale them by the industry's total market value in T2-1 and T2-2 respectively, and then pick the maximum of the scaled values between T2-1 and T2-2. I look at the fraud detected in T2-1 and T2-2 instead of only T2-1 because it usually takes more than one year for the SEC to respond to past fraud detections. Also, the maximum rather than the average of the scaled values in the two years is used because the SEC is most likely to react to the maximum values.

Third, external auditor's adverse opinion about a firm could trigger the SEC's investigation and thus raise the firm's probability of being detected. Auditor's opinion variable is measured as the worst opinion among the years from T0 (the first year of fraud) to Ti-1 (one year prior to the investigation). In this paper, the opinion has three levels: 1 (good) is standard unqualified opinion, 2 (middle) is unqualified opinion with explanatory language, and 3 (bad) is qualified opinion, adverse opinion, disclaimer, or auditor turnover. Auditor's opinion information is from Compustat.

Finally, more resources may lead to greater effectiveness in the SEC's detection activities, so the SEC budget will be a variable affecting the actual detection. Budget in the regressions is measured as the annual inflation-adjusted SEC budget per firm averaged among the investigation period (from Ti to T2). I use budget per firm instead of total budget because the number of firms the SEC regulates changes from year to year and the same budget in a year with fewer firms might be more effective in detecting fraud than in a year with more firms. In addition, the budget per firm variable is not endogenous in the model for the following reason. The mean budget per firm during the period from Ti to T2 is determined **before** T2 (the enforcement year). And the dependent variable, the actual detection, is realized **at** T2. Therefore, mean budget per firm is predetermined and thus not endogenous. The budget data is obtained from the SEC's annual reports and the number of firms used in calculating the budget per firm is the number of firms in Compustat.

Figure 2 reports the SEC budget, the SEC budget adjusted for inflation, and the SEC budget per firm adjusted for inflation. The amounts adjusted for inflation are measured in 1992 constant dollars. From 1992 through 2003, the SEC's annual budget adjusted for inflation is around $310 million on average. It gradually increased from $230 million in 1992 to $280 million in 1995, kept around $270 million from 1996 to 1998, and started to increase sharply from $290 million in 1999 to $550 million in 2003. During the period between 1992 and 2003, the budget per firm is roughly $33,000 per year on average. It was almost flat between 1992 and 1998, around $26,000, and started to increase since 1999. The increase was about $7,000 per year from $30,000 in 1999 to $60,000 in 2003 with the exception of an increase of $9,000 in 2002. The above pattern of large increase in the SEC budget after 1999 is consistent with more and larger fraud detections in the early 2000s than in the 1990s (Table IV).

To measure the above variables in the detection equations, the information on T0, T1, Ti, T2 is required for both firms accused of fraud and firms not accused of fraud. T0, T1, Ti, T2 are available for firms accused of fraud, but not for firms not accused of fraud. For the latter, I first randomly choose a year and assume it to be T0 (the first year of fraud). Then, I assume these firms' fraud period, investigation period, and the time between the first year of fraud and SEC enforcement are equal to the averages of those periods for firms accused of fraud. By doing this, I can determine T0, T1, Ti, and T2 for firms not accused of fraud. To check the robustness, I randomly generate different T0's for firms not accused of fraud and conduct the empirical test. The main results remain unchanged.

Summary Statistics Table VI contains summary statistics and univariate comparisons of variables in the two detection equations. Firms accused of fraud have more insider trading, lower total market value of fraudulent firms in the same industry detected prior to a firm's fraud ($IndMveDetBeforeT0$), higher total market value of fraudulent firms in the same industry detected prior to a firm's detection ($IndMveDetBeforeT2$), worse auditors' opinions, and greater budget per firm than firms not accused of fraud. The differences in means and medians of these variables are significant except the difference in means of $IndMveDetBeforeT2$.

4 Results

4.1 Main Results

Table VII specification (1) contains the main regression results. The results of the model with both simultaneity and partial observability are shown under the heading "SimulEq". The results of the single equation model without simultaneity or partial observability are presented as a comparison under the heading "SingleEq". The table contains three panels. Panel A is the coefficient and marginal effect (slope) estimates of the fraud equation, Panel B is the estimates of the perceived ex ante detection equation, and Panel C is the estimates of the actual ex post detection equation.

4.1.1 Results of the Fraud Equation

I examine the results of the fraud equation in the simultaneous model and compare them with the results of the single equation model.

Marginal effects of pay performance sensitivity (PPS), fraction of inside board directors ($FracInsideDir$), and external financing needs ($Financing$) on the probability of fraud, in the simultaneous system are about two and a half times as high as those in the single equation model. In other words, the marginal effects in the single equation model are biased downward by around 60%. The marginal effect (slope) represents the effect of an independent variable on the dependent variable ($\frac{\partial \, dependent \, variable}{\partial \, independent \, variable}$). In a probit model, it is not equal to the coefficient estimate. Instead, it is equal to the coefficient estimate multiplied by the standard normal density function ($\phi(x\beta) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x\beta)^2}{2}}$). As can be seen from the table, in the simultaneous model, the marginal effects of PPS, fraction of inside directors, and financing needs are 1.87, 0.24, 0.20, respectively, compared with 0.74, 0.09, 0.08 in the single equation model.

The understatements of the marginal effects in the single equation model are both statistically and economically significant. The t-statistics of the differences between the marginal effects of the two models are -3.53, -2.22, and -3.67 for PPS, fraction of inside directors, and financing needs respectively. The economic significance is shown in Figure 4 in terms of the change in the fraud likelihood given a one standard deviation change in the independent variables. One standard deviation increase of PPS from its mean corresponds to a 5% increase in the fraud probability in the simultaneous model and a 2% increase in the single equation model. This 3% difference in the fraud probability is economically significant for the following reason. On average, the loss in market capitalization due to fraud is about $140 million per firm.[24] From 1992 to 2002, the average number of firms in Compustat that have common stocks is about 9,000. So the difference of 3% fraud probability actually translates into an understatement of 270 fraudulent firms or $40 billion shareholder loss due to fraud, which is a large amount. The increase in the fraud probability caused by a one standard deviation increase in the fraction of inside directors from its mean is 2% in the simultaneous model, compared with 1% in the single equation model. A firm with financing needs is 21% more likely to commit fraud than a firm without financing needs in the simultaneous model, while in the single equation model, this number is 11%. By similar reasoning, the differences of 1% and 10% are equivalent to $13 and $130 billion shareholder losses. In other words, the shareholder loss due to fraud will be greatly understated if we do not consider the monitoring role of the SEC

[24] I will discuss the calculation of the shareholder loss due to fraud in more detail in Section 4.1.3.

and the incomplete detection issue.

There are two reasons why the marginal effects in the single equation model are biased downward. First, the single equation model ignores the negative impact of the detection likelihood on fraud that the simultaneous model considers. In the simultaneous model, to offset this negative impact, the effects of the other independent variables on the likelihood of fraud have to be larger. To simplify the illustration, suppose there are two regressions using the same data. Both regressions have the probability of fraud as the dependent variable. The first regression has only one independent variable: PPS. The second regression has two independent variables: PPS and the perceived detection likelihood. Since the coefficient in front of the perceived detection is negative, the marginal effect of PPS will have to be larger in the second regression than in the first regression.[25] The omission of the SEC deterrence effect contributes about 25% of the total bias.

The second reason is the following. Because the single equation model assumes detected fraud to be all the fraud, it understates the true extent of fraud and thus understates the dependent variable, the probability of fraud. Therefore, the marginal effects in front of PPS and other independent variables are biased downward.[26] The single equation model estimates the average probability of detected fraud to be 7% and the simultaneous model estimates the average probability of fraud to be 17%.[27] Therefore, the single equation model understates the probability of fraud by about one half. This understatement contributes the remaining 75% of the total bias.

Finally, I calculate two different measures of pseudo R-squares to compare goodness of fit of the

[25] In an OLS regression of $Y = \delta_1 W_1 + \delta_2 W_2 + \epsilon$, the bias from omission of the variable W_2 is equal to $M \times \delta_2$, where M is equal to the OLS coefficient of regressing W_2 on W_1. In the regressions of this paper, the perceived detection probability is the omitted variable W_2 and has a negative coefficient δ_2. And M in my regressions always have the same sign as δ_1. This is because W_1 has a positive or negative effect on Y, depending on the sign of δ_1. And larger fraud likelihood (Y) leads to higher perceived detection probability (W_2). So the sign of the effect of W_1 on W_2 is the same as that of δ_1. Therefore, when δ_1 is positive (for example, PPS), the bias is negative and when δ_1 is negative (for example, size), the bias is positive. The conclusion is that the coefficients are underestimated in the model that omits variables (the single equation model).

[26] Feinstein (1990) Theorem 2.1. provides a formal proof that a model without considering partial observability has a downward bias.

[27] The simultaneous model estimates the average probability of fraud to be 16.5% and the average probability of detection if fraud to be 37.4%. These probabilities are the probabilities in the period I am studying, which is eight years (1992-1999). Converting these probabilities into probabilities per year gives the fraud probability of 2.2% per year and the detection probability of 5.7% per year.

two models and report them at the bottom of Panel C. One measure, R-sqr (LRI), is the likelihood ratio index proposed by Macfadden and is based on the log-likelihood. The other measure, R-sqr (Cramer's λ), is based on the model's within-sample predictability. The simultaneous system has a R-sqr (LRI) of 30% and a R-sqr (Cramer's λ) of 27%, higher than those of the single equation model, 24% and 22%, respectively.

4.1.2 Results of the Detection Equations

This section examines the results of the detection equations in the simultaneous model. There is no comparison with the single equation model because the single equation model does not have the detection equations.

Statistical significances of variables in the detection equations are presented in Panels B and C of Table VII. First, insider trading and $IndMveDetBeforeT0$ significantly affect the perceived detection. Insider trading, $IndMveDetBeforeT2$, auditor opinion, and budget per firm significantly affect the actual detection. The statistical significance levels of all these variables are at least 95%. In addition, γ_2, the coefficient of the fraud probability in both detection equations, is significantly positive at the 90% level. γ_1, the coefficient of the perceived detection probability in the fraud equation, is significantly negative at the 99% level.

