The SEC's Deterrence Effect on Corporate Fraud *

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Abstract

I develop and estimate, using hand-collected data, a game-theoretic model of strategic corporate fraud, that incorporates and quantifies firms' adjustments in fraud propensities in response to regulators' information processing capacity. The findings are economically significant. A one standard deviation change in different regulatory interventions is associated with an annual increase of 10 to 58 fraudulent cases. I exploit the 2005 option backdating scandal as an exogenous shock to regulatory attention, and find further support for both the opportunism in fraud and the deterrence effect. I document that fraudulent behavior is heterogeneous in executive incentives and firm complexity.

Keywords: *corporate fraud, opportunistic behavior, fraud detection, SEC, security law enforcement, regulatory intervention, detection controlled estimation, criminology*

JEL Classification: *G38, K42, M41, C30, C35, C57*

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1 Introduction

One of the most fundamental questions in the corporate fraud literature is how managers decide on whether or not to commit fraud. Understanding what determines fraud is important, as it is essential for policymakers' ability to design effective and efficient regulation. Though fraud may bring temporary benefits to firms, the belief or revelation of fraud challenges the credibility of firms' information, which can be costly, and the prevalence of fraud can even distort the allocation of capital in aggregate. Given the adverse effects of fraud on capital allocation and the potential financial distress to shareholders,[1] regulators have striven to fight corporate misconduct and imposed punishment on fraudulent activities. Thus, to truly understand corporate misconduct and design optimal policies, we must also recognize the role of regulators, and consider the potential impact of regulation on misconduct.

In this paper, I develop a game-theoretic model of strategic corporate fraud that incorporates the effect of regulatory intervention on fraud. Using a hand-collected data set of SEC characteristics, I estimate the model to address the following questions: 1) By how much are firms' fraud decisions affected by the SEC? 2) Do firms conduct more fraud when they anticipate a lower level of SEC scrutiny? 3) Is misconduct truly deterred by the SEC and how? The model and the unique dataset allow me to address several key challenges typically found in studies of corporate fraud: partial observability of fraudulent behavior, the interdependent relationship between firms and the regulator, and data shortage. Moreover, I exploit the option backdating scandal as an exogenous shock to regulatory attention following the publication of Lie (2005). The combination of the game-theoretic model and the difference-in-differences specification provides further support to the findings of opportunistic behavior in misconduct documented in the paper.

[1] Karpoff, Koester, Lee, and Martin (2017) find an average cumulative abnormal return of -40.1% associated with fraud revelation

I apply an extended version of the detection-controlled estimation (DCE) framework (e.g. Feinstein, 1990; Wang, Winton, and Yu, 2010; Foley, Karlsen, and Putniņš, 2019) that enables me to model the fraud and detection processes separately and estimate them jointly as well as incorporate firms' strategic response to the detection process. When a fraud case is detected by the SEC, two economic processes are involved: the firm decision of whether or not to commit fraud, and the conditional detection process of the SEC given that the fraud has been committed. Though both of these processes are unobservable, the DCE framework is able to provide consistent estimators for the parameters of each process based on the likelihood of observed detected fraud that comes from the joint outcome of the fraud and detection processes. In addition, the effect of detection on the fraud decision, stemming from the interdependent relation between firms and the SEC, is captured by an extended DCE model with one-sided expectation simultaneity, where firms' expectation of the probability of being caught is also included as a determinant in the fraud decision. To estimate the model, I create a unique dataset that links firm fundamentals to a set of SEC characteristics during the period from 2000 to 2012. I obtain data on SEC enforcement activities through several Freedom of Information Act requests, and hand-collect all the information on public prosecutions of the SEC from approximately 13,500 original legal documents.

I find that a firm is more likely to commit fraud after observing changes in SEC regulatory intervention that lead to a lower expected detection probability. In order to examine SEC intervention systematically, I adopt the classification of policing tactics from the criminology literature, and the findings are consequential. Specifically, under the "hot-spots" tactic, when the SEC disproportionately cuts one standard deviation ($2 million) in labor expenses, approximately 10 more fraudulent cases would be committed, which is associated with a total estimated loss of $30 million.[2] Under the "proactive" tactic, when the SEC re-

[2]During the sample period, the median number of firms per year is 3,400, and the inflation-adjusted median loss for detected financial fraud is $3 million (Association of Certified Fraud Examiners, 2002, 2004, 2006, 2008, 2010, 2012)

duces the intensity of prosecution by one standard deviation (12%), approximately 20 more fraudulent cases would be committed with the potential loss of $60 million. Compared to the "hot-spots" and "proactive" tactics, the "misconduct-oriented" tactic emphasizes the SEC's priority in the enforcement of accounting fraud, and hence the economic significance of the deterrent effect from SEC intervention on accounting fraud is even more striking. For example, when the SEC increases the number of non-fraud actions by one standard deviation (47 actions), firms recognize this relative regulatory inattention to accounting fraud and become more likely to commit fraud. As a result, approximately 58 more fraudulent cases will be committed, which is associated with a total potential loss of $174 million. Therefore, the framework in this paper not only quantifies the opportunistic strategy in corporate fraud, but also provides support to the positive theory that the SEC intervention deters corporate fraud. Importantly, without the extended DCE framework, it would be very difficult to make inference about fraudulent behavior of the population based on data on detected fraud due to partial observability. Take the example under the "misconduct-oriented" tactic as an illustration, when the number of non-fraud-related legal actions increases, even though more fraud would be committed, the observed number of fraudulent cases is actually lower since the probability of detecting fraud is lower.

Moreover, I use the option backdating scandal in 2005, triggered by the publication of Lie (2005). The academic publication serves as an unexpected shock to the detection process, which at the same time did not affect firms' fraud decisions, except through the changes in the expectation of the likelihood of getting caught. I estimate a modified version of the extended DCE framework, incorporating a difference-in-differences specification, and find that while this event drives variation in firms' detection probabilities over the sensitivity of executive compensations to options, firms' opportunistic strategy in fraud and the SEC deterrence effect remain robust. In addition, I document the heterogeneity of firms' fraudulent behavior, where I allow firms to have different levels of incentives to commit fraud or face different levels of difficulty in detection. I find that managers whose compensation is more tightly linked to firm performance are more likely to commit fraud, but they are also more strategic given the higher opportunity cost of time and labor. I also find that more complex firms exploit the additional room for accounting manipulation, and thus are relatively more likely to commit fraud. Lastly, I complement the main findings with several additional tests that address a number of alternative stories, and find that the opportunism in fraud and the deterrence from the SEC are robust to geographic clustering of crime, industry crime waves, industry regulatory conditions, local economic conditions, firm litigation concerns, nor firms' self-selection into fraud.

2 Literature Review and Contribution

This paper contributes to our understanding of corporate fraud, in particular about firms' decisions of whether or not to commit fraud, and the impact of SEC regulatory intervention on fraud decisions. The majority of previous literature has focused on how executive compensation (e.g., Burns and Kedia, 2006; Goldman and Slezak, 2006; Armstrong, Jagolinzer, and Larcker, 2010) or corporate governance (e.g., Dechow, Sloan, and Sweeney, 1996; Lennox and Pittman, 2010) is associated with corporate fraud, while a few focus on the monitoring role of the SEC (e.g., Kedia and Rajgopal, 2011; Blackburne, 2014). Different from the existing studies, I document and quantify the strategic interdependence by showing how firms opportunistically adjust their fraud propensities based on the regulator's actions through their effect on the expected detection probability.

The paper also contributes to the debate regarding the role of regulation. Though the focus of this paper is not to propose an optimal policy, it provides empirical support to the positive theory of regulation where the SEC deters corporate fraud, which to the best of my knowledge, has not yet been documented directly. Previous literature has introduced three main theories about the role of regulation in general: (1) the public interest theory by (Pigou, 1929), where regulation is beneficial; (2) the contracting theory by Coase (1960), where regulation is unnecessary due to the potential effect driven by competition, private ordering, and private litigation; and (3) the capture theory by (Stigler, 1971), where regulation can be harmful to the economy since the regulatory agency may work for the industry in exchange for private benefits, such as future employment opportunities. Motivated by these theories, empirical studies have investigated the relationship between the SEC and firms from various perspectives, but the evidence regarding the role of the SEC is inconclusive Yu and Yu (2011); Correia (2014); Heese, Khan, and Ramanna (2017).

Moreover, this paper extensively embraces the quintessence from the criminology literature, broadening the current literature on corporate misconduct with a new perspective. Particularly, I extensively incorporate concepts about criminal deterrence in empirical design (e.g., Nagin et al., 2013; Lazear, 2015; Chalfin and McCrary, 2017). This paper also addresses the questions of how and through which specific mechanism fraudulent behavior is deterred. Echoing the findings, corporate fraud is deterred by perceptual deterrence, which refers to the behavior adjustment of offenders after observing changes in policing (e.g., Apel, 2013). In addition, I provide direct evidence that both carrots (e.g., in the form of better labor compensation) and sticks (e.g., in the form of more intensive regulatory intervention) deter corporate fraud. Furthermore, I employ the classification of policing tactics - in particular, “hot-spots", “proactive", and “problem-oriented" - to analogously characterize the SEC tactics in the analysis. This characterization, well-established in criminology, allows me to systematically investigate the effect of the SEC regulatory intervention on fraud decisions. The extensive collaboration with the criminology literature, to my knowledge, is also a first attempt in the study of corporate misconduct.

Lastly, this paper makes a methodological contribution by applying the DEC model with one-sided expectation simultaneity in a game-theoretic framework, which can be used to study topics involving partial observability as well as to investigate interdependent relations between multiple parties. Though previous studies have adopted the DCE model to study accounting fraud (e.g., Wang, Winton, and Yu, 2010; Li, 2013; Shi, Connelly, and Hoskisson, 2017), this paper extends the model setup to analyze firms' strategic fraud decisions, representing a game-theoretic component in the interactive relation between firms and the SEC.

3 Data

3.1 Sample

The sample is constructed from several data sources. The main data on corporate misconduct are the cases prosecuted by the SEC and the Department of Justice (DOJ) as enforcement actions against firms. In particular, I focus on the SEC actions related to accounting fraud under the Accounting and Auditing Enforcement Releases category (AAERs). The AAER data come from the Center for Financial Reporting and Management (CFRM), complemented with additional Central Index Keys (CIKs) hand-collected from SEC EDGAR filings. In addition, I supplement the CFRM data with the Karpoff, Koester, Lee, and Martin (2017) fraud data to include enforcement actions brought by the DOJ and potential missing SEC actions due to missing firm identifying information or misstatement periods in CFRM dataset.

To capture the enforcement environment, I hand-collect information from several sources about the Division of Enforcement (DoE) of the SEC, whose role is enforcing securities laws by investigating illegal activities and prosecuting civil actions. First, for the nonpublic investigations, I file a Freedom of Information Act (FOIA) request and obtain a list of all the investigations carried out by the SEC regardless of the outcome of the probe. This FOIA data are organized by cases, and include an internal case number with an office identifier and the investigation period for each listed case. The information in this dataset is, however, very limited. Other than the total number of cases under investigation for each office in a given period, there are no details about the type of misconduct (i.e., accounting-related or not) nor the violation periods.

To complement the investigation data, I extract information from public announcements of the DoE to separate the legal actions addressing different types of misconducts, which are released in the *Litigation Releases* and *Administrative Proceedings* sections on the SEC website, respectively. These releases are enforcement actions addressing all types of misconducts, where the civil actions are the civil lawsuits brought by the SEC in federal courts and the administrative proceedings are the notices or orders that are adjudicated internally by an administrative law judge. Different from the investigation data, the accounting and auditing related actions are separated out under the *AAER* section on the SEC website. For the public releases, I collect in total 13,499 unique actions for the period from 2000 to 2012, and read through each announcement to identify the office in charge of each enforcement action. Some of the releases explicitly disclose the responsible office for the prosecution. For the rest of the releases, I identify the office by the district of federal courts if the information is available. If no official information is provided in the document, I follow the enforcement manual and use the headquarter of the company to assign the responsible office. Moreover, I obtain the annual reports from the SEC archive of reports. Based on the *Agency Financial Reports*, I collect data on the jurisdiction and location of each regional office in each year.[3] The detailed office-level budget and employee data for the 2002 to 2012 period are generously provided by Kalmenovitz (2019).[4]

In addition to the data on financial misconducts, I obtain data on several other types of crime and misconducts. I hand-collect information on violent crime and property crime through

[3] As an example, Appendix B.1 shows how jurisdiction was assigned to each office in 2018.

