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We examine the link between information produced by auditors and analysts and fraud duration. Using a hazard model, we analyze misstatement periods related to SEC accounting and auditing enforcement releases (AAERs) between 1982 and 2012. Results suggest that misconduct is more likely to end just after firms announce an auditor switch or issue audited financial statements, particularly when the audit report contains explanatory language. Analyst following increases the fraud termination hazard. However, increases (decreases) in analyst coverage have a negative (positive) marginal impact on the termination hazard, suggesting that analysts signal whistleblowers with their choice to add or drop coverage. Finally, our results suggest that misconduct lasts longer when it is well planned, more complex, or involves more accrual manipulation. Taken together, our findings are consistent with auditors and analysts playing a key informational role in fraud detection, while managerial effort to conceal misconduct significantly extends its duration.

JEL classification: G34; G38; K22; K42; L51; M41.

Keywords: Fraud duration; Information production; Fraud effort; Auditing; Hazard models.

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1 Introduction

Prior literature suggests that auditors and analysts play a relatively small role in directly detecting accounting fraud. For instance, Dyck, Morse, and Zingales [2010] find that only 10.5% and 13.5% of frauds are detected by auditors and analysts, respectively. In this paper, we explore another avenue through which these intermediaries affect fraud detection: information production. Specifically, we develop and test a simple model where a fraud's duration depends on the signals generated by information produced by auditors and analysts, as well as management's effort to hide the fraud.

In our model, information producers periodically scrutinize firms and produce signals indicating that the firms' financial reporting either seems normal or suspicious. An information producer can only detect a suspicious (bad) signal with positive probability if it is scrutinizing a firm that is engaging in financial misconduct. Based on the observed signals, monitors (e.g., the SEC, board members, etc.) decide to intervene or not. Since intervention is costly, monitors intervene only if a bad signal is revealed. Our model shows that the expected duration of misconduct is negatively related to the likelihood of a bad signal being disclosed. Hence, detection increases with the number of information producers and with their ability to detect misconduct. However, this effect is attenuated if the information producers' signals are not independent or if management exerts effort to conceal misconduct.

To empirically test the predictions of the model, we use a sample of SEC Accounting and Auditing Enforcement Releases (AAERs) drawn from an updated version of the data set used in Dechow, Ge, Larson, and Sloan [2011]. This data provides full misstatement periods (including the 10Q and 10K statements affected by the fraud) for 928 instances of accounting misconduct between 1982 and 2012. The availability of clear beginning and end dates of AAER-related misstatements allows us to estimate a discrete time duration model without issues of truncation, which could otherwise complicate and potentially bias our analysis. Moreover, following Karpoff, Koester, Lee, and Martin [2017], we restrict our sample to cases when the SEC brought charges against either the firm or its managers alleging violations of anti-fraud provisions in the Securities Act of

1933 ("Securities Act") and the Securities Exchange Act of 1934 ("Exchange Act"). It is important to note that while the AAERs in our sample involve financial misrepresentation, they are often not associated with a formal admission of guilt or legal ruling of fraud (Karpoff *et al.* [2017]).[1]

Auditors provide information that likely plays a role in fraud detection because they have access to their clients' non-public accounting information. This access may allow auditors to detect signals about fraudulent activities that others cannot. To test the effect of auditor information on fraud duration, we start by considering variation in the financial reporting process. Interim financial reports are only subject to review while annual reports are subject to a full financial audit. It is more costly to hide information from an audit than a review, and an audit report contains more information than an interim review report. Thus, accounting fraud is more likely to be revealed through the annual audit process. Consistent with this hypothesis, we find that the termination hazard for AAERs spikes following the end of the fourth fiscal quarter when the audit occurs and the annual financial statements are released.

While our fourth quarter result suggests that auditing may play an informational role in fraud termination, the fourth quarter is fundamentally different than other quarters. Hence, our results may be driven by confounding events. To directly test the auditor's informational role, we examine the use of explanatory language in otherwise unqualified audit reports. These "audit explanations" provide additional information to investors (e.g., highlighting changes in accounting standards by the firm) without any implications about the auditor's view on the report's quality. Although seemingly innocuous, the explanatory language appears to contain valuable signals. Beasley, Carcello, Hermanson, and Neal [2010] find evidence that these additional explanations are more likely to appear in the financial statements of fraudulent firms than in a control group. We find that the marginal impact of the fourth fiscal quarter on the fraud termination hazard rate mainly stems from explanatory language in the auditor report. This evidence is consistent with audit report information being an important driver of increased misconduct detection after the annual report.

[1] By focusing on AAERs, we can only observe misconduct that is ultimately revealed. Thus it may be the case that our results are not informative for frauds that escape detection. However, we believe it is likely that the same factors that determine misconduct termination hazard in detected frauds apply for undetected frauds.

In our final test of auditor information, we consider changes in auditors. A change in auditors may indicate that there was disagreement between management and the auditor, thereby prompting scrutiny by potential whistleblowers. Our results suggest that misconduct is more likely to end in the year after the auditor switch is announced. Further, this result is stronger when we only include auditor switches where the related 8k specifically mentions that the auditor resigned. Together, these results suggest that an auditor switch is an informative event that prompts scrutiny and increases the probability that misconduct will be brought to an end. However, we do not find any evidence that potentially higher quality auditors such as "Big N" auditors reduce fraud duration more than other auditors.

Next, we examine the effect of financial analyst information production on fraud duration. Analysts generate information by processing available information into earnings forecasts and recommendations. Thus, red flags in an analyst report could influence others to scrutinize and eventually blow the whistle on misconduct. We start by looking at analyst following and find that AAER spells are shorter if the company is followed by at least one analyst. However, the impact of analyst following declines for firms that are covered by more than one analyst. This pattern implies that coverage by additional analysts may be counterproductive for fraud detection, at the margin. This counter-intuitive result may be explained by considering changes in analyst coverage as an information event. We show in an extension to our model that the analysts' decision to start or continue firm coverage may be seen by market participants as a sign of certification. Analysts choose whether to follow a firm. If the cost of following increases with the likelihood of financial misconduct[2] then increases in analyst following may be perceived as good news by market participants. Consistent with this line of reasoning, we find that increases (decreases) in analyst coverage during the misstatement period are related to reduced (increased) fraud termination hazard. This result appears to explain the negative marginal value of additional analyst following for fraud detection.

[2]Analysts' costs of following a firm incurring in financial misrepresentation may be higher due to either reputational cost or direct costs of scrutinizing the statements that may be more complex given management's efforts to hide wrongdoing.

Finally, we examine the effect of management's effort to conceal fraud from information producers, thereby prolonging misconduct. We use three proxies for managerial effort. Our first proxy is an indicator for frauds started in the first fiscal quarter. These frauds are likely to be better planned because managers are able to take advantage of as much time as possible before the audit occurs at year end. As hypothesized, we find that estimated AAER termination hazard rates are significantly lower (both in economic and statistical terms) for frauds started in the first fiscal quarter.[3]

Our second proxy for managerial effort is the number of financial statement areas affected by the fraud. In principle, a more pervasive misstatement requires considerable managerial effort to make financial statement accounts agree with each other. Similar to the first fiscal quarter indicator, this measure has a negative and significant relation to AAER termination hazard rate.

Our final measure of managerial effort is total accruals. Higher total accruals may indicate that management is exerting effort to manipulate its accruals in order to prolong misconduct. An advantage this measure has over the other two proxies for effort is that it is time-varying. We find that accruals management is also significantly associated with lower fraud termination hazard rates. Taken together, these results indicate that managerial effort is effective at extending fraud duration.

This paper relates directly to the literature on fraud detection. This literature focuses primarily on the characteristics of whistleblowers and whistleblowing policies in fraud cases (e.g. Bowen, Call, and Rajgopal [2010], Dyck *et al.* [2010], and MILLER [2006]).[4] A central finding of this literature is that there is a broad variety of stakeholders who might reveal fraud. Studying a sample of 216 cases of alleged corporate frauds, Dyck *et al.* [2010] find that six types of players account for

[3]This result is not mechanically obtained. AAERs started in the first quarter are not only more than five quarters longer than AAERs started in other quarters, they also have other distinct characteristics, such as affecting more areas of the financial statement.

[4]Another related paper, Karpoff and Lou [2010], studies the relation between short selling and financial misconduct and finds that short selling is associated with a quicker time to fraud revelation. The authors interpret this finding as short sellers being important for uncovering fraud, which would make them another potential class of information producers in our model. Although we do not explicitly consider short selling activity in our empirical analysis, we indirectly capture its effect by including firms' contemporaneous quarterly stock returns as a control variable. We observe a significant negative relation between this variable and fraud termination hazard rates, which is consistent with Karpoff and Lou [2010] results to the extent that lower stock returns are driven by short selling activity.

at least 10% of detection each, while none is responsible for more than 17%. Together, these classes account for 82% of all cases. Specifically, these classes of players are: employees (17%), media (13%), industry regulators (13%), auditors (10.5%), short sellers (14.5%) and analysts (13.5%).

Our paper contributes to the fraud detection literature by taking an alternative approach. Instead of focusing on who revealed the fraud, we focus on the role that information producers play in generating an environment where potential whistleblowers are informed and able to act. Our results indicate that intervention by monitors and whistleblowers does not happen in a vacuum. Instead, information producers that raise red flags are crucial in inducing other agents to act. Hence, even though auditors and analysts are not the whistleblowers in many cases, the reports that they issue appear to trigger fraud termination.

Furthermore, our results validate the literature that proposes fraud detection methods. This stream of research aims to provide techniques for detecting fraud (e.g., Beneish, Lee, and Nichols [2012], Dechow *et al.* [2011]). If effective, these techniques enable information producers, such as auditors and analysts, to provide signals to whistleblowers. This is in line with our findings.

Finally, we contribute to the fraud literature by directly examining fraud duration. Analyzing fraud duration is important for at least three reasons. First, long-lasting frauds affect more accounting reports and are associated with larger penalties in formal SEC enforcement actions (see Files [2012] and Call, Martin, Sharp, and Wilde [2017]).[5] Second, reducing duration of fraud might discourage managers from engaging in fraud if managers believe that they will not have enough time to unwind a fraud before getting caught. Third, from a more technical perspective, by focusing on frauds already in place, we mitigate concerns about jointly testing fraud detection and fraud commitment (Wang [2011]).

In summary, we present a framework for analyzing the role of information production in fraud detection, and provide evidence that auditors and analysts play an important role in fraud mitigation beyond outright whistleblowing. Our results and framework should be of interest to regulators and

[5] Table 7 of Files [2012] shows that longer misconduct spells (measured as number of days from start to end of the misstatement period) are positively and significantly related to both individual and firm penalties in SEC enforcement actions, thus indicating that longer misconduct is more serious on average. Table 4 of Call *et al.* [2017] shows similar results.

other capital market participants concerned with maintaining the propriety of financial statements.

2 Theory

In appendix A, we develop a simple theoretical model that connects the duration of accounting fraud to signals detected by information producers, such as auditors and analysts, as well as to management's effort to conceal the fraud. In this section, we summarize the model and its key empirical implications.

In our model, information producers periodically scrutinize firms and detect signals indicating that either there is no need for concern (good signal) or there is something unusual going on (bad signal). Information producers can only detect a bad signal with positive probability if they are scrutinizing firms that are committing financial misconduct – called manipulators. Based on the observed signals, monitors (e.g., institutional investors, the SEC, board members, etc.) decide to intervene in a firm or not. Because intervention is costly, monitors intervene only if a bad signal is revealed to minimize the chance of a superfluous action. Manipulators decide to initiate or maintain a fraud episode by trading off their expected benefits from the fraud against the cost they incur when the fraud is detected. By exerting costly effort to better conceal the fraud, the manipulators can lower the likelihood an information producer generating a bad signal and, therefore, prolong the duration of the misconduct. As described in detail in appendix A, the model delivers the following implications that form the basis for the empirical hypotheses we develop in the next section:

Implication 1: *The introduction of a new information producer increases the likelihood of detection, thereby reducing the expected duration of a fraud. Moreover, the better the new information producer is at spotting a fraud – i.e., the higher the probability of spotting it – the larger the effect.*

Implication 1 justifies testing the impact of both the number and quality of information producers on fraud termination hazard rates. When the signals detected by different information producers can be correlated, the model yields the following related and intuitive implication:

Implication 2: *The effect of a new information producer on the fraud detection hazard rate becomes smaller the more correlated the new information producer's signals are to signals already identified by existing information producers.*

Analysts are free to choose which companies to follow. Consequently, analysts' decision to start, continue, or stop coverage may contain information. As we show in the model's extension presented in section A.4 in appendix A, if the cost of following a company increases with the likelihood of financial misconduct, the fact that more analysts decide to follow the firm may be perceived as good news by market participants. In principle, the likelihood that information producers detect a bad signal may increase with the prior beliefs about malfeasance. Consequently, changes in the number of analysts following may partially or fully counteract the effect of an additional information producer as described in implication 1. As a result, the net effect of the increase or decrease in the number of analyst on the misconduct's duration is unclear.

In terms of the decision to commit fraud, the model predicts that the higher the likelihood of a bad signal, the higher the fraud benefit needs to be for the manipulator to decide to engage in fraud. Similarly, if the likelihood of a bad signal goes up over time (for example, due to inconsistencies being easier to spot over time as more and more financial statements are misstated), frauds become less profitable in expected terms as time passes. Consequently, manipulators are more likely to terminate their misconduct before detection, especially for frauds that were not particularly profitable from the beginning. In this sense, only very profitable frauds for manipulators are likely to endure, since they tend to go on until they are caught due to a bad signal from information producers. Implication 3 summarizes these results:

Implication 3: *In terms of fraud incidence, the model delivers the following results:*

(a) *The better information producers are at detecting bad signals, the higher the expected benefit of fraud among firms that decide to engage in fraudulent behavior*;

(b) *If the hazard rate of detection increases over the duration of a fraud then firms that benefit greatly from the fraud are more likely to be caught, while firms with low fraud benefit are more likely to voluntarily terminate the fraud.*

While implication 3(b) implies that our sample of AAERs may be biased, the bias is toward including the most harmful cases of misconduct. These are likely the most economically relevant. Moreover, this implication is consistent with findings in Dyck, Morse, and Zingales [2017] that the largest and most costly frauds continue until they are ultimately caught.

In terms of how much effort manipulators incur trying to avoid or delay detection, our model shows effort is positively correlated with the manipulator's benefit of fraud. Moreover, optimal effort has a non-trivial connection to how the hazard rate evolves through time and how effective the effort is to slow down the increase of the hazard rate over the fraud's duration. These results are captured by implication 4:

Implication 4: *In terms of the effort to avoid or delay detection, the model predicts that:*

(a) *Managerial concealing effort is associated with lower fraud termination hazard rates;*

(b) *Managers of firms with the largest benefit of fraud incur the highest effort to hide it;*

(c) *Consider that the hazard rate exogenously grows over time. Effort only rises over time if it becomes more effective at decelerating the likelihood of a bad signal being generated.*

Implication 4(a) follows directly from the assumption that a manipulator's costly effort can reduce the probability of a bad signal being generated (see appendix A.C.2). If there is a positive correlation between a firm's fraud benefit and the cost of fraud for investors, implication 4(b) shows that the costlier frauds are also the ones that a fraudulent firm spends the most effort concealing. Furthermore, implication 4(c) shows that if efforts to conceal become less effective over time, the firm progressively reduces its efforts to hide an ongoing fraud. Hence, if the firm exerts a lot of effort planning a fraud, then additional effort after the fraud has commenced is arguably less effective than it is for frauds that are not well planned.

3 Empirical Model and Hypotheses

3.1 Hazard Model

We apply a survival analysis method to investigate the determinants of the duration of financial misconduct. Our observations are grouped in discrete time intervals – the number of financial quarters that have passed since the first misstated quarter related to an AAER. We utilize a discrete time hazard model to estimate the probability that misstatements related to the fraud will end in a financial quarter given that misstatements have occurred up until that point. While these models have been utilized prior literature (e.g., Mayew, Sethuraman, and Venkatachalam [2014]; Bischof and Daske [2013]; Beaver, Correia, and McNichols [2012]) we provide a brief description of the model we use.

Specifically, we estimate the following discrete hazard rate: the probability of transition out of the initial state (active fraud) in period j conditional on having survived up until period $j-1$ and on a vector of of covariates ($\mathbf{x}$). Denoting the survival time by T:

$$h_j(\mathbf{x}) \equiv \Pr(t_{j-1} < T \leq t_j | T > t_{j-1}, \mathbf{x}). \tag{1}$$

Assuming a proportional hazard form and discrete time intervals of equal length (quarterly periods in our case), we can estimate $h_j(\mathbf{x})$ using the complementary log transformation (cloglog):

$$\log\left(-\log\left[1 - h_j(\mathbf{x})\right]\right) = \beta'\mathbf{x} + \gamma_j, \tag{2}$$

where γ_j represents the baseline hazard at period j, i.e. the functional form of γ_j captures the pattern of duration dependence. If survival time follows a Weibull distribution, γ_j is captured by

$\log(j)$ as an additional new variable along the vector of covariates ($\mathbf{x}$):[6]

$$\log\left(-\log\left[1-h_j\left(\mathbf{x}\right)\right]\right)=\beta'\mathbf{x}+\log(j). \tag{3}$$

In our estimations we take into account unobserved firm heterogeneity in a manner similar to dealing with random firm effects in a linear regression setting. We present a more detailed description of our methodology in internet appendix B.

3.2 Empirical Hypotheses

In this section, we develop empirical hypotheses based on the model implications discussed in section 2 and also describe the variables we use in our hazard model to test these hypotheses. In addition, we briefly discuss other potential determinants of fraud termination hazard rates that we include as control variables in our hazard model. See appendix B for complete definitions of the variables discussed in this section.

3.2.1 Information Produced During the Audited Annual Financial Reporting Process

The annual financial reporting process is particularly important for fraud detection because it requires an external, independent auditor to verify that firm's financial statements are reported in accordance with generally accepted accounting principles. The audit process may reveal misconduct to whistleblowers for at least two reasons. First, the audit makes it more difficult for management to conceal fraud-related information in its annual reports relative to interim reports. Second, auditors directly provide information about their client's financial reporting in the audit report and assessment of internal controls which are also included in the annual report. We consider each of these information channels in our analysis.

[6] Alternatively, following Cox [1972] we can choose to not impose a specific functional form on γ_j and instead include individual duration period dummies together with $\mathbf{x}$ (which cannot contain an intercept). In this case, we estimate the following semi-parametric cloglog model: $\log\left(-\log\left[1-h_j\left(\mathbf{x}\right)\right]\right)=\beta'\mathbf{x}+\gamma_1 D_1+\gamma_2 D_2+\ldots+\gamma_j D_j$. All estimates of fraud termination hazard rates reported in the paper are based on the Weibull specification, but the results are all robust to instead using the Cox semi-parametric specification (these estimation results are available upon request).

Implication 1 states that additional information producers increase the likelihood of detection, reducing the expected fraud duration. Moreover, the better the new information producer is at detecting misrepresentation, the larger the effect. Given that the audited annual financial reporting process involves a new information producer – the auditor – we expect that this event will increase the probability of fraud detection. Thus, our first hypothesis is:

H1: The annual audited financial reporting process produces information that is positively associated with fraud termination hazard.

To test this hypothesis we examine several aspects of the annual financial reporting process. We begin by considering the fourth fiscal quarter information event. If the annual report contains information that is relevant for fraud detection, we expect an increase in fraud termination hazard following the report's release. Thus, we include an indicator variable, 4^{th} *Quarter*, that equals one if it is the fourth fiscal quarter and zero otherwise.[7] If H1 is true, this variable will be positive and significantly related to the misconduct termination hazard rate.