All the independent variables in the detection equations are economically significant (Figure 5). Panel A shows a one standard deviation increase of $IndMveBeforeT0$ from its mean lowers the fraud probability from 17% to 6% through the increase in perceived detection probability. Panels B and C show that when insider trading and $InvMveBeforeT2$ increase by one standard deviation from their means, the actual probabilities of detection rise from 37% to 79% and 37% to 89%, respectively. Panel D shows that when auditor's opinion changes from good to bad, the detection probability more than doubles, from 27% to 68%. Finally, it can be seen from Panel E that a one standard deviation increase in budget per firm is associated with an increase in the detection probability from 37% to 51%.

4.1.3 Policy Implications

I conduct a cost-benefit analysis of the SEC based on the regression estimates. Specifically, I calculate how an increase in the SEC's budget would reduce the fraud probability and then the shareholder loss. The model estimates indicate that a one standard deviation increase of $100 million in the annual SEC budget from the mean value (from $319 million to $406 million) is associated with an increase of 14% in the actual ex post detection probability (from 37% to 51%). I assume this 14% increase will lead to the same magnitude (14%) of increase in the expected detection probability in the future. This in turn leads to a future decline of 0.5% in the fraud probability per year. There are around 9,000 firms in Compustat and the average shareholders' loss due to fraud is about $140 million per firm.[28] Multiplying 9,000 by the decline in fraud probability per year, 0.5%, and then by the market value loss per firm, $140 million, gives an amount of $6 billion. As a result, a $100 million increase of the SEC's annual budget would reduce shareholder losses due to fraud by $6 billion annually. In other words, The SEC's additional $1 spending will bring $60 in benefit to shareholders.

The above calculations indicate that the marginal benefit to shareholders greatly exceeds the marginal cost of SEC law enforcement. This implies that the SEC has been in a serious budget crunch and should continue to increase its budget.

4.2 Robustness Tests

I have performed the following robustness tests.

First, I conduct two additional regressions, as shown in specifications (2) and (3) in Table VII. Specification (2) controls for the macroeconomic effects on fraud and detection by adding boom-

[28]Shareholders' loss due to fraud is measured by the decline in market capitalization from before fraud to after detection. Specifically, let A be the market value of a firm before it commits fraud, B be the maximum market value of the firm during the fraud period, and C be the market value of the firm after the fraud is discovered. Shareholders' loss due to fraud is estimated as the difference between A and C instead of that between B and C. The average loss is $140 million per firm for median-sized firms accused of fraud in the sample. In addition, according to Simmons and Ryan (2004), the median damage of all the settled securities lawsuits from 1997 through 2003 is estimated to be $134.6 million. Further, a report by the United States General Accounting Office indicates that the market-adjusted loss in market capitalization for financial statement restatement companies is about $138.75 million per firm (GAO-03-138).

recession dummies. There might be more fraud in the bull market and more fraud detections in the bear market because the profits of fraud for firms may be higher in the bull market and the SEC may be more watchful in the bear market. Specification (3) controls for both macroeconomic and industry effects using boom-recession and one digit SIC dummies. The reason I also control for the industry effects is that fraud detections tend to concentrate in some specific industries, as mentioned in Section 3.1.2.

Second, I conduct the three regressions of Table VII without constraining the coefficient of $IndMveDetBeforeT0$ in the perceived detection equation and the coefficient of $IndMveDetBeforeT2$ in the actual detection equation to be the same (Table VIII). The reason is that $IndMveDetBeforeT0$ and $IndMveDetBeforeT2$ are similar variables measured at different time points and thus their coefficients might be different. I keep the equality constraints of the coefficients of prob(fraud) and insider trading in perceived and actual detection equations. This is because these two variables are measured the same in both equations.

Third, in this paper, for firms not accused of fraud, I randomly select a year and use the data of those firms in that year to match the cross-sectional data of firms accused of fraud. To examine whether this random selection of years may affect the results of the paper, I randomly select different years than those in the regressions of Table VII to perform the empirical tests. The results are presented in Table IX.

Fourth, time effects are controlled in Table X. I control for the duration between fraud occurrence and detection by adding the variable T2-T0 to the actual detection equation in the main specification (1) of Table VII. This is because it is possible that the longer the time from fraud occurrence, the greater the likelihood of detection. The result is shown in regression (1) of Table X. In regression (2) of Table X, I introduce year effects to the main specification by adding year dummies to both fraud and detection equations. Year effects are used to capture the unobservable strategic and tactical changes within the SEC with respect to fraud monitoring during the sample period.

Fifth, I perform a regression assuming firms can forecast the SEC's budget using the first order autoregressive (AR(1)) model and perfectly forecast auditor's opinion (Table XI). In this regression, I add budget forecast and auditor's opinion to the perceived detection equation of the main specification.

Finally, I conduct a logit analysis of the main specification (1) of Table VII (Table XII). The probit model assumes the probabilities of fraud and detection follow a normal distribution. The logit model assumes the probabilities follow a logistic distribution. I perform the logit analysis to address the concern that the results of this paper may not be robust with respect to different distributional assumptions.

The main results are essentially the same in the above robustness tests.

5 Conclusions

This paper addresses the simultaneity and incomplete detection issues in corporate fraud. An empirical model is set up to take into account the incomplete detection and the interaction between corporate fraud and the SEC's monitoring.

Using a sample of firms accused of corporate fraud by the SEC, I estimate the empirical model and obtain the following findings. I find the effects of stock-based incentives, corporate governance, and external financing needs on the probability of fraud are more than double those in the models in previous studies. The shareholder loss due to fraud is understated by about 60% if we do not consider the monitoring role of the SEC and the incomplete detection issue. I also examine factors affecting the SEC's actual detection and find that a higher SEC budget, more insider trading, more negative auditor's opinion, and higher total market value of detected fraudulent firms in the same industry in prior years contribute to higher detection likelihood.

This paper has a policy implication for the SEC. Using the model estimates, I conduct a cost-benefit analysis and find the marginal shareholder benefit largely exceeds the marginal cost of SEC law enforcement. Specifically, a $100 million increase in the SEC's annual budget would reduce shareholder losses by \$6 billion annually. This indicates that the SEC has been in a serious budget crunch and should continue to increase its budget.

Finally, the empirical model in this paper has potential applications in a number of areas, such as corporate and individual tax evasions, accounting audits, insurance fraud, regulation, crime, etc., because the issues in these areas all have similar interdependence and incomplete detection features.

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Appendix

A. Existence and Uniqueness of the Solutions F and G

The evaluation of the log-likelihood function (6) requires solving for F and G in terms of parameters to be estimated. The existence and uniqueness of the solutions are required to ensure that the likelihood function is properly defined. Let $E_1 = \beta_1 X + c_1$ and $E_2 = \beta_2 EW + c_2$. Then Pr(Y1=1) can be written as:

$$F = \Phi(\gamma_1 \Phi(\gamma_2 F + E_2) + E_1) \equiv h(F) \tag{10}$$

Theorem:

A fixed point always exists in equation (10). The sufficient and necessary condition for the uniqueness of fixed point is $\gamma_1\gamma_2 < 2\pi$.

Proof:

Existence:

Since $h(F)$ is continuous on $[0,1]$ and $h(F) \in [0,1], \forall F \in [0,1]$, according to Brouwer's fixed point theorem, $h(F)$ has a fixed point in $[0,1]$.

Uniqueness:

Letting $A_1 = \gamma_2 F + E_2$ and $A_2 = \gamma_1 \Phi(A_1) + E_1$. Then $\frac{\partial h(F)}{\partial F} = \gamma_1\gamma_2\phi(A_1)\phi(A_2)$.

i) When $\gamma_1\gamma_2 \leq 0$, $h(F)$ is monotonically decreasing and thus has at most one intersection with F, which is increasing along 45 degree line. Therefore, the fixed point is unique.

ii) When $0 < \gamma_1\gamma_2 < 2\pi$, let $k = \gamma_1\gamma_2/2\pi$. Then $0 < k < 1$. Since $0 < \phi(A_1)\phi(A_2) \leq 1/(2\pi)$, we have $\frac{\partial h(F)}{\partial F} = \gamma_1\gamma_2\phi(A_1)\phi(A_2) \leq k < 1$. Then the function $h : [0,1] \to [0,1]$ is a contraction mapping. According to Banach fixed point theorem, which says every contraction has a unique fixed point, uniqueness is obtained when $0 < \gamma_1\gamma_2 < 2\pi$.

iii) When $\gamma_1\gamma_2 = 2\pi$, by setting $E_2 = -0.5\gamma_2$ and $E_1 = -0.5\gamma_1$, $F = 1/2$ is a fixed point because $h(1/2) = 1/2$. The derivative of $h(F) - F$ evaluated at $1/2$ is $h'(1/2) - 1 = \gamma_1\gamma_2\phi(0)\phi(0) - 1 = \frac{\gamma_1\gamma_2}{2\pi} - 1 = 0$. If $h(F)$ is concave (convex), there exists a δ such that $h(F-\delta) < F-\delta (h(F+\delta) > F+\delta)$. Hence, at $F - \delta$ $(F + \delta)$, $h(F - \delta)$ $(h(F + \delta))$ lies below (above) $F - \delta$ $(F + \delta)$. Because $h(0) > 0$ $(h(1) < 1)$, according to the Intermediate Value Theorem, there exists a x in $[0, F - \delta]$ $([F + \delta, 1])$ such that $h(y) = y$. Therefore, the fixed point is not unique. Notice that when $\gamma_1\gamma_2 = 2\pi$, the case of setting $E_2 = -0.5\gamma_2$ and $E_1 = -0.5\gamma_1$ is the only peculiar case in which there are multiple fixed points.

iv) When $\gamma_1\gamma_2 > 2\pi$, by setting $E_2 = -0.5\gamma_2$ and $E_1 = -0.5\gamma_1$, $F = 1/2$ is a fixed point because $h(1/2) = 1/2$. The derivative of $h(F) - F$ evaluated at $1/2$ is $h'(1/2) - 1 = \gamma_1\gamma_2\phi(0)\phi(0) - 1 = \frac{\gamma_1\gamma_2}{2\pi} - 1 > 0$. This means that there exists a δ such that $h(F - \delta) < F - \delta$. Hence at $F - \delta$, $h(F - \delta)$ lies below $F - \delta$. Because $h(0) > 0$, according to the Intermediate Value Theorem, there exists a x in $[0, F - \delta]$ such that $h(y) = y$. Therefore, the fixed point is not unique.