[4] The original data is also hand-collected by the author through Freedom of Information Act requests to several federal bureaus. The details of the data can be found in Kalmenovitz (2019).

the *Uniform Crime Reporting (UCR)* Program. The UCR Program provides crime data, which is gathered, compiled, published, and reported by the Federal Bureau of Investigation (FBI) annually at the state level.[5] I also hand-collect the data about federal convictions for corruption-related crimes by elected officials from the *"Report to Congress on the Activities and Operations of Public Integrity Section"*. The reports are published by the DOJ, and contain the number of DOJ-prosecuted convictions for each DOJ district headquarter, which I use to generate state-level counts of political corruption for each year during the sample period.[6] I also consider investment adviser fraud, data on which is graciously provided by Dimmock, Farizo, and Gerken (2018). Investment advisers are required to disclose the states of operation and any violation of the anti-fraud provisions in the Investment Advisers Act of 1940. For August 2001 to December 2012 period, I calculate annual state-level counts of violations, which were later prosecuted by the SEC.[7]

Lastly, I gather information about firm characteristics, business segments, and executive compensation. The firm financial information is from Compustat, the segment data are from Compustat Historical Segments File, the stock price information is from CRSP, the analyst forecasts are from I/B/E/S and the information of the executive compensation is from Execucomp.

3.2 Descriptive Statistics

My final sample consists of 43,462 firm-year observations of 6,369 unique firms for the 2000 to 2012 period. Table 1 shows the descriptive statistics for the sample, where Panel A contains

[5] The data are collected by law enforcement agencies and voluntarily reported to the FBI, and categorized into violent crime (murder and non-negligent manslaughter, rape, robbery and aggravated assault) and property crime (burglary, larceny-theft and motor vehicle theft). The details of the data can be found at https://www.fbi.gov/services/cjis/ucr.

[6] The details of the reports and the data can be found at DOJ Public Integrity Section website: https://www.justice.gov/criminal/pin.

[7] Details about the data are provided in Dimmock, Farizo, and Gerken (2018)

firm characteristics and Panel B contains the enforcement-related variables. A typical firm in the sample has 55.3% soft assets, leverage of 0.159, -2.2% market-adjusted annual stock return, and 20.1% expected industry EPS growth. Across the SEC offices, the average total salary paid to accountants, lawyers and investigators[8] is 24.1 million, the average prosecution to investigation ratio is 0.349, the average number of investigations conducted is 266 cases, the average number of accounting-related legal actions is 15, the average number of all other non-accounting related legal actions is 74, and the average ratio of accounting-related legal actions to the non-accounting-related legal actions is 0.231.

[Table 1 about here.]

4 Empirical Framework

Because we cannot observe all the fraud that has been committed, but only the detected fraud, we cannot identify a firm's unconditional fraud propensity based on observed information. In fact, the probability of detected fraud is a product of two latent probabilities: the probability of committing a fraud and the conditional probability of detecting this fraud. Moreover, considering the regulatory and market penalties, the decision of whether or not to commit fraud should also be influenced by the likelihood of being caught. Ignoring the interdependent relation between firms and the regulator, estimation using the detected fraud could be biased and inconsistent. Together, the partial observability and the interdependent relation represent the main challenges in the empirical analysis of misconducts.

[8]The data provided by Joseph Kalmenovtiz contains the salary for different occupations. To reduce measurement error in approximating the resources allocated to preventing accounting fraud, I only include the salaries paid to accountants, lawyers and investigators in the calculation of the *Budget* variable. The results remain qualitatively the same when using total salaries to all employees.

4.1 DCE Model

I apply an extended version of detection-controlled estimation (DCE) framework to study firms' fraud decisions, which explicitly includes a model of detection, allowing for the possibility of an imperfect detection process. This model was developed in Feinstein (1990, 1989), and has since been applied to study topics such as tax evasion (Feinstein, 1991), safety regulation of nuclear power plants (Feinstein, 1989), corporate fraud in IPOs (Wang, Winton, and Yu, 2010), channel stuffing (Das, Shroff, and Zhang, 2012), market manipulation (Comerton-Forde and Putniņš, 2011) and illegal activities through cryptocurrencies (Foley, Karlsen, and Putniņš, 2019). One of the main advantages of DCE is the ability to explicitly model the two latent economic processes, fraud violation and fraud detection, simultaneously, and to generate consistent parameter estimates even with partial observability. Moreover, the DCE framework with one-sided expectation simultaneity allows the inclusion of the expected detection probability in the fraud equation, which enables me to study firms' fraud decision and the deterrent effect of the SEC on fraud.

[Figure 1 about here.]

The decision process follows the tree shown in Figure 1. In Stage 1, a firm decides whether or not to commit fraud, given the trade-off between the expected cost and the expected benefit of fraud. If a fraud was committed, it could be detected, or it could remain undetected in Stage 2. What we observe is only detected fraud. Firms that did not commit fraud and firms that committed fraud but are not detected will cluster together, and cannot be distinguished from one another in the data.[9]

[9] The assumption to apply the model is that in Stage 2, there is no false detection. In the context of accounting fraud and the SEC, false detection rarely happens, and these cases are in the category of the SEC settled cases (Baker, 2007; Johnson, 2007).

Specifically, the DCE framework with one-sided expectation simultaneity can be implemented to encompass a game-theoretic component through the following structure. When a manager decides whether or not to commit fraud, he considers the cost-and-benefit tradeoff of the crime, including an expectation of the likelihood of being caught, denoted as $D(x_{2i}\beta_2)$. The fraud equation becomes

$$Y_{1i} = x_{1i}\beta_1 + D(x_{2i}\beta_2)\delta_1 + \epsilon_1, \tag{1}$$

$$F_i = \begin{cases} 1 \text{ (fraud committed)} & \text{if } Y_{1i} \geq 0 \\ 0 \text{ (no fraud committed)} & \text{if } Y_{1i} < 0 \end{cases} \tag{2}$$

where F_i is the unobserved binary indicator that equals to 1 if the manager chooses to commit fraud. Y_{1i} is a continuous latent variable that captures the incentive to commit fraud. x_{1i} is a vector of firm characteristics, which are associated with firms' fraud propensity. The parameters δ_1 and β_1 are estimated together. Since δ_1 captures how much firms adjust their decisions of whether or not to commit fraud given the expected probability of being caught, firms' strategic response and the deterrent effect from detection predict a negative sign for δ_1, as an increased likelihood of being caught should be negatively associated with the fraud propensity(Becker, 1968). Completing the DCE model, I incorporate a detection equation characterizing the detection process. Given that fraud has been committed, that is $F_i = 1$, the detection equation is:

$$Y_{2i} = x_{2i}\beta_2 + \epsilon_2, \tag{3}$$

$$D_i = \begin{cases} 1 \text{ (fraud detected)} & \text{if } Y_{2i} \geq 0 \\ 0 \text{ (fraud not detected)} & \text{if } Y_{2i} < 0 \end{cases} \tag{4}$$

Analogously with the fraud equation, D_i is the unobserved binary indicator that equals to 1 if firm i's violation is detected, Y_{2i} is the continuous latent variable that captures the potential for getting caught given the fraud has been committed, and x_{2i} is a vector of characteristics that affect the detection probability of a given fraud. As in the data, F_i and D_i are individually unobservable, but their product, detected fraud, is. That is,

$$Z_i = F_i * D_i, \tag{5}$$

where $Z_i = 1$ if fraud was committed and later detected, and $Z_i = 0$ when either fraud was not committed or the fraud was committed but not detected.

Though it is likely that the SEC also forms an expectation of firms' fraud propensities, the detection of fraud normally happens after the fraud was committed. Due to this time lag, I choose not to include the contemporaneous fraud propensity in the detection equation. Instead, in order to capture the potential influence of fraudulent activities on the detection process, I include a number of firm characteristics, which have been documented as ex-post flags of fraudulent firms by the previous literature. In addition, to alleviate the concern of the non-random detection process, I exploit a natural event, which exogenously shocks firms' detection probabilities without affecting firm fundamentals that may influence firms' fraud decisions. Details of this analysis are discussed in the following section.

4.2 Fraud Equation

To capture the cost and benefit of committing fraud, I include decision-relevant firm characteristics and a measure of investors' expectations for the firm's industry as well as the expected detection probability in the fraud equation. The firm characteristics are chosen to describe the condition or state underlying the decision of whether or not to commit fraud, and hence all the firm characteristics are measured one year prior to the violation period, i.e., in year $t-1$ for the violation year t. Investors' expectations capture the incentive and peer pressure from the market, and hence are calculated contemporaneously, i.e., in year t. Given the model setup, it is important to point out that the variables are included to capture the condition when a fraud decision is being made. This also means that some variables used in previous studies are not included in the fraud equation, such as characteristics shared by fraudulent firms (e.g., severe negative shock in firm performance). Such variables represent alternative ways of studying corporate fraud decisions, and are therefore not included as explanatory variables in the fraud equation but in the detection equation, which I explain more in detail below.

Variables in the fraud equation can be categorized into three sets.[10] The first set of firm characteristics intends to capture firms' incentives from the market, in particular for raising external capital as discussed in Sherman (1999); Povel, Singh, and Winton (2007). I include *External Financing Needs* following Demirgüç-Kunt and Maksimovic (1998); Wang, Winton, and Yu (2010); Wang (2011); Wang and Winton (2014), *Leverage* as a proxy for how close covenant restrictions are to being binding following previous literature (e.g., Dechow, Sloan, and Sweeney, 1996; Healy and Wahlen, 1999), *Market-Adjusted Stock Return* to capture the market expectation in stock price and the cost of equity, and *Industry EPS Growth Rates* for institutional investors' belief of firms' performance based on analyst forecasts following Wang, Winton, and Yu (2010). Another set of variables characterize firm performance, since firms are likely to engage in accounting manipulation to avoid the negative consequences from the market associated with bad firm performance (e.g., Crutchley, Jensen, and Marshall, 2007; Dechow, Ge, Larson, and Sloan, 2011). Specifically, I include *change in return on asset* to capture growth in earnings and *change in cash sales* to capture the growth in sales that are not subject to accrual management. The last set of firm characteristics intends to capture firms' ability to conceal information through the accounting numbers. Before aggressive manipulation, managers are likely to manage the accruals within generally accepted accounting principles (GAAP). In other words, the extent to which a firm can conceal infor-

[10] Definitions and calculations of all variables are listed in the Appendix.

mation is negatively associated with the current level of accounting manipulate within the GAAP. Thus, exhausting the GAAP allowance would push the managers to severe accounting manipulation. To capture firms' ability to conceal information, I include the Richardson, Sloan, Soliman, and Tuna (2005) measure of accruals and *% soft assets* following (Barton and Simko, 2002; Dechow, Ge, Larson, and Sloan, 2011; Allen, Larson, and Sloan, 2013).

4.3 Detection Equation

The factors that influence the detection probability include SEC characteristics and ex-post signals, where the SEC characteristics, motivated by the criminology literature on policing intervention on crime, capture the enforcement environment, and the ex-post signals are the factors whose effects only emerge after the fraud has been committed following previous literature on accounting fraud. Different from the variables in the fraud equation, variables in the detection equation are calculated contemporaneously, i.e., at year t, because the detection occurs after the fraud has been committed.