One aspect that may affect the fourth quarter information event is audit quality. Implication 1 states that we should see a stronger effect on fraud duration when higher quality information producers are added. Prior literature documents that "Big N" auditors produce higher quality audits (Lennox and Pittman [2010]). We test whether Big N auditors increase the fraud termination hazard around the annual report. In particular, we include an interaction between 4^{th} *Quarter* and an indicator variable that is equals one if the firm's auditor is a Big N accounting firm and zero otherwise (*Big N Auditor*). We expect a positive and significant coefficient on this interaction term.

The prior tests of the fourth quarter information event do not disentangle whether information in the audit report increases fraud termination following the 4^{th} fiscal quarter, or if some other aspect of the audit or general scrutiny of the firm's annual statements induces whistleblowers to act. To isolate the effect of the audit report, we consider variations in the information content of the audit report directly by considering explanatory language in the audit report. In principle, the presence

[7] Note that we are predicting the final quarter misstated as a result of the AAER. Thus, this indicator tests whether the misstatements end after the 4th quarter

of explanatory language in otherwise unqualified audit reports should be considered innocuous information. The most frequent audit explanations discuss changes in accounting standards and departures from normal audit procedure. Nonetheless, previous literature shows that explanatory language is more prevalent in audit reports for firms that are likely to issue restatements (Czerney, Schmidt, and Thompson [2014]). Moreover, Beasley *et al.* [2010] show that audit explanations are more common in the audit reports of fraud firms. Taken together, these results suggest that explanatory language in the audit report is informative, particularly about misreporting. We predict that the increase in fraud termination hazard rates following the 4^{th} fiscal quarter is greater for firms with an audit report containing explanatory language. To test this prediction we include in our model the interaction between 4^{th} *Quarter* and an indicator variable that is equal to one if explanatory language is included in the audit report and zero otherwise (*Audit Explanation*).[8] If explanatory language is a way for auditors to signal accounting irregularities, we expect a greater positive marginal effect on the fraud termination hazard following the 4^{th} quarter if the auditing report includes such explanatory language.

Finally, we consider auditor switches, an information event that, while tied to the annual reporting process, occurs throughout the year and is reported in SEC form 8k. A change in auditor disrupts the auditor-client relationship and involves significant start up and separation costs (DeAngelo [1981]). Thus the firm's decision to incur these costs is a signal that there may have been disagreement between management and the auditor about the financial reporting process. Prior literature documents that auditor litigation risk stemming from risky behavior at the client is a strong driver of auditor resignation (Krishnan and Krishnan [1997] and Shu [2000]). The market appears to recognize auditor switches as a negative signal and responds with a negative market reaction to these switches (Griffin and Lont [2010], Shu [2000]). Moreover, auditor switches may also lead to a higher cost of capital (Francis, Hunter, Robinson, Robinson, and Yuan [2017]). In a fraud

[8] About three percent of our sample observations had qualified audit opinions (auop=2). In our main analysis *Audit Explanation* also equals one for these observations to ensure that the control group only includes unqualified audit opinions without explanations. However, in untabulated analyses we code qualified opinions as zero for the *Audit Explanation* indicator. Our results are qualitatively the same under this alternative specification. Furthermore, we find no significant results when a similar indicator is included for qualified opinions on their own. We suspect the lack of significance for qualified opinions is due to small sample size.

context, we believe that an auditor switch may convey auditor information about fraud risk at the client firm. Thus a switch is an informative signal and could induce closer inspection by potential whistleblowers.

To test this prediction we obtain the sample of firms that have a new auditor at the end of the fiscal year and hand collect each 8k announcing the auditor switch. We then record the date that the switch was announced (the switch date) and the stated reason for the switch. To test if the news of an auditor switch may create additional scrutiny of the firm following the release of the 8k announcement, we include three different indicator variables in our model. The first variable (*Auditor Switch 1*) is an indicator variable equal to one for the four quarters after the 8k announcing the switch and zero otherwise. The second variable (*Auditor Switch 2*) is the same as the first but excludes auditor switches due to mergers and acquisitions, and the Enron collapse. The third variable (*Auditor Switch 3*) includes only those auditor switches where the 8k explicitly states that the auditor resigned. A positive and significant coefficient on any of these variables supports our hypothesis that auditor switches by themselves may convey information that increases the fraud detection hazard.[9]

3.2.2 Information Produced by Analysts

Analysts compile and analyze publicly available information in order to make earnings forecasts and recommendations. They primarily produce this information for investors, but their reports are also available to other interested parties. Given that analysts produce information about a firm, implication 1 directly suggests that the fraud termination hazard rate increases with the amount of information they produce. This leads to our second hypothesis:

H2: Information produced by analysts is positively associated with fraud termination hazard.

[9] We note that the different variables indicating an auditor switch could potentially also be crude proxy variables for auditor tenure. Previous research has found that firms with longer tenured auditors have a lower incidence of AAERs (Carcello and Nagy [2004]). To the extent longer auditor tenure would also reduce the duration of a fraud episode, it is ultimately an empirical question whether an auditor switch would alter the ability of the auditing process to bring a fraud to end.

To test whether analyst information production induces fraud detection we begin by considering analyst following. We include an indicator variable that is equal to one if at least one analyst issued an annual earnings per share (EPS) forecast for the company (*Analyst Indicator*). A positive and statistically significant coefficient on this variable would support H2. We extend this analysis to consider the effect of additional analysts by including indicators for each quintile of analyst following calculated each quarter. This specification allows us to relax the assumption that each additional analyst will have a similar, linear effect on fraud detection. While additional analysts provide another information producer, prior literature on analysts suggests that, when there are multiple analysts covering the same firm, they may suffer from herding and other biases that impair their information production (Clement and Tse [2005]). Thus we do not make a prediction about the marginal effect of additional analysts.

Next, we directly consider the information in analyst forecasts. Analysts set expectations for earnings through their forecasts. Deviations from these expectations provide information to investors that something out of the ordinary may be happening at the business. Thus, in accordance with implication 1, forecast errors may be considered a "bad" signal that leads to further scrutiny. To test this prediction, we calculate analyst forecast error as the absolute difference between the mean consensus analyst forecast of annual EPS prior to the fiscal year end and the actual EPS reported that year, scaled by the corresponding end-of-fiscal year stock price.[10] The variable takes the value of zero if there are no analysts following the firm. Thus, the coefficient needs to be interpreted conditional on at least one analyst following the firm. If H2 is true, we expect analyst forecast error to be positively and statistically significantly related to the financial misconduct termination hazard.

Finally, an analyst's decision to start, continue, or drop coverage may contain information that is relevant for fraud detection. In appendix A.4, we extend the model to capture the analyst's choice to start or stop covering a given firm. This simple extension shows that this choice is

[10]We use annual EPS forecasts instead of quarterly forecasts to be consistent with our analyst following variable. Because more analysts forecast annual earnings than quarterly earnings, we believe that analyst coverage is better captured with annual forecast data.

an informative signal. In particular, added coverage may induce agents to believe that the firm is a non-manipulator.[11] If these beliefs reduce the likelihood of a bad signal being detected by information producers, added coverage may induce longer fraud duration, even after taking into account the effect of the added signals produced by the new analysts. To test the effect of a drop in analyst coverage on fraud duration we include two variables. The first, *Analyst Departure Indicator*, is an indicator variable that is equal to one if the number of analysts following the firm declined compared to the previous year and zero otherwise. Since the effect of a decline in analyst coverage may not have a linear effect on fraud detection, we also include the natural log of one plus the number of analysts that stopped covering the firm during the fiscal year. Similarly, in order to evaluate the impact of additional coverage, we include two variables. First, we include *Analyst Addition Indicator*, which is an indicator variable that is equal to one if the number of analysts following the firm increased compared to the previous year and zero otherwise. Then, in order to account for a non-linear effect of each additional analyst, we include the log of one plus the number of analysts that started covering the firm since the last fiscal year.

3.2.3 Managerial Fraud Effort

In our last category of tests, we consider management's actions. In line with implication 4, we expect that if a manager exerts more effort to contain information about the fraud then the fraud will persist for longer, all else equal:

H3: Managerial effort is negatively associated with fraud termination hazard rates.

There are various ways that management might exert effort to contain information that could expose their fraud. We consider three different aspects of management's effort to conceal: planning, complexity, and ongoing manipulation.

We capture well-planned frauds by including an indicator variable equal to one if the fraud starts in the 1^{st} fiscal quarter (1^{st} *Quarter Start*). A firm's financial reporting is most scrutinized

[11]The model shows that if following a firm is particularly costly when the firm is likely to commit fraud, the fact that analysts decide to start or continue coverage of a given firm is interpreted as a sign of quality.

when they prepare and release their audited annual financial statements. Thus, if management optimally chooses when to start a fraud it is likely to choose the 1^{st} fiscal quarter because the firm has more time to prepare for auditor scrutiny. Given that starting in the 1^{st} fiscal quarter indicates management's effort in designing a harder-to-detect fraud, we would expect that these frauds are associated with a higher fraud benefit. If that is true, implications 3 and 4 from our model predict that these frauds are likely to be longer as well as less likely to be stopped by management. Moreover, if starting a fraud in the 1^{st} fiscal quarter indicates a well-planned fraud, we would expect effort to decrease over time as the marginal benefit of effort is likely lower in this case (see implication 4(c)).

We capture the complexity of a fraud by including a variable that measures the number of areas of the financial statement affected by the fraud (*log(Number of Areas)*). A fraud affecting more areas of the financial statement may indicate managerial effort to conceal misconduct by ensuring that no "red flags" appear due to inconsistencies across accounts. Hence, we would expect frauds that affect multiple areas to last longer.[12]

Finally, we capture ongoing manipulation by including the magnitude of total accruals (*Total Accruals*). Prior evidence suggests that management uses the discretion available in accrual estimates to manipulate earnings, mislead investors, and achieve personal objectives (e.g., Jones [1991] and Dechow, Sloan, and Sweeney [1995]). Because accruals reverse at the end of each accounting period, a manager who wishes to maintain a fraud through accrual manipulation must continue to make a suspect accrual every year. If a firm's financial condition deteriorates and more accrual manipulation is required, it becomes more costly to the firm (and therefore requires more effort by the manager) because it needs to report the new suspect accrual as well as all prior ones. Thus, large amounts of accruals suggest that the manager is exerting extra effort to maintain the fraud.

A benefit of using total accruals as an effort proxy is that it provides both cross-sectional and time-series variation and can therefore proxy for mangers' ongoing manipulation effort. For this

[12]We rely on the classification of misstatement areas defined by Dechow *et al.* [2011] in order to construct this variable.

reason, we can see how changes in total accruals and, consequently, changes in effort impact changes in the hazard rate over time. A potential drawback of using this measure is that increasing accruals may also generate a red flag to information producers, so managers' discretionary power over accruals is constrained by the extra scrutiny excessive accruals may generate.

3.2.4 Control Variables

In our empirical model we control for fundamental firm, industry, and market characteristics that may be correlated with both the amount of scrutiny a firm receives and the efficacy of managerial effort to conceal fraud.

We include firm size as a control, where we measure size by the log of book value of total assets adjusted for inflation (*log(Total Assets)*). Large firms have relatively richer information environments than small firms, which may increase the probability of fraud detection. However, large firms also tend to have a wider scope of operations, which may allow a manager to conceal misconduct.

Firm performance is also likely related to fraud duration. While poor firm performance may motivate a manager to begin, or prolong a fraud (Harris and Bromiley [2007]), it might also induce more scrutiny from outsiders. We include accounting-based and stock market-based measures of firm performance in our analysis. Our accounting-based measure is return on equity (*RoE*), and the market-based measure is the concurrent quarter abnormal firm stock return (*Abnormal Stock Return*). Abnormal returns are calculated as the quarterly stock return minus the corresponding CRSP value-weighted (VW) index return).[13]

We also include a measure of firm leverage. High leverage may indicate that the firm is in financial distress, which may incentivize management to conduct and maintain fraud. However, excessive leverage could also increase scrutiny by creditors as well as other stakeholders such as shareholders, employees, customers, suppliers, business media, etc.

The nature of a firm's assets and operations may influence fraud duration. Managers of firms

[13]We use return on equity rather than return on assets since not all firms report operating income in their quarterly statements. However, because we also control for firm leverage, any bias inherent in this should be mitigated.

with more intangible assets or other assets without well-established replacement or market values have more discretion in their financial accounting. Consequently, such accounts may be easier to manipulate over a long time span. We control for the nature of the firm's assets-in-place by including the ratio of soft assets to total assets (*Soft Assets*) as a control variable, where soft assets are the ones that a manager has relatively more accounting discretion. These include assets other than cash and cash equivalents; and property, plant, and equipment (see Dechow *et al.* [2011]). Growth opportunities may also impact the length of misconduct spells. For example, managers of firms with few growth opportunities arguably have greater incentives to conduct and maintain accounting fraud in order to inflate their values. Alternatively, firms with many growth opportunities may be difficult to evaluate and have an easier time perpetrating fraud. In our empirical model, we proxy for growth opportunities using the Market-to-Book ratio (*Market-to-Book*). Of course, there could be other characteristics of a firms' assets and operations that affect the cost of information production and the ease of conducting fraud. However, inasmuch as these other features are industry-based, we control for their influence in our tests by including Fama-French 17 industry fixed effects .

Finally, monitoring by market actors may vary with market conditions. For example, Povel, Singh, and Winton [2007] model how investors' beliefs about business conditions affect their monitoring intensity, resulting in more monitoring in perceived bad times than in good. As a result, more frauds are started when market conditions are relatively good, and detected when market conditions turn for the worse. We control for market conditions by including the overall stock market return in our empirical model, defined as the corresponding quarterly CRSP VW market index return for each fraud quarter (*Market Return*). To capture more slow-moving market conditions that may be related to overall monitoring and enforcement activity we also include indicator variables for six different sub-periods (of approximately equal length) of the total sample time period. These periods are: 1982-1986, 1987-1991, 1992-1996, 1997-2001, 2002-2006, and 2007-2010. Our results are robust to instead using individual calendar year indicators.

4 Data

4.1 Accounting and Auditing Enforcement Releases (AAERs)

The SEC regularly reviews companies for violations of securities laws pertaining to financial statements. Reviews can be triggered by media attention, anonymous tips, or by something within an SEC filing itself, such as a restatement that brings attention to a company. Moreover, the SEC examines about one third of public companies annually to ensure compliance with GAAP (Dechow *et al.* [2011]). If, as a result of the review, the SEC believes that the company, an officer, or auditor has engaged in accounting or auditing misconduct, enforcement action may be taken resulting in restatements, lawsuits, or some other remedy. These actions are summarized in AAERs issued by SEC. The AAERs have been used extensively in accounting and finance research as a sample of financial accounting frauds. Our initial dataset is composed of quarterly AAER data from the Center for Financial Reporting and Management at the University of California at Berkeley, which we complement by hand-gathered information on some firms' Central Index Key codes that were missing in the original dataset. This dataset includes details about the misstatement periods for all AAERs issued by the SEC between May $17^{th.}$ 1982 and August 31^{st} 2012. The initial sample includes 706 unique AAER firms and 926 primary AAERs that cover 7,702 AAER-quarters. For a detailed description of this dataset please see Dechow *et al.* [2011]. Note that the set of AAERs does not include firms with intentionally misstated earnings that were not identified by the SEC. For other potential shortcomings of this data set, see the discussion in Karpoff *et al.* [2017].

Table 1 explains how we arrive at our final sample. We drop those AAERs without both start and end dates, those that target more than one company, and those related to banks and other financial institutions (SIC 6000-6999) due to their unique regulatory environment. We also drop companies with multiple AAERs occurring at the same time because it is unclear which AAER duration to use. In addition, we remove AAERs related to backdating options because of the apparent increase in enforcement proceedings regarding this behavior by the SEC following the widespread attention backdating attracted in the mid-2000s (see Choi, Wiechman, and Pritchard [2013]). The increased focus by the SEC resulted in several backdating episodes that had been ongoing for a long time being discovered and issued AAERs. Because of this background of the backdating AAERs and because misconduct related to backdating options is comparatively different in nature from other accounting misconduct, we think it is prudent to exclude these observations from our sample.[14] We also remove AAERs that start prior to 1982 or after 2006 to address sample selection issues. Specifically, we are concerned that some misconduct periods starting after 2006 are yet to be caught and misconduct that occurred prior to 1982 may have been caught before the inception of the AAER program. Finally, we follow Karpoff *et al.* [2017] and keep only AAERs that involves charges of financial misrepresentation under Section 13(b) under the Exchange Act and Code of Federal Regulations, and that also involves charges of violations of anti-fraud provisions of the Securities Act (Section 17(a)) or the Exchange Act (Section 10(b)). In the end, our sample includes 191 unique AAER-firm pairs that cover 1,439 misconduct-quarters.

We believe that our sample is preferable to other samples of fraud related misstatement. Potential alternatives would be lawsuit datasets such as the Stanford Securities Class Action Clearinghouse (SSCAC). While these datasets may do a better job of capturing the entire set of potential frauds relative to AAER datasets, they are unable to capture alleged fraud that has not yet been brought to court. Additionally, these datasets may include frivolous cases, a concern that we do not have with AAERs.

Panel A in table 2 shows the fraction of AAERs that affect certain areas of the financial statements. The areas of misstatement are from Dechow *et al.* [2011]. In particular, we can see that about 77% of the misstatements concern gross profit related accounts (revenue or cost of goods sold). While gross profit is the most prominent area of misstatement, a wide variety of areas of the financial statements are affected by the AAERs in our sample. Panel B in table 2 shows the distribution of our final sample of AAERs by the years that they start and end, as well as the average fraud duration in terms of consecutive fiscal quarters affected. The average length of an accounting fraud spell in our sample is 7.5 quarters. Panel C in table 2 displays the cumulative frequency of

[14] However, note that our results are robust to including these backdating related AAERs in the sample.

the fraud duration. Although 55% of the fraud spells end within six fiscal quarters, some continue for almost eight years (max sample duration is 31 quarters).

4.2 Other Data

As outlined above in section 2, we also include quarterly data from a number of sources in our analysis. Auditor and financial statement data comes from Compustat's Quarterly and Annual databases. Stock return data comes from the Center for Research in Securities Prices (CRSP) database. Analyst and institutional investor holdings data comes from I/B/E/S and Thomson Reuters' 13-F databases, respectively. For inclusion in our sample, we require non-missing quarterly data on stock returns and core firm characteristics (RoE, Total Assets, Market-to-Book, Leverage, and Soft Assets). Because financial statements are reported at the end of the quarter, we lag the accounting information one quarter relative to the end-of-fraud indicator (=1 if the misstatement quarter is the last quarter of the fraud spell; =0 otherwise) to ensure that these measures represent information available to all interested parties, even those outside the firm.[15]

4.3 Summary Statistics

Table 3 shows descriptive statistics for variables used in our study. In this table, we present statistics for both the fraud's first and last quarters. By looking at the beginning and ending of the fraud we are able to identify characteristics that change during the fraud's life. For variables that are constant over the course of the fraud, we present their summary statistics in the fraud's first quarter columns. Exact definitions of all variables are provided in appendix B.

In our sample, most changes in firm characteristics over the life of the fraud are not statistically significant. Only market-to-book is significantly higher at fraud onset than at the fraud's termination[16]. Moreover, we observe that abnormal stock returns are significantly higher during the

[15]We note that while interested parties observed unrestated financial information, we use the standard Compustat Quarterly dataset in our main tests, which includes restated financial statement values. We employ the standard dataset because Compustat's Unrestated Quarterly data is not available before the year 1987. However, in untabulated tests we confirm our results by re-running our analysis using unrestated quartely data for frauds initiated after 1987.