Table I: Sample Selection Procedure

Firms accused of fraud are from SEC enforcement releases issued between January 1st, 1992 and May 31st, 2003.

Screening conditions	Total number of unique fraud events	Total number of unique firms
	849	
Less:		
1)Not firm top management	(139)	
2)Not stock	(84)	
3)No misinformation	(38)	
	588	
588 include:		
1)Overstatement of earnings:	255	
2)Other misrepresentations in financial statements:	81	
3)False press releases:	252	
Less:		
Missing Compustat data	(278)	
	310	303
Less:		
Missing executive compensation or corporate governance data from ExecuComp or proxy statements	(178)	
	132	130
Less:		
Firms whose first years of fraud are greater than 1999	(17)	(16)
	115	**114**
For these 114 firms, the first year of fraud is between 1992 and 1999		

Firms not accused of fraud are the remaining **1507** unique Firms on ExecuComp with valid data.

Table II: Number and Percentage of Firms Accused of Fraud by the Initial Year of Fraud
(committed between 1992 and 2002)

The table presents the number and percentage of 130 firms accused of fraud by the initial year of fraud.

Initial Year of Fraud(T0)	Count	Percent
1992	13	10.00
1993	14	10.77
1994	13	10.00
1995	5	3.85
1996	22	16.92
1997	14	10.77
1998	17	13.08
1999	16	12.31
2000	9	6.92
2001	7	5.38
2002	0	0.00
2003	0	0.00
Total	130	100

Table III: Number and Percentage of Sample Firms by Industry

The table presents the number and percentage of sample firms by SIC division (Panel A) and two digit SIC (Panel B).

Panel A: Number and Percentage of Sample Firms by SIC Division

		Firms Accused of Fraud	No		Yes	
Division	2-Digit SIC	Division Name	Count	Percent	Count	Percent
A	01-09	Agriculture, Forestry, and Fishing	5	0.33	0	0.00
B	10-14	Mining	68	4.51	2	1.75
C	15-17	Construction	10	0.66	0	0.00
D	20-39	Manufacturing	730	48.44	54	47.37
E	40-49	Trans., Comm., Elec., Gas, & Sani. Serv.	218	14.47	5	4.39
F	50-51	Wholesale Trade	52	3.45	5	4.39
G	52-59	Retail Trade	136	9.02	8	7.02
H	60-67	Finance, Insurance, and Real Estate	38	2.52	5	4.39
I	70-89	Services	247	16.39	32	28.07
J	91-99	Public Administration	3	0.20	3	2.63
Total			1507	100	114	100

Panel B: Number and Percentage of Sample Firms by Two Digit SIC

	Firms Accused of Fraud	No		Yes	
2-digit SIC	Industry Name	Count	Percent	Count	Percent
73	Business Services	144	9.56	23	20.18
36	Electronic Equip., Except Computer Equip.	113	7.50	13	11.40
35	Machinery & Computer Equip.	107	7.10	11	9.65
38	Measuring Instruments; Photo Goods; Watches	79	5.24	8	7.02
28	Chemicals And Allied Products	114	7.56	6	5.26
59	Miscellaneous Retail	32	2.12	5	4.39
80	Health Services	38	2.52	4	3.51
20	Food And Kindred Products	44	2.92	3	2.63
23	Apparel & Other Finished Pds	15	1.00	3	2.63
34	Fabricated Metal Products	21	1.39	3	2.63
48	Communications	47	3.12	3	2.63
51	Wholesale Trade-non-durable Goods	17	1.13	3	2.63
99	Nonclassifiable Establishments	3	0.20	3	2.63
31	Leather And Leather Products	3	0.20	2	1.75
37	Transportation Equipment	40	2.65	2	1.75
49	Electric, Gas, And Sanitary Svcs	122	8.10	2	1.75
50	Wholesale Trade-durable Goods	35	2.32	2	1.75
56	Apparel And Accessory Stores	19	1.26	2	1.75
61	Non-depository Credit Institutions	1	0.07	2	1.75
79	Amusement And Recreation Svcs	19	1.26	2	1.75
87	Eng., Acc., Research, Mgmt, Related Svcs	19	1.26	2	1.75
	Other Industries	475	31.52	10	8.77
Total		1507	100	114	100

Table IV: Number, Percentage, and Market Value of Firms Accused of Fraud by Year
(committed between 1992 and 1999)

The table presents the number, percent, total market value, and total market value as a percent of U.S. stock market capitalization of 114 firms accused of fraud in the final sample. These firms committed fraud between 1992 and 1999. Panel A, B, and C present statistics grouped by the initial year of fraud, the initial year of investigation, and the enforcement year, respectively.

Panel A: Number, Percent, and Market Value of Firms Accused of Fraud by the Initial Year of Fraud

Initial Year of Fraud(T0)	Count	Percent	Total Market Value ($\$10^6$)	Total Market Value (% of U.S. Market Value)
1992	13	11.40	2131	0.06
1993	14	12.28	8495	0.22
1994	13	11.40	3312	0.07
1995	5	4.39	247	0.00
1996	22	19.30	11365	0.17
1997	14	12.28	26075	0.42
1998	17	14.91	15024	0.18
1999	16	14.04	72132	0.71
Total	114	100	138782	1.82

Panel B: Number, Percent, and Market Value of Firms Accused of Fraud by the Initial Year of Investigation

Initial Year of Investigation(Ti)	Count	Percent	Total Market Value ($\$10^6$)	Total Market Value (% of U.S. Market Value)
1992	0	0.00	0	0
1993	0	0.00	0	0
1994	2	1.75	162	0.00
1995	7	6.14	1126	0.03
1996	14	12.28	9371	0.24
1997	9	7.89	1620	0.04
1998	9	7.89	5775	0.07
1999	11	9.65	2076	0.04
2000	13	11.40	4666	0.06
2001	26	22.81	31439	0.47
2002	19	16.67	66741	0.71
2003	4	3.51	15805	0.17
Total	114	100	138782	1.82

Panel C: Number, Percent, and Market Value of Firms Accused of Fraud by the Enforcement Year

Enforcement Year(T2)	Count	Percent	Total Market Value ($\$10^6$)	Total Market Value (% of U.S. Market Value)
1992	0	0.00	0	0
1993	0	0.00	0	0
1994	1	0.88	15	0.00
1995	1	0.88	5	0.00
1996	6	5.26	1263	0.03
1997	12	10.53	5343	0.13
1998	9	7.89	5425	0.14
1999	9	7.89	5252	0.06
2000	17	14.91	4902	0.07
2001	11	9.65	3187	0.05
2002	35	30.70	94786	1.14
2003	13	11.40	18603	0.21
Total	114	100	138782	1.82

Table V: Summary Statistics of Variables in the Fraud Equation

The table presents summary statistics of variables in the fraud equation for firms accused of fraud and firms not accused of fraud. All the variables are measured as of the year prior to fraud. PPS, pay performance sensitivity, is equal to PPS of unrestricted stocks plus PPS of vested stock options averaged among firm top five executives, where PPS of unrestricted stocks is the number of unrestricted shares owned by an executive as a fraction of total shares outstanding and PPS of vested stock options is the number of shares in vested options granted to an executive multiplied by Black-Scholes hedge ratio divided by total shares outstanding. $FracInsideDir$ is the number of inside board directors as a fraction of board size, where an inside director is defined as a director who is current or former firm managers or their family members. I define a firm's external financing needs at time t as an indicator variable $Financing_t = I(0 < C_t < 2)$. When $0 < C_t < 2$, $Financing_t$ equals 1, meaning the firm has external financing needs. C_t is equal to $\frac{\text{Current assets}_{t-1}}{\text{Average capital expenditures}_{t-3\ to\ t-1} - \text{Cash from operations}_t}$. $Sales$ is Compustat data12 and $Size$ used in the regressions is equal to log($Sales$). $Z\text{-}score = 1.2 \times \frac{working\ capital}{total\ assets} + 1.4 \times \frac{retained\ earnings}{total\ assets} + 3.3 \times \frac{EBIT}{total\ assets} + 1.0 \times \frac{sales}{total\ assets}$. *Debt-to-Assets* is long-term debt (Compustat data9) divided by total assets (Compustat data6). *Book-to-Market* is book value of common equity (Compustat data60) divided by market value of equity (Compustat data199$\times$data25).

Variable Name	Firms Accused of Fraud	N	Mean	Stdev	Q1	Median	Q3	Mean Dif (P-value)	Median Dif (P-value)
PPS	No	1507	0.01	0.02	0.00	0.00	0.01		
	Yes	114	0.06	0.10	0.01	0.02	0.07	0.00 ***	0.00 ***
FracInsideDir	No	1507	0.30	0.14	0.20	0.30	0.38		
	Yes	114	0.39	0.17	0.25	0.40	0.50	0.00 ***	0.00 ***
Financing	No	1507	0.05	0.22	0.00	0.00	0.00		
	Yes	114	0.36	0.48	0.00	0.00	1.00	0.00 ***	0.00 ***
Sales ($Million)	No	1507	1993.81	5306.32	184.61	521.52	1716.00		
	Yes	114	1132.14	3558.98	11.68	51.50	242.12	0.02 **	0.00 ***
Z-score	No	1507	1.97	1.48	1.18	1.98	2.75		
	Yes	114	0.56	3.41	0.31	1.56	2.13	0.00 ***	0.00 ***
Book-to-Market	No	1507	0.45	0.31	0.23	0.40	0.60		
	Yes	114	0.32	0.51	0.14	0.30	0.45	0.01 ***	0.00 ***
Debt-to-Assets	No	1507	0.20	0.18	0.03	0.18	0.31		
	Yes	114	0.17	0.22	0.01	0.09	0.25	0.28	0.02 **

Table VI: Summary Statistics of Variables in the Detection Equations

The table presents summary statistics of variables in the detection equations for firms accused of fraud and firms not accused of fraud. $InsiderTrading$ is the maximum of annual net insider sales during the fraud period (from T0 to T1) scaled by the firm's market value of equity, where annual net insider sales equals annual open market sales minus purchases by firm top management. $IndMveDetBeforeT0$ is the total market value of fraudulent firms in the same industry detected prior to a firm's fraud. It is equal to total market value of all fraudulent firms in the industry detected in T0-1 (i.e., one year prior to fraud) scaled by the industry's total market value of that year. $IndMveDetBeforeT2$ is the total market value of fraudulent firms in the same industry detected prior to a firm's detection. To measure this variable, I calculate total market value of all fraudulent firms in the firm's industry detected in T2-1 and that in T2-2 (i.e., one year and two years prior to the enforcement year), scale them by the industry's total market value in T2-1 and T2-2 respectively, and then pick the maximum of the scaled values in T2-1 and T2-2. $Auditor's\ Opinion$ is the worst opinion among the years from T0 (the first year of fraud) to Ti-1 (one year prior to the investigation). The opinion has three levels: 1 (good) is standard unqualified opinion, 2 (middle) is unqualified with explanatory language, and 3 (bad) is qualified opinion, adverse opinion, disclaimer, or auditor turnover. *Budget Per Firm* is the average annual SEC budget per firm adjusted by inflation during the investigation period (from Ti to T2).