I analyze three aspects of the enforcement environment following the three main policing tactics established in the criminology literature. The first tactic is "hot-spots" policing, which refers to the strategy where policing resources are disproportionately deployed to specific locations. For example, the intensity of police patrols tends to be higher in crime hot spots, such as places with substantial social disorders or with the presence of open-air drug markets, than other areas in a city. To capture the disproportionate amount of resource that the SEC allocates to specific regions, I adjust the total salaries to accountants, lawyers and investigators by location and year, and generate the $AbnExp$ variable as the abnormal amount of total expense to the SEC staff whose jobs are more relevant to regulating misconducts. The second tactic is "proactive" policing, which refers to a strategy that makes policing more intensive, even for minor infractions. Examples of proactive policing are misdemeanor arrests or the "stop-and-frisk" policy in New York City, and the goal of this tactic is to create an image of active policing in fighting all crimes so that people should feel safe about their neighborhood. In the context of the SEC activities, I use the ratio of the total number of public enforcement actions to the total number of investigations regardless of the probe's outcomes to measure the intensity of prosecution, which is an "image" of how active the SEC is towards misconduct in general. The final tactic is "problem-oriented" policing, which refers to a strategy that is designed to change the behavior of specific types of offenders. One example of the problem-oriented policing tactics is the Ceasefire Operation in 1996 to reduce youth gun violation in Boston, where the police not only disrupt the supply of illegal weapons to Massachusetts but also directly communicate with gang members to discourage gun carrying. Specifically, I adopt two approaches to characterize the "problem-oriented" activities of the SEC regarding corporate fraud: one approach is to use the ratio of the number of accounting-related enforcement actions to the number of the enforcement actions about all other types of misconducts, and the other approach is to use the count numbers of these enforcement actions directly. For the ex-post signals, previous literature shows that certain characteristics of the firms targeted by the SEC are distinct from the other firms (Dechow, Ge, Larson, and Sloan, 2011; Karpoff, Koester, Lee, and Martin, 2017), and certain characteristics of the fraudulent firms are different between the violation period and other periods (Dechow, Ge, Larson, and Sloan, 2011). It is important to note that though the ex-post signals measure the relative firm/stock performance or stock liquidity, a specific value does not imply that fraud was committed. Instead, they represent some common characteristics that fraudulent firms tend to share, and hence they are used in the detection equation for identification together with the variables for SEC intervention. In particular, I include *Accrual* for accrual quality following Dechow, Ge, Larson, and Sloan (2011), cash sales for non-accrual-driven sales and unexpected performance shock to capture abnormal firm performance following Dyck, Morse, and Zingales (2010); Dechow, Ge, Larson, and Sloan (2011); Karpoff, Koester, Lee, and Martin (2017), *book-to-market* and *earnings-to-price* for the market valuation relative to firm fundamentals, and abnormal stock volatility and abnormal turnover as ex-post signals from the stock market following previous literature (Jones and Weingram, 1996; Cox, Thomas, and Kiku, 2003; Kim and Skinner, 2012; Habib, Jiang, Bhuiyan, and Islam, 2014).

5 Main Results

In this section, I present and discuss the results of the empirical analysis. First, I document the opportunism in corporate fraud and the deterrent effect of the SEC detection on fraud decisions. This is accomplished by estimating the strategic response in the fraud decision and further analyzing the impact of SEC tactics for regulatory intervention on fraud propensity through their effect on the detection probability. For identification, I exploit the option backdating scandal as a natural experiment. I also investigate the heterogeneity of opportunism in fraudulent behavior driven by executive incentives and firm complexity.

5.1 Opportunism in Fraud

5.1.1 Strategic Response in Fraud Decision

I first consider a model that incorporates strategic adjustments of the fraud decision to the detection probability without the specific SEC intervention in the detection process. The DCE model with one-sided expectation simultaneity is well-suited for this purpose as it not only overcomes the challenge of partial observability but also explicitly estimates firms' strategic response to the expected detection probability, i.e., the deterrent effect of the SEC detection on fraud behavior. The findings are provided in Table 2 using three different models.

The first two Columns present the results using a logistic regression where the dependent variable is the dummy variable Z, which is equal to 1 if a firm commits fraud in year t and later is prosecuted by the SEC. Though the logistic regression is commonly applied to analyze binary outcomes, it cannot fully address my research questions because of partial observability and the interdependent relationship between firms and the SEC. It thus serves as a comparison to the results from the DCE framework. In Columns 3 and 4, I apply the basic DCE model without expectations simultaneity, which allows for partial observability but not interactions between firms and the SEC. The comparison between the results using these two models, the logit model *vs.* the basic DCE model, shows that the partial observability indeed affects the estimated parameters. For example, firms with larger external financing needs are expected to have a stronger incentive to engage in accounting manipulation in order to raise capital at more favorable terms. Consistent with this intuition, I find a significant positive effect of $ExtFinNeed$ on the fraud propensity in the DCE framework. However, the results from the logit model do not suggest that such an effect exists. Moreover, despite that the estimated coefficients of $IndEPSGrowth$ appear to be similar in magnitude, a one standard deviation increase in industry EPS growth from its median value, holding other variables constant at their median values, is estimated to increase the fraud propensity from 3.46% to 4.73% according to the DCE model, yielding a change in the probability of observing detected fraud from 1.1% to 1.5%, while the corresponding marginal effect from the logit model is only 0.067% on the probability of observing detected fraud. In other words, a reduction in detected fraud does not necessarily suggest a lower likelihood of firms committing fraud. Given the importance of quantification in guiding practical implementation, the difference between the logistic and the DCE models further supports the use of the DCE model in a situation with partially observed outcomes.

[Table 2 about here.]

The final two Columns of Table 2 show the results using the DCE model with one-sided expectations simultaneity. In addition to overcoming the issue of partial observability, this model also includes the expected detection probability in the fraud equation, denoted as

$Pr(D)$, capturing the strategic aspect of the decision of whether to commit fraud based on how likely the fraud is to be caught and the deterrent effect of the SEC detection on firms' fraud decision. The coefficient on $Pr(D)$ captures the change in the latent value of the incentive to commit fraud when the expected detection probability increases from 0 to 1. The estimate of this coefficient is -2.1, and significant both statistically and economically. At median values of firm characteristics, the fraud propensity is 6.6% and the conditional detection probability is 25.6%. A one standard deviation increase in the detection probability, from these levels, leads to a significant drop in the fraud propensity, from 6.6% to 4.0%. The results from the DCE model with one-sided expectation simultaneity demonstrate substantial strategic response in firms' fraud decisions and a deterrent effect from the likelihood of being detected by the SEC, which is essential for the opportunistic behavior documented in this paper.

5.1.2 Opportunistic Behavior and Perceptual Deterrence

Table 3 reports the main results of this study, where I document firms' opportunism in fraud decisions and the perceptual deterrence of the SEC detection on fraudulent behavior. That is, as changes in regulator characteristics lead to changes in the likelihood that fraud will be detected, firms strategically adjust their propensities to commit fraud taking to account the changes in detection likelihood driven by the changes in regulator characteristics. This mechanism of fraud deterrence also resonates with the concept of perceptual deterrence in criminology, where offenders adjust their behavior accordingly after observing a change in policing(e.g., Apel, 2013). Furthermore, I introduce the concepts of policing intervention classification established in the criminology literature to characterize the SEC activities analogously, which enables me to systematically study the interdependent relation between firms and the SEC. I start by testing the “hot-spots" tactics, which refers to the disproportionate deployment of policing resources to specific locations. In the analysis of

SEC's "hot-spots" tactics, I use location- and time-adjusted abnormal total wage to relevant personnel, denoted as $AbnExp$, to capture the total amount of available resources allocated to a specific office for oversight of misconduct.[11] In Model 1 of Table 3, the coefficient on the variable $AbnExp$ is positive and significant. Together with the negative coefficient on the detection probability, the results show the opportunistic behavior of firms who adjust their fraud propensity based on the abnormal amount of available resources of the SEC allocated to offices and support the perceptual deterrence of the SEC "hot-spots" tactics in regulating corporate fraud. In terms of economic significance, a one standard deviation reduction in $AbnExp$ (approximately $2Mil) from the median value lowers the detection probability from 25.4% to 22.3%, which leads to an increase in the fraud propensity from 5.8% to 6.1%, holding other variables constant at their median values. I test the effect of the "proactive" tactic, which refers to a more intensive strategy adopted by the police, even to minor infractions, to create a more active image of the police and send deterrent messages. In the context of SEC intervention, I calculate the prosecution intensity as the ratio of the number of legal actions to the number of investigations, denoted as $Pros.Intensity$, which captures the SEC efficiency and enforcement intensity in regulating public firms. I again demonstrate the opportunism in fraud decisions and the perceptual deterrence of the SEC proactive litigation in Model 2. Even with the prosecution intensity calculated broadly including all types of misconducts, the effect of $Pros.Intensity$ on firms' fraud decisions is still notable. A one standard deviation reduction in the variable $Pros.Intensity$ lowers the detection probability from 24.2% to 18.8%, which, through the strategic response of firms, increases the fraud propensity from 5.7% to 6.3%.

I then examine the effect of the SEC "problem-oriented", or "misconduct-oriented" tactic by

[11]The findings also hold using: 1) alternative measures of abnormal expense allocation, such as total wages of all employees, mean salary of all employees or mean salary of accountants, lawyers and investigators; 2) expense information from year $t-1$; 3) expense information from the third and fourth quarter in year $t-1$ and first and second quarter in year t.

analyzing how the SEC's attention to different types of misconducts affects fraud propensity through the detection probability. Since the SEC intends to send a deterrence message by publicly pursuing certain cases given the limited resources,[12] I treat the number of legal actions in accounting-related and non-accounting-related misconducts as proxies for the SEC's attention in regulating the corresponding misconducts. In particular, I adopt two approaches to characterize the SEC "misconduct-oriented" intervention. The first approach is to include the total number of investigations and a proxy for relative attention in regulating accounting fraud, measured as the ratio of the number of accounting-related legal actions to the number of non-accounting-related legal actions, *AcctRatio*. As shown in Model 3 of Table 3, when the SEC exerts relatively more effort in regulating accounting fraud, the detection probability is higher, and through strategic response, firms become less likely to commit fraud. Quantitatively, a one standard deviation increase in the relative attention ratio, *AcctRatio*, from the median value, increases the detection probability from 23.2% to 30.5%. This increase in the detection probability reduces the fraud propensity, from 6.7% to 5.5%. However, based on the DCE framework, the probability of observed fraud increases from 1.34% to 1.68%, which is challenging to predict using a standard logistic model given the increase in the detection probability and the decrease in the fraud probability. Meanwhile, the coefficient on the number of total investigations, $No.Cases$, is negative and significant, which supports the idea of resource constraints at the office level. That is, when an office is kept occupied with more investigations, firms under the jurisdiction of that office are more likely to commit fraud because the probability of getting caught is perceived to be lower. In terms of economic significance, a one standard deviation increase in the $No.Cases$, which is approximately 160 cases, from the median value, is associated with a reduction in the detection probability from 23.2% to 12.9% and an increase in the fraud propensity from 6.7% to 7.6%, holding the other variables constant at the median values. The probability of

[12] The institutional background on the SEC litigation is discussed in the appendix, and sources are the SEC manuals, annual reports and conversations with the SEC staff.

detected fraud appears to be lower, from 1.34% to 0.98%, even though firms are more likely to commit fraud.

[Table 3 about here.]

The other approach to capture the "misconduct-oriented" intervention is to use the number of accounting-related legal actions ($No.AAER$) and the number of non-accounting-related legal actions ($No.Other$) directly in the detection equation. Compared to using the relative attention proxy (*AcctRatio*), this approach aims to disentangle the effects of the SEC's attention in regulating different types of misconducts. The results are shown in Model 4 of Table 3. Consistent with Model 3, the coefficient on the $No.AAER$ is positive and significant. A one standard deviation increase in $No.AAER$, which is 10 legal actions, from the median value, increases the detection probability from 25.1% to 35.2%, and reduces the fraud propensity from 6.8% to 5.6%, while a one standard deviation increases in $No.Other$, which is 47 legal actions, from the median value, reduces the detection probability from 25.1% to 14.0%, and increases the fraud propensity from 6.8% to 8.5%. In Figure 2, I plot detection probabilities and fraud propensities over the number of accounting-related misconducts ($No.AAER$) and the number of non-accounting-related misconducts ($No.Other$). From the plot, we can see that the detection probability is increasing in $No.AAER$ and decreasing in $No.Other$, while the fraud propensity is decreasing $No.AAER$ and increasing over $No.Other$. Similar to Model 3, we cannot infer the change in true fraud propensity solely from the likelihood of detected fraud without the DCE model, because the change in fraud propensity and the change in detection probability are in the opposite directions. In sum, Table 3 shows that firms engage in accounting fraud opportunistically according to the SEC regulatory tactics and their effect on detection probability, providing both direct evidence and quantification of the opportunism in corporate fraud decisions and the perceptual deterrence of different SEC intervention tactics in regulating corporate misconduct.