[16]These results are different if we extend our sample in order to account for other types of financial misconduct

fraud's first quarter. Interestingly, only 16% of frauds in our sample start by misstating 4^{th} quarter financial statements while 38% of frauds end after reporting 4^{th} quarter financial statements. In a similar vein, 57% of frauds start by misstating 1^{st} quarter reports, leaving the firm with the maximum amount of time before an auditing episode. This initial evidence points toward an effort to avoid the scrutiny of auditors for as long as possible, potentially in order to better design and structure the fraudulent scheme. Our results in the following sections will present further evidence corroborating this conjecture. Finally, we see that total accruals are negative, on average, during the first fraud quarter and are significantly more negative in the fraud's last quarter.

Also of note are some of the statistics on analysts. There is at least one analyst present at the onset of the fraud in 67% of the cases. Moreover, during the frauds' last quarter, the presence of analysts continues to be commonplace among fraudulent firms. In fact, we find no statistically significant difference in the presence or number of analyst coverage between the 1^{st} and last quarters of the fraud. For this reason, we believe that our results are not driven by a widespread exodus of analysts after fraudulent behaviour is revealed.

5 Estimation Results

5.1 Baseline Results on Fraud Termination Hazard Rates

Table 4 presents estimation results for our baseline empirical model. Column 1 of table 4 shows the effect of fraud duration dependence without controlling for any other covariates. Consistent with implication 3 of our model, the fraud termination hazard rate is significantly increasing in the length of the fraud spell (measured by log(Period)).

Column 2 of table 4 shows the estimation results for the full set of firm characteristics and market factors discussed above that are included as controls in all subsequent estimations. Industry

that are also the focus of AAERs, but not violations of the 13(b) of the Exchange Act, and that also involves charges of misconduct related to anti-fraud provisions of the Securities Act or the Exchange Act. In this case, several firm characteristics change over the life of the fraud. In particular, firms at the fraud termination quarter are bigger and less profitable.

and time period fixed effects are also included, but not reported. However, their coefficients are all insignificant. The same is true for *Market-to-Book*, *Soft Assets* and the CRSP value-weighted market index return.

In terms of significant results, column 2 shows that the *log(Total Assets)* enters significantly (at the 1%-level) with a negative sign. That is, larger firms are associated with longer spells of accounting fraud. To illustrate the magnitude of the size effect, we estimate hazard rates of fraud termination across the range of fraud spells in our sample (1-31 quarters) for firms at the 25^{th} and 75^{th} percentiles of the firm size distribution, respectively. All other variables are fixed at their median values. Figure 1A shows the results of this exercise. We see that the hazard rates are substantially larger for firms at the 25^{th} percentile of total assets (assets of around $43 million in year 2000 values) than for firms at the 75^{th} percentile (assets of around $2.27 billion). For example, firms at the 6^{th} quarter of a fraud spell (which is the median spell length) have a misconduct termination hazard rate of 15% at the 25^{th} percentile of size, while a firm at the 75^{th} percentile of size has a 12.3% hazard rate. Thus, although large firms are likely to be the subject of more scrutiny, they are able to maintain accounting fraud for longer time periods. One possible explanation for this could be that the scale and scope of a large firm's activities make it easier to hide misconduct.

Firm capital structure, measured by (*Leverage*), enters significantly (at the 5%-level) with a positive sign. That is, more leveraged firms are associated with shorter spells of accounting fraud. Figure 1B shows hazards of ending a misconduct spell for firms with *Leverage* values at the 25^{th} and 75^{th} percentiles, keeping all other variables at their median values. At a spell length of 6 quarters, a firm at the 25^{th} percentile value of *Leverage* (leverage rate of 6.1%) has an estimated hazard that is 2.7%-points lower than a firm at the 75^{th} percentile value of *Leverage* (leverage rate of 36.3%). Thus, more leveraged firms are likely to be subjected to more scrutiny by market actors.

Firm performance, measured by both return on equity (*RoE*) and firm stock returns (*Abnormal Stock Return*), has a strongly significant negative relation to the probability that accounting misconduct is terminated. However, when estimating the marginal effects of firm performance on the hazard rate for different spell lengths, only the effect of *Abnormal Stock Return* appears to be important in economic magnitude. Figure 1C shows hazards of ending a misconduct spell for firms with *RoE* values at the 25^{th} and 75^{th} percentiles, keeping all other variables at their median values. The estimated hazards for 25^{th} and 75^{th} percentiles are relatively close across the whole range of time, suggesting that the economic effect of *RoE* is modest for the average firm in our sample. For example, at the 6^{th} quarter of duration, the difference in hazard rates is only 0.2%. Therefore, only extremely poor profitability would have a material effect on the hazard rates. The marginal effect of *Abnormal Stock Return* is illustrated in Figure 1D by showing estimated hazards for firms at the 25^{th} and 75^{th} percentile values of this independent variable. Unlike for *RoE*, the economic magnitude of the effect appears important for the average firm. At a spell length of 6 quarters, a firm at the 25^{th} percentile value of *Abnormal Stock Return* ($= -0.182$) has an estimated hazard that is 3.5%-points higher than a firm at the 75^{th} percentile value ($= 0.164$). This result likely reflects that firms doing well in the stock market attract less critical scrutiny by market actors.

5.2 The Effect of Auditors on Fraud Duration

We next analyze the effect of auditors on fraud termination hazard rates. Consistent with the audited financial statements generating important fraud related information, column 1 of table 5 shows a significantly positive effect on the fraud termination hazard rate immediately following the fourth fiscal quarter. The coefficient on 4^{th} *Quarter* is positive (0.787) and strongly significant (p-value < 0.01). We also include the full set of variables included in column 2 of table 4, although we do not report those results due to space considerations.[17]

In columns 2 and 3 of table 5 we consider whether auditor and auditor report characteristics affect the informativeness of audited annual financial statements for fraud termination. In column 2 we include the interaction between the 4^{th} Quarter dummy and an indicator for whether the firm uses a Big N auditing firm (4^{th} *Quarter x Big N*) in order to test whether larger, higher-quality auditors produce a stronger fourth quarter effect. In our sample, Big N firms were responsible for 80% of all audited financial statements. The coefficient on the interaction is insignificant and the

[17] Full results are available from the authors upon request.

coefficient on 4^{th} *Quarter* itself barely changes. Hence, there is no evidence that Big N auditors are better at issuing signals of fraud compared to other auditors.

In order to test if the fourth quarter effect is directly related to the information produced by auditors, we consider the content of the audit report. We include an indicator that is equal to one when the audit report contains explanatory language and zero otherwise. Column 3 of table 5 shows the effect from adding an interaction between 4^{th} Quarter indicator and an indicator for the auditor report containing explanatory language (4^{th} *Quarter x Audit Explanation*). The coefficient on the interaction is positive and significant, and larger than the coefficient on the 4^{th} *Quarter*. However, the coefficient on 4^{th} *Quarter* is still significant, indicating that there is a positive effect on fraud termination hazard rates following the fourth fiscal quarter even when there is no explanatory language in the auditor report. Nevertheless, the results suggest that while there is a significant baseline fourth quarter effect on the fraud termination hazard rate, the effect is significantly enhanced if the auditing report contains explanatory language.

Figure 2A illustrates the magnitude of the effect that the audited annual report has on fraud termination. At a spell length of 6 quarters, the estimated fraud termination hazard rate if the quarter is not a fourth fiscal quarter is 11.7%. If the quarter is the fourth fiscal quarter, but the auditor report contained no explanatory language, the corresponding hazard rate is 17.2%. Finally, when the quarter is the fourth fiscal quarter and the auditor report contains explanatory language, the hazard rate jumps to 38.4%. The strong impact of explanatory language in the audit report is consistent with the finding in Czerney *et al.* [2014] that explanatory language is related to restatement risk of the audited financial statements.

An auditor switch may convey a negative signal about a firms financial reporting and induce closer scrutiny of the annual report by market actors following the switch. We consider the effect of auditor switch announcements in table 6. Starting with instances where the auditor is different in the current year than in the prior year, we read all available 8k announcements of an auditor switch. We generate three indicator variables based on the reason for the switch. Each indicator is equal to one in the four quarters after an auditor switch is announced in an 8k, and zero otherwise. *Auditor*

Switch 1 includes all auditor switches. *Auditor Switch 2* includes only auditor switches related to the audit. Specifically, *Auditor Switch 2* excludes switches related to Arthur Andersen's collapse, and M&A activity. *Auditor Switch 3* includes only those auditor switches where management mentions in the 8k that the auditor resigned, suggesting a conflict between management and the auditor.

Our results for auditor switches are presented in table 6. Columns 1 through 3 show the effect of each auditor switch variable. All auditor switch variables are associated with increased fraud termination hazard rates. Furthermore, there is a monotonic increase in the magnitude of the association moving from all switches (*Auditor Switch 1*) to switches that clearly represent a conflict between management and auditors (*Auditor Switch 3*). These results suggest that an auditor switch is an informative signal about fraud, particularly when the switch represents a conflict between management and the auditor. In columns 4 through 6 of table 6, we include both the auditor switch variables and their interactions with the 4^{th} Quarter indicator. While *Auditor Switch 2* and *Auditor Switch 3* are still statistically significant, no interaction term is significant. Consequently, the impact of an auditor switch appears to come mostly from the announcement of the switch bringing more scrutiny to the firm and not from a new auditor evaluating the year-end financial statements.

Figure 2B illustrates the magnitude of the effect of an auditor switch announcement based on column 2 of table 6. At a spell length of 6 quarter, the estimated fraud termination hazard rate without an auditor switch is 10.4%. Differently, the hazard rate in the four quarters after a auditor switch is 18.8%. This is in line with arguments that a switch to a new auditor invites more scrutiny.

Our results in this section support our first hypothesis as well as implication 1 of our model. Specifically, we find that auditors generate credible fraud signals that reduce fraud duration. These findings, along with those in Czerney *et al.* [2014], provide evidence that auditors produce signals about financial statement risk, even when they cannot (or choose not to) directly communicate the risk. Thus, although research suggests auditors only blow the whistle on fraud around 10% of the time (Dyck *et al.* [2010]), they seem to be important information intermediaries that facilitate fraud detection and intervention by others.

5.3 The Effect of Analysts on Fraud Duration

The second group of information producers we consider is financial analysts. Based on our hypothesis development in section 3.2.2 we generate tests of the effect of financial analyst information on fraud duration. We gather data on analyst following from the I/B/E/S summary file. As shown in table 3, around 70% of firms in our sample are followed by at least one analyst. Conditional on analyst following in a firm-quarter, the mean (median) number of analysts in our sample is around 7 (4).

To test whether information produced by analysts is associated with fraud detection, we first add an indicator variable equal to one if at least one analyst follows the firm, and zero otherwise (*Analyst Indicator*). Along with this indicator, our model includes the full set of control variables used in column 2 of table 4 as well as the significant 4^{th} Quarter variables from table 5. Column 1 of table 7 shows that there is a positive and significant effect of having at least one analyst following the firm. Figure 3A presents the marginal effect of introducing analyst coverage. Hazard rates are substantially larger for firms with analyst coverage than for firms without coverage. For example, assuming firms are at the 6^{th} quarter of a fraud spell (which is the median spell length), the hazard rate of the misconduct ending the next quarter for a firm with coverage is 12.3% whereas the same hazard rate for a firm without coverage is 6.6%. Consequently, similarly to the auditor effect, the presence of analyst following triggers an increase in the fraud termination hazard.

We extend our empirical analysis to consider the effect of having multiple analysts covering a firm. As presented in the model's implication 2, the introduction of additional analysts may have a subdued, nonlinear effect due to correlated signals. In order to capture for this effect, we include indicator variables for each quintile of the analyst following distribution in column 2 of table 7. Our results show that the indicator for the first quintile is positive and statistically significant at the 5% level, while the indicator for the fifth quintile is negative and statistically significant at the 5% level. Moreover, while the coefficients for the indicators of the remaining quintiles are not statistically significant, they are all negative. Consequently, while coverage is important, the inclusion of additional analyst coverage has either no clear impact on the likelihood of termination or even negative impact. However, as we show below, the negative impact of increased analyst coverage is likely related to added/dropped coverage during the misconduct spell.

Analysts' impact on fraud termination hazard is also related to their role in setting investor expectations with their forecasts. Inaccurate or contradicting forecasts may suggest that something unusual is going on with the firm's financial reporting and may generate scrutiny. We measure the information content of analyst forecasts by including analyst earnings forecast error in our model. Column 3 of table 7 shows the results from including analyst forecast error along the other analyst following variables. We find that greater forecast error is associated with shorter accounting fraud spells. This result is consistent with the view that a greater forecast error attracts greater scrutiny of the firm, shortening the fraud. It is important to realize that the forecast variable is still heavily skewed towards zero. Thus, the result is driven by observations in the far right tail of the distribution of forecast error, implying that only extremely large deviations generate scrutiny. For most firms, forecast error is too small to materially alter the estimated fraud termination hazard. As we see in figure 3B, the marginal effect of moving from the 25^{th} to the 75^{th} percentile of the mean forecast error distribution is quite small. For example, for firms at the 6^{th} quarter of a fraud spell, a move from the 25^{th} to the 75^{th} percentile represents a 0.13%-point increase in the termination hazard. Consequently, there is no clear indication that either the presence of multiple analysts or the accuracy of their forecasts induce fraud termination.

Next, we consider the impact of analysts' choice to add or drop coverage on the fraud termination hazard. As described in section 3.2.2 this choice may be informative to potential whistle-blowers. In table 8 we present results for tests of the effect of changes in analyst coverage on the likelihood of fraud termination. In particular, we compare the baseline results for analyst coverage in column 1 of table 7 (reproduced in column 1 of table 8) to the results from models that capture the effect of adding or dropping analysts in columns 2 through 6 of table 8.

Columns 2 and 3 in table 8 consider the impact of drops in analyst coverage. Column 2 includes an indicator variable for dropped coverage (*Analyst Departure Indicator*) that is equal to one if the number of analysts following the firm is smaller than in the previous year, and zero otherwise.

This variable captures the effect of a decline in coverage, without controlling for the intensity of the drop. Differently, column 3 includes a measure of the intensity of the drop in coverage: the logged number of analysts that dropped coverage (*log(1+No. of departed analysts)*). Notice that both specifications also include the analyst following indicator. Consequently, the variables for dropped coverage capture the marginal impact of changes in the degree of coverage and not the main effect of analyst coverage. Results in columns 2 and 3 of table 8 show that both the *Analyst Departure Indicator* as well as a measure of intensity in the decline in coverage (*log(1+No. of departed analysts*) are positive and statistically significant at the 5 and 1% levels, respectively. Figure 3C shows the marginal effect of dropped coverage using the model in column 3. This figure reports the marginal effect when all other variables are at their median values. Consequently, we are already factoring in the effect of analyst coverage by itself since the analyst indicator is kept constant at one. Therefore the marginal effect displayed in the graph comes solely from the decline in coverage. The increase in the termination hazard appears economically meaningful for the first dropped analyst. In terms of magnitude, assuming firms are at the 6^{th} quarter of a fraud spell (which is the median spell length), the hazard rate of the misconduct ending the next quarter for a firm with no change in analyst coverage is 10%. In contrast, the hazard rates for firms that have observed a coverage drop of one and two analysts are 13.9% and 16.8% respectively.

Columns 4 and 5 in table 8 consider the impact of added analyst coverage. Column 4 includes an indicator variable for added coverage (*Analyst Addition Indicator*) that is equal to one if the number of analysts following the firm is larger than in the previous year, and zero otherwise. As with the departure indicator, this variable captures the effect of an increase in coverage, without controlling for the intensity of the increase. However, column 5 includes a measure of the intensity of the increase in coverage, (*log(1+No. of added analysts)*). As in columns 2 and 3, these specifications include an analyst indicator thus they capture the marginal impact of an increase in coverage. Results in table 8, column 4 show that added coverage is associated with a reduction in the fraud termination hazard rate (significant at the 1% level). Similarly, in column 5, (*log(1+No. Added analysts)*) is associated with a decline in the hazard rate (significant at 5%). Figure 3D shows the marginal effect of added coverage using the empirical model in column 5. In this figure, the decrease in the termination hazard is significantly larger at the first added analyst. In terms of magnitude, assuming firms are at the 6^{th} quarter of a fraud spell, the hazard rate of the misconduct ending the next quarter for a firm with no change in analyst coverage is 13.7%. In contrast, the hazard rates for firms that have observed added coverage of one and two analysts are 11% and 9.6%, respectively.

Finally, column 6 in table 8 presents results with both measures of the intensive margin of analyst additions and departures. In this sense, it compares both cases of increased and decreased coverage against a benchmark of no change in coverage. Results in column 6 show that while the presence of coverage significantly increase the likelihood of detection (*Analyst Indicator* positive and significant at the 5% level), the departure of analysts results in a increase in the termination hazard that is statistically significant at 1% level. In contrast, the addition of analysts has a statistically insignificant effect. In summary, the results in table 8 suggest that market participants extract information from analysts' decision to start, continue, or stop covering a firm. However, the results are asymmetric, with dropped coverage having a more significant effect on fraud duration than added coverage.

5.4 The Effect of Managerial Effort on Fraud Duration

We next turn to our tests of H3, the impact of managers' efforts to conceal the fraud. As outlined in section 3.2.3, we use three different proxy variables for managerial effort: (i) a dummy indicating that the fraud starts in the first fiscal quarter, (ii) the log of the number of accounting areas being misstated, and (iii) the magnitude of total accruals.

In our sample of 191 AAERs, 57% started misstating financial reports in the first fiscal quarter; significantly more than the 25% that we would expect if frauds started uniformly at random throughout the year. This result, along with evidence presented above suggesting a large fourth quarter effect on fraud termination hazard, indicates that frauds started in the first fiscal quarter are likely to be well planned, entailing more managerial effort. If starting a fraud in the first fiscal quarter captures managerial fraud effort, we expect it to have a significantly longer duration based on our model's implications. Column 1 of table 9 shows the results from adding 1^{st} *Quarter Start*, an indicator for frauds that start in the first fiscal quarter, to the set of variables used in the estimation of column 2 in table 7. We note that the coefficient on the 1^{st} fiscal quarter indicator is negative and statistically significant at the 1%-level, confirming H3.

In column 2 of table 9 we include our second proxy for managerial effort, the log of number of areas contaminated by the fraud (*log(Number of Areas)*). This measure captures the idea that complex frauds take more effort, but may make it harder for information producers to spot inconsistencies. Our results corroborate H3. The coefficient on *log(Number of Areas)* is negative and significant at the <1%-level. Thus, the more accounting areas that the fraud affects, the lower the hazard rate of fraud termination.

It is possible that these two proxies capture different aspects of fraud effort. For example, starting the fraud in the first fiscal quarter may indicate more effort in terms of planning whereas the number of areas affected may indicate more effort in the execution of the fraud. To allow for this possibility, we include both proxies in column 3 of table 9. The coefficients of both variables are somewhat attenuated in this specification. While 1^{st} fiscal quarter indicator remains negative and statistically significant at the 1%-level, number of areas is now marginally statistically significant at 10%.