Variable Name	Firms Accused of Fraud	N	Mean	Stdev	Q1	Median	Q3	Mean Dif (P-value)	Median Dif (P-value)
Insider Trading(%)	No	1507	0.604	1.438	0.00	0.033	0.446		
	Yes	114	1.045	1.997	0.00	0.120	0.969	0.03**	0.09*
IndMveDetBeforeT0(%)	No	1507	0.254	3.003	0	0	0		
	Yes	114	0.060	0.207	0	0	0	0.02 **	0.01 **
IndMveDetBeforeT2(%)	No	1507	0.403	2.797	0	0	0		
	Yes	114	1.211	6.111	0	0	0.297	0.16	0.00***
Auditor's Opinion	No	1507	1.55	0.70	1	1	2		
	Yes	114	2.09	0.84	1	2	3	0.00 ***	0.00 ***
Budget Per Firm($Thousand)	No	1507	35	10	26	31	45		
	Yes	114	37	10	27	34	45	0.04 **	0.05 **

Table VII: Regression Result–Fraud Equation (main regression results)

The table presents the main regression results. The results of the model with both simultaneity and partial observability are shown under the heading "SimulEq". The results of the single equation model without simultaneity or partial observability are presented as a comparison under the heading "SingleEq". Specification (1) is the main specification, specification (2) adds boom and recession dummies, and specification (3) adds industry dummies in addition to boom and recession dummies. The table contains three panels. Panel A is the coefficient and marginal effect (slope) estimates of the fraud equation, Panel B is the estimates of the perceived ex ante detection equation, and Panel C is the estimates of the actual ex post detection equation. Log-likelihood and two measures of pseudo R-squares are reported at the bottom of Panel C. $Pr(fraud)$ is the probability of fraud and *Ex Ante* $Pr(D|F)$ (*Ex Post* $Pr(D|F)$) is the perceived ex ante (actual ex post) probability of detection given fraud. *Boom* is a dummy variable equal to one if the first year of fraud is between 1996 and 1999. *Recession* in the perceived (actual) detection equation is a dummy variable equal to one if the first year of fraud (investigation) is between 1992 and 1994 or between 2000 and 2002. Industry dummies are one-digit SIC dummy variables. All the other variables are defined in Tables V and VI. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1) SingleEq Coef/Slope	SimulEq Coef/Slope	(2) SingleEq Coef/Slope	SimulEq Coef/Slope	(3) SingleEq Coef/Slope	SimulEq Coef/Slope
Panel A:						
Pr(fraud)						
Ex Ante Pr(D|F)		-1.52/-0.32		-1.47/-0.30		-1.34/-0.26
		(-2.76)***		(-2.83)***		(-3.47)***
PPS	7.13/0.74	9.00/1.87	7.25/0.75	8.94/1.83	7.31/0.75	9.35/1.85
	(4.68)***	(4.21)***	(4.74)***	(4.23)***	(4.71)***	(4.85)***
FracInsideDir	0.87/0.09	1.16/0.24	0.90/0.09	1.13/0.23	0.87/0.09	1.03/0.20
	(2.31)**	(2.49)**	(2.37)**	(2.44)**	(2.26)**	(2.28)**
Financing	0.74/0.08	0.95/0.20	0.73/0.08	0.96/0.20	0.73/0.08	0.96/0.19
	(4.40)***	(4.24)***	(4.35)***	(4.37)***	(4.30)***	(4.67)***
Size	-0.15/-0.02	-0.20/-0.04	-0.16/-0.02	-0.20/-0.04	-0.15/-0.02	-0.18/-0.04
	(-3.88)***	(-3.33)***	(-4.05)***	(-3.40)***	(-3.77)***	(-3.33)***
Z-score	-0.04/-0.00	-0.02/-0.01	-0.04/-0.00	-0.02/-0.00	-0.04/-0.00	-0.03/-0.01
	(-1.34)	(-0.63)	(-1.16)	(-0.50)	(-1.36)	(-0.40)
Debt-to-Assets	-0.12/-0.01	-0.16/-0.03	-0.08/-0.01	-0.15/-0.03	0.08/0.01	-0.02/-0.00
	(-0.41)	(-0.43)	(-0.26)	(-0.41)	(0.26)	(-0.05)
Book-to-Market	-0.19/-0.02	-0.15/-0.03	-0.16/-0.02	-0.15/-0.03	-0.16/-0.02	-0.16/-0.03
	(-1.16)	(-0.50)	(-1.03)	(-0.50)	(-0.98)	(-0.62)
Boom			0.22/0.02	-0.08/-0.02	0.20/0.02	-0.14/-0.03
			(1.92)*	(-0.36)	(1.72)*	(-0.70)
Constant1	-1.06	0.17	-1.17	0.16	-1.22	-0.04
	(-4.21)***	(0.25)	(-4.52)***	(0.24)	(-3.99)***	(-0.08)

Table VII (continued): Regression Result–Detection Equations (main regression results)

	(1) SingleEq Coef/Slope	SimulEq Coef/Slope	(2) SingleEq Coef/Slope	SimulEq Coef /Slope	(3) SingleEq Coef/Slope	SimulEq Coef/Slope
Panel B:						
Ex Ante Pr(D|F)						
Pr(fraud)		2.09/0.51		1.97/0.46		1.72/0.29
		(1.72)*		(1.71)*		(1.91)*
Insider Trading		1.00/0.25		1.04/0.25		1.15/0.19
		(2.12)**		(2.08)**		(2.51)***
IndMveDetBeforeT0		0.61/0.15		0.66/0.16		0.53/0.09
		(2.01)**		(2.07)**		(2.11)**
Recession				-0.10/-0.02		-0.13/-0.02
				(-0.31)		(-0.39)
Constant2		-1.38		-1.39		-1.70
		(-1.86)*		(-1.81)*		(-1.88)*

Panel C:						
Ex Post Pr(D|F)						
Pr(fraud)		2.09/0.46		1.97/0.43		1.72/0.35
		(1.72)*		(1.71)*		(1.91)*
Insider Trading		1.00/0.22		1.04/0.23		1.15/0.23
		(2.12)**		(2.08)**		(2.51)***
IndMveDetBeforeT2		0.61/0.13		0.66/0.15		0.53/0.11
		(2.01)**		(2.07)**		(2.11)**
Auditor's Opinion		0.80/0.18		0.82/0.18		0.92/0.19
		(3.49)***		(3.34)***		(3.41)***
Budget Per Firm		1.89/0.42		2.24/0.49		2.74/0.56
		(3.27)***		(2.37)**		(2.80)***
Recession				-0.10/-0.02		-0.13/-0.03
				(-0.31)		(-0.39)
Constant3		3.83		5.07		6.80
		(2.01)**		(1.61)		(2.05)
Industry Dummies	No	No	No	No	Yes	Yes
LogL	-314.28	-290.05	-312.40	-289.83	-309.41	-285.55
R-sqr (LRI)	0.24	0.30	0.24	0.30	0.25	0.31
R-sqr (Cramer's λ)	0.22	0.27	0.22	0.27	0.23	0.28

Table VIII: Regression Result–Fraud Equation (with relaxed constraints)

The table presents the results from the regressions without constraining the coefficient of $IndMveDetBeforeT0$ in the perceived detection equation and the coefficient of $IndMveDetBeforeT2$ in the actual detection equation to be the same. I keep the equality constraints of the coefficients of prob(fraud) and insider trading in perceived and actual detection equations. The results of the model with both simultaneity and partial observability are shown under the heading "SimulEq". The results of the single equation model without simultaneity or partial observability are presented as a comparison under the heading "SingleEq". Specification (1) is the main specification, specification (2) adds boom and recession dummies, and specification (3) adds industry dummies in addition to boom and recession dummies. The table contains three panels. Panel A is the coefficient and marginal effect (slope) estimates of the fraud equation, Panel B is the estimates of the perceived ex ante detection equation, and Panel C is the estimates of the actual ex post detection equation. Log-likelihood and two measures of pseudo R-squares are reported at the bottom of Panel C. $Pr(fraud)$ is the probability of fraud and $Ex\ Ante\ Pr(D|F)$ ($Ex\ Post\ Pr(D|F)$) is the perceived ex ante (actual ex post) probability of detection given fraud. *Boom* is a dummy variable equal to one if the first year of fraud is between 1996 and 1999. *Recession* in the perceived (actual) detection equation is a dummy variable equal to one if the first year of fraud (investigation) is between 1992 and 1994 or between 2000 and 2002. Industry dummies are one-digit SIC dummy variables. All the other variables are defined in Tables V and VI. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1) SingleEq Coef/Slope	SimulEq Coef/Slope	(2) SingleEq Coef/Slope	SimulEq Coef/Slope	(3) SingleEq Coef/Slope	SimulEq Coef/Slope
Panel A:						
Pr(fraud)						
Ex Ante Pr(D|F)		-1.33/-0.26		-1.57/-0.32		-1.85/-0.44
		(-3.23)***		(-4.36)***		(-4.29)***
PPS	7.13/0.74	8.70/1.72	7.25/0.75	8.75/1.80	7.31/0.75	8.75/2.06
	(4.68)***	(4.19)***	(4.74)***	(4.58)***	(4.71)***	(4.59)***
FracInsideDir	0.87/0.09	1.08/0.21	0.90/0.09	1.12/0.23	0.87/0.09	1.03/0.24
	(2.31)**	(2.42)**	(2.37)**	(2.46)**	(2.26)**	(2.21)**
Financing	0.74/0.08	0.93/0.18	0.73/0.08	0.97/0.20	0.73/0.08	1.02/0.24
	(4.40)***	(4.40)***	(4.35)***	(4.68)***	(4.30)***	(4.80)***
Size	-0.15/-0.02	-0.20/-0.04	-0.16/-0.02	-0.20/-0.04	-0.15/-0.02	-0.20/-0.05
	(-3.88)***	(-3.58)***	(-4.05)***	(-3.58)***	(-3.77)***	(-3.28)***
Z-score	-0.04/-0.00	-0.02/-0.00	-0.04/-0.00	-0.02/-0.00	-0.04/-0.00	-0.02/-0.01
	(-1.34)	(-0.47)	(-1.16)	(-0.51)	(-1.36)	(-0.60)
Debt-to-Assets	-0.12/-0.01	-0.15/-0.03	-0.08/-0.01	-0.21/-0.04	0.08/0.01	0.04/0.01
	(-0.41)	(-0.42)	(-0.26)	(-0.56)	(0.26)	(0.09)
Book-to-Market	-0.19/-0.02	-0.13/-0.04	-0.16/-0.02	-0.17/-0.04	-0.16/-0.02	-0.20/-0.05
	(-1.16)	(-0.42)	(-1.03)	(-0.55)	(-0.98)	(-0.74)
Boom			0.22/0.02	0.17/0.04	0.20/0.02	0.32/0.08
			(1.92)*	(0.60)	(1.72)*	(1.21)
Constant1	-1.06	-0.00	-1.17	0.09	-1.22	0.14
	(-4.21)***	(-0.01)	(-4.52)***	(0.16)	(-3.99)***	(0.23)