[Figure 2 about here.]

In Figure 3, I show the variation in the predicted fraud propensity and the predicted conditional detection probability for firms in different industries. Based on Model 4 in Table 3, I first calculate the fraud propensity and the detection probability for each firm in each year, and then generate the average fraud propensity and detection probability for each industry based on the Fama French industry classification.[13] The negative correlation between the detection probability and the fraud propensity again speaks to the economic approach of crime (Becker, 1968), that firms in industries with a relatively high detection probability are the ones who have relatively low fraud propensity. Interestingly, the pattern in Figure 3 is also reminiscent of industry characteristics. Firms, for example, in the automobile industry are closely monitored by regulators, and hence the average predicted detection probability for these firms is over 95%, while firms, for example, in the drug industry have relatively high discretion for accounting manipulation due to high expenses in research and development, and hence the average detection probability for these firms is only around 10%. It is important to recognize that the pattern in Figure 3 does not necessarily represent the pattern of the accounting fraud we observe given each industry, since the likelihood of the detected fraud, which is what we observe, is a joint product of the fraud propensity and the conditional detection probability. With the application of the DCE framework, we can point out what the driving force of the observed outcome is, which has been challenging to identify and could be of considerable importance in practice.

[Figure 3 about here.]

Lastly, I generate heat maps to display the geographic variation in the state-level average predicted fraud propensity and predicted conditional detection probability based on the

[13] The 17 industries are chosen for the purpose of better illustration in the figure.

estimates from Model 4 in Table 3. As shown in Figure 4, the states with firms who on average are less likely to commit fraud (states with darker colors in the top figure) are the states where fraud that has been committed is more likely to be detected (states with lighter colors in the bottom figure), which further supports firm's opportunistic strategy in misconduct and the perceptual deterrence of the SEC regulatory intervention, manifesting the interdependent relation between the decision of fraud and the process of detection.

[Figure 4 about here.]

5.2 The Option Backdating Scandal as a Natural Experiment

Two major challenges may be raised in this study, omitted firm characteristics in fraud decision and non-random detection of the SEC. To overcome these challenges, I use the option backdating scandal as a natural event that exogenously alters the likelihood of fraud being detected without affecting firms' fundamentals. Option backdating refers to the practice that executives intentionally marked the option granting date as a past date when the stock price was low to inflate the option value in their compensation. The evidence associated with this practice is presented in Lie (2005). Further, called "the MapQuest" of this scandal (Spitzer, 2007), Lie (2005) triggered a series of the SEC investigations on option backdating, which were closely followed by the media. Importantly, though firms can easily infer an increasing amount of the SEC attention and resources to regulating option backdating, this event does not directly impact the cost and benefits associated with firms' decision on whether or not to commit fraud except through the expected detection probability, which is well-suited to study firms' opportunism in fraud.

I exploit the variation in the detection probability due to the option backdating scandal and incorporate a difference-in-differences specification into Equation (3) of the main model, yielding the following:

$$Y_{2i} = x_{2i}\beta_2 + Vega_{i,2004}\gamma_1 + Shock\gamma_2 + Vega_{i,2004} * Shock\gamma_3 + \epsilon_2.$$

where I use the executives' sensitivity of stock options payoff to stock volatility, $Vega$, to capture firms' exposure to this event. In particular, I use $Vega$ of 2004 to avoid the confounding impact from potential modifications in executives' compensation ex-post the scandal's breakout. Moreover, since the time when firms are informed about the increased regulatory attention in option backdating is different from when the SEC is aware of this illegal practice,[14] I define the $Shock$ variable to be 1 for 2005 and after for firms and for 2004 and after for the SEC. To alleviate the influence of future confounding factors, I use the period from 2002 to 2009 for this analysis. As shown in Test 4 of Table 4, I again document significant opportunism in fraud decisions and perceptual deterrence from the SEC detection. Together with the negative coefficient on the $Pr(D)$, the positive and significant coefficient on $Vega*Shock$ shows that managers whose compensation is less sensitive to options, expecting a lower likelihood of getting caught given that the increased regulatory attention on option backdating is less relevant to them, will be more likely to commit fraud.

[Table 4 about here.]

To visualize the impact of option backdating scandal on different firms, I plot the average predicted fraud propensity and average predicted detection probability of firms with $Vega$

[14]Even though the paper was disseminated early in 2004, the public attention was very much likely attracted later. The SEC's attention to option backdating started with the informal probe into the Silicon Valley software company Mercury Interactive Corp. in November 2004. However, since the informal probe is confidential, the public only noticed this event from the firm's announcement in July 2005. Following the Mercury case and other SEC investigations, the *Wall Street Journal* published a big story about option backdating in November 2005. The media continued to pay attention to the issue of backdating after the big story, and I assume the public became aware of the practice of and the SEC's attention in regulating option backdating after 2005.

in the top tertile *vs.* the bottom tertile in 2004 over the period of 2002 to 2009 in Figure 5. Compared to firms with $Vega$ in the top tertile, firms with $Vega$ in the bottom tertile are likely to receive less attention from the SEC after the breakout of the option backdating scandal. Expecting lower detection probabilities, these firms become more likely to commit fraud, which is again consistent with opportunism in firms' fraud decision, and the perceptual deterrence of SEC intervention.

[Figure 5 about here.]

5.3 Heterogeneity in Firms' Fraudulent Behavior

I further examine how firms' fraudulent behavior varies in the trade-off of committing fraud and the likelihood of getting detected by the SEC. In the main results, the implicit assumptions are that all firms have the same strategic response to the expected detection probability, and face the same detection technology. However, the incentive to commit fraud and the difficulty of detecting existing fraud can vary substantially between firms. In this section, I relax these implicit assumptions for the investigation of firms' fraudulent behavior.

I first explore the heterogeneity in fraud originating from executives' incentives, where I exploit the relation between the sensitivity of executive compensation to firm performance and the benefits of committing fraud as documented in previous literature (e.g., Burns and Kedia, 2006; Goldman and Slezak, 2006; Johnson, Ryan, and Tian, 2009; Armstrong, Jagolinzer, and Larcker, 2010; Wang, Winton, and Yu, 2010). In particular, I include an additional variable, $CompensationSensitivity$, in the fraud equation, which measures the sensitivity of executives' wealth to changes in stock price.[15] A manager whose wealth is more sensitive to stock price has a stronger incentive to commit fraud, since his compensation links

[15] Since the information of executive compensation is only available for firms in the ExecuComp database, including the variable $CompensationSensitivity$ leads to a drop in sample size from 43,462 to 17,910 firm-year observations over the sample period.

more tightly with the stock price (Wang, Winton, and Yu, 2010; Wang, 2011). At the same time, both the amount of total compensation and the sensitivity of compensation to firm performance are greater for executives of the ExecuComp firms than the non-ExecuComp firms (Cadman, Klasa, and Matsunaga, 2010). Thus, executives of the ExecuComp firms are expected to require higher benefits of fraud due to the higher opportunity costs of time and labor than firms in the full sample. Consistent with previous literature, the coefficient on $CompensationSensitivity$ is positive and significant, implying that firms with executives whose wealth is more sensitive to stock prices are more likely to commit accounting fraud. Moreover, compared to the estimates in the main result, the coefficient on $Pr(D)$ is more significant in this subsample, -3.41 *vs.* -1.99. That is, firms with managers who have higher opportunity costs to commit fraud are on average more strategic, which shows that better compensation can also serve as a deterrent to fraud, besides the commonly-known approach of harsher punishment.

[Table 5 about here.]

In addition, I explore how the difficulty of the detection process affects firms' fraudulent behavior. In particular, I use the number of business segments to measure firm complexity, and investigate how firm complexity affects the detection process and the fraud decision through firms' strategic response. When a firm has more segments, the financial conditions become more complex, and hence detection becomes more difficult. If firms make strategic decisions about whether or not to commit fraud, the fraud propensity for complex firms should be higher. Empirically, I construct a subsample of 13,537 complex firms whose number of business segments is higher than the sample average. The findings in Table 5 are consistent with this prediction. For complex firms in this subsample, the detection probability is only 6.87% for this subsample, but the fraud propensity is much higher than that of the full sample, 16.98%. It is interesting to note that the detected accounting fraud is actually lower for complex firms than all firms (1.17% *vs.* 1.37%). However, based on this observation alone, we should not mistakenly conclude that complex firms are less likely to commit fraud, when in fact, the lower number of detected fraud is the outcome of more complex firms committing more fraud but being detected less often.

6 Further Analysis: Alternative Stories

While the main results show opportunism in fraud and perceptual deterrence from SEC detection, identification of the parameters characterizing the fraud decision and detection process is still potentially challenging. In particular, there could be unobserved factors influencing firms' decision of whether or not to commit fraud, which complicates the identification of firms' strategic response to SEC detection, in particular, the identification of the coefficient on the expected detection probability in the fraud equation. In this section, I, therefore, consider a set of alternative stories and conduct analyses aimed at addressing the identification challenges associated with unobserved variables, which includes geographic clustering of crime, industry crime waves, industry regulatory conditions, local economic conditions, firms' litigation concerns, and potential selection associated with the detection process.

6.1 The Geographic Effect on Fraud

I first consider the geographic clustering of crime. Parsons, Sulaeman, and Titman (2018) shows that there is a strong correlation between financial misconducts and other types of wrongdoings at the city-level, rooted in regional social norms. To capture the potential influence from social norms on a firm's fraud propensity, I include a proxy for the culture of misconduct in the fraud equation in order to account for the correlation between different types of wrongdoings. The proxy is based on one of four different types of crime or misconduct:

$ViolentCrime$, $PropertyCrime$, $PoliticalCorruption$ and $InvestmentAdviserMisconduct$.[16] $ViolentCrime$ and $PropertyCrime$[17] are calculated each year for each state, and are adjusted by the state population. $PoliticalCorruption$ is the state-level count of federal convictions for corruption-related crimes by elected officials in each year. $InvestmentAdviserMisconduct$ is the yearly state-level count of violations of the anti-fraud provisions in the Investment Advisers Act of 1940. The data include violations that were committed during the period of August 2001 to December 2012 and later prosecuted by the SEC.

As shown in Table 6, firms' fraud propensities are positively correlated with three out of four types of crime and misconduct. More importantly, the inclusion of other types of wrongdoings does not affect the significance of opportunism in the fraud decision nor the perceptual deterrence from the SEC. That is, though the social norm of the state where a firm is located also influences the firm's decision of whether or not to commit fraud, the firm's strategy of adjusting the fraud propensity based on the expected detection probability is distinct from social norms, which supports the main findings of this study.

[Table 6 about here.]

6.2 Industry Crime Waves

Another endogeneity concern is unobserved industry characteristics that may affect firms' fraud decisions, thus may also explain the opportunism and deterrence. To capture unobserved industry characteristics that potentially correlate with fraudulent activities and to exploit the organizational structure of the SEC, I construct a subsample of firms under the jurisdiction of regional offices who have brought up at least one accounting-related legal ac-

[16] Details of the data on crime are discussed in Data Section

[17] Based on *Uniform Crime Reporting*, $ViolentCrime$ consists of murder and non-negligent manslaughter, rape, robbery and aggravated assault. $PropertyCrime$ consists of burglary, larceny-theft and motor vehicle theft.

tion to firms in the same industry in the same year. For example, after the San Francisco Office brought up an accounting manipulation case to a computer company in 2003, all firms in the computer/technology industry under the jurisdiction of the San Francisco Office are included in this subsample for 2003. The results using this subsample again demonstrate the opportunism in fraud and the perceptual deterrence of SEC intervention, which cannot be explained by potential industry crime waves given that firms in this subsample share the same industry characteristics and face the same scrutiny from the SEC. Moreover, the results also lend support to the existence of industry crime waves, in the sense that the predicted fraud propensity of firms in this subsample is much higher than the one using the full sample (12.2% *vs.* 7.3%, estimated with firm characteristics at median values). At the same time, the scrutiny on these firms from the SEC is also more intense, as the predicted conditional detection probability is also higher than the full sample (22.6% *vs.* 18.9%). Because both the probability of fraud and the probability of detection are higher, the probability of detected fraud is higher in this subsample (2.77% *vs.* 1.37%).