Figure 4A illustrates the economic impact of starting the fraud in the first fiscal quarter on the fraud termination hazard rate based on the estimates in column 3 of table 9, while holding all other variables constant at their median values. We find a substantial negative effect. For a fraud spell that has reached 6 quarters of duration, the probability of fraud termination the next quarter is about 19.6%-points lower if the firm started its misconduct in the first fiscal quarter relative to firms that did not start the misconduct in the first fiscal quarter. Figure 4B illustrates the corresponding economic magnitude for the number of areas affected. For a fraud that has been ongoing for 6 quarters, the marginal effect on the fraud termination hazard of going from the 25^{th} percentile value of areas affected (one area) to the 75^{th} percentile (three areas) is a reduction of 3.8%-points.

The two proxies for managerial effort that we have considered so far are not time-varying. As discussed in section 3.2.3, we also study a third proxy for managerial effort that we are able to track across time: total accruals. This is defined as the difference between net income and operating cash flows scaled by the average of total assets over the period. We observe this variable on an annual basis (we get too many missing observations if we instead use quarterly data). Column 4 of table 9 shows the estimation results from adding this variable alongside the other two proxies for managerial fraud effort. Consistent with our predictions, we find a significantly negative impact on fraud hazard rates from the total accruals measure. Figure 4C illustrates the economic impact. Holding all other variables constant at the median values and considering a fraud spell in its 6^{th} quarter, moving total accruals from the 25^{th} percentile sample value to the 75^{th} percentile value decreases the fraud termination hazard by 0.83%-points. Therefore, the economic magnitude of the impact of accruals manipulation on the termination hazard seems small.

5.5 Additional Tests

In this section, we include two additional tests. The first explores fraudulent misstatements of gross profit, and the second considers institutional blockholders as an alternative information producer. In the internet appendix, we also include additional robustness tests that address the impact of outliers on our results. Moreover, the internet appendix also provides results for an extended sample that includes misstatement periods for all AAERs with available data, without the constraints suggested by (Karpoff *et al.* [2017]). The results for the robustness tests in the internet appendix are qualitatively the same as the ones presented in this paper.

5.5.1 The Effect of Misstatements of Gross Profit on Fraud Duration

A straightforward extension to our model yields the prediction that frauds that affect areas of the accounting statements that information producers scrutinize harder are more likely to be shorter. We hypothesized that information producers (and monitors) care especially about the accuracy of reported gross profit, which would then make gross profit (i.e, revenue and costs of goods sold) related fraud harder to maintain than fraud affecting other financial accounts.

In columns 1 and 2 of table 10 we add an indicator variable (*Gross Profit Related*) equal to one if the fraud affected reported revenues or operating costs (or both) alongside the full set of variables included in columns 2 and 3 of table 9, respectively. These results show that frauds affecting gross profit tend to be shorter. The coefficient on *Gross Profit Related* is positive and significant in both columns. Figure 5 shows the magnitude of the estimated effect based on model 1 of table 10. For example, if a misconduct spell is in its 6^{th} quarter and the misstatement is gross profit-related, the hazard of ending the fraud next quarter is 8.8% versus 5.9% if the misstatement is not gross profit-related.

5.5.2 Robustness Test - Institutional Blockholders

Institutional investors can also act as information producers. As sophisticated investors, institutions may undertake costly analysis of financial information in order to determine whether to trade a stock. The actions of institutional investors convey the results of their analysis to the market. These actions are informative to investors that were unwilling or unable to undertake the costs associated with analyzing the available information (e.g., Indjejikian [1991]). For example, empirical evidence suggests that institutions produce additional information in response to stock splits (Chemmanur, Hu, and Huang [2015]) and induce information production around the Russell 2000/1000 split (Boone and White [2015]). In table 11, we test the impact of institutional blockholders' ownership on the fraud termination hazard. We focus on institutional blockholders with more than 5% of ownership to ensure we capture owners that have financial incentives to more carefully monitor and produce information about the firm over time. Smaller institutional owners may find it too costly to produce information about the firm on their own and rather rely on other information producers, such as the auditors and analysts that are the main focus of this study.

Columns 1 through 3 in table 11 attempt to control for the impact of institutional ownership in different ways. Column 1 includes a blockholder indicator variable that is equal to 1 whenever there is an institutional investor that holds more than 5% of the company's shares. Similarly, column 2 controls for the fraction of the shares that are held by blockholders (again defined as institutional investors holding more than 5% of the shares). Finally, column 3 controls for the ownership stake of the largest blockholder. All specifications in table 11 also control for the full set of variables included in column 1 of table 10. Results for all specifications show no statistically significant impact of the blockholder variables on the fraud termination hazard. Consequently, we have no clear indication that blockholders have an independent role as information producers that may trigger fraud termination.

6 Conclusion

In this paper, we build a simple model that shows how accounting fraud duration is related to the presence and quality of information producers – in particular auditors and financial analysts – as well as the firm's efforts to hide the fraud. In order to test the model implications, we gather a database of 191 unique AAER-firm pairs that cover 1,439 firm-quarters – with start dates from 1982 until 2006. Our main sample only includes financial misrepresentation associated with charges of violations of the anti-fraud provisions of the Securities Act or the Exchange Act.

Overall, our empirical results corroborate the implications of the model. The presence of the auditor as an information producer during the year-end financial reporting process significantly increases the likelihood of detection, particularly when explanatory language has been added to the auditor report. Similarly, we find that auditor switches are associated with fraud termination and that the association is stronger when the switch is due to auditor resignation. Moreover, this effect is independent of audit quality. We also consider analysts as information producers. Results suggest that analyst coverage significantly increases the likelihood of fraud termination. However, additional analyst coverage appears to have a detrimental effect on fraud termination. The effect of changes in analyst coverage provide one explanation for this result. Market participants appear to interpret increased analyst following as a sign of quality and decreased analyst following as a sign of financial reporting risk.

Managerial effort to conceal fraud also appears to extend fraud. We show that starting a fraud in the first fiscal quarter, and consequently having time before financial statements are audited, significantly increases fraud duration. Moreover, frauds that affect more areas of the financial statements are longer, indicating that more complex frauds are also harder to spot. Finally, firms that have higher total accruals, an indication of using aggressive accounting to distort information, also have longer frauds on average. In summary, we show that managerial effort can significantly prolong the expected duration of financial statement fraud.

Appendix

A Model

In this appendix, we develop a stylized model of information production and fraud duration that guides our empirical analysis. A detailed presentation of the proofs, which do not affect the economic intuition of the results, is presented in the internet appendix.

A.1 Basic Model

Consider two types of risk-neutral, long-lived firms: Manipulators (M) and Non-Manipulators (NM). We assume that NMs never misrepresent their financial statements. Differently, Ms regularly manipulate their financial statements to their own benefit. Even though later we endogenize the firm's choice of becoming a manipulator, let's initially denote the probability that any given firm is a manipulator by $\xi \in (0,1)$.

Every time a financial statement is issued, a group of information producers and intermediaries scrutinize the accounting data. These are auditors, analysts, institutional investors, among others. In this basic model, we assume a unique information producer – we generalize the results for multiple information producers in the next subsection. The signals detected by the information producers can be good ($s = G$) or bad ($s = B$). The probability that an information producer detects a bad signal while scrutinizing a manipulator is given by $\Pr(B|M) = p$. On the other hand, information produces only detect good signals while screening non-manipulators' statements, i.e.,

$\Pr(B|NM) = 0$. Signals across different financial statements are assumed i.i.d. in this section – we relax this assumption later.

Risk neutral monitors – comprised of regulators, institutional investors, and board members – observe the signals detected by the information producers and decide if they intervene in the firm or not, i.e. a monitor's action space is $A = \{I, NI\}$, where I and NI represent intervention and non-intervention, respectively. In order to intervene in a firm and scrutinize it for accounting misbehavior, monitors must incur a cost $\mathscr{C} > 0$. Whenever a manipulator is caught, intervening monitors obtain a gain of $P > \mathscr{C}$. However, if they intervene in a non-manipulator, their return is normalized to zero. Both $\mathscr{P} > 0$ and $\mathscr{C} > 0$ may be monitor-specific, but for ease of notation and because our results do not depend on such heterogeneity, we assume $\mathscr{P}$ and $\mathscr{C}$ are common for all monitors. Accordingly, in period t, a monitor's instantaneous expected utility is given by:

$$u(a_t, \mathscr{H}_t) = \begin{cases} \Pr(M|\mathscr{H}_t) \times P - \mathscr{C}, & \text{if } a_t = I, \\ 0, & \text{if } a_t = NI. \end{cases} \tag{A1}$$

where the probability of a manipulator conditional on the history of signals is

$$\Pr(M|\mathscr{H}_t) = \begin{cases} 1, & \text{if} \quad h_i = B, \text{ for some } h_i \in \mathscr{H}_t \\ \frac{\xi(1-p)^t}{(1-\xi)+\xi(1-p)^t}, & \text{otherwise.} \end{cases} \tag{A2}$$

Based on the instantaneous utility function, the value function for monitors is given by

$$V(\mathscr{H}_t) = \max_{a_t \in A} \{\Pr(M|\mathscr{H}_t) \times P - \mathscr{C}, \delta E_t[V(\mathscr{H}_{t+1})]\}, \tag{A3}$$

where $\delta \in (0, 1)$ is the discount rate.[18] Now, we can show a few results, but let's first define $\mathscr{H}_t(B) = \{\mathscr{H}_t \text{ s.t. } \exists\ h_i = B \in \mathscr{H}_t\}$ as the set of histories in which a bad signal was observed at some point and denote the history at the beginning of the firm by $\mathscr{H}_\emptyset = \emptyset$.

[18]From equation (A3), it is clear that $\mathscr{P}$ includes the discounted difference between the value obtained by the monitor from correct intervention and from superfluous intervention, whereas $\mathscr{C}$ includes his/her discounted value of needless intervention.

LEMMA 1. *If $\mathscr{H}_t \in \mathscr{H}_t(B)$, monitors should intervene, i.e., $V(\mathscr{H}_t) = P - \mathscr{C}$.*

Then, the following conclusion is a straightforward consequence:

COROLLARY 1. *Monitors should immediately intervene if they observe a bad signal.*

We can now state the main proposition in the Monitor's problem.

PROPOSITION 1. *If $\xi P < \mathscr{C}$, then monitors only intervene if they observe a bad signal.*

Therefore, based on Proposition 1, if it is not optimal to immediately intervene in a firm – even before observing any signal – it is never optimal to intervene before observing a bad signal. From this point on, we keep the assumption $\xi P < \mathscr{C}$, so monitors only intervene once they observe a bad signal.[19] Consequently, the length of a fraud is described by a geometric distribution, which leads to the following proposition:

PROPOSITION 2. *The expected length of a fraud is given by $E[N] = \frac{1}{p}$.*

As a result, the better the information producers are at spotting frauds, by detecting bad signals, the lower the life expectancy of a fraud. Before we move to the extensions, keep in mind that the hazard rate function, i.e. the probability that a fraud is detected in period t conditional on having survived until period $t-1$, is given by p, a constant, as the geometric distribution is memoryless. In the extensions, we consider cases in which the hazard rate is time dependent, due to the fact that longer frauds may become easier to catch.

A.2 Extensions

A.2.1 Multiple information producers

Independent signals

Let $\mathscr{I} := \{1, ..., \mathbf{I}\}$ be the set of information producers. In order to study the case in which they are the most efficient, assume that they detect signals independently from each other. As

[19]Due to the fact that monitors intervene whenever they observe a bad signal, it is also not optimal for firms that plan to engage in fraudulent behavior to build up reputation by delaying the fraud start.

before, assume that information producers never detect a bad signal while scrutinizing *NM* firms. Differently, we assume that information provider i detects a bad signal while scrutinizing a type M firm with probability p_i. Then, the probability that at least one information provider detects a bad signal is given by:

$$\Pr(B|M) = 1 - \prod_{i \in \mathscr{I}} (1 - p_i), \tag{A4}$$

and, the expected duration of a fraud is given by:

$$E[N] = \frac{1}{1 - \prod_{i \in \mathscr{I}} (1 - p_i)}. \tag{A5}$$

As before, the better information providers are at spotting a fraud – i.e., the higher p_i for at least some $i \in \mathscr{I}$ – the shorter the fraud. Likewise, the introduction of an additional information producer increases the probability of fraud detection and reduces its expected length.

PROPOSITION 3. *The introduction of a new information producer at any given period increases the likelihood of a bad signal detection, shortening the fraud's length. The better the new information producer is catching frauds – i.e., the higher his/her p – the larger the effect.*

Correlated signals

In this case, since signal detection is not independent across information producers, we take into account the interactions among detected signals through their joint p.d.f.. Therefore, we have that the probability that at least one information producer detects a bad signal is $\Pr(B|M) = 1 - \Pr(s_1 = G, s_2 = G, ..., s_{\mathbf{I}} = G)$, and the expected fraud duration is given by:

$$E[N] = \frac{1}{1 - \Pr(s_1 = G, s_2 = G, ..., s_{\mathbf{I}} = G)}. \tag{A6}$$

As expected, as long as the signals are not perfectly correlated, in the sense that $\Pr(s_i = G|s_1 = G, s_2 = G, ..., s_{i-1} = G, s_{i+1} = G, ..., s_I = G) < 1, \forall i \in \mathscr{I}$, all previous results are qualitatively the same, even though they are quantitatively weaker.

Due to the fact that notation becomes cumbersome in the case of correlated signals across information producers, we focus on the case with independent signals. However, the reader should keep in mind that all results are preserved once we allow for partial correlation.

We can also consider the incentives for firms to exert effort to make frauds harder to detect. Before we discuss that, let's consider the case in which the probability of detection varies over time.

A.2.2 Time-varying probability of a bad signal

As we mentioned previously, in the basic model the hazard rate is constant over time. This lack of memory is a feature of the geometric distribution that may not be particularly suited to our case. In this sense, we may consider that the probability of producing a bad signal may change over time, i.e.:

$$\Pr(B|M,t) = p(t). \tag{A7}$$

A natural assumption would be $p'(t) > 0$, i.e., as time passes, the probability of obtaining a bad signal increases. For example, a longer fraud means that more financial statements are affected by the fraud and it may be easier to spot inconsistencies. We also assume that $p(t) < 1, \forall t \in \mathbb{N}$ and $\lim_{t\to\infty} p(t) = 1$, i.e., the probability of getting a bad signal increases but it is never 1 at a finite time. Then, the expected duration of the fraud is now:

$$E[N] = \sum_{t=1}^{\infty} t\,p(t) \prod_{t'=1}^{t-1} (1 - p(t')). \tag{A8}$$

While the hazard rate is now $h(t) = p(t)$.[20]

Moreover, even though we imagine that the probability of being detected has an upward trend, the actual probability may vary around the trend. In particular, we may expect that market and firm time-varying characteristics may affect the detection probability, pushing it above or below the long-term trend. For example, good or bad performance in the stock market may increase

[20]In the internet appendix we present a simple example in which $p(t)$ is an increasing and concave function.

or decrease incentives to scrutiny, making it easier or harder for information producers to detect signs of manipulation. A similar argument can be made about the firm's own operational and stock market performance.

A.2.3 Firm-specific factors and the probability of a bad signal

Observable firm characteristics may influence the likelihood that a information producer may detect a bad signal. For example, firm size may be related to the duration of accounting misconduct in a few ways. Large firms have relatively richer information environments than small firms. A richer information environment should make the marginal cost of issuing an additional fraud signal lower for information producers and thus reduce the duration of accounting misconduct. Conversely, large firms also tend to have a wider scope of operations than small firms, which may make it easier for a manager to conceal misconduct. In this sense, we expect that the probability that a IP issues a bad signal for a manipulator i is given by $p(\mathbf{x}_{i,t}, t)$ where $\mathbf{x}_{i,t}$ is a vector of firm i characteristics at time t that make it easier or harder for IPs to spot a bad signal.[21]

A.3 Firm's decision on fraud commission and fraud-hiding efforts

A.3.1 Firm's decision to commit fraud

Up to now, we consider the decision of committing fraud or not as exogenous, representing the firm's type. In this section, we consider the firm's decision of committing fraud.

We assume that firms differ in their benefit of committing fraud or not, i.e. the firm's benefit of committing fraud $\mathscr{B}$ is a draw in the distribution $F(.)$ with support $(0, \overline{\mathscr{B}})$. We also assume that if the firm is caught, it incurs in a loss of $L \equiv \overline{\mathscr{B}}$, independent of its type. Finally, a firm decides each moment if it continues to commit fraud or if it decides to stop. For simplicity, we assume that only ongoing frauds can be discovered. In this sense, the firm can decide if it commits (or continues) a fraud period by period.

[21] We allow $\mathbf{x}_{i,t}$ to depend on t since several important firm characteristics – such as size, leverage, fraction of soft assets, among others – vary over time.

Then, the period t expected benefit (or loss) of committing a fraud that has been ongoing for t periods for a type $\mathscr{B}$ firm is given by:

$$\mathbf{Profit}(\mathscr{B},\mathbf{t}) = (1-p(t))\mathscr{B} + p(t)(-L). \tag{A9}$$

Even though firms live forever and the decision to start or continue a misrepresentation is a dynamic problem, proposition 4 below shows that the decision ultimately depends only on the current period expected benefit or loss. Therefore, a firm decides to start or continue an ongoing fraud if **Profit($\mathscr{B}$,t)**> 0.

PROPOSITION 4. *In an economy in which firms choose optimally to commit fraud and frauds do not become harder to spot over time - i.e.* $p'(t) \geq 0$ *- the following is true:*

1. *Non-Manipulation is the optimal policy for all firms with $\mathscr{B} \leq \mathscr{B}^*$, where $\mathscr{B}^*$ is given by:*

$$(1-p(1))\mathscr{B}^* + p(1)(-L) = 0. \tag{A10}$$

2. *If $p(t) = p, \forall t$ then if a firm decides to commit fraud it will never stop until it gets caught.*
3. *If $p'(t) > 0$ and $\lim_{t\to\infty} p(t) = 1$, for every $\mathscr{B} > \mathscr{B}^*$ there is a $T(\mathscr{B}) < \infty$ in which if the firm has not been caught up to that point, management decides that it is not profitable to continue the fraud anymore. $T(\mathscr{B})$ is defined by:*

$$(1-p(T(\mathscr{B})))\mathscr{B} + p(T(\mathscr{B}))(-L) = 0. \tag{A11}$$

From implicit function theorem, notice that

$$\frac{dT(\mathscr{B})}{d\mathscr{B}} = \frac{(1-p(T(\mathscr{B}))}{p'(T(\mathscr{B}))(\mathscr{B}+L)} > 0. \tag{A12}$$

Since $p'(T) > 0, \forall T$. Based on this result, we have the following corollary:

COROLLARY 2. *Firms that benefit the most out of a fraud are more likely to get caught instead of stopping the fraud by themselves*

Finally, based on the proof of proposition 4, we can also easily conclude that all results presented here are still true for time varying benefit of fraud and loss due to detection – $\mathscr{B}(t)$ and $L(t)$ – as long as $(1-p(t))\mathscr{B}(t)+p(t)L(t)$ decreases over time. In this sense, as long as $\mathscr{B}(t)$ does not increase faster than $L(t)$ over time, our results are still valid.

A.3.2 Fraudster's effort

Consider that the fraudster can exert an effort $e_M > 0$ in order to make harder for information producers to spot irregularities. In order to simplify notation, let's initially assume that the probability of a bad signal does not change over time. Therefore, we assume that $\frac{\partial p_i(e_M)}{\partial e_M} < 0$, i.e., by exercising effort, the manipulator reduces the likelihood of a bad signal for any information provider $i \in \mathscr{I}$. We also assume that the cost of effort is given by a convex, strictly increasing function $C(e_M)$, while $\lim_{e_M \to e_M^*} C(e_M) = \infty$, where $p_i(e_M^*) = 0$, $\forall i \in \mathscr{I}$. In other words, it would be prohibitively expensive to completely eliminate the risk of getting caught.