Table VIII (continued): Regression Result–Detection Equations (with relaxed constraints)

	(1) SingleEq Coef /Slope	SimulEq Coef/Slope	(2) SingleEq Coef/Slope	SimulEq Coef/Slope	(3) SingleEq Coef/Slope	SimulEq Coef/Slope
Panel B:						
Ex Ante Pr(D|F)						
Pr(fraud)		1.85/0.35		1.81/0.36		2.43/0.45
		(1.72)*		(2.03)**		(1.93)*
Insider Trading		1.13/0.21		1.13/0.22		1.25/0.23
		(2.27)**		(1.99)**		(2.26)**
IndMveDetBeforeT0		2.53/0.47		1.65/0.33		1.46/0.27
		(1.21)		(1.27)		(1.43)
Recession				-1.47/-0.29		-0.77/-0.14
				(-1.18)		(-1.17)
Constant2		-1.69		-1.21		-1.80
		(-2.12)**		(-2.09)**		(-2.25)**
Panel C:						
Ex Post Pr(D|F)						
Pr(fraud)		1.85/0.41		1.81/0.38		2.43/0.46
		(1.72)*		(2.03)**		(1.93)*
Insider Trading		1.13/0.25		1.13/0.24		1.25/0.24
		(2.27)**		(1.99)**		(2.26)**
IndMveDetBeforeT2		0.61/0.13		0.55/0.12		0.05/0.10
		(1.77)*		(2.08)		(1.24)
Auditor's Opinion		0.84/0.19		0.79/0.17		0.74/0.14
		(3.42)***		(3.63)***		(4.18)***
Budget Per Firm		2.07/0.46		2.53/0.53		1.54/0.29
		(3.36)***		(2.75)***		(1.99)**
Recession				-0.02/-0.00		0.10/0.02
				(-0.06)		(0.34)
Constant3		4.48		5.99		2.16
		(2.21)**		(1.97)**		(0.80)
Industry Dummies	No	No	No	No	Yes	Yes
LogL	-314.28	-289.28	-312.40	-286.57	-309.41	-283.04
R-sqr (LRI)	0.24	0.30	0.24	0.31	0.25	0.31
R-sqr (Cramer's λ)	0.22	0.28	0.22	0.28	0.23	0.28

Table IX: Regression Result–Fraud Equation (another random sample)

The table presents the results from another random sample. In this paper, for firms not accused of fraud, I randomly select a year and use the data of those firms in that year to match the cross-sectional data of firms accused of fraud. In this table, I randomly select different years than those in the regressions of Table VII to perform the empirical tests. The results of the model with both simultaneity and partial observability are shown under the heading "SimulEq". The results of the single equation model without simultaneity or partial observability are presented as a comparison under the heading "SingleEq". Specification (1) is the main specification, specification (2) adds boom and recession dummies, and specification (3) adds industry dummies in addition to boom and recession dummies. The table contains three panels. Panel A is the coefficient and marginal effect (slope) estimates of the fraud equation, Panel B is the estimates of the perceived ex ante detection equation, and Panel C is the estimates of the actual ex post detection equation. Log-likelihood and two measures of pseudo R-squares are reported at the bottom of Panel C. $Pr(fraud)$ is the probability of fraud and *Ex Ante* $Pr(D|F)$ (*Ex Post* $Pr(D|F)$) is the perceived ex ante (actual ex post) probability of detection given fraud. *Boom* is a dummy variable equal to one if the first year of fraud is between 1996 and 1999. *Recession* in the perceived (actual) detection equation is a dummy variable equal to one if the first year of fraud (investigation) is between 1992 and 1994 or between 2000 and 2002. Industry dummies are one-digit SIC dummy variables. All the other variables are defined in Tables V and VI. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1) SingleEq Coef/Slope	SimulEq Coef/Slope	(2) SingleEq Coef/Slope	SimulEq Coef/Slope	(3) SingleEq Coef/Slope	SimulEq Coef/Slope
Panel A:						
Pr(fraud)						
Ex Ante Pr(D|F)		-1.21/-0.21		-0.92/-0.16		-1.13/-0.20
		(-3.06)***		(-3.47)***		(-3.53)***
PPS	5.98/0.63	7.40/1.31	6.10/0.64	6.67/1.13	6.29/0.65	7.21/1.31
	(4.21)***	(3.71)***	(4.29)***	(4.31)***	(4.34)***	(4.46)***
FracInsideDir	0.88/0.09	1.03/0.18	0.89/0.09	1.01/0.17	0.82/0.09	0.93/0.17
	(2.35)**	(2.52)**	(2.36)**	(2.65)***	(2.17)**	(2.22)**
Financing	0.72/0.08	0.92/0.16	0.71/0.07	0.94/0.16	0.70/0.07	0.99/0.18
	(4.30)***	(4.47)***	(4.21)***	(4.98)***	(4.12)***	(4.96)***
Size	-0.16/-0.02	-0.22/-0.04	-0.17/-0.02	-0.20/-0.03	-0.16/-0.02	-0.21/-0.04
	(-4.24)***	(-4.07)***	(-4.42)***	(-4.15)***	(-4.08)***	(-4.05)***
Z-score	-0.03/-0.00	-0.01/-0.00	-0.03/-0.00	-0.01/-0.00	-0.03/-0.00	-0.01/-0.00
	(-1.03)	(-0.31)	(-0.89)	(-0.26)	(-1.12)	(-0.15)
Debt-to-Assets	0.10/0.01	0.14/0.02	0.14/0.02	0.12/0.02	0.27/0.03	0.23/0.04
	(0.34)	(0.43)	(0.49)	(0.41)	(0.90)	(0.72)
Book-to-Market	-0.16/-0.02	-0.20/-0.04	-0.15/-0.02	-0.26/-0.04	-0.15/-0.02	-0.25/-0.04
	(-1.03)	(-0.68)	(-0.96)	(-1.06)	(-0.92)	(-1.05)
Boom			0.24/0.03	-0.44/-0.08	0.21/0.02	-0.37/-0.07
			(2.12)**	(-1.62)	(1.88)**	(-1.60)
Constant1	-1.03	-0.01	-1.14	0.04	-1.16	0.24
	(-4.15)***	(-0.03)	(-4.48)***	(0.09)	(-3.84)***	(0.46)

Table IX (continued): Regression Result–Detection Equations (another random sample)

	(1) SingleEq Coef/Slope	SimulEq Coef/Slope	(2) SingleEq Coef/Slope	SimulEq Coef/Slope	(3) SingleEq Coef/Slope	SimulEq Coef/Slope
Panel B:						
Ex Ante Pr(D|F)						
Pr(fraud)		1.62/0.32		1.65/0.29		2.02/0.35
		(1.77)*		(1.88)*		(2.31)**
Insider Trading		1.04/0.21		1.12/0.19		1.15/0.20
		(2.16)**		(2.30)**		(2.24)**
IndMveDetBeforeT0		1.28/0.26		0.57/0.10		0.56/0.10
		(2.28)**		(2.76)***		(2.64)***
Recession				0.90/0.16		0.33/0.06
				(1.92)*		(0.88)
Constant2		-1.55		-2.06		-2.02
		(-1.90)*		(-2.37)**		(-1.99)**

Panel C:						
Ex Post Pr(D|F)						
Pr(fraud)		1.62/0.36		1.65/0.26		2.02/0.35
		(1.77)*		(1.88)*		(2.31)**
Insider Trading		1.04/0.23		1.12/0.17		1.15/0.20
		(2.16)**		(2.30)**		(2.24)**
IndMveDetBeforeT2		1.28/0.28		0.57/0.09		0.56/0.10
		(2.28)**		(2.76)***		(2.64)***
Auditor's Opinion		0.88/0.19		0.95/0.15		0.97/0.17
		(2.98)***		(2.92)***		(2.99)***
Budget Per Firm		2.62/0.58		6.94/1.08		5.00/0.85
		(3.03)***		(3.00)***		(3.08)***
Recession				0.90/0.14		0.33/0.06
				(1.92)*		(0.88)
Constant3		6.54		21.41		0.24
		(2.36)**		(2.72)***		(0.46)
Industry Dummies	No	No	No	No	Yes	Yes
LogL	-316.46	-290.78	-314.16	-289.85	-311.40	-285.86
R-sqr (LRI)	0.23	0.29	0.24	0.30	0.24	0.31
R-sqr (Cramer's λ)	0.22	0.27	0.22	0.27	0.22	0.28

Table X: Regression Result–Fraud Equation (control for time effects)