6.3 Industry Regulatory Conditions

Given the complexity of firms' regulatory conditions, it is possible that the oversight from other regulatory agencies contributes to the deterrence and impels the opportunism in corporate fraud. In particular, firms in different industries face different regulatory conditions, and frequently the SEC is not the only regulator that oversees firm operations. For example, besides the SEC, banks are also regulated by the Federal Reserve System, the Federal Deposit Insurance Corporation, Office of the Comptroller of the Currency and National Credit Union Administration. Taking into account firms' regulatory conditions, I construct a subsample that excludes firms in industries of petroleum and natural gas, utilities, communication, transportation and financial services, and re-estimate Model 4 in Table 3. As shown in Table 7, the opportunism in fraud and the perceptual deterrence from the SEC remain robust for firms in relatively less regulated industries, which undermines the confounding explanation of the supervision from other government agencies nor the broad regulatory conditions of industries for the main findings.

6.4 Local Economic Conditions

As discussed in Povel, Singh, and Winton (2007), the overall economic conditions can also be an important factor in firms' decisions of whether or not to commit fraud. To alleviate the concern of potential fraud cycles driven by the underlying economic conditions, I include state-level GDP in the fraud equation as an extension to Model 4 in Table 3. As shown in Table 7, there is no significant effect from state-level GDP on fraud propensity, which is possible given that the industry expectation could have already integrated the overall economic conditions. More importantly, taking into account the potential incentive to commit fraud that is driven by economic conditions, the finding remains the same as in the main results, which support the strategic and opportunistic fraud decision and the perceptual deterrence of SEC detection.

6.5 Firm Litigation Concerns

One alternative explanation is a firm's litigation concerns, where firms that are currently experiencing high litigation risks are the ones driving the opportunism and perceptual deterrence. To investigate this alternative explanation, I exploit the SEC litigation process and construct a subsample with only the firms that are not currently under investigation. For any alleged misconduct, there will first be an investigation to collect information, and firms under investigation are likely to experience high litigation risks. As shown in Table 7, the coefficient on the expected detection probability in the fraud equation is again negative and significant. That is, firms take the likelihood of being detected into account when making fraud decisions, even though these firms are not currently under investigation of the

SEC and have relatively less litigation concern, which further supports the generality of the opportunism in fraud and the perceptual deterrence from the SEC intervention.

[Table 7 about here.]

6.6 Selection Effect on Fraud

The last issue I consider is a potential selection effect. In the setting of this paper, a selection issue can arise if variables in the detection equation are correlated with unobserved firm quality which affects firms' decision of whether or not to commit fraud, and this unobserved firm quality cannot be captured by the likelihood of getting caught. Regarding this concern, I include all the firm characteristics from the detection equation in the fraud equation and re-estimate the model. In an untabulated table,[18] the findings remain qualitatively the same, suggesting that characteristics, which serve as ex-post signals in the detection process, do not explain the opportunism in fraud decisions nor the perceptual deterrence from the SEC intervention.

7 Conclusion

I study firms' opportunistic strategies in corporate fraud, that is, firms strategically engaging in fraudulent activities when the perceived detection probability is low and opportunistically adjusting the fraud propensity based on the intensity of SEC regulatory intervention. This opportunistic behavior also underlines the specific mechanism that leads to the deterrence from the SEC - perceptual deterrence following the criminology literature. I apply the detection-controlled estimation (DCE) framework to analyze the two economic processes that are involved when fraudulent activity is detected: the decision process of whether or

[18]Variables in the fraud and detection equations are highly overlapping, and the results are available upon request.

not to commit fraud and the detection process conditional on that fraud has been committed. The combination of the DCE framework and a unique hand-collected dataset enables me to overcome the empirical challenges of partial observability and the interdependent relationship between firms and the SEC. By modeling the fraud decision and the detection process separately and estimating them jointly using maximum likelihood, I am able to analyze the determinants of each process, as well as study how the detection process affects the fraud decision.

This paper provides evidence that firms decide to commit fraud strategically as a response to the detection probability, which supports the positive theory of the role of the SEC in deterring accounting fraud. Further, embracing the criminology literature, I quantify how different intervention tactics used by the SEC affect a firm's fraud propensity through their effects on the detection probability. This paper also serves as an example of methods that can be applied in studies facing partial observability, such as regulation outcomes, auditing of public spending, or organized crime. In addition, the DCE model can be extended to general interrelation analysis that involves multiple decision processes that are not directly observable but can be modeled separately, such as the relation between firms and rating agencies or analysts.

Overall, this paper documents a strategic relationship between firms and the regulator that deepens our understanding of firms' fraudulent behavior. Given the regulator's actions, firms choose to commit fraud strategically and opportunistically, supporting the predictions of Becker's economic approach to crime (Becker, 1968). By estimating a model of the ongoing relationship between firms and the regulator, the analysis and the quantification from this paper offer important insights, aiding the regulation of misconduct and the improvement of social efficiency.

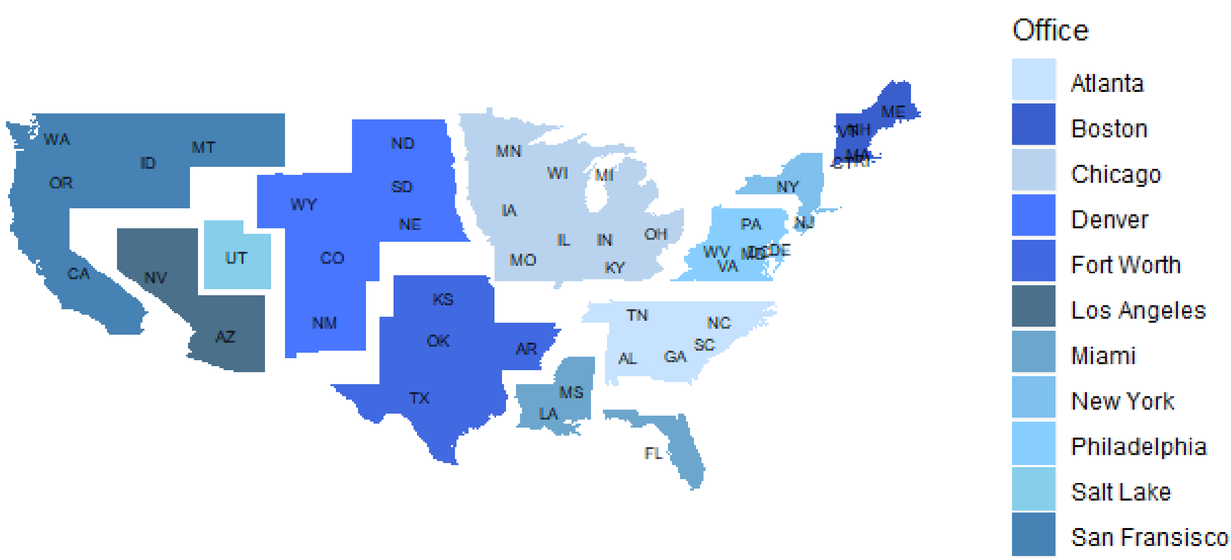
Appendix A: Variable Definitions

Variable	Definition	Description
$RSSTAcc$	RSST accruals	(ΔWC + ΔNCO + ΔFIN)/Average Total Asset, where WC =(Current Asset - Cash and Short-term Investments)-(Current Liabilities - Debt in Current Liabilities); NCO = (Total Assets - Current Assets - Investment and Advances) - (Total Liabilities - Current Liabilities - Long-term Debt); FIN = (Short-term Investments + Long-term Investment) - (Long-term Debt + Debt in Current Liabilities + Preferred Stock)
$ChRec$	Change in Receivables	ΔAccount Receivable/Average Total Assets
$ChInv$	Change in Inventory	ΔInventory/Average Total Assets
$SoftAssets$	%Soft Assets	(Total Assets - PP&E - Cash and Cash Equivalent)/Total Assets
$ChROA$	Change in Return on Assets	Earnings$_t$/Average Total Assets$_t$ - Earnings$_{t-1}$/Average Total Assets$_{t-1}$
$ChCS$	Percentage Change in Cash Sales	Percentage change in Cash Sales, where Cash Sales = Sales - ΔAccount Receivable
$IndEPSGrwoth$	Industry Level EPS Growth	Industry median forecasted EPS growth, where EPS growth is measured as the forecasted annual EPS divided by the prior year realized EPS and then minus one. Industries are classified based on 3-digit SIC code.
$AdjRet$	Market-adjusted Stock Return	Annual buy-and-hold return minus the annual buy-and-hold value-weighted market return
$ExtFinNeed$	External Financing Need	Assets growth rate - ROA2/(1-ROA2), where ROA2 = (Income Before Extraordinary Items)/Total Assets
$Leverage$	Leverage	Long-term Debt/Total Assets

Variable	Definition	Calculation
$AbnROA$	Abnormal Return on Asset	Residual from regression: $ROA_t = \alpha_0 + \alpha_1 ROA_{t-1} + \alpha_2 ROA_{t-2} + \epsilon_t$, where ROA = Operating Income after Depreciation/Total Assets
$AbnRetVol$	Abnormal Return Volatility	Demeaned standard deviation of monthly stock returns in a year
$AbnTurnover$	Abnormal Stock Turnover	Demeaned average monthly turnover in a year
BM	Book-to-market	Equity/Market Value
EP	Earnings-to-price	Earnings/Market Value
$AAER$	Accounting and Auditing Enforcement Releases	An indicator variable coded 1 if the firm committed fraud as of the end of the fiscal year and later became a target in a civil action brought by the SEC.
$AbnExp$	Abnormal Expense	The total wages paid to accountants, lawyers and investigators adjusted by year and SEC office location
$No.Cases$	Number of Investigations	The total number of investigations conducted by each regional office of the SEC
$Pros.Intensity$	Prosecution Intensity	The ratio of the number of total public actions to total number of investigations for each regional office
$No.AAER$	Number of AAER Actions	The number of accounting and auditing enforcement releases by the SEC's regional offices
$No.Other$	Number of Non-Accounting-Related Actions	The number of total non-accounting-related actions by the SEC's regional offices = the number of total public cases - $No.AAER$
$AccRatio$	Relative AAER Prosecution Intensity	$No.AAER$ / $No.Other$

Appendix B.1: SEC Regional Office Jurisdictions

The SEC has its headquarters in Washington, DC, and 11 regional offices located in various states. This figure illustrates the areas of jurisdiction of each regional office. Each regional office is in charge of the investigation and litigation against firms who have potentially violated the securities laws under its jurisdiction. Though the areas of jurisdiction are distinctly clustered by the regional offices, there are several details that are not included in this figure for the purpose of demonstration clarity. Guam and Hawaii are under the jurisdiction of the Los Angeles Regional Office. Puerto Rico, U.S. Virgin Islands are under the jurisdiction of the Miami Regional Office. California is split into Southern California and Northern California, where the Southern California is under the jurisdiction of the Los Angeles Regional Office and the Northern California is under the jurisdiction of the San Francisco Regional Office. The Southern California includes ZIP codes 93599 and below, except 93200-93299, and the Northern California includes ZIP codes 93600 and above, and 93200-93299.



Appendix B.2: Institutional Background for the Litigation Process

The U.S. Securities and Exchange Committee (SEC), founded in 1934, is a regulatory agency of the United States federal government that enforces security laws. The Division of Enforcement (DoE) is the division that brings legal actions to firms who violate the law. These violations include but are not limited to accounting fraud, insider trading and market manipulation.

For a given allegation, the investigative process starts with a lead, which could be an external tip from concerned investors, whistleblowers, or based on surveillance activities conducted by the SEC, such as, e.g, reviews of firms' annual reports. With a lead to an alleged violation, the DoE staff will assess the relevant material and decide whether to initiate a Matter Under Inquiry, which later may result in an investigation, or an investigation directly, based on the severity of the case and the amount of evidence. The goal of investigation is not only correcting misbehavior and protecting investors, but also addressing misconduct that is consistent with the SEC's enforcement priorities. Once the investigation starts, resources will be allocated to collect firm information, interview executives or employees, etc. Though a number of investigations can be opened at that same time, the cases that have the highest likelihood of winning and sending a deterrence message will receive the most attention and resources.