Then, it is easy to see that the expected duration of the fraud is given by:

$$E[N|e_M] = \frac{1}{1-\prod_{i\in\mathscr{I}}(1-p_i(e_M))}. \tag{A13}$$

Therefore, as expected $\frac{\partial E[N|e_M]}{\partial e_M} > 0$.

A.3.3 Optimal choice of effort

Now, let's consider that the firm committing fraud can optimally choose its effort to hide an ongoing fraud. As in the previous section, we consider that the firm not only chooses if it starts or continues an ongoing fraud every period[22] but also its efforts hiding the fraud, paying a flow cost $C(e_M) > 0$. Then, if the firm decides to commit a fraud, the optimal choice of effort in period t is

[22]We assume here that only ongoing frauds can be detected in order to simplify our expressions. Results are still true if we assume that stopped frauds see a significant decrease in their likelihood of detection.

given by:

$$\max_{e_M}(1-p(t,e_M))\mathscr{B}+p(t,e_M)(-L)-C(e_M). \tag{A14}$$

Then, from the first order condition (F.O.C), we have

$$-\frac{\partial p(t,e_M)}{\partial e_M}(\mathscr{B}+L)-C'(e_M)=0. \tag{A15}$$

where $\frac{\partial p(t,e_M)}{\partial e_M}<0$. From the second order condition, we have:

$$-\frac{\partial^2 p(t,e_M)}{\partial e_M^2}(\mathscr{B}+L)-C''(e_M). \tag{A16}$$

So, as long as $\frac{\partial^2 p(t,e_M)}{\partial e_M^2}>0$, the problem is strictly concave and there is a unique optimal effort $e^*(t,\mathscr{B})$ pinned down by the F.O.C.

Notice that the firm's choice of committing or continuing a fraud is now given by:

$$(1-p(t,e^*(t,\mathscr{B})))\mathscr{B}+p(t,e^*(t,\mathscr{B}))(-L)-C(e^*(t,\mathscr{B}))>0. \tag{A17}$$

where $e^*(t,\mathscr{B})$ is pinned down by the F.O.C..

Finally, from F.O.C., we also obtain the following results:

PROPOSITION 5. *Based on a manipulator's optimal effort decision $e^*(t,\mathscr{B})$, the following is true:*

1. $\frac{\partial e^*(t,\mathscr{B})}{\partial \mathscr{B}}>0$*, i.e., the firms that benefit the most incurring in fraud are also the ones that put more effort to hide it;*
2. $\frac{\partial e^*(t,\mathscr{B})}{\partial t}$ *depends on* $\frac{\partial^2 p(t,e_M)}{\partial e_M \partial t}$*. In particular, if* $\frac{\partial^2 p(t,e_M)}{\partial e_M \partial t}>0$ *the effect of the fraudster's efforts concealing the misconduct decreases over time, so* $\frac{\partial e^*(t,\mathscr{B})}{\partial t}<0$.

A.4 Information Producers' decision of monitoring a firm or not

In section, we extend the model in order to consider the information producers' decision to monitor a company or not. Our goal it is to understand how the analysts' decision to follow a company or not may impact the information revealed to market participants. Since the cost of following a company is higher the higher the probability a company is a manipulator, the simple fact that an analyst decides to start or to continue following a company is seen as good news by market participants. Similarly, the decision to stop following a company is perceived as bad news. In particular, let's consider that there is a cost C_{IP} for the Information Producer to follow a firm. Imagine that the cost of following can be high (H) or low (L). Moreover, assume that this cost depends on the firm being M or NM, i.e., $Pr(C_{IP} = L|NM) \equiv \gamma_{NM} > Pr(C_{IP} = L|M) \equiv \gamma_M$. Then, assume that the benefit of following a firm is constant $\tilde{B}$ and that $\tilde{B} - L > 0$ and $\tilde{B} - H < 0$.

In terms of timing, we consider that the information producer first observe how costly it is to follow a given company. Given that the benefit of following a company is given by $\tilde{B} - C_{IP}$, the analyst decides to follow the company if $C_{IP} = L$.

Then, let's consider how market participants adjust their beliefs about the likelihood a given firm is a manipulator based on the analyst's decision of following the company or not. Assume that ξ_0 is the initial probability of a firm being a manipulator. Then, imagine that there is only one possible analyst. In this case, the probability of a firm being a manipulator given that the analyst decided to follow the firm is given by:

$$\xi_1 = \frac{\Pr(L|M) \times \Pr(M)}{\Pr(L|M) \times \Pr(M) + \Pr(L|NM) \times \Pr(NM)} = \frac{\gamma_M \xi_0}{\gamma_M \xi_0 + \gamma_{NM}(1 - \xi_0)} \tag{A18}$$

where ξ_1 is the probability that the firm is a manipulator given that it is followed by 1 out of 1 potential analyst. Notice that the posterior depends on the number of potential analysts that could follow the firm.

Then, consider the probability of N analysts deciding to follow the company out of $\mathscr{M}$ potential analysts. Let's initially assume that the costs of following the firm observed by analysts are independent. Then, the probability of N out of $\mathscr{M}$ analysts deciding to follow the firm, conditional on the firm being a manipulator, is given by a binomial probability, i.e.:

$$\Pr(N;\mathscr{M}|M) = \binom{N}{\mathscr{M}} \gamma_M^N (1-\gamma_M)^{\mathscr{M}-N} \tag{A19}$$

Then, the posterior probability that a firm is a manipulator, given that N analysts out of $\mathscr{M}$ follow the firm is given by:

$$\xi_N = \frac{\Pr(N;\mathscr{M}|M)\times\Pr(M)}{\Pr(N;\mathscr{M}|M)\times\Pr(M)+\Pr(N;\mathscr{M}|NM)\times\Pr(NM)} \tag{A20}$$

Then, substituting (A19) into (A20), we obtain:

$$\xi_N = \frac{\left[\binom{N}{\mathscr{M}}\gamma_M^N(1-\gamma_M)^{\mathscr{M}-N}\right]\xi_0}{\left[\binom{N}{\mathscr{M}}\gamma_M^N(1-\gamma_M)^{\mathscr{M}-N}\right]\xi_0+\left[\binom{N}{\mathscr{M}}\gamma_M^N(1-\gamma_M)^{\mathscr{M}-N}\right](1-\xi_0)} \tag{A21}$$

Figure A.1.illustrates this result graphically.

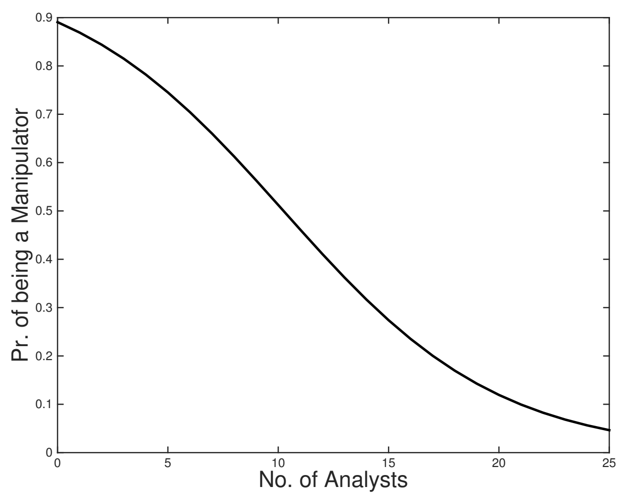

Figure A.1. Posterior Probability as a function of No. of Analysts

However, notice that this effect only matters for duration if p is affected by the posterior, i.e., $p'(\xi) > 0$, showing that the likelihood of termination is increasing in the posterior probability of being a manipulator. Otherwise, apart from increasing the probability of immediately stopping a firm, results should not change.

Finally, consider the case in which the costs of following a firm observed by different analysts are not independent. Then, the probability of N out of $\mathscr{M}$ analysts deciding to follow the firm, conditional on the firm being a manipulator, is given by a correlated binomial probability. We follow Witt [2004] in order to come up with an specification for the correlated binomial model. In particular, we consider a universe of $\mathscr{M}$ analysts that have identically distributed probabilities of following a given company with these two assumptions:

Assumption (1): Each analyst has a probability γ of following the company.

Assumption (2): Each pair of analysts has correlation ρ between them.

In order to specify the joint probability distribution, this correlated binomial also relies on a third assumption.

Assumption (3): The correlation between analyst $j+1$ and analyst $j+2$ remains equal to ρ regardless of the number of known analysts following the firm among the other analysts.

Mathematically, assumption (3) can be written as $\gamma_{j+1} = \gamma_j + (1-\gamma_j)\rho$, for $j = 1, ..., \mathscr{M}-1$. Assumption (3) implies that in the Correlated Binomial, the default probability of analyst $j+1$ following the firm conditional on j analysts following is increasing as j increases. This increasing probability given other analysts following is one aspect of the fatter tails of the correlated binomial distribution.

This simplified version of the correlated binomial has the benefit of having a closed form distribution. In particular, for $k > 0$, the probability that k analysts decide to follow the firm, while $\mathscr{M}-k$ decide not to follow the company have the probability distribution:

$$C(\mathscr{M},k)\sum_{j=0}^{\mathscr{M}-k}\left[(-1)^j C(\mathscr{M}-k,j)\prod_{i=1}^{j+k}\gamma_i\right] \tag{A22}$$

and the probability of no analysts following is:

$$1+\sum_{j=1}(-1)^j C(\mathscr{M},j)\prod_{i=1}^{j}\gamma_i \tag{A23}$$

where $C(\cdot,\cdot)$ represents the combinatorial function.

Finally, considering the posterior probability that a firm is a manipulator, given that N analysts out of $\mathscr{M}$, we notice that the correlation reduces the informativeness of added analysts in signaling the likelihood of a firm being a manipulator. In particular, if we replicate the graphical example presented in figure A.1, adding the case of positive correlation, we have:

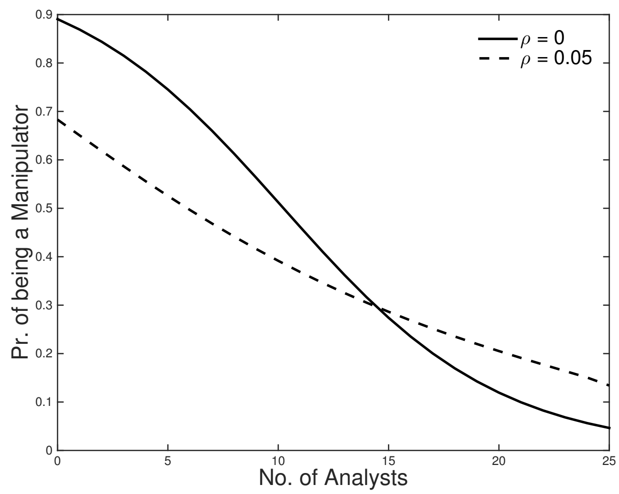

Figure A.2. Posterior Probability as a function of No. of Analysts

A.4.1 Dropping Analysts

Similarly, consider that, at any given period, there is a probability δ_M that an analyst decides to stop following a firm if the firm is a manipulator. For example, an increase in the financial statements' complexity can be seen as an increase in the analyst's cost of following the firm, which we refer as a "cost shock" from now on. Assume that the probability of a cost shock in the case of a non-manipulator is given by $\delta_{NM} < \delta_M$. Then, let's consider that $\tilde{N}$ analysts follow the firm in a given period. Initially, let's assume that cost shocks are independent and identically distributed. Then, the likelihood that n_1 out of $\tilde{N}$ stop following the firm is given by:

$$\Pr(n_1|\tilde{M}) = \binom{n_1}{\tilde{N}} \delta_M^{n_1} (1-\delta_M)^{\tilde{N}-n_1} \tag{A24}$$

Then, the posterior once n_1 drop out is given by:

$$\xi_{N-n_1|\mathscr{M}} = \frac{\left[\binom{n_1}{N}\delta_M^{n_1}(1-\delta_M)^{N-n_1}\right]\xi_{N|\mathscr{M}}}{\left\{\begin{array}{c}\left[\binom{n_1}{N}\delta_M^{n_1}(1-\delta_M)^{N-n_1}\right]\xi_{N|\mathscr{M}} \\ +\left[\binom{n_1}{N}\delta_{NM}^{n_1}(1-\delta_{NM})^{N-n_1}\right](1-\xi_{N|\mathscr{M}})\end{array}\right\}} \tag{A25}$$

As we can see in figure A.3, the posterior probability of being a manipulator increases as the number of dropped analysts goes up. Moreover, the posterior also depends on the number of analysts that initially decided to follow the company. Hence, the impact of a analyst dropping coverage is different if the firm was initially followed by 15 or 5 analysts.

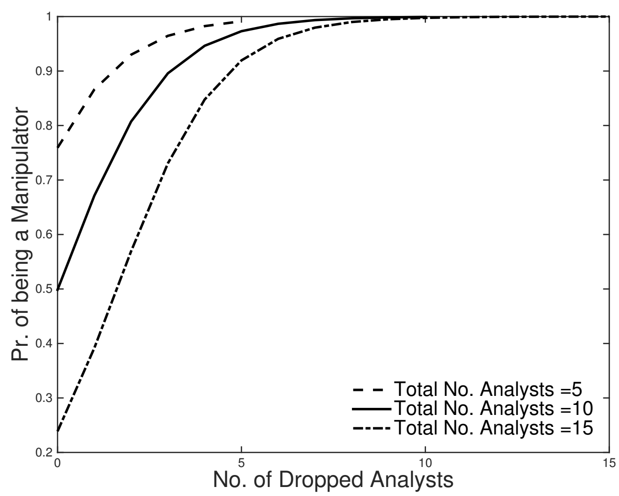

Figure A.3. Posterior Prob. as a fcn. of No. of Dropped Analysts

Consequently, if again we assume that $p'(\xi_{N-n_1|\mathscr{M}}) > 0$, we should expect that the likelihood of termination goes up as the number of analysts following the firm goes down. The result with correlated signals should be similar to the correlated binomial discussion we presented in section A.4. Finally, if we consider that the arrival rates are the same, i.e. $\gamma_M = \delta_M$ and $\gamma_{NM} = \delta_{NM}$, we can combine the different binomial distributions and jointly describe the analysts decisions of starting and stopping to follow a given firm.

B Variable Definitions

Variable	Description
End of Fraud	An indicator variable equal to 1 for the final quarter misstated and 0 otherwise
4^{th} Quarter	An indicator variable equal to 1 if the quarter is the fourth fiscal quarter
Big N	An indicator variable equal to 1 if the auditor is KPMG, Ernst & Young, PricewaterhouseCoopers, Deloitte & Touche, Arthur Anderson or their precursors (=1 if Compustat Quarterly AU = 1,2,3,4,5,6,7 or 8) and 0 otherwise
Audit Explanation	An indicator variable equal to 1 if Compustat variable auop is different from 1 (unqualified opinion with no explanatory language) and 0 otherwise
Auditor Switch 1	An indicator variable equal to one for the four quarters after the 8k announcing an auditor switch and zero otherwise
Auditor Switch 2	Same as Auditor Switch 1 but excludes auditor switches related to the Enron collapse and mergers
Auditor Switch 3	An indicator variable equal to one for the four quarters after the 8k announcing an auditor switch due to auditor resignation and zero otherwise
Analyst Indicator	An indicator variable equal to one if the firm has at least one analyst issuing year end forecasts in the I/B/E/S detail data set and zero otherwise
Analysts $i^{th.}$ Quintile	An indicator variable equal to one if the firm has a number of analysts issuing year end forecasts in the I/B/E/S detail data set that puts the firm in the $i^{th.}$ quintile of the distribution of analysts in our sample and zero otherwise
abs(Mean Forecast Error)	The absolute value of the average analyst forecast error for EPS in fiscal year t scaled by the stock price at the end of fiscal year t
Analyst Departure Indicator	An indicator variable equal to one if the number of analysts following the firm declined compared to the previous fiscal year and zero otherwise
log(1+No. of departed analysts)	The natural log of one plus the number of analysts that discontinued issuing year-end forecasts in the I/B/E/S detailed dataset, compared to the previous fiscal year
Analyst Addition Indicator	An indicator variable equal to one if the number of analysts following the firm increased compared to the previous fiscal year and zero otherwise
log(1+No. of added analysts)	The natural log of one plus the number of analysts that started issuing year-end forecasts in the I/B/E/S detailed dataset, compared to the previous fiscal year

1^{st} Quarter Start	An indicator variable equal to 1 if the first misconduct quarter is the first fiscal quarter
log(Number of Areas)	The natural log of the total number of areas misstated by the company (including revenue, receivables, cogs, inventory, reserves, debt, mkt securities, assets, pay, and liabilities)
Gross Profit Related	An indicator variable equal to 1 if the misstatement affected gross profit related areas in the income statement and 0 otherwise
Total Accruals	(Net income - Operating Cash Flows) / Average Total Assets (Compustat Annual)
log(Total Assets)	The natural log of total assets (Compustat Quarterly atq) adjusted for inflation
RoE	Income before extraordinary items / average total equity (Compustat Quarterly ibt/(teqt - teqt-4))
Abnormal Stock Return	Firm quarterly stock return - CRSP value-weighted index quarterly return
Leverage	Debt to assets ratio (Compustat Quarterly (dlcq + dlttq)/atq)
Soft Assets	Percentage of assets with accounting flexibility from Dechow *et al.* [2011] (Compustat Quarterly (atq-ppentq-cheq)/atq)
Market-to-Book	Market value of assets to book value of assets (Compustat Quarterly (atq-ceqq+cshoq*prccq)/atq))
Market Return	CRSP value-weighted index quarterly return
log(Period)	The natural log of the count of quarters misstated at time t (count continues until fraud is caught; i.e. failure =1)

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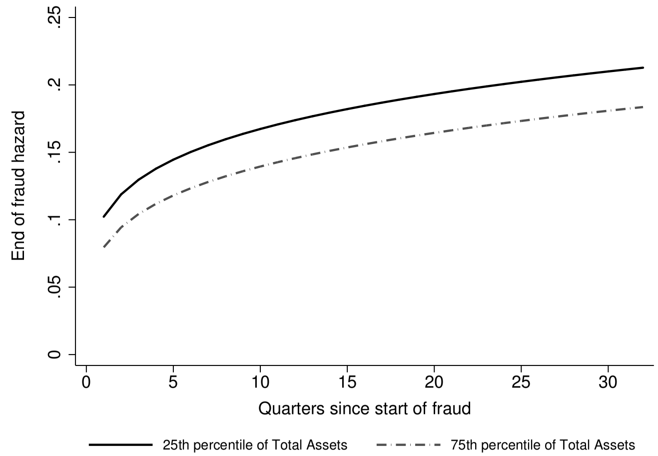

Figure 1A. Firm size and end of fraud hazards. The figure shows the estimated hazards of end of fraud as a function of quarters elapsed since the start of the misconduct. The hazards are estimated at the 25th percentile and 75th percentile sample values of book value of total assets, holding all other variables constant at their median sample values. The hazard estimates are based on column 2 of table 4.