The table presents the results from the regressions that have controlled time effects. In regression (1), I control for the duration between fraud occurrence and detection by adding the variable T2-T0 to the actual detection equation in the main specification (1) of Table VII. In regression (2), I introduce the year effects to the main specification by adding year dummies to both fraud and actual detection equations. The results of the model with both simultaneity and partial observability are shown under the heading "SimulEq". The results of the single equation model without simultaneity or partial observability are presented as a comparison under the heading "SingleEq". The table contains three panels. Panel A is the coefficient and marginal effect (slope) estimates of the fraud equation, Panel B is the estimates of the perceived ex ante detection equation, and Panel C is the estimates of the actual ex post detection equation. Log-likelihood and two measures of pseudo R-squares are reported at the bottom of Panel C. $Pr(fraud)$ is the probability of fraud and $Ex\ Ante\ Pr(D|F)$ ($Ex\ Post\ Pr(D|F)$) is the perceived ex ante (actual ex post) probability of detection given fraud. All the other variables are defined in Tables V and VI. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1) SingleEq Coef/Slope	SimulEq Coef/Slope	(2) SingleEq Coef/Slope	SimulEq Coef/Slope
Panel A:				
Pr(fraud)				
Ex Ante Pr(D|F)		-1.47/-0.31 (-2.86)***		-2.25/-0.58 (-2.88)***
PPS	7.13/0.74 (4.68)***	9.01/1.86 (4.15)***	7.48/0.76 (4.78)***	7.67/1.97 (3.93)***
FracInsideDir	0.87/0.09 (2.31)**	1.20/0.25 (2.54)**	0.89/0.09 (2.32)**	0.91/0.23 (1.93)*
Financing	0.74/0.08 (4.40)***	1.03/0.21 (4.33)***	0.75/0.08 (4.44)***	0.81/0.21 (3.57)***
Size	-0.15/-0.02 (-3.88)***	-0.19/-0.04 (-3.17)***	-0.15/-0.02 (-3.82)***	-0.17/-0.04 (-2.79)***
Z-score	-0.04/-0.00 (-1.34)	-0.02/-0.00 (-0.49)	-0.05/-0.00 (-1.43)	-0.03/-0.01 (-0.73)
Debt-to-Assets	-0.12/-0.01 (-0.41)	-0.14/-0.03 (-0.38)	-0.12/-0.01 (-0.41)	-0.03/-0.01 (-0.09)
Book-to-Market	-0.19/-0.02 (-1.16)	-0.13/-0.03 (-0.39)	-0.15/-0.02 (-0.93)	-0.26/-0.07 (-1.04)
Constant1	-1.06 (-4.21)***	0.03 (0.05)	-1.06 (-3.62)***	2.72 (1.24)

Table X (continued): Regression Result–Detection Equations (control for time effects)

	(1) SingleEq Coef/Slope	SimulEq Coef/Slope	(2) SingleEq Coef/Slope	SimulEq Coef/Slope
Panel B:				
Ex Ante Pr(D|F)				
Pr(fraud)		2.71/0.63		4.47/1.00
		(1.99)**		(2.73)***
Insider Trading		0.88/0.21		0.10/0.02
		(1.97)**		(1.60)
IndMveDetBeforeT0		1.15/0.27		0.30/0.07
		(1.98)**		(2.16)**
Constant2		-1.54		-1.07
		(-2.10)**		(-0.51)

Panel C:				
Ex Post Pr(D|F)				
Pr(fraud)		2.71/0.53		4.47/0.68
		(1.99)**		(2.73)***
Insider Trading		0.88/0.17		0.10/0.01
		(1.97)**		(1.60)
IndMveDetBeforeT2		1.15/0.23		0.30/0.05
		(1.98)**		(2.16)**
Auditor's Opinion		1.05/0.21		0.68/0.11
		(3.17)***		(3.05)***
Budget Per Firm		2.02/0.40		6.22/0.96
		(2.73)***		(2.19)**
T2-T0		0.47/0.09		
		(0.45)		
Constant3		1.78		17.83
		(0.39)		(1.68)*
Year Dummies	No	No	Yes	Yes
LogL	-314.28	-282.86	-306.81	-271.11
R-sqr (LRI)	0.24	0.31	0.26	0.34
R-sqr (Cramer's λ)	0.22	0.28	0.23	0.31

Table XI: Regression Result–Fraud Equation (with budget forecast and auditor's opinion in perceived detection equation)

The table presents the results from a regression assuming firms can forecast budget using the first order autoregressive (AR(1)) model and perfectly forecast auditor's opinion. In this regression, I add budget forecast and auditor's opinion to the perceived detection equation of the main specification. The results of the model with both simultaneity and partial observability are shown under the heading "SimulEq". The results of the single equation model without simultaneity or partial observability are presented as a comparison under the heading "SingleEq". The table contains three panels. Panel A is the coefficient and marginal effect (slope) estimates of the fraud equation, Panel B is the estimates of the perceived ex ante detection equation, and Panel C is the estimates of the actual ex post detection equation. Log-likelihood and two measures of pseudo R-squares are reported at the bottom of Panel C. $Pr(fraud)$ is the probability of fraud and *Ex Ante* $Pr(D|F)$ (*Ex Post* $Pr(D|F)$) is the perceived ex ante (actual ex post) probability of detection given fraud. *Budget Forecast* is the budget predicted ex ante using the AR(1) model. All the other variables are defined in Tables V and VI. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	SingleEq Coef/Slope	SimulEq Coef/Slope
Panel A:		
Pr(fraud)		
Ex Ante Pr(D|F)		-1.31/-0.29 (-3.68)***
PPS	7.13/0.74 (4.68)***	8.81/1.93 (4.59)***
FracInsideDir	0.87/0.09 (2.31)**	1.08/0.24 (2.44)**
Financing	0.74/0.08 (4.40)***	0.89/0.20 (4.58)***
Size	-0.15/-0.02 (-3.88)***	-0.18/-0.04 (-3.42)***
Z-score	-0.04/-0.00 (-1.34)	-0.04/-0.01 (-1.08)
Debt-to-Assets	-0.12/-0.01 (-0.41)	-0.11/-0.02 (-0.32)
Book-to-Market	-0.19/-0.02 (-1.16)	-0.11/-0.02 (-0.34)
Constant1	-1.06 (-4.21)***	-0.03 (-0.06)

Table XI (continued): Regression Result–Detection Equations (with budget forecast and auditor's opinion in perceived detection equation)

	SingleEq Coef/Slope	SimulEq Coef/Slope
Panel B:		
Ex Ante Pr(D|F)		
Pr(fraud)		1.79/0.25 (2.05)**
Insider Trading		1.17/0.16 (2.21)**
IndMveDetBeforeT0		0.57/0.08 (2.25)**
Auditor's Opinion		0.70/0.10 (2.51)**
Budget Forecast		2.00/0.27 (3.79)***
Constant2		3.35 (2.00)**

Panel C:		
Ex Post Pr(D|F)		
Pr(fraud)		1.79/0.38 (2.05)**
Insider Trading		1.17/0.25 (2.21)**
IndMveDetBeforeT2		0.57/0.12 (2.25)**
Auditor's Opinion		0.70/0.15 (2.51)**
Budget Per Firm		2.00/0.42 (3.79)***
Constant3		4.22 (2.36)**
LogL	-314.28	-295.65
R-sqr (LRI)	0.24	0.28
R-sqr (Cramer's λ)	0.22	0.26

Table XII: Regression Result–Fraud Equation (logit analysis)

The table presents the results from a logit analysis of the main specification (1) of Table VII. The results of the model with both simultaneity and partial observability are shown under the heading "SimulEq". The results of the single equation model without simultaneity or partial observability are presented as a comparison under the heading "SingleEq". The table contains three panels. Panel A is the coefficient and marginal effect (slope) estimates of the fraud equation, Panel B is the estimates of the perceived ex ante detection equation, and Panel C is the estimates of the actual ex post detection equation. Log-likelihood and two measures of pseudo R-squares are reported at the bottom of Panel C. $Pr(fraud)$ is the probability of fraud and $Ex\ Ante\ Pr(D|F)$ ($Ex\ Post\ Pr(D|F)$) is the perceived ex ante (actual ex post) probability of detection given fraud. All the other variables are defined in Tables V and VI. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	SingleEq Coef/Slope	SimulEq Coef/Slope
Panel A:		
Pr(fraud)		
Ex Ante Pr(D|F)		-2.80/-0.30 (-2.70)***
PPS	12.54/0.63 (4.56)***	15.57/1.67 (3.96)***
FracInsideDir	2.00/0.10 (2.68)***	2.18/0.23 (2.45)**
Financing	1.27/0.06 (4.19)***	1.63/0.18 (4.11)***
Size	-0.40/-0.02 (-4.78)***	-0.44/-0.05 (-3.82)***
Z-score	-0.03/-0.00 (-0.57)	-0.01/-0.00 (-0.14)
Debt-to-Assets	0.20/0.01 (0.35)	0.00/0.00 (0.00)
Book-to-Market	-0.28/-0.01 (-0.84)	-0.28/-0.03 (-0.52)
Constant1	-1.52 (-3.03)	0.78 (0.58)

Table XII (continued): Regression Result–Detection Equations (logit analysis)

	SingleEq Coef/Slope	SimulEq Coef/Slope
Panel B:		
Ex Ante Pr(D|F)		
Pr(fraud)		3.14/0.48 (1.73)*
Insider Trading		1.47/0.23 (1.76)*
IndMveDetBeforeT0		0.96/0.15 (1.87)*
Constant2		-2.00 (-1.69)*

	SingleEq Coef/Slope	SimulEq Coef/Slope
Panel C:		
Ex Post Pr(D|F)		
Pr(fraud)		3.14/0.41 (1.73)*
Insider Trading		1.47/0.19 (1.76)*
IndMveDetBeforeT2		0.96/0.12 (1.87)*
Auditor's Opinion		1.45/0.19 (3.45)***
Budget Per Firm		3.46/0.45 (3.24)***
Constant3		7.41 (2.16)**
LogL	-310.40	-287.73
R-sqr (LRI)	0.25	0.30
R-sqr (Cramer's λ)	0.24	0.28

Figure 1: Time-line of Fraud and Detection

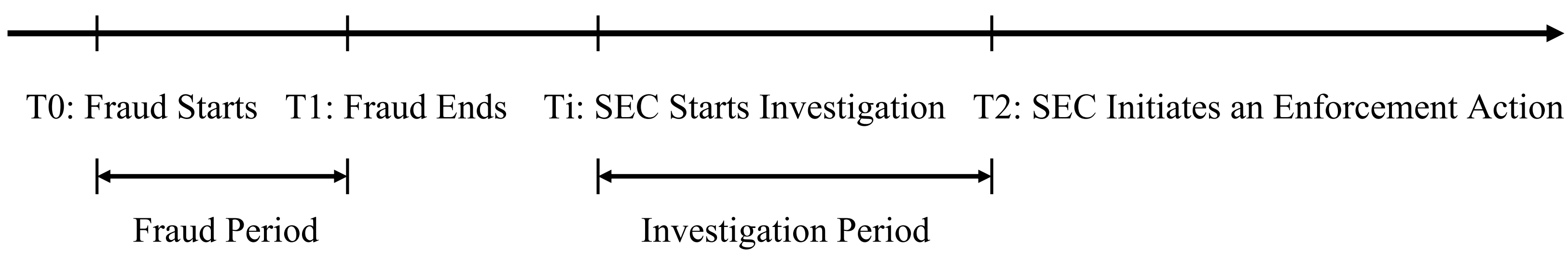

Figure 2: SEC Budget History

The figure presents the SEC budget from 1992 through 2003. Panel A contains budget and budget adjusted for inflation and Panel B contains budget per firm adjusted for inflation. Amounts adjusted for inflation are measured in 1992 constant dollars. Budget per firm is equal to budget divided by the number of firms in Compustat that have common stocks (CRSP share code=10,11).