Out of all the investigations, only a fraction will be authorized to institute an enforcement action. As indicated in the enforcement manual, for each investigation, if a delay in enforcement action would cause significant harm to investors or the violation is considerately serious, then the Commission would authorize to institute an enforcement action. This enforcement action can be either a civil action in a U.S. District Court or in an administrative proceeding, which is presided over by an independent administrative law judge[19]. Because of the public attention, when the SEC considers whether or not to prosecute a case, the seriousness of the violation, the likelihood of winning and the deterrent message that the SEC intend to send to the public are all important factors according to SEC staff. With limited resources, the legal actions prosecuted reflect the attention and priority of the SEC. In addition, though the enforcement actions do not capture to the full extent of the work done by the DoE, they are a good approximation because of their urgency and severity. Hence, through the relative number of enforcement actions about accounting fraud versus all non-accounting types of misconducts, for example, the allocation of resources by the DoE reveals the attention allocation to accounting fraud receives relative to all other misconducts.

[19]Before authorizing an enforcement action, the SEC notifies the firm of its intent to pursue an enforcement action via a "Wells notice" and offer the firm an opportunity to response. Though not keeping a detailed counts of the Wells notices before 2010, during the period from October 2009 to September 2012, the SEC dropped about 20% of the probes (Eaglesham, 2013) in the process of Wells notices.

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Table 1: Descriptive Statistics

This table contains summary statistics for the final sample, consisting of 43,462 firm-year observations from 2000 to 2012. The statistics shown are mean, standard deviation, the 25th percentile, median and the 75th percentile. Panel A provides information on firm characteristics and Panel B provides information on the enforcement variables. Variable definitions are listed in Appendix A.

Panel A: Firm Statistics

Variable	Mean	Std. Dev.	P25	P50	P75
RSSTAcc	.011	.284	-.044	.009	.081
SoftAssets	.528	.252	.332	.553	.735
ChROA	-.005	.3	-.038	0	.028
ChCS	.113	.443	-.039	.052	.189
IndEPSGrwoth	.376	1.31	-.231	.201	.679
AdjRet	.123	.994	-.291	-.022	.291
ExtFinNeed	.169	1.56	-.046	.022	.144
Leverage	.215	.277	.006	.159	.335
AbnROA	0	.28	0	.019	.069
AbnRetVol	.122	.122	.057	.103	.165
AbnTurnover	.068	1.56	-.472	-.086	.383
Book-to-market	.529	6.35	.264	.48	.803
Earnings-to-price	-.269	5.67	-.082	.028	.061

Panel B: Enforcement Statistics

Variable	Mean	Std. Dev.	P25	P50	P75
AAER	.016	.125	0	0	0
Expense(/Mil)	24.1	15.1	14.4	17.8	30.3
No.Cases(/1000)	.266	.160	.168	.230	.305
No.AAER(/100)	.15	.10	.08	.13	.19
No.Other(/100)	.74	.47	.41	.58	.89
AccRatio	.231	.143	.145	.191	.293
Pros.Intensity	.349	.12	.258	.333	.406

Table 2: The Strategic Response of Fraud to Detection Probability

This table contains results from models where the dependent variable is a dummy variable that equals 1 if a firm committed fraud in year t and later became a targeted entity in the SEC legal actions of accounting fraud. The first two columns show the estimation using a standard logit model, and the rest of the table shows the estimation of two different Detection-Controlled Estimation (DCE) models, a basic version and an extended version with one-sided expectation simultaneity. For the DCE models, Panel A shows the estimated parameters of the fraud equation and Panel B shows the estimated parameters of the detection equation. T-statistics are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Logit		DCE Model (Basic)		DCE Model (Simul. Exp.)	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
			Panel A: Fraud Equation			
RSSTAcc_{t-1}	0.409^{**}	(2.33)	0.500^{*}	(1.86)	0.629^{*}	(1.89)
SoftAssets_{t-1}	1.615^{***}	(8.22)	0.469	(.42)	0.508	(.63)
ChROA_{t-1}	-0.198	(-1.44)	-0.704^{*}	(-1.81)	-0.921^{**}	(-2.05)
ChCS_{t-1}	0.290^{***}	(3.11)	1.414^{***}	(3.92)	1.525^{***}	(7.08)
ExtFinNeed_{t-1}	-0.005	(-.20)	0.313^{***}	(2.94)	0.361^{***}	(3.14)
Leverage_{t-1}	-0.163	(-.78)	-0.401^{*}	(-1.79)	-0.361	(-1.57)
AdjRet_{t-1}	0.057	(1.42)	0.069^{*}	(1.67)	0.073	(1.56)
IndEPSGrowth_{t}	0.046^{***}	(6.13)	0.051^{***}	(5.85)	0.055^{***}	(6.03)
Pr(D)_{t}					-2.101^{***}	(-7.96)
Constant			-4.800^{***}	(-15.49)	-2.855^{***}	(-10.84)
			Panel B: Detection Equation			
RSSTAcc_{t}	-0.001^{***}	(-2.88)	-0.030^{*}	(-1.78)	-0.013^{***}	(-3.56)
AbnROA_{t}	-0.359^{***}	(-2.93)	-0.529	(-.38)	-0.231	(-.56)
CS_{t}	0.002^{***}	(3.76)	1.261^{**}	(2.47)	0.565^{***}	(6.57)
BM_{t}	0.035	(.92)	-0.872	(-1.45)	-0.301	(-1.12)
EP_{t}	0.030	(.69)	-0.696	(-1.00)	-0.319	(-1.13)
AbnRetVol_{t}	1.620^{***}	(5.82)	5.042	(.37)	3.085^{***}	(3.89)
AbnTurnover_{t}	0.022	(1.11)	0.299	(1.24)	0.107	(1.19)
Constant	-5.551^{***}	(-38.33)	-0.767	(-.56)	-2.972^{***}	(-8.40)
Log Likelihood	-2723.65		-2711.46		-2707.4	
Observations	43,462		43,462		43,462	

Table 3: Opportunism in Corporate Fraud

This table contains results from models where the dependent variable is a dummy variable that equals 1 if a firm committed fraud in year t and later became a targeted entity in the SEC legal actions of accounting fraud. All results are from a Detection-Controlled Estimation (DCE) model with one-sided expectation simultaneity. Panel A shows the estimated parameters of the fraud equation and Panel B shows the estimated parameters of the detection equation. All four models investigate the firms' opportunistic fraudulent behavior, expecting different SEC tactics would impact the detection probability given fraud has been committed. Model 1 focuses on the impact of the SEC's abnormal expense, Model 2 focuses on prosecution intensity, and Models 3 and 4 focus on the relative attention on regulating accounting fraud. T-statistics are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Hot-Spots Model 1		*Proactive* Model 2		*Misconduct-Oriented* Model3		Model 4	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Panel A: Fraud Equation								
$RSSTAcc_{t-1}$	0.549**	(1.99)	0.578**	(2.28)	0.619**	(2.49)	0.651***	(2.59)
$SoftAssets_{t-1}$	1.651***	(7.08)	0.704	(.73)	0.757	(.91)	0.638	(.66)
$ChROA_{t-1}$	-0.129	(-.44)	-0.941**	(-2.24)	-1.245***	(-3.58)	-1.298***	(-3.39)
$ExtFinNeed_{t-1}$	0.364***	(3.17)	0.355***	(3.07)	0.365***	(3.26)	0.381***	(3.26)
$Leverage_{t-1}$	-1.018***	(-3.58)	-0.349	(-1.46)	-0.333	(-1.41)	-0.310	(-1.28)
$AdjRet_{t-1}$	0.049	(.98)	0.052	(1.08)	0.063	(1.40)	0.072	(1.60)
$IndEPSGrowth_t$	0.188**	(2.43)	0.061***	(5.87)	0.059***	(6.29)	0.059***	(6.39)
$Pr(D)_t$	-2.189***	(-8.00)	-2.123***	(-7.45)	-1.992***	(-7.42)	-2.098***	(-7.88)
Constant	-2.868***	(-11.86)	-2.866***	(-11.88)	-2.931***	(-11.51)	-2.823***	(-11.22)
Panel B: Detection Equation								
$AbnExp_t$	1.146**	(1.97)						
$Pros.Intensity_t$			3.191***	(4.01)				
$No.Cases_t$					-3.518***	(-3.85)		
$AcctRatio_t$					3.273***	(3.78)		
$No.AAER_t$							4.881***	(2.61)
$No.Other_t$							-1.623***	(-4.29)
$RSSTAcc_t$	0.466	(-.72)	0.002	(.77)	0.002	(.43)	-0.011	(-1.61)
$AbnROA_t$	-0.427	(-1.17)	-0.528	(-1.61)	-0.493	(-1.56)	-0.425	(-1.45)
CS_t	0.369***	(4.47)	0.456***	(3.30)	0.428***	(4.61)	0.561***	(6.12)
BM_t	-0.241	(-1.46)	0.038	(.32)	0.106	(.57)	0.127	(.81)
EP_t	-0.07607	(-1.43)	0.079	(.93)	0.053	(.42)	0.037	(.34)
$AbnRetVol_t$	3.107***	(3.08)	2.503**	(2.04)	2.358**	(2.22)	2.763***	(2.96)
$AbnTurnover_t$	0.052	(.43)	0.250***	(3.11)	0.174**	(1.98)	0.133	(1.56)
Constant	-3.928***	(-7.50)	-3.828***	(-10.96)	-2.835***	(-5.95)	-2.825***	(-6.92)
Log Likelihood	-2718.92		-2705.39		-2687.49		-2692.24	
Observations	35,158		43,462		43,462		43,462	

Table 4: The Option Backdating Scandal as a Natural Experiment

This table contains results from models where the dependent variable is a dummy variable that equals 1 if a firm committed fraud in year t and later became a targeted entity in the SEC legal actions of accounting fraud. Specifically, the model in this table incorporates a difference-in-differences design into the extended version of the Detection-Controlled Estimation (DCE) framework. The publication of Lie (2005) attracts the SEC's attention to the practice of option backdating, shocking the detection process without influencing firms' fundamentals. Executives with different compensation sensitivities of options are exposed differently to this particular regulatory shock. Panel A shows the estimated parameters of the fraud equation and Panel B shows the estimated parameters of the modified detection equation, which incorporates the shock to detection triggered by Lie (2005). T-statistics are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Coef.	t-stat
Panel A: Fraud Equation		
IndEPSGrowth	-0.224	(-.93)
Ch ROA	2.431**	(2.42)
Ret	0.136	(.76)
Leverage	-1.541**	(-2.19)
RSST acc	0.047	(.07)
Soft Assets	2.334***	(3.94)
ExtFinNeed	-0.138	(-.37)
Pr(D)	-2.051**	(-2.31)
Constant	-3.544***	(-7.72)
Panel B: Detection Equation		
No.AAER	3.176**	(2.46)
No.Other	-1.123**	(-2.43)
CS	-0.001	(-.31)
BM	0.428	(.78)
EP	0.557***	(5.41)
RSST acc	1.690	(1.17)
AbnROA	0.179	(.09)
AbnRetVol	9.097**	(2.18)
AbnTurnover	-0.130	(-.97)
Vega	-0.012	(-.84)
Shock	1.416**	(2.35)
Vega * Shock	0.026***	(2.82)
Constant	-4.018***	(-3.03)
Log Likelihood	-508.49	
Observations	10,076	