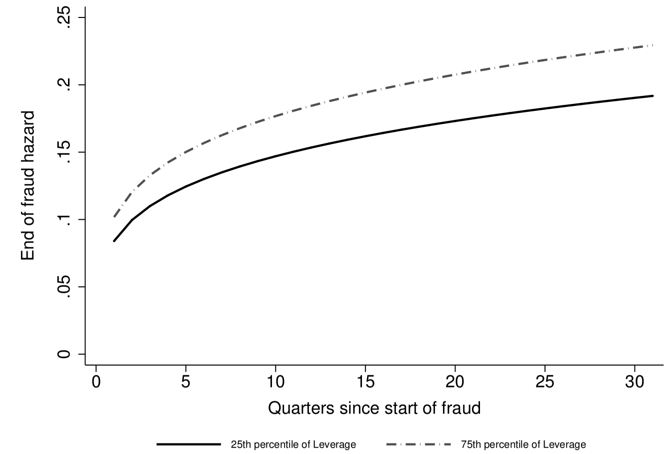

Figure 1B. Leverage and end of fraud hazards. The figure shows the estimated hazards of end of fraud as a function of quarters elapsed since the start of the fraud. The hazards are estimated at the 25th percentile and 75th percentile sample values for leverage, holding all other variables constant at their median sample values. The hazard estimates are based on column 2 of table 4.

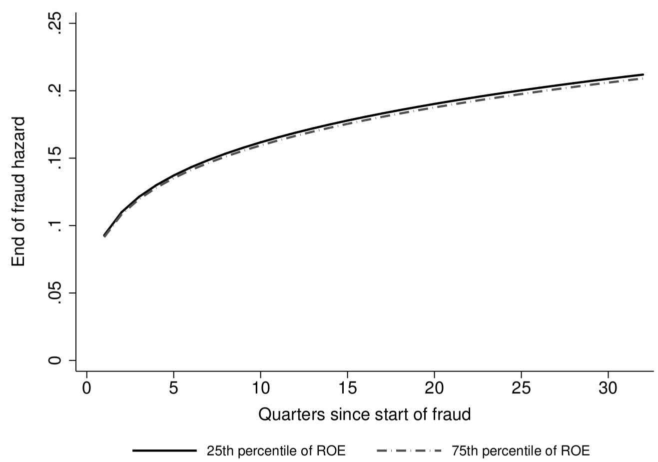

Figure 1C. Profitability and end of fraud hazards. The figure shows the estimated hazards of end of fraud as a function of quarters elapsed since the start of the fraud. The hazards are estimated at the 25th percentile and 75th percentile sample values for return on equity (RoE), holding all other variables constant at their median sample values. The hazard estimates are based on column 2 of table 4.

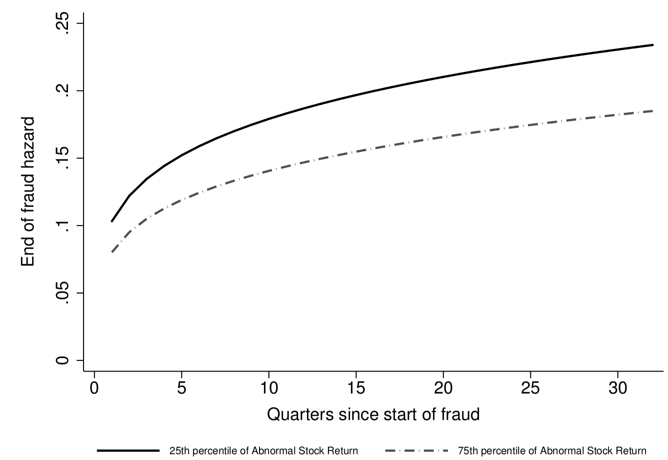

Figure 1D. Firm stock performance and end of fraud hazards. The figure shows the estimated hazards of end of frau as a function of quarters elapsed since the start of the fraud. The hazards are estimated at the 25th percentile and 75th percentile sample values for the firms quarterly abnormal stock return, holding all other variables constant at their median sample values. The hazard estimates are based on column 2 of table 4.

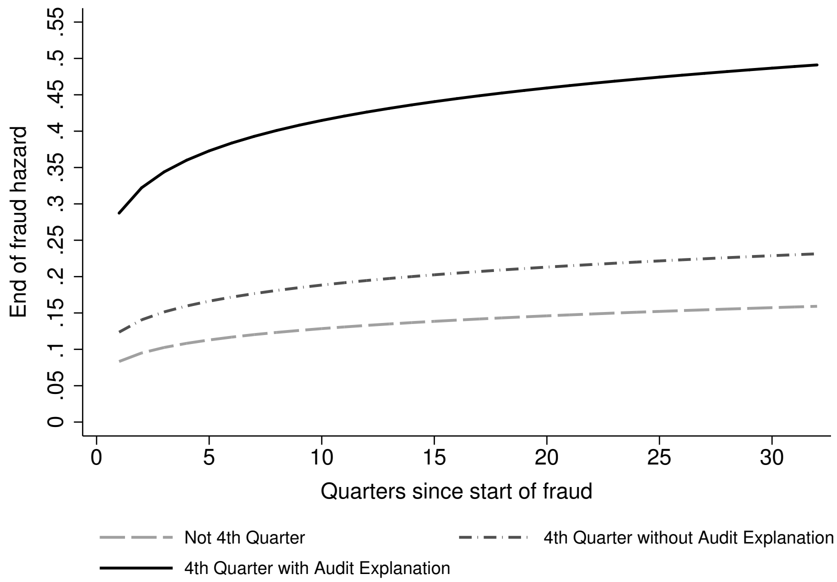

Figure 2A. Fourth fiscal quarter and end of misconduct hazards. The figure shows the estimated hazards of end of fraud as a function of quarters elapsed since the start of the fraud. The hazards are estimated based on the quarter not being the 4th fiscal quarter, being the 4th fiscal quarter without an audit explanation, and being the 4th fiscal quarter with an audit explanation. The hazard estimates are based on column 3 of table 5.

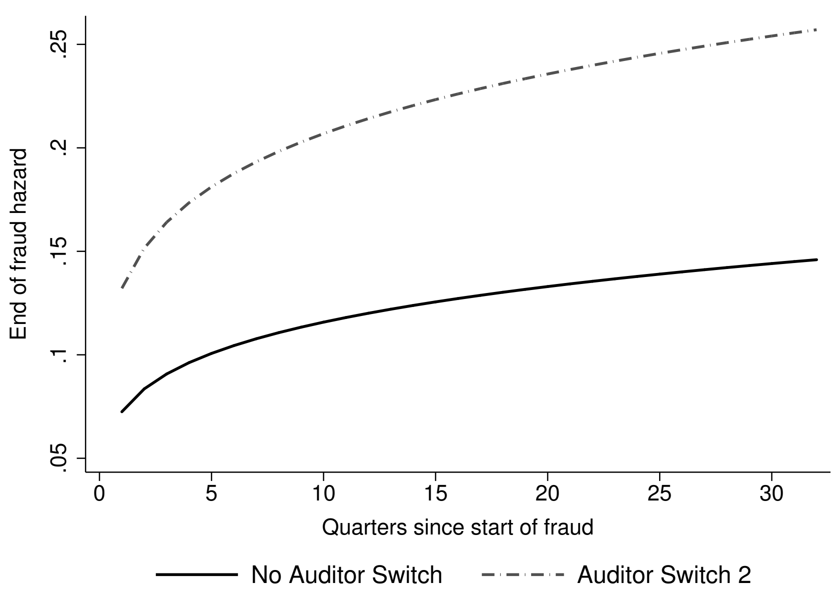

Figure 2B. Auditor Switch and end of misconduct hazards. The figure shows the estimated hazards of end of fraud as a function of quarters elapsed since the start of the fraud. The hazards are estimated based on the quarter being the 4th fiscal quarter, with and without a new auditor evaluating the fiscal year-end financial statements. The hazard estimates are based on column 4 of table 5.

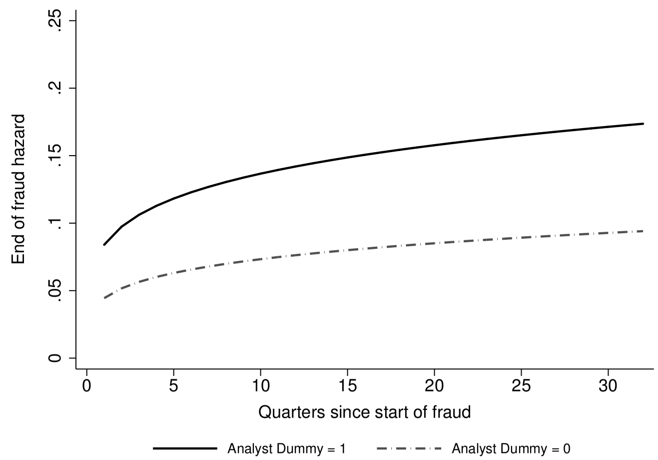

Figure 3A. Analyst Coverage and end of fraud hazards. The figure shows the estimated hazards of end of fraud as a function of quarters elapsed since the start of the misconduct. The hazards are estimated for firms with and without analyst coverage, holding all other variables constant at their median sample values. The hazard estimates are based on column 1 of table 7.

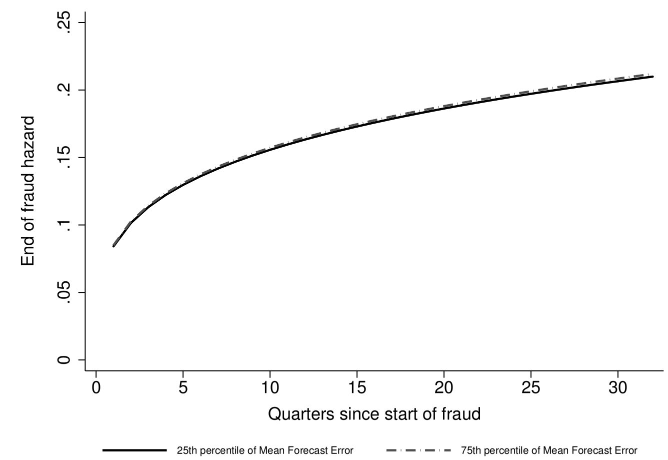

Figure 3B. Mean forecast Error and end of fraud hazards. The figure shows the estimated hazards of end of fraud as a function of quarters elapsed since the start of the fraud. The hazards are estimated at the 25th percentile and 75th percentile sample values for the Analysts' mean forecast error, holding all other variables constant at their median sample values. The hazard estimates are based on column 3 of table 7.

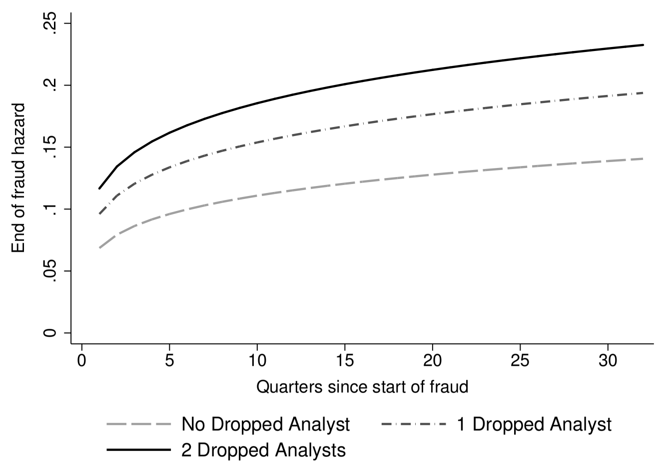

Figure 3C. Dropped Coverage and end of fraud hazards. The figure shows the estimated hazards of end of fraud as a function of quarters elapsed since the start of the fraud. The hazards are estimated considering frauds with no drop in coverage, 1 analyst dropped, and 2 analysts dropped, holding all other variables constant at their median sample values. The hazard estimates are based on column 3 of table 8.

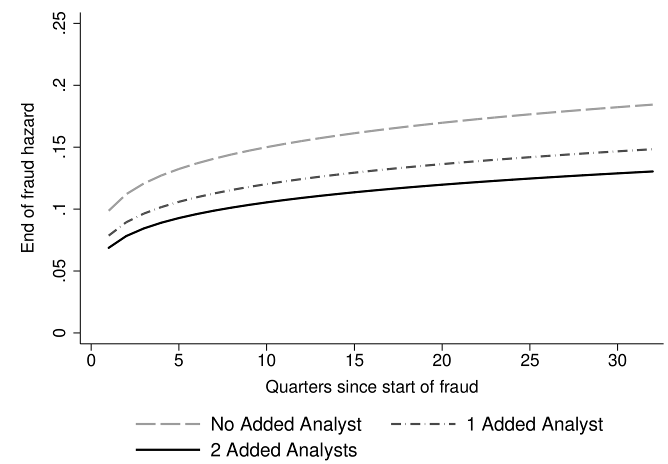

Figure 3D. Added Coverage and end of fraud hazards. The figure shows the estimated hazards of end of fraud as a function of quarters elapsed since the start of the fraud. The hazards are estimated considering frauds with no added coverage, 1 analyst added, and 2 analysts added, holding all other variables constant at their median sample values . The hazard estimates are based on column 5 of table 8.

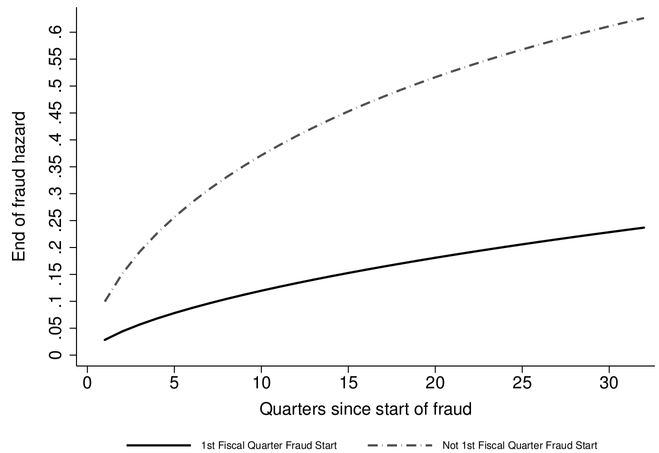

Figure 4A. First fiscal quarter fraud start and end of fraud hazards. The figure shows the estimated hazards of end of fraud as a function of quarters elapsed since start of the fraud. The hazards are estimated for firms that started their fraud in the first fiscal quarter and firms that started their fraud any other fiscal quarter, holding all other variables constant at their median sample values. The hazard estimates are based on column 3 of table 9.

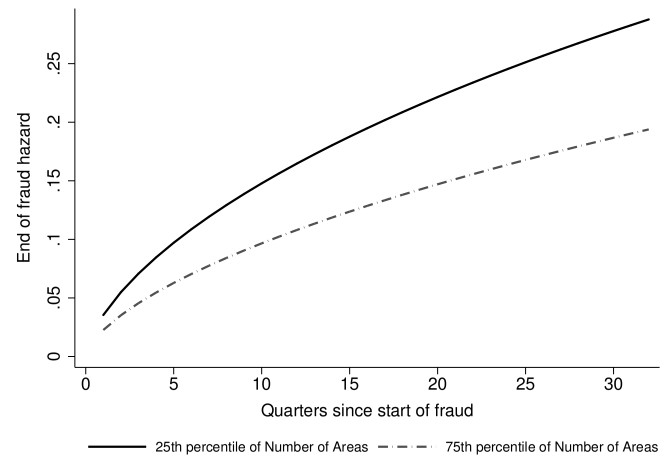

Figure 4B. Number of affected accounting areas and end of fraud hazards. The figure shows the estimated hazards of end of fraud as a function of quarters elapsed since the start of the fraud. The hazards are estimated at the 25th percentile and 75th percentile sample values of affected accounting areas (one and three areas, respectively), holding all other variables constant at their median sample values. The hazard estimates are based on column 3 of table 9.

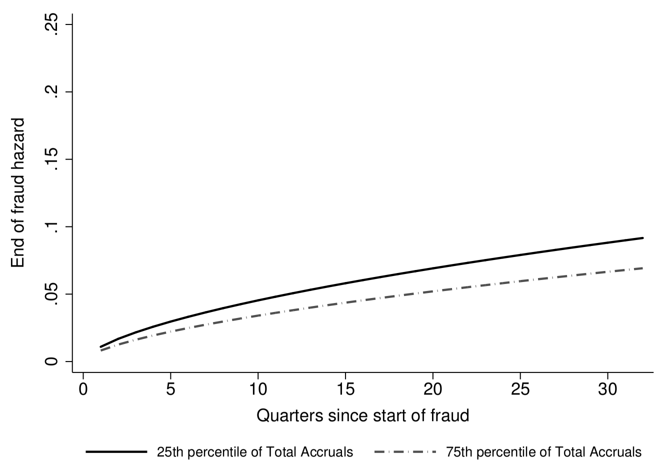

Figure 4C. Total accruals and end of fraud hazards. The figure shows the estimated hazards of end of fraud as a function of quarters elapsed since the start of the fraud. The hazards are estimated at the 25th percentile and 75th percentile sample values of total accruals, holding all other variables constant at their median sample values. The hazard estimates are based on column 4 of table 6.

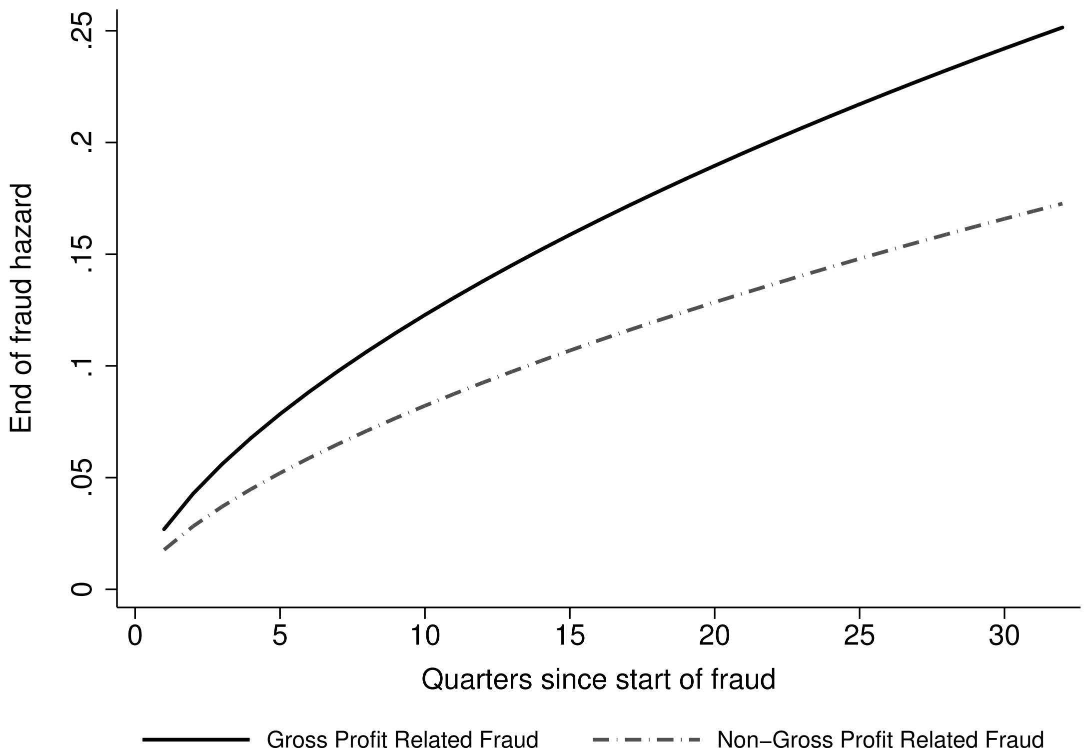

Figure 5. gross profit related fraud and end of misconduct hazards. The figure shows the estimated hazards of end of fraud as a function of whether the accounting misstatement is directly related to gross profit or not. The hazards are estimated for firms that had an earnings related misstatement (Gross Profit Related=1) as well as for firms that did not (Gross Profit Related=0), holding all other variables constant at their median sample values. The hazard estimates are based on column 1 of table 7.