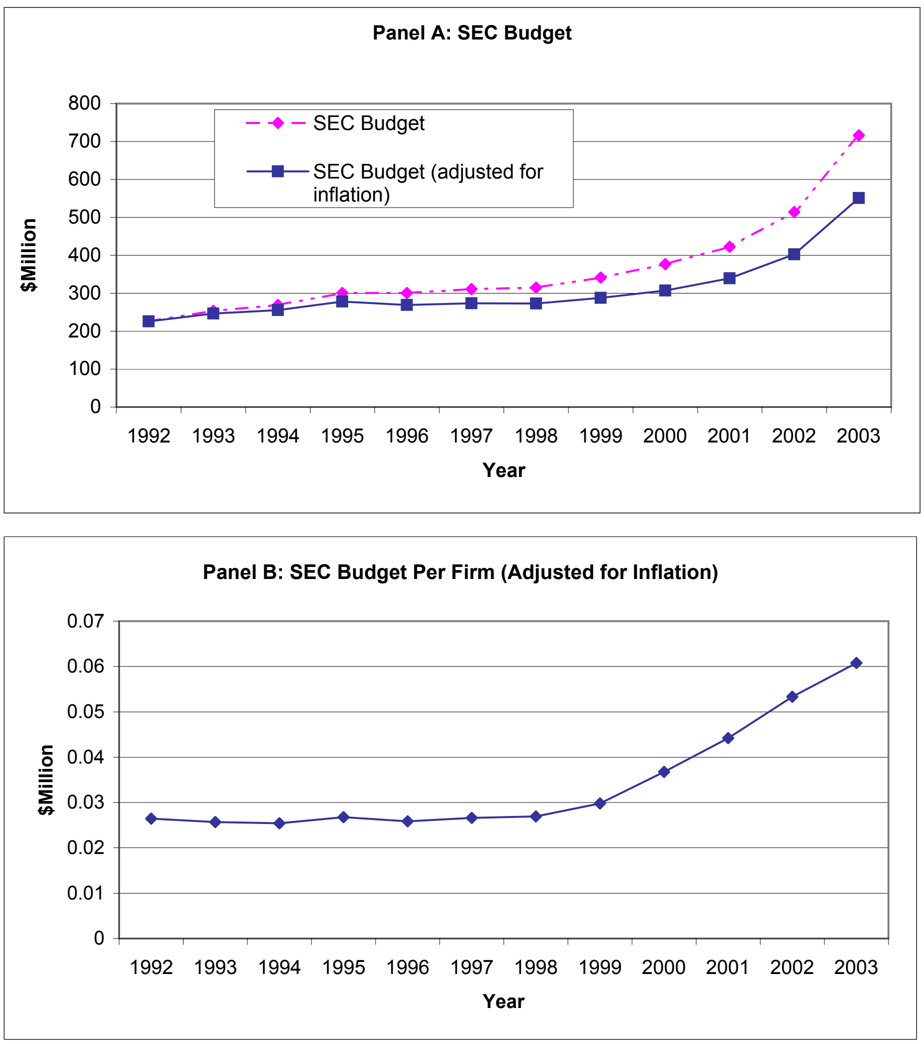

Figure 3: Time Distributions of Detected Fraud

The figure presents the distributions of fraud period (T1-T0+1), number of years between the first year of fraud and the first year of investigation (Ti-T0), number of years between the first year of fraud and SEC enforcement (T2-T0), and investigation period (T2-Ti+1) for the 114 firms accused of fraud in the final sample.

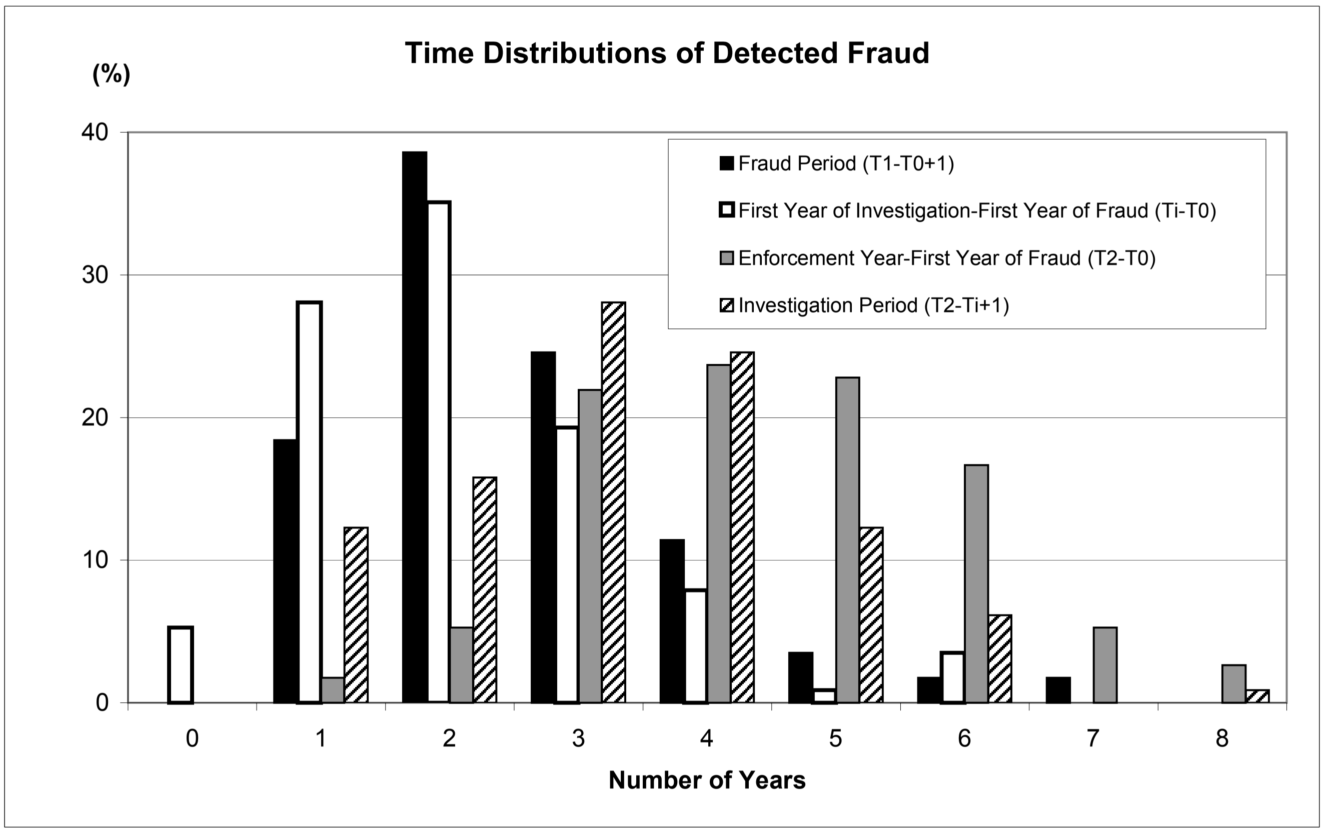

Figure 4: Economic Significance of Variables (Fraud Equation)

The figure presents the economic significance of the effects of pay performance sensitivity, fraction of inside board directors, external financing needs on the probability of fraud in both the simultaneous system and the single equation model. Economic significance is measured as the change in the probability of fraud given a one standard deviation change in the continuous independent variables or a one-unit change in the discrete independent variables.