Table 5: Heterogeneity in Fraud and Detection

This table contains results from models where the dependent variable is a dummy variable that equals 1 if a firm committed fraud in year t and later became a targeted entity in the SEC legal actions of accounting fraud. All the results are estimated using Detection-Controlled Estimation (DCE) models with one-sided simultaneity. Panel A shows the estimated parameters of the fraud equation and Panel B shows the estimated parameters of the detection equation. *Fraud Heterogeneity* refers to estimates using the subsample of firms with available information on the sensitivity of executives' wealth to changes in stock price (*CompensationSensitivity*). *Detection Heterogeneity* refers to estimates using the subsample of firms with the number of business segments above the sample average in each year. T-statistics are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Fraud Heterogeneity		Detection Heterogeneity	
	Coef.	t-stat	Coef.	t-stat
Panel A: Fraud Equation				
IndEPSGrowth	0.056***	(3.28)	0.068***	(4.76)
Ch ROA	0.477	(.81)	-0.155	(-.51)
Ret	0.178	(1.28)	0.008	(.13)
Leverage	-0.141	(-.26)	0.163	(.59)
RSST acc	0.569	(.83)	0.363	(1.18)
Soft Assets	1.561	(.83)	2.012***	(6.83)
ExtFinNeed	0.864**	(2.37)	0.018	(.34)
CompensationSensitivity	1.025***	(4.37)		
Pr(D)	-3.412***	(-3.15)	-2.467***	(-2.60)
Constant	-2.494***	(-6.14)	-2.633***	(-7.48)
Panel B: Detection Equation				
No. Cases	-0.273	(-.58)	-1.288***	(-2.80)
AcctRatio	2.079***	(4.00)	3.094***	(3.33)
CS	0.000*	(-1.71)	0.004***	(3.01)
BM	0.765***	(3.60)	0.052	(.59)
EP	0.489*	(1.90)	0.150	(1.30)
RSST acc	0.618	(1.07)	0.750**	(1.99)
AbnROA	-0.765*	(-1.80)	-0.753**	(-2.29)
AbnRetVol	7.998***	(15.04)	4.652***	(4.01)
AbnTurnover	-0.074	(-1.23)	0.062	(1.04)
Constant	-4.416***	(-20.99)	-3.385***	(-8.30)
Log Likelihood	-1266.32		-2295.22	
Observations	17,910		13,537	

Table 6: Geographic Effect of Crime

This table contains results from models where the dependent variable is a dummy variable that equals 1 if a firm committed fraud in year t and later became a targeted entity in the SEC legal actions of accounting fraud. All the results are estimated using Detection-Controlled Estimation (DCE) models with one-sided simultaneity. Panel A shows the estimated parameters of the fraud equation and Panel B shows the estimated parameters of the detection equation. In addition, I include a proxy for social norms in each test to capture the correlation between different types of crime. Specifically, I use the annual population-adjusted violent crime rate, population-adjusted property crime rate, the number of political corruption, and the number of investment adviser misconduct for each state to account for the geographic clustering of crime. T-statistics are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Violent Crime		Property Crime		Corruption		Investment Adviser	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Panel A: Fraud Equation								
IndEPSGrowth	-0.184**	(-2.33)	-0.183**	(-2.38)	-0.191**	(-2.44)	-0.183**	(-2.35)
Ch ROA	-0.128	(-.43)	-0.131	(-.41)	-0.141	(-.47)	-0.129	(-.44)
Ret	0.059	(1.16)	0.056	(1.10)	0.059	(1.18)	0.059	(1.17)
Leverage	-1.059***	(-3.60)	-1.076***	(-3.78)	-0.949***	(-3.37)	-0.877***	(-3.19)
RSST acc	0.483*	(1.65)	0.495*	(1.71)	0.528*	(1.90)	0.553**	(2.00)
Soft Assets	1.623***	(6.77)	1.643***	(7.00)	1.646***	(7.02)	1.694***	(7.27)
ExtFinNeed	0.012	(.89)	0.011	(.81)	0.012	(.84)	0.012	(.87)
SocialNorm	0.111	(3.45)	0.156***	(2.92)	-0.197	(-1.05)	0.351***	(3.66)
Pr(D)	-2.168***	(-5.87)	-2.143***	(-7.37)	-2.140***	(-7.56)	-2.115***	(-7.72)
Constant	-3.348***	(-10.43)	-3.388***	(-11.05)	-2.876***	(-11.09)	-3.180***	(-12.52)
Panel B: Detection Equation								
No.AAER	4.520**	(2.23)	4.355***	(2.96)	4.529***	(3.15)	4.594***	(3.96)
No.Other	-1.487***	(-4.05)	-1.300***	(-3.62)	-1.419***	(-3.57)	-1.581***	(-4.74)
CS	0.444***	(4.43)	0.460***	(4.50)	0.446***	(4.30)	0.430***	(4.15)
BM	-0.595*	(-1.92)	-0.674**	(-2.20)	-0.606*	(-1.94)	-0.553*	(-1.92)
EP	-0.510	(-1.59)	-0.579*	(-1.72)	-0.524	(-1.60)	-0.473	(-1.58)
RSST acc	0.565	(.68)	0.559	(.76)	0.564	(.94)	0.591	(1.02)
AbnROA	-0.349	(-.76)	-0.355	(-.84)	-0.346	(-.83)	-0.336	(-.82)
AbnRetVol	3.333*	(1.87)	3.638	(1.38)	3.436**	(2.28)	3.081***	(3.88)
AbnTurnover	-0.028	(-.35)	-0.033	(-.42)	-0.027	(-.33)	-0.019	(-.22)
Constant	-2.148***	(-4.61)	-2.228***	(-3.71)	-2.185***	(-4.71)	-2.050***	(-4.97)
LogLikelihood	-2175.66		-2177.21		-2180.92		-2175.36	
Observations	43,462		43,462		43,462		39,302	

Table 7: Addressing Alternative Stories

This table shows the findings addressing several alternative explanations. The dependent variable is a dummy variable that equals 1 if a firm committed fraud in year t and later became a targeted entity in the SEC legal actions of accounting fraud. All the results are estimated using Detection-Controlled Estimation (DCE) models with one-sided simultaneity. Panel A shows the estimated parameters of the fraud equation and Panel B shows the estimated parameters of the detection equation. *Industry Crime* refers to estimates using the subsample of firms under the jurisdiction of regional offices who have brought accounting-related legal action(s) to at least one firm in the same industry. *Regulatory Condition* refers to estimates using the subsample which excludes firms in industries under relatively strict monitoring (petroleum and natural gas, utilities, communication, transportation and financial services). *Local Economics* extends Model 4 in Table 3 by including the state-level GDP in the fraud equation . *Non-Investigation* refers to estimates using the subsample of firms that are not currently under any SEC investigation. T-statistics are reported in brackets. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Industry Crime		Regulatory Condition		Local Economics		Non-Investigation	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Panel A: Fraud Equation								
IndEPSGrowth	0.038***	(4.36)	-0.012	(-.42)	0.065***	(6.20)	-0.010	(-.38)
Ch ROA	-0.030	(-.12)	0.177	(1.33)	-0.103	(-.38)	0.125	(.99)
Ret	0.021	(.39)	0.074	(1.58)	0.043	(.88)	0.075	(1.61)
Leverage	0.046	(.18)	-0.440	(-1.04)	-0.465*	(-1.86)	-0.536	(-1.19)
RSST acc	0.085	(.33)	0.061	(.26)	0.175	(.67)	0.123	(.59)
Soft Assets	1.505***	(6.50)	-2.518	(-1.58)	1.633***	(7.37)	-6.778***	(-8.03)
ExtFinNeed	0.364***	(3.17)	0.051*	(1.70)	0.302***	(3.34)	0.013	(1.04)
StateGDP					-0.831	(-.98)		
Pr(D)	-1.991***	(-7.67)	-2.029***	(-7.35)	-2.150***	(-6.92)	-1.989***	(-7.04)
Constant	-2.228***	(-9.63)	-1.924***	(-8.37)	-2.538***	(-4.30)	-2.051***	(-8.72)
Panel B: Detection Equation								
No.AAER	0.700	(.62)	4.887***	(3.24)	5.049***	(3.00)	4.627***	(4.11)
No.Other	-0.991***	(-3.29)	-1.629***	(-4.74)	-1.396***	(-4.04)	-1.461***	(-4.78)
CS	0.316***	(2.67)	0.511***	(4.75)	0.144**	(2.24)	0.452***	(5.00)
BM	0.078	(.54)	-0.517**	(-2.49)	0.159	(1.00)	-0.487**	(-2.39)
EP	0.074	(.83)	-0.697***	(-2.63)	0.042	(.50)	-0.664**	(-2.55)
RSST acc	0.401	(.95)	5.754***	(3.81)	0.631	(1.45)	5.164***	(3.22)
AbnROA	-0.138	(-.75)	-0.303	(-.66)	-0.208	(-1.18)	-0.287	(-.65)
AbnRetVol	2.055**	(2.23)	-2.044***	(-3.16)	2.663**	(2.05)	-2.187***	(-3.92)
AbnTurnover	0.168**	(1.96)	0.189	(1.51)	0.187***	(2.58)	0.194	(1.45)
Constant	-2.029***	(-6.12)	-2.118***	(-5.47)	-2.461***	(-7.53)	-2.128***	(-5.36)
LogLikelihood	-2,298.18		-2,527.43		-2,684.56		-2,646.30	
Observations	17,040		31,749		43,462		35,428	

Figure 1: Detection-controlled Estimation Model of Corporate Fraud

This figure shows the structure of the two-stage detection-controlled estimation model of corporate fraud used in this study. First, Firm i decides whether to commit fraud or not. Following this decision process of the firm, the detection process determines whether the fraud is detected conditional on that the fraud has been committed. Both processes are estimated simultaneously by maximizing the likelihood of observed data as shown at the bottom of this figure.