TABLE 1

AAER Sample Selection

Description	AAER Firms	AAERs
Total Sample from Dechow *et al.* [2011] Quarterly Database	706	926
Drop AAERs without start and end dates, AAERs that sued more than 1 company, AAERs where the reason is unclear & companies with multiple AAERs	(177)	(397)
Drop Banks and Financial institutions (SIC 6000-6999) and missing industry information	(98)	(98)
Drop option backdating AAERs	(14)	(14)
Drop case dismissed by court	(1)	(1)
Drop AAERs that start prior to 1982 or after 2006	(12)	(12)
Drop firms with missing stock price data in CRSP or missing financial statement data in Compustat Quarterly	(96)	(96)
Drop AAERs that are not violations of the 13(b) provisions of the 1934 Securities Exchange Act and Code of Federal Regulations	(18)	(18)
Drop AAERs that are not violation of either the Section 17(a) of the 1933 Securities Act or Section 10(b) of the 1934 Securities Exchange Act	(97)	(97)
Sample for initial regressions	**191**	**191**

TABLE 2

Characteristics of AAER Sample

The table reports key characteristics of a sample of 191 SEC AAERs over the 1982 to 2010 period. Panel A shows how frequently different areas of the financial statements are affected by the misconduct in the AAERs. Panel B shows the distribution of the sample AAERs across time, both in terms of time of origination as well as termination. Finally, Panel C shows the cumulative frequency distribution of the sample AAERs in terms of misconduct duration (in quarters).

Panel A: Misconduct by area

Type of Misconduct	Fraction
Revenue	73.30%
Cost of goods sold (cogs)	13.61%
Gross earnings-related (revenue or cogs)	76.96%
Other expense/shareholder equity account	29.32%
Accounts receivable	27.23%
Inventory	19.37%
Capitalized costs as assets	15.18%
Reserve Account	7.85%
Liabilities	7.85%
Payables	3.66%
Allowance for bad debt	3.14%
Marketable Securities	0.52%

TABLE 2 - *Continued*

Characteristics of AAER Sample

Panel B: Frequency and duration of misconduct by start and end years

	Start year of misconduct		End year of misconduct	
Year	**Frequency**	**Avg. Duration** (in quarters)	**Frequency**	**Avg. Duration** (in quarters)
1982	4	6.5	1	2.0
1983	3	7.0	1	5.0
1984	3	7.0	4	4.8
1985	7	5.6	6	5.3
1986	4	7.2	3	4.7
1987	6	3.2	5	4.8
1988	1	13.0	6	7.7
1989	4	2.0	4	4.0
1990	7	4.3	4	2.5
1991	8	5.5	6	6.2
1992	9	6.9	9	5.3
1993	9	3.6	9	3.6
1994	4	6.8	6	4.8
1995	1	4.0	2	7.0
1996	7	8.6	4	7.0
1997	9	11.2	4	8.5
1998	14	8.4	7	4.0
1999	21	8.8	12	5.2
2000	24	8.5	19	6.2
2001	22	7.7	20	6.3
2002	8	13.1	17	8.7
2003	7	4.7	13	9.9
2004	5	14.0	9	15.3
2005	2	3.5	9	12.3
2006	2	6.5	3	10.0
2007			5	18.2
2008			1	24.0
2009			1	21.0
2010			1	23.0
Total	**191**	**7.5**	**191**	**7.5**

TABLE 2 - *Continued*

Characteristics of AAER Sample

Panel C: Cumulative Frequency for Misconduct Duration

Misconduct Duration (in quarters)	Freq.	Percent	Cum.
1	25	13.09	13.09
2	17	8.90	21.99
3	13	6.81	28.80
4	20	10.47	39.27
5	11	5.76	45.03
6	19	9.95	54.97
7	14	7.33	62.30
8	17	8.90	71.20
9	4	2.09	73.30
10	3	1.57	74.87
11	6	3.14	78.01
12	11	5.76	83.77
13	4	2.09	85.86
15	4	2.09	87.96
16	3	1.57	89.53
19	6	3.14	92.67
20	5	2.62	95.29
21	2	1.05	96.34
22	1	0.52	96.86
23	1	0.52	97.38
24	3	1.57	98.95
30	1	0.52	99.48
31	1	0.52	100.00

TABLE 3

Descriptive Statistics

Variable	Fraud's First Quarter				Fraud's Last Quarter				
	Mean	**Median**	**Std. Dev.**	**N**	**Mean**	**Median**	**Std. Dev.**	**N**	**Diff. means**
log(Total Assets)	5.10	4.70	2.31	191	5.39	4.95	2.29	191	-0.341
RoE	-0.33	0.03	1.34	191	-0.58	-0.04	1.68	191	0.292
Market-to-Book	3.26	2.16	3.00	191	2.54	1.65	2.52	191	0.839**
Leverage	0.23	0.19	0.22	191	0.25	0.21	0.21	191	-0.0197
Soft Assets	0.65	0.68	0.22	191	0.66	0.70	0.21	191	-0.0193
Abnormal Stock Return	0.07	0.01	0.40	191	-0.07	-0.09	0.32	191	0.160***
CRSP Value-Weighted Index	0.03	0.04	0.09	191	0.01	0.02	0.09	191	0.0198*
4^{th} Quarter	0.16	0.00	0.37	191	0.38	0.00	0.49	191	-0.253***
Analyst Indicator	0.67	1.00	0.47	191	0.74	1.00	0.44	191	-0.0802
No. of Analysts	7.22	4.00	9.22	191	7.09	4.00	8.98	191	0.151
Total Accruals	-0.05	-0.03	0.20	161	-0.16	-0.10	0.24	153	0.128***
1^{st} Quarter Start	0.57	1.00	0.50	191	-	-	-		
log(Number of Fraud Areas)	0.55	0.69	0.54	191	-	-	-		
Gross Profit Related	0.77	1.00	0.42	191	-	-	-		

The table reports summary statistics for a sample of 191 SEC AAERs over the 1982 to 2010 period gathered from an updated version of the sample in Dechow *et al.* [2011]. The definitions of all variables are presented in appendix B. Differences of means are used in two-tail t-tests. *, **, and *** represent significance levels at 10, 5, and 1%, respectively.

TABLE 4

Baseline Model

	(1) **End of Fraud**	(2) **End of Fraud**
log(Period)	0.244**	0.230**
	(0.097)	(0.090)
log(Total Assets)		-0.100***
		(0.034)
RoE		-0.125***
		(0.043)
Market-to-Book		-0.020
		(0.038)
Leverage		0.761**
		(0.358)
Soft Assets		-0.227
		(0.397)
Abnormal Stock Return		-0.796***
		(0.256)
CRSP Value-Weighted Index		-0.766
		(0.783)
Constant	-2.068***	-1.786***
	(0.186)	(0.396)
Industry Dummies	NO	YES
Time Period Dummies	NO	YES
N	1,439	1,439

The table reports the results of implementing a random effects panel complementary log-log regression of the quarterly fraud termination hazard rate using a sample of SEC AAERs over the 1982 to 2010 period. The definitions of all variables are presented in appendix B. Standard errors are reported in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

TABLE 5

The Role of Auditors

	(1) End of Fraud	(2) End of Fraud	(3) End of fraud
4^{th} Quarter	0.787***	0.965***	0.417**
	(0.154)	(0.261)	(0.196)
4^{th} Quarter x Big N		-0.237	
		(0.287)	
4^{th} Quarter x Audit Explanation			0.943***
			(0.250)
log(Period)	0.220**	0.221**	0.199**
	(0.100)	(0.100)	(0.100)
Control Variables	YES	YES	YES
Industry Dummies	YES	YES	YES
Time Period Dummies	YES	YES	YES
N	1,439	1,439	1,439

The table reports the results of implementing a random effects panel complementary log-log regression of the quarterly fraud termination hazard rate using a sample of SEC AAERs over the 1982 to 2010 period. The full set of variables used in column 2 of table 4 is included but not reported. Full estimation results are available from the authors upon request. The definitions of all variables are presented in appendix B. Standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

TABLE 6

The Role of Auditor Switches

	(1) **End of Fraud**	(2) **End of Fraud**	(3) **End of fraud**	(4) **End of fraud**	(5) **End of fraud**	(6) **End of fraud**
Auditor Switch 1	0.422*			0.419		
	(0.233)			(0.305)		
Auditor Switch 2		0.633**			0.730**	
		(0.277)			(0.347)	
Auditor Switch 3			2.018***			1.889***
			(0.584)			(0.658)
4^{th} Quarter x Auditor Switch 1				0.008		
				(0.465)		
4^{th} Quarter x Auditor Switch 2					-0.236	
					(0.537)	
4^{th} Quarter x Auditor Switch 3						0.769
						(1.530)
4^{th} Quarter x Audit Explanation	0.902***	0.892***	0.937***	0.902***	0.895***	0.952***
	(0.257)	(0.257)	(0.258)	(0.258)	(0.257)	(0.260)
4^{th} Quarter	0.432**	0.430**	0.442**	0.431**	0.451**	0.429**
	(0.201)	(0.201)	(0.201)	(0.208)	(0.206)	(0.203)
log(Period)	0.208**	0.214**	0.210**	0.208**	0.215**	0.211**
	(0.104)	(0.104)	(0.103)	(0.104)	(0.104)	(0.103)
Control Variables	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES
Time Period Dummies	YES	YES	YES	YES	YES	YES
N	1,370	1,370	1,370	1,370	1,370	1,370

The table reports the results of implementing a random effects panel complementary log-log regression of the quarterly fraud termination hazard rate using a sample of SEC AAERs over the 1982 to 2010 period. The full set of variables used in column 2 of table 4 is included but not reported. Full estimation results are available from the authors upon request. The definitions of all variables are presented in appendix B. Standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

TABLE 7

The Role of Analysts

	(1)	(2)	(3)
	End of Fraud	**End of Fraud**	**End of Fraud**
Analyst Indicator	0.643**		
	(0.250)		
Analysts $1^{st.}$ Quintile		0.519**	0.401
		(0.241)	(0.248)
Analysts $2^{nd.}$ Quintile		-0.370	-0.424
		(0.287)	(0.286)
Analysts $3^{rd.}$ Quintile		-0.176	-0.228
		(0.341)	(0.341)
Analysts $4^{th.}$ Quintile		-0.574	-0.625*
		(0.375)	(0.374)
Analysts $5^{th.}$ Quintile		-0.991**	-1.074**
		(0.457)	(0.454)
Mean Forecast Error			5.964**
			(2.394)
4^{th} Quarter	0.412**	0.395**	0.369*
	(0.201)	(0.201)	(0.202)
4^{th} Quarter x Audit Explanation	0.867***	0.958***	1.002***
	(0.259)	(0.261)	(0.261)
Auditor Switch 2	0.587**	0.637**	0.663**
	(0.279)	(0.280)	(0.280)
log(Period)	0.242**	0.301***	0.307***
	(0.106)	(0.111)	(0.110)
Control Variables	YES	YES	YES
Industry Dummies	YES	YES	YES
Time Period Dummies	YES	YES	YES
N	1,370	1,370	1,368

The table reports the results of implementing a random effects panel complementary log-log regression of the quarterly fraud termination hazard rate using a sample of SEC AAERs over the 1982 to 2010 period. The full set of variables used in column 2 of table 4 is included but not reported. Full estimation results are available from the authors upon request. The definitions of all variables are presented in appendix B. Standard errors are reported in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

TABLE 8

The Role of Analysts

	(1)	(2)	(3)	(4)	(5)	(6)
	End of Fraud	**End of Fraud**	**End of Fraud**	**End of Fraud**	**End of Fraud**	**End of Fraud**
Analyst Indicator	0.643**	0.584**	0.578**	0.837***	0.748***	0.610**
	(0.250)	(0.252)	(0.252)	(0.261)	(0.255)	(0.261)
Analyst Departure Indicator		0.409**				
		(0.189)				
log(1+No. of departured analysts)			0.518***			0.473***
			(0.142)			(0.171)
Analyst Addition Indicator				-0.492***		
				(0.183)		
log(1+No. of added analysts)					-0.346**	-0.087
					(0.156)	(0.182)
4^{th} Quarter	0.412**	0.455**	0.489**	0.464**	0.462**	0.494**
	(0.201)	(0.202)	(0.203)	(0.202)	(0.202)	(0.203)
4^{th} Quarter x Audit Explanation	0.867***	0.851***	0.837***	0.881***	0.870***	0.840***
	(0.259)	(0.259)	(0.259)	(0.259)	(0.259)	(0.259)
Auditor Switch 2	0.587**	0.615**	0.661**	0.615**	0.627**	0.666**
	(0.279)	(0.280)	(0.281)	(0.280)	(0.280)	(0.281)
log(Period)	0.242**	0.241**	0.237**	0.215**	0.214**	0.230**
	(0.106)	(0.105)	(0.104)	(0.106)	(0.106)	(0.104)
Control Variables	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES
Time Period Dummies	YES	YES	YES	YES	YES	YES
N	1,370	1,370	1,370	1,370	1,370	1,370

The table reports the results of implementing a random effects panel complementary log-log regression of the quarterly fraud termination hazard rate using a sample of SEC AAERs over the 1982 to 2010 period. The full set of variables used in column 2 of table 4 is included but not reported. Full estimation results are available from the authors upon request. The definitions of all variables are presented in appendix B. Standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

TABLE 9

The Role of Managerial Effort

	(1)	(2)	(3)	(4)
	End of Fraud	**End of Fraud**	**End of Fraud**	**End of Fraud**
1^{st} Quarter Start	-1.351***		-1.273***	-1.318***
	(0.194)		(0.198)	(0.228)
log(Number of Areas)		-0.525***	-0.305*	-0.133
		(0.167)	(0.168)	(0.187)
Total Accruals				-2.488***
				(0.507)
4^{th} Quarter	0.286	0.390*	0.284	0.522**
	(0.203)	(0.201)	(0.203)	(0.229)
4^{th} Quarter x Audit Explanation	1.064***	0.959***	1.053***	1.265***
	(0.263)	(0.259)	(0.262)	(0.285)
Analysts $1^{st.}$ Quintile	0.556**	0.405*	0.526**	1.080***
	(0.243)	(0.238)	(0.241)	(0.302)
Analysts $2^{nd.}$ Quintile	-0.268	-0.440	-0.306	0.532
	(0.282)	(0.283)	(0.282)	(0.341)
Analysts $3^{rd.}$ Quintile	-0.186	-0.306	-0.253	0.415
	(0.330)	(0.336)	(0.330)	(0.382)
Analysts $4^{th.}$ Quintile	-0.317	-0.658*	-0.359	0.570
	(0.365)	(0.365)	(0.362)	(0.411)
Analysts $5^{th.}$ Quintile	-0.778*	-1.137**	-0.876**	0.133
	(0.434)	(0.454)	(0.437)	(0.488)
Auditor Switch 2	0.488*	0.563**	0.436	0.636*
	(0.282)	(0.280)	(0.284)	(0.328)
log(Period)	0.640***	0.365***	0.661***	0.642***
	(0.128)	(0.112)	(0.128)	(0.142)
Control Variables	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES
Time Period Dummies	YES	YES	YES	YES
N	1,370	1,370	1,370	1,243

The table reports the results of implementing a random effects panel complementary log-log regression of the quarterly fraud termination hazard rate using a sample of SEC AAERs over the 1982 to 2010 period. The full set of variables used in column 2 of table 4 is included but not reported. Full estimation results are available from the authors upon request. The definitions of all variables are presented in appendix B. Standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

TABLE 10

Frauds Affecting Gross Profit

	(1)	(2)
	End of Fraud	**End of Fraud**
Gross Profit Related	0.424**	0.534**
	(0.210)	(0.244)
1^{st} Quarter Start	-1.300***	-1.337***
	(0.200)	(0.230)
log(Number of Areas)	-0.359**	-0.230
	(0.168)	(0.191)
Total Accruals		-2.539***
		(0.509)
4^{th} Quarter	0.293	0.524**
	(0.203)	(0.230)
4^{th} Quarter x Audit Explanation	1.023***	1.254***
	(0.264)	(0.287)
Auditor Switch 2	0.345	0.523
	(0.287)	(0.332)
Analysts $1^{st.}$ Quintile	0.592**	1.084***
	(0.244)	(0.303)
Analysts $2^{nd.}$ Quintile	-0.360	0.422
	(0.283)	(0.341)
Analysts $3^{rd.}$ Quintile	-0.295	0.301
	(0.329)	(0.382)
Analysts $4^{th.}$ Quintile	-0.341	0.528
	(0.359)	(0.404)
Analysts $5^{th.}$ Quintile	-0.856**	0.088
	(0.435)	(0.481)
log(Period)	0.682***	0.661***
	(0.129)	(0.143)
Control Variables	YES	YES
Industry Dummies	YES	YES
Time Period Dummies	YES	YES
N	1,370	1,243

The table reports the results of implementing a random effects panel complementary log-log regression of the quarterly fraud termination hazard rate using a sample of SEC AAERs over the 1982 to 2010 period. The full set of variables used in column 2 of table 4 is included but not reported. Full estimation results are available from the authors upon request. The definitions of all variables are presented in appendix B. Standard errors are reported in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

TABLE 11

Institutional Blockholders

	(1) **End of Fraud**	(2) **End of Fraud**	(3) **End of Fraud**
Blockholder Indicator	0.045		
	(0.207)		
Fraction Ownership by All Blockholders		0.024	
		(0.748)	
Fraction Ownership by Largest Blockholder			1.162
			(2.138)
1^{st} Quarter Start	-1.298***	-1.300***	-1.296***
	(0.200)	(0.200)	(0.200)
log(Number of Areas)	-0.358**	-0.359**	-0.361**
	(0.168)	(0.168)	(0.168)
4^{th} Quarter	0.292	0.293	0.286
	(0.203)	(0.203)	(0.203)
4^{th} Quarter x Audit Explanation	1.023***	1.023***	1.034***
	(0.264)	(0.264)	(0.265)
Auditor Switch 2	0.337	0.344	0.331
	(0.290)	(0.289)	(0.289)
Analysts $1^{st.}$ Quintile	0.572**	0.590**	0.540**
	(0.260)	(0.251)	(0.262)
Analysts $2^{nd.}$ Quintile	-0.379	-0.363	-0.417
	(0.296)	(0.295)	(0.302)
Analysts $3^{rd.}$ Quintile	-0.316	-0.298	-0.358
	(0.343)	(0.341)	(0.350)
Analysts $4^{th.}$ Quintile	-0.356	-0.342	-0.384
	(0.366)	(0.362)	(0.368)
Analysts $5^{th.}$ Quintile	-0.864**	-0.856**	-0.870**
	(0.437)	(0.435)	(0.436)
Gross Profit Related	0.422**	0.424**	0.418**
	(0.210)	(0.210)	(0.210)
log(Period)	0.682***	0.682***	0.681***
	(0.129)	(0.129)	(0.129)
Control Variables	YES	YES	YES
Industry Dummies	YES	YES	YES
Time Period Dummies	YES	YES	YES
N	1,370	1,370	1,370

The table reports the results of implementing a random effects panel complementary log-log regression of the quarterly fraud termination hazard rate using a sample of SEC AAERs over the 1982 to 2010 period. The full set of variables used in column 2 of table 4 is included but not reported. Full estimation results are available from the authors upon request. The definitions of all variables are presented in appendix B. Standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Internet Appendix to

"Information Production, Misconduct Effort, and the Duration of Financial Misrepresentation"

Appendix I.A: Proofs

Proof of Lemma 1: If $\mathscr{H}_t \in \mathscr{H}_t(B)$, we have that $\Pr(M|\mathscr{H}_t) = 1$. But then, it is not optimal to wait to intervene in the company, since $\delta < 1$ and $\mathscr{H}_{t+1} \in \mathscr{H}_t(B)$. □

Proof of Proposition 1: If $\xi P < \mathscr{C}$, we have that at $\mathscr{H}_\emptyset = \emptyset$ it's optimal to wait for a signal instead of immediately intervening to the firm. But then at $t = 1$, if monitors observe a bad signal, as seen in *Corollary 1*, they should intervene to the firm, since $\Pr(M|\mathscr{H}_1) = 1$. On the other hand, if $s_1 = G$, then $\Pr(M|\mathscr{H}_1) = \frac{(1-p)\xi}{(1-\xi)+(1-p)\xi} < \xi$. More generally, we have that, $\forall \mathscr{H}_t \notin \mathscr{H}_t(B), \Pr(M|\mathscr{H}_t) = \frac{(1-p)^t\xi}{(1-\xi)+(1-p)^t\xi} < \xi$. Therefore, $\Pr(M|\mathscr{H}_t)P - \mathscr{C} < 0$, $\forall \mathscr{H}_t \notin \mathscr{H}_t(B)$. Since $\delta E_t[V(\mathscr{H}_{t+1}) \geq 0$, it is not optimal to intervene until a bad signal is observed. □

Proof of Proposition 2:

$$\begin{aligned} E[N] &= \textstyle\sum_{n=1}^{\infty} np(1-p)^{n-1} = p\sum_{n=1}^{\infty} \frac{d}{d(1-p)}(1-p)^n \\ &= p\frac{d}{d(1-p)}\textstyle\sum_{n=1}^{\infty}(1-p)^n = p\frac{d}{d(1-p)}\left[\frac{1-p}{1-(1-p)}\right] = \frac{1}{p}. \end{aligned} \tag{I.A.1}$$

□

Proof of Proposition 3: Consider that the current number of information providers is $\mathbf{I}$. Then, the probability of a bad signal for a manipulator is

$$\Pr(B|M) = 1 - \prod_{i=1}^{\mathbf{I}}(1-p_i). \tag{I.A.2}$$

Now let's introduce an additional information provider, then, the probability of a bad signal becomes:

$$\Pr(B|M) = 1 - \prod_{i=1}^{\mathbf{I+1}}(1-p_i). \tag{I.A.3}$$

Therefore, the likelihood of a bad signal increases by:

$$1-(1-p_{\mathbf{I+1}})=p_{\mathbf{I+1}}. \tag{I.A.4}$$

Therefore, the better the new information producer, the higher the likelihood of a bad signal for a manipulator.