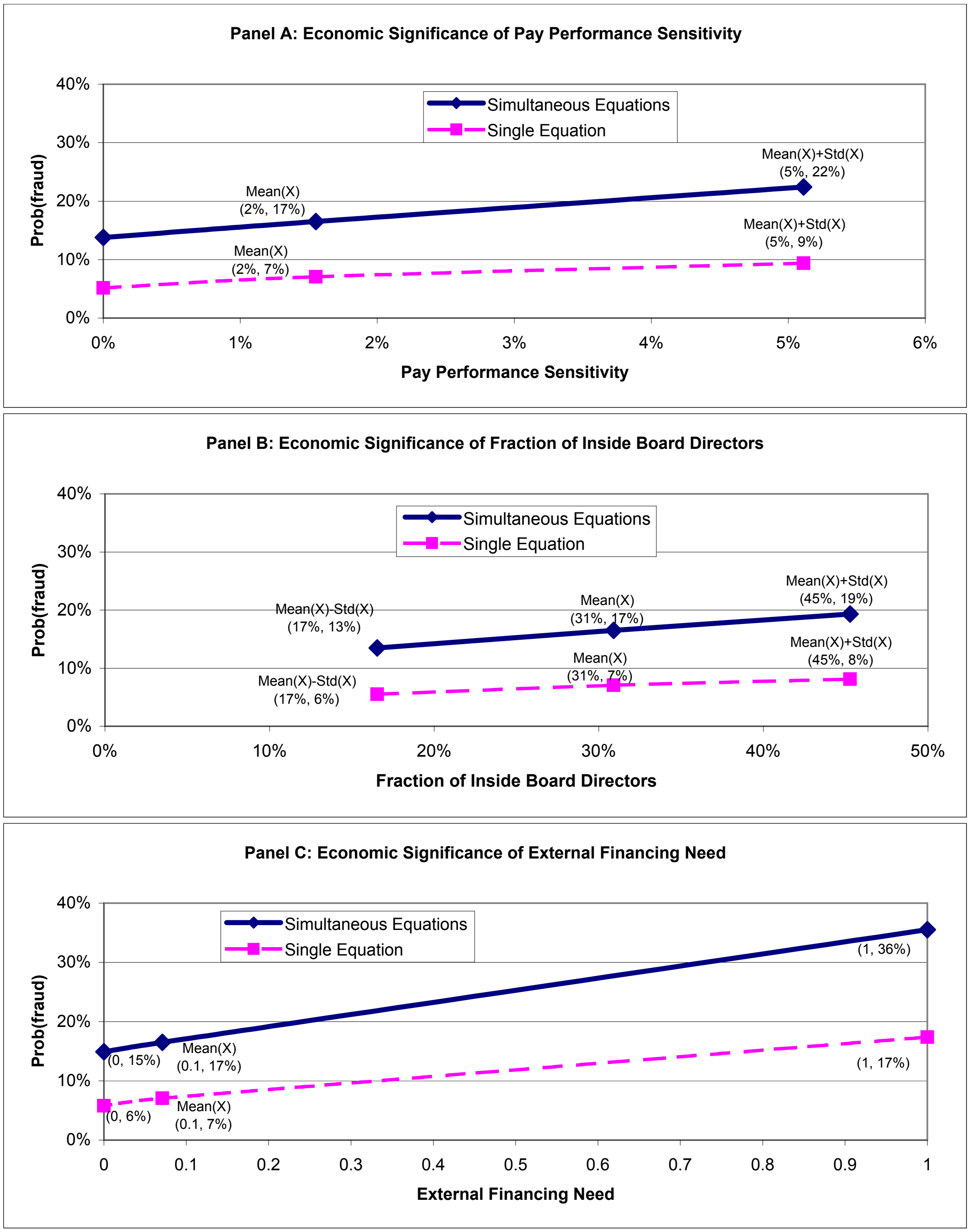

Figure 5: Economic Significance of Variables (Detection Equations)

The figure presents the economic significance of the effects of variables in the detection equations in the simultaneous system. Economic significance is measured as the change in the probability of fraud given a one standard deviation change in the continuous independent variables or a one-unit change in the discrete independent variables.

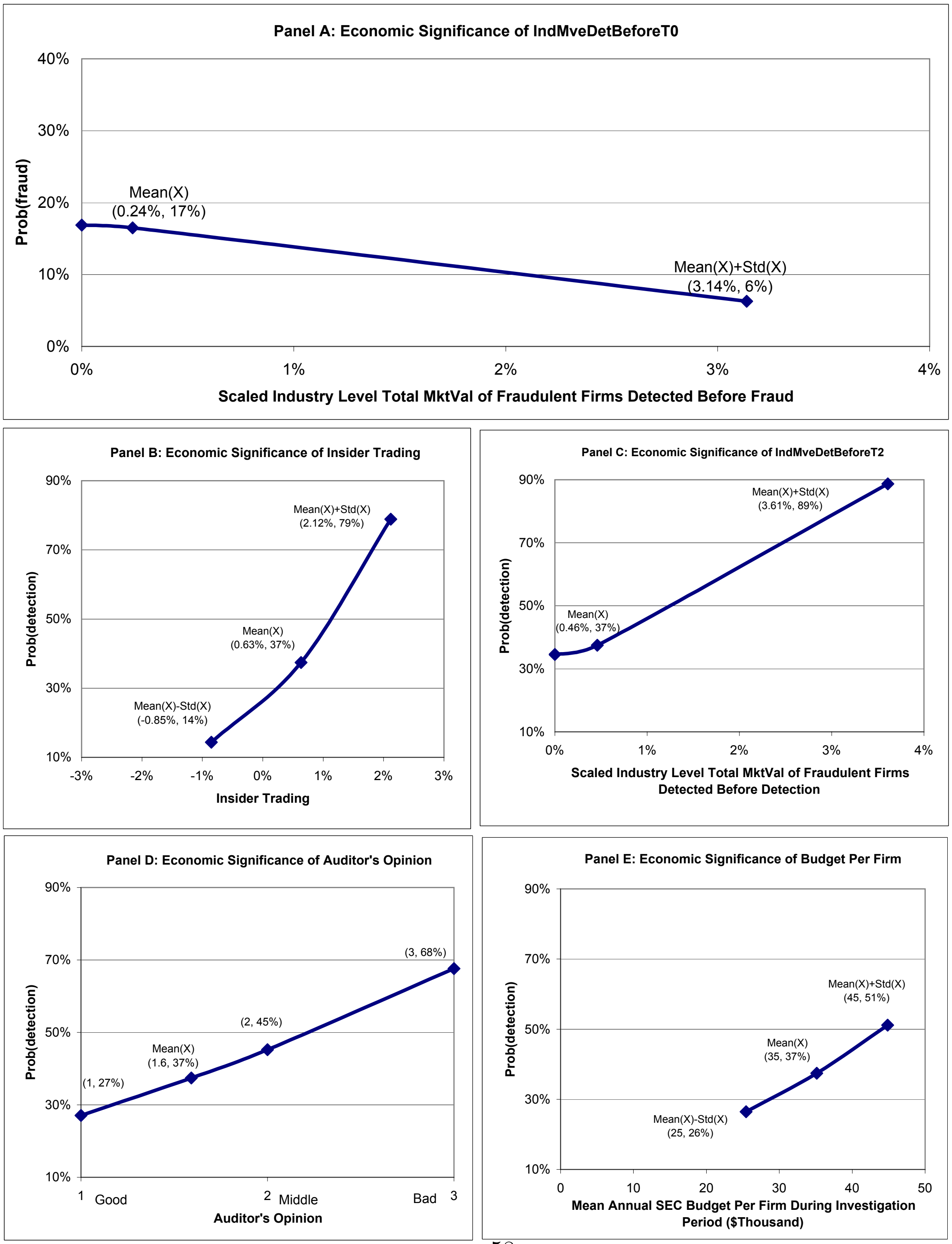

Figure 6: SEC's Investigative and Enforcement Process

The figure presents the SEC's investigative and enforcement process. The source of the figure is GAO's analysis of SEC's enforcement process (see United States General Accounting Office, "Financial Statement Restatements: Trends, Market Impacts, Regulatory Responses, and Remaining Challenges", GAO-03-138).

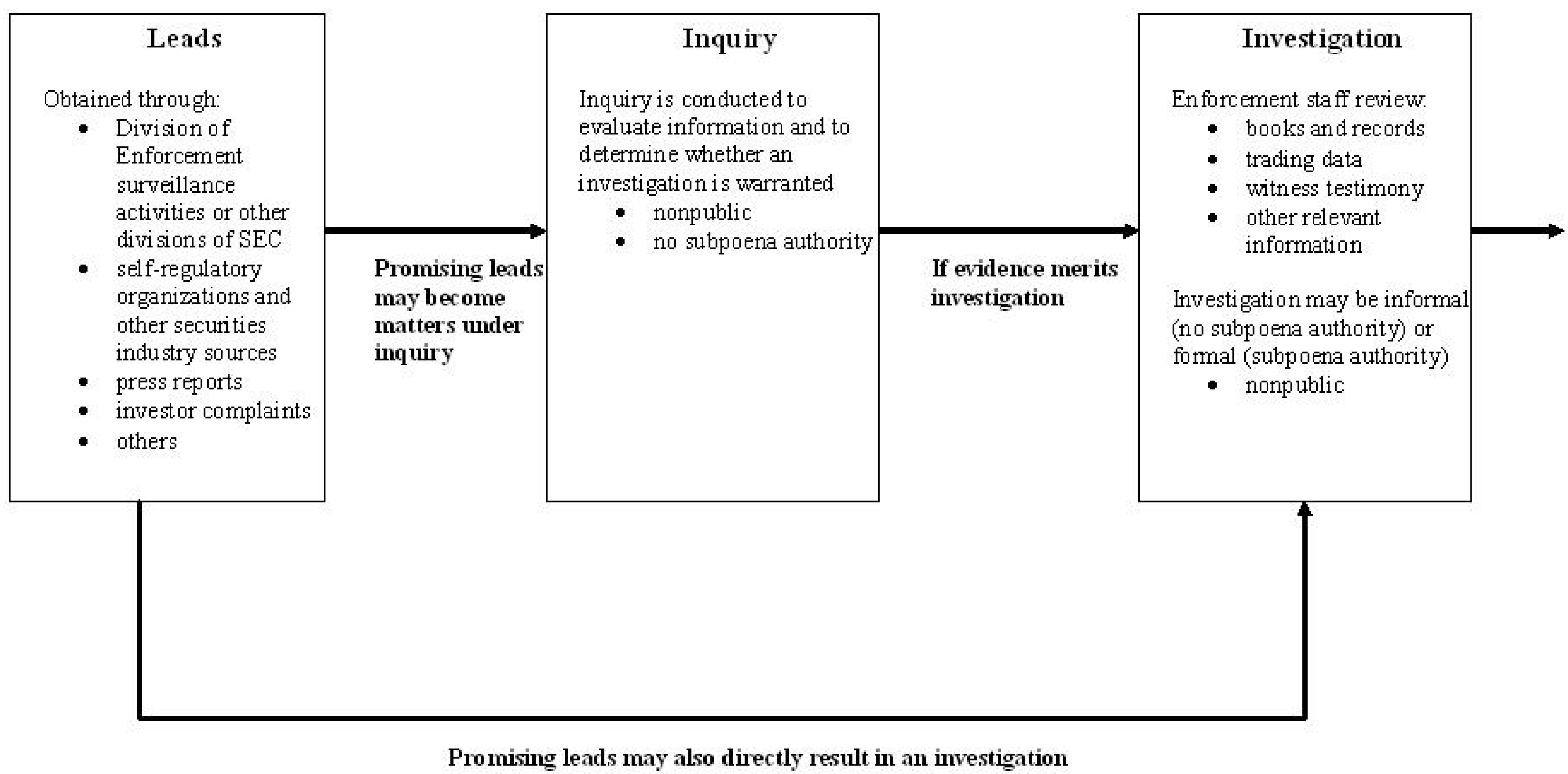

Figure 6 (continued): SEC's Investigative and Enforcement Process