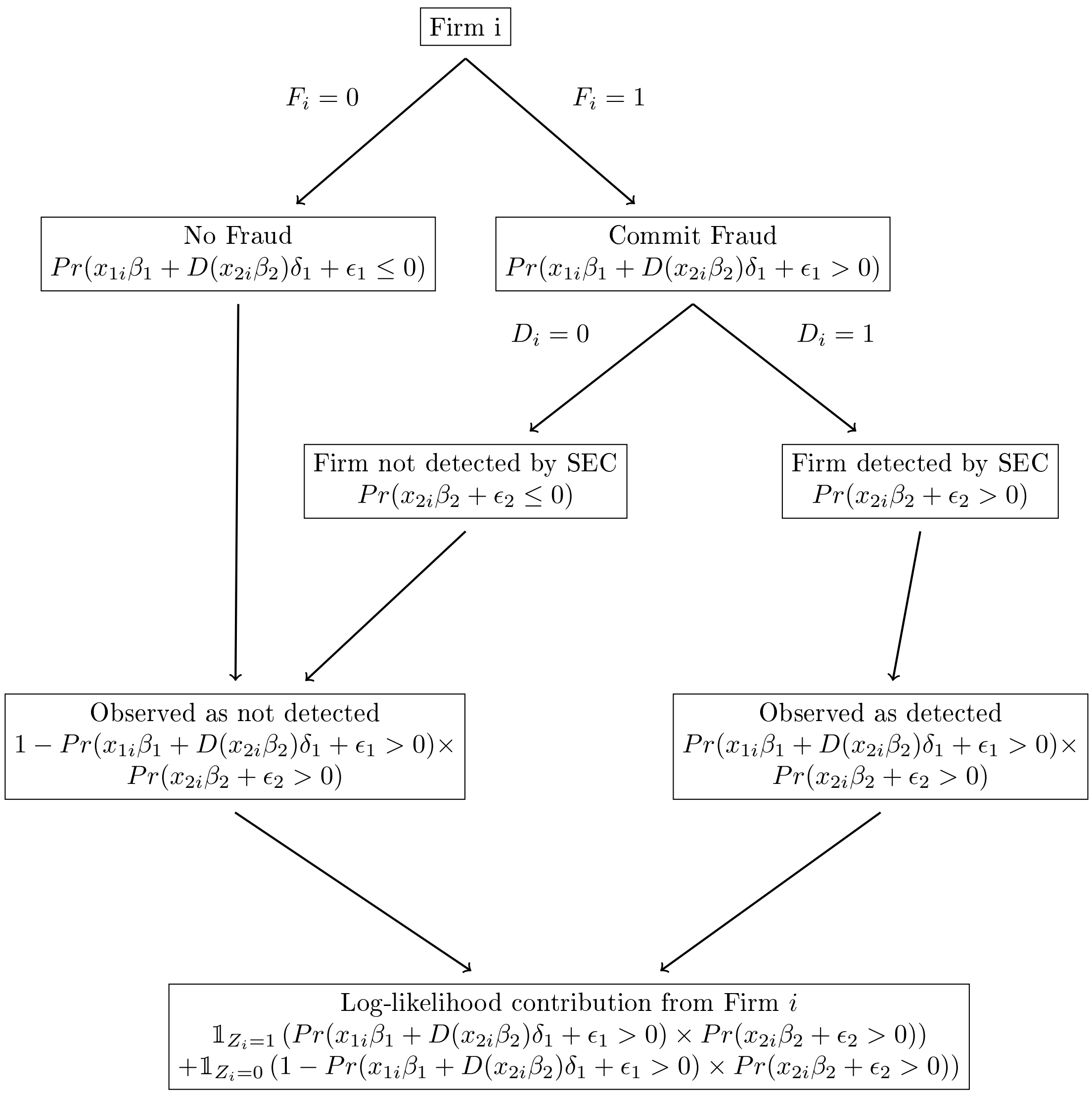

Figure 2: Examples of the Effects of the SEC Regulatory Intervention

This figure shows how the predicted conditional detection probability and the predicted fraud propensity as a function of the SEC intervention, in particular the characteristics capturing how the SEC chooses to allocate the attention and resources to the accounting-related misconducts versus other types of misconducts. The predicted values of the fraud propensity and the conditional detection probability are calculated at the median values of all variables using the estimated parameters from the Detection-Controlled Estimation (DCE) framework with one-sided expectation simultaneity. The estimates are based on Model 4 of Table 3, where the number of accounting-related legal actions and the number of non-accounting-related legal actions are included in the model as the SEC intervention. The top figure shows predicted values of the fraud propensity and the conditional detection probability given a fraud has been committed, as a function of the number of accounting-related legal actions ($AAER$s), where the number of $AAER$s is divided by 100. The bottom figure shows predicted values of the fraud propensity and in the conditional detection probability as a function of the number of non-accounting-related legal actions, denoted as $Other$, where the number of $Other$ actions is divided by 100. In both figures, the superimposed histogram in the background shows the empirical distribution of the variable on the x-axis, the dashed line depicts the predicted fraud propensity, denoted as $Pr(Fraud)$, and the solid line depicts the predicted conditional detection probability given fraud has been committed, denoted as $Pr(Detection|Fraud)$.

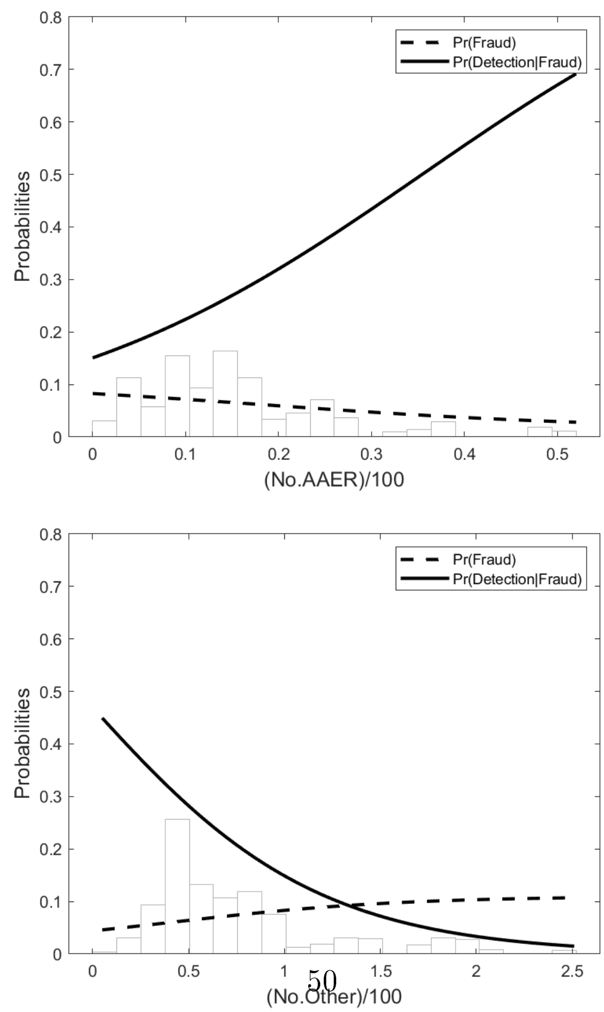

Figure 3: Fraud Propensity and Detection Probability across Industries

This figure shows how the predicted conditional detection probability and the predicted fraud propensity vary across industries. The predicted values of the fraud propensity and the conditional detection probability are calculated at the median values of all variables using the estimated parameters from the Detection-Controlled Estimation (DCE) framework with one-sided expectation simultaneity. The estimates are based on Model 4 of Table 3, where the number of accounting-related legal actions and the number of non-accounting-related legal actions are included in the model as the SEC intervention. I use the Fama French 17 industry classification to calculate the industry average fraud propensity and average detection probability. The x-axis represents the predicted fraud propensity, the y-axis represents the predicted detection probability given fraud has been committed. The plots depict the average values of the predicted fraud propensity and predicted conditional detection probability for each industry.

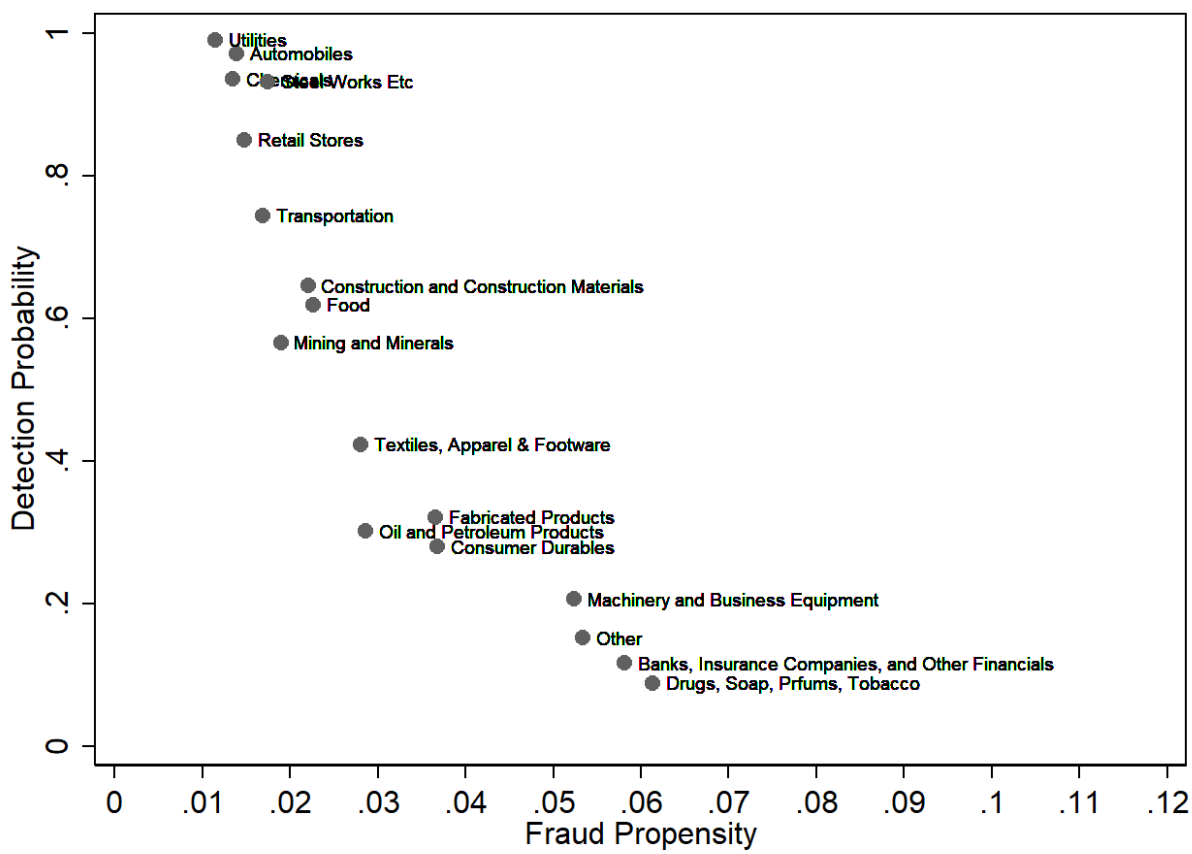

Figure 4: Geographical Variation in Fraud Propensity and Detection Probability

This figure shows the state-level variation in the median levels of fraud propensity and detection probability. The predicted values of the fraud propensity and the conditional detection probability are calculated at the median values of all variables using the estimated parameters from the Detection-Controlled Estimation (DCE) framework with one-sided expectation simultaneity. The estimates are based on Model 4 of Table 3, where the number of accounting-related legal actions and the number of non-accounting-related legal actions are included in the model as the SEC intervention.

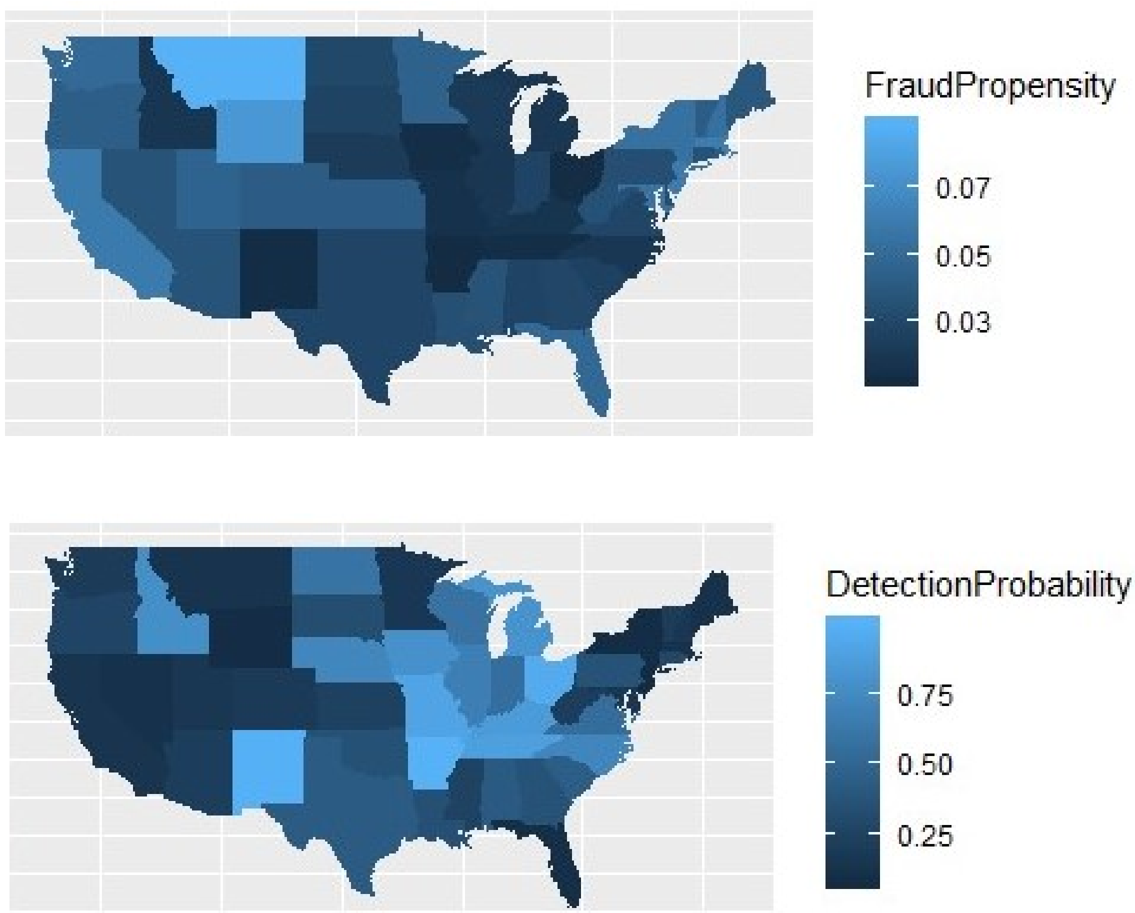

Figure 5: Fraud Propensity and Detection Probability around the Option Backdating Scandal

This figure displays the average fraud propensity and the average detection probability of firms with the executives' sensitivity of options payoff to stock volatility in the top *versus* bottom tertiles in 2004. The predicted values of the fraud propensity and the conditional detection probability are calculated using the estimated parameters from the model that incorporates a difference-in-differences design into the Detection-Controlled Estimation (DCE) framework with one-sided expectation simultaneity as in Table 4.