Similarly, the new expected duration of a fraud is given by

$$E[N]=\frac{1}{1-\prod_{i\in\mathscr{I}+1}(1-p_i)}. \tag{I.A.5}$$

While the expected length of a fraud has been reduced by

$$\begin{aligned}&\tfrac{1}{1-\prod_{i\in\mathscr{I}+1}(1-p_i)}-\tfrac{1}{1-\prod_{i\in\mathscr{I}}(1-p_i)}=\\&=\tfrac{[1-\prod_{i\in\mathscr{I}}(1-p_i)]-[1-\prod_{i\in\mathscr{I}+1}(1-p_i)]}{[1-\prod_{i\in\mathscr{I}+1}(1-p_i)]\times[1-\prod_{i\in\mathscr{I}}(1-p_i)]}\\&=\tfrac{-p_{\mathbf{I+1}}\prod_{i\in\mathscr{I}}(1-p_i)}{[1-\prod_{i\in\mathscr{I}+1}(1-p_i)]\times[1-\prod_{i\in\mathscr{I}}(1-p_i)]}.\end{aligned} \tag{I.A.6}$$

As before, the better the new information provider spotting a fraud, the shorter the expected length of the fraud. □

Proof of Proposition 4: We initially present the proofs for items 1 and 3.

Proof of 1. and 3.:

The optimal decision of starting/continuing a fraud at period $t\in\{1,2,...\}$ is given by:

$$\Pi(\mathscr{B},t)=\max\{0+\delta\Pi(\mathscr{B},t),(1-p(t))[\mathscr{B}+\delta\Pi(\mathscr{B},t+1)]+p(t)(-L)\}. \tag{I.A.7}$$

If $0+\delta\Pi(\mathscr{B},t)>(1-p(t))[\mathscr{B}+\delta\Pi(\mathscr{B},t+1)]+p(t)(-L)$, then, we have that:

$$\Pi(\mathscr{B},t)=0+\delta\Pi(\mathscr{B},t). \tag{I.A.8}$$

Rearranging it, we have:

$$\Pi(\mathscr{B},t)=\frac{0}{1-\delta}=0. \tag{I.A.9}$$

Therefore, $\Pi(\mathscr{B},t)>0$ implies that the fraud is started or continued. Consequently:

$$(1-p(t))[\mathscr{B}+\delta\Pi(\mathscr{B},t+1)]+p(t)(-L)>0. \tag{I.A.10}$$

Rearranging it, we have:

$$(1-p(t))\mathscr{B}+p(t)(-L) > -\delta\Pi(\mathscr{B},t+1). \tag{I.A.11}$$

By definition $\Pi(\mathscr{B},t+1)\geq 0$. If $\Pi(\mathscr{B},t+1)=0$, the above expression becomes $(1-p(t))\mathscr{B}+p(t)(-L) > 0$, which concludes the proof. On the other hand, imagine that $(1-p(t))\mathscr{B}+p(t)(-L)<0$ but $(1-p(t))\mathscr{B}+p(t)(-L) > -\delta\Pi(\mathscr{B},t+1)$. Notice that $\Pi(\mathscr{B},t+1)$ is given by

$$\Pi(\mathscr{B},t+1)=\left\{\begin{array}{c} (1-p(t+1))\mathscr{B}+p(t+1)(-L)+ \\ +\sum_{j=1}^{T-t-1}[(1-p(t+1+j))\mathscr{B}+p(t+1+j)(-L)]\delta^j\prod_{i=0}^{j-1}(1-p(t+1+i)) \end{array}\right\}. \tag{I.A.12}$$

where T is the optimal time to stop the fraud (if there is no optimal time to stop the fraud, then we can take $T\to\infty$ without changing the argument).

Since $p(.)$ is strictly increasing in its argument, we would have that $\Pi(\mathscr{B},t+1)<0$, since all its arguments would be negative. As a result, we have a contradiction.

Once we have this result, it is easy to see that as t increases $(1-p(t))\mathscr{B}+p(t)(-L)$ decreases and eventually crosses the zero threshold.

Proof of 2.:

Now we have $p(t)\equiv p$. In this case the problem becomes stationary. Then $\Pi(\mathscr{B},t)\equiv\Pi(\mathscr{B})$

$$\Pi(\mathscr{B})=\max\{0+\delta\Pi(\mathscr{B}),(1-p)[\mathscr{B}+\delta\Pi(\mathscr{B})]+p(-L)\}. \tag{I.A.13}$$

in which we assume that if the fraud is discontinued, the firm still have the right to continue with the fraud next period, but the duration of the fraud is considered frozen at period t. As we will see, our result is independent of this particular assumption.

So, if the first term in the max operator is the highest, we can easily see that $\Pi(\mathscr{B})=0$. Similarly, if starting the fraud is optimal, we have that $\Pi(\mathscr{B})=\frac{(1-p)\mathscr{B}+p(-L)}{1-\delta}$ which is positive if $1-p)\mathscr{B}+p(-L)>0$. But once the problem is stationary, the value of continuing the fraud the next period is still the same, so it will be optimal to continue the fraud. So the fraud will continue until the firm is caught. □

Proof of Proposition 5: Both items are proved applying implicit function theorem (IFT) to FOC. For item 1., we have:

$$\frac{\partial e^*(t,\mathscr{B})}{\partial\mathscr{B}}=\frac{-\frac{\partial p(t,e_M)}{\partial e_M}}{\frac{\partial^2 p(t,e_M)}{\partial e_M^2}+C''(e_M)}>0. \tag{I.A.14}$$

While, for item 2, applying IFT we have:

$$\frac{\partial e^*(t,\mathscr{B})}{\partial t} = \frac{-\frac{\partial^2 p(t,e_M)}{\partial e_M \partial t}(\mathscr{B}+L)}{\frac{\partial^2 p(t,e_M)}{\partial e_M^2}(\mathscr{B}+L)+C''(e_M)}. \tag{I.A.15}$$

Therefore, the sign of $\frac{\partial e^*(t,\mathscr{B})}{\partial t}$ depends on $\frac{\partial^2 p(t,e_M)}{\partial e_M \partial t}$, i.e., if $\frac{\partial^2 p(t,e_M)}{\partial e_M \partial t} > 0$ we must have $\frac{\partial e^*(t,\mathscr{B})}{\partial t} < 0$. Similarly, if $\frac{\partial^2 p(t,e_M)}{\partial e_M \partial t} < 0$ we must have $\frac{\partial e^*(t,\mathscr{B})}{\partial t} > 0$. □

Example of time-varying hazard function

Assume that the probability of a bad signal for a manipulator that has an ongoing fraud for t periods is given by:

$$p(t) = 1 - \frac{\alpha}{t}. \tag{I.A.16}$$

Naturally

$$\frac{\partial p(t)}{\partial \alpha} = -\frac{1}{t} < 0 \quad \text{and} \quad \frac{\partial^2 p(t)}{\partial \alpha \partial t} = \frac{1}{t^2} > 0. \tag{I.A.17}$$

The figure below presents a couple of examples for $p(t)$ as we vary α

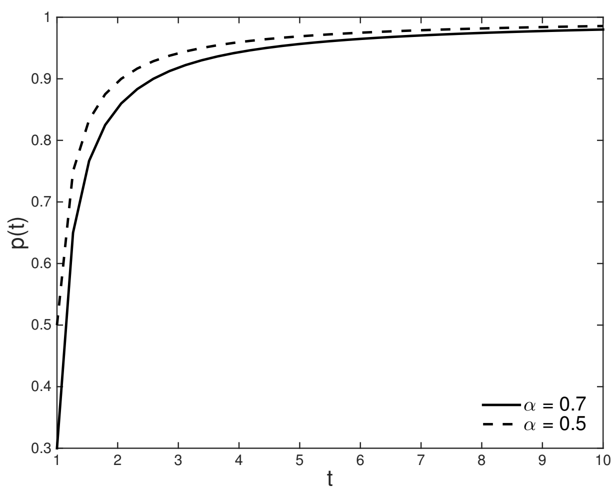

Figure I.A.1. Probability of a Bad Signal for a Manipulator

Notice also that $(1-p(t)) = \frac{\alpha}{t}$. In this case, the expected duration of the fraud is given by

$$E[N] = \sum_{t=1}^{\infty} t\left(1-\frac{\alpha}{t}\right)\prod_{t'=1}^{t-1}\frac{\alpha}{t'}. \tag{I.A.18}$$

Rearranging it, we have:

$$E[N] = \sum_{t=0}^{\infty}(t+1)\frac{\alpha^t}{t!} - \alpha\sum_{t=0}^{\infty}\frac{\alpha^t}{t!}. \tag{I.A.19}$$

Solving it, we obtain:

$$E[N] = (1+\alpha)e^{\alpha} - \alpha e^{\alpha} = e^{\alpha}. \tag{I.A.20}$$

Therefore, the higher α, the longer the duration of the fraud.

Moreover, even though we imagine that the probability of being detected has an upward trend, the actual probability may vary around the trend. In particular, we may expect that market and firm time-varying characteristics may affect the detection probability, pushing it above or below the long-term trend. For example, good or bad performance in the stock market may increase or decrease incentives to scrutiny, making it easier or harder for information producers to detect signs of manipulation. A similar argument can be made about the firm's own operational and stock market performance. Back to the example presented above, we would have that the graph for $p(t)$ over time would look more like the one in the figure below:

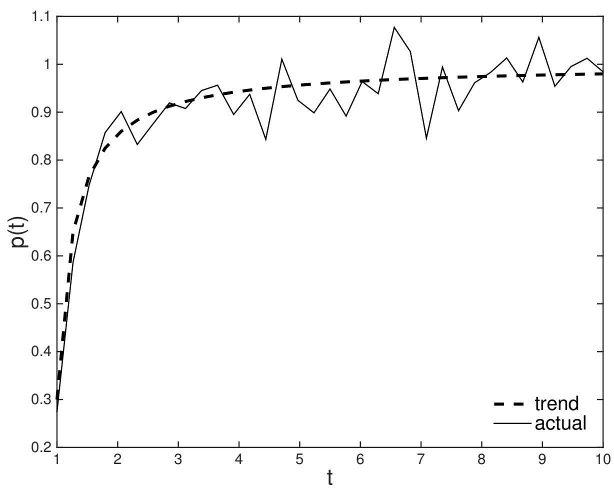

Figure I.A.2. Evolution of $p(t)$: Trend vs. Actual

Appendix I.B: Brief Description of Hazard Model

In this section, we provide a more detailed review of the econometric methodology we use to estimate the determinants of the duration of an accounting misconduct spell. However, before proceeding, it should be pointed out that the literature on duration analysis is quite extensive and that, for this reason, we do not mean to be exhaustive on the subject. Instead, our purpose is to define the basic concepts and to provide the intuition as well as justification for the discrete time duration methods we employ in this paper.[1]

To begin, we note that although time evolves continuously, duration data, notably in social sciences, is often grouped in time intervals: $[t_0,t_1],(t_1,t_2],...,(t_{K-1},t_K]$. For ease of exposition, let's assume that all intervals are of equal length and, whenever there is no ambiguity, refer to period $(t_{j-1},t_j]$ simply as period j. In our particular case, the data is recorded at a quarterly frequency and each period j thus represents a three-month interval.

Duration data may be generated in a number of different ways. In our case, data is derived from outflow sampling as we trace back accounting misconduct events from the moment they ended. Thus, we observe the whole misconduct spells. This fact is important, because it implies that we are free of censoring concerns, which are otherwise very prevalent in survival analysis. Hence, since our data is not censored and we aim for concision, we ignore censoring issues in this section.

Let $T>0$ be the time spent in a certain initial state. In our case, T is the time that a fraud remains active. The probability that a fraud is terminated before or at period j is $F(t_j)$ and the probability that it does not end until period j is $S(t_j)\equiv 1-F(t_j)$, which is referred to as the *survivor function*. The probability that a fraud is ended within period j is $\Pr(t_{j-1}<T\le t_j)=F(t_j)-F(t_{j-1})=S(t_{j-1})-S(t_j)$. The (discrete) *hazard rate*, h_j, which gives the probability of transition from the initial state in period j conditional on having survived up until period $j-1$, is defined as $h_j\equiv \Pr(t_{j-1}<T\le t_j|T>t_{j-1})$. The central purpose of this paper is to estimate the (discrete) hazard rate as a function of j and of a vector of covariates $\mathbf{x}$, $h_j(\mathbf{x})$, while allowing for influence of individual heterogeneity.

It is important to note that, from the series of hazard rates over time periods, it is possible to recover the value of the survivor function at the end of period, $S_j\equiv S(t_j)$. Because the probability of survival until the end of period j is equal to the probability of surviving up until period $j-1$ times the probability of not experiencing a transition out of the initial state in period j conditional on not having failed up until period $j-1$, it follows that:

$$S_j=\prod_{k=1}^{j}(1-h_k). \tag{I.B.1}$$

Equation (I.B.1) naturally suggests a way to estimate the survivor function nonparametrically. Let R_k be the number of observations at risk of failing at period k, i.e. the ones that have not transitioned out of

[1] More thorough discussions on duration analysis can be found in, e.g., Lancaster [2011] and Wooldridge [2010].

the initial state until t_{k-1}. Let M_k be the number of individuals who leave the initial state in period k. A consistent estimator of $\Pr(T > t_k | T > t_{k-1}) = 1 - h_k$ is given by $(R_k - M_k)/R_k$. Therefore, a consistent estimator of the survivor function at t_j is given by:

$$\hat{S}_j = \prod_{k=1}^{j} \frac{R_k - M_k}{R_k}. \tag{I.B.2}$$

This is the Kaplan-Meier estimator. In addition to it there exists a variety of non-parametric estimators in duration analysis. A prominent one is Nelson-Aalen, which is defined as:

$$\hat{H}_j = \sum_{k=1}^{j} \frac{M_k}{R_k}, \tag{I.B.3}$$

which is the sum of empirical hazard rates. Combining equation (I.B.1) with equation (I.B.3), it is possible to estimate the survivor function as $\hat{S}_j = \exp(-\hat{H}_j)$, which is sometimes called the Fleming-Harrington estimator. Although Kaplan-Meier and Nelson-Aalen estimators have different small sample properties, they are asymptotically equivalent. Obtaining a non-parametric characterization of the survivor function is informative first for its own sake as it provides a visual pattern of $S(t_j)$. Moreover, one can compare survival behavior for different categories of a qualitative variable, such as industry, without imposing any distribution for failure time. Lastly, the examination of the non-parametric estimates may prove helpful in imposing constraints on the parametric models.

In order to estimate the latter, first define a binary response variable y_{ij} taking on value one in case cross section unit i is out of the initial state in period j and value zero otherwise. Reorganize data into an unbalanced panel format, so that each cross section observation has as many rows as the number of periods it is in risk of leaving the initial state. Thus, each cross observation consists of a vector of binary responses of length T_i, $\mathbf{y}_i$, and a $(T_i \times Q)$ matrix of covariates, $\mathbf{x}_i$. Since the interest lays on the interval in which $y_{ij} = 1$ for the first time, the model can be expressed in terms of $\Pr(y_{ij} = 1 | y_{ij-s} = 0 \text{ for all } s > 0, \mathbf{x}_i) = \Pr(y_{ij} = 1 | y_{ij-1} = 0, \mathbf{x}_i) = h_j(\mathbf{x}_i)$, where $\mathbf{x}$ may include time-constant as well as time-varying covariates. Once a functional form for $h_j(\mathbf{x}_i)$ is specified, the model is estimated by maximum likelihood.

In the parametric approach, in addition to time-constant and time-varying regressors, the hazard model also includes a description of the duration dependence. For instance, if survival time follows a Weibull distribution, then duration dependence is captured by $\log(j)$ as a new variable to the vector of covariates. In contrast, the Cox Cox [1972] semi-parametric models place no restrictions on duration dependence.

It is possible to incorporate unobserved heterogeneity into duration models. The way this is usually done is by entering the individual idiosyncratic term, $v > 0$, multiplicatively in the hazard function, where it is also often assumed that v is independent of $\mathbf{x}$ and that the distribution of v is known up to a finite number of parameters with mean normalized to one, for identification reasons, and finite variance σ_v^2. Hence, models of this kind are are essentially random effects models in a duration setting. Two popular choices for the distribution of v are gamma and normal. We assume the latter and estimate the cloglog model with unobserved heterogeneity using the **xtcloglog** program in Stata.[2]

[2] See http://www.stata.com/manuals13/xtxtcloglog.pdf for a further description of this program.

Appendix I.C: Robustness Tests

I.C.1: Robustness Test - Outliers

We conduct three robustness tests to confirm that outliers are not driving our results. First, we examine whether there is anything intrinsically different about short frauds that may bias our results by limiting our sample to frauds that last at least three quarters. Second, we check whether our main results are driven by very small or very large firms. We consider a sample trimmed at the 10^{th} and 90^{th} size percentiles, calculated based on the log(Total Assets) at the last quarter before the fraud starts. Finally, we investigate how sensitive our results are to the fraudulent firm's size, by dividing our total sample into two subsamples. One subsample (small firms) comprised of firms that are below the median of log(Total Assets) at the last quarter before the fraud starts, and the other subsample (large firms) with firms above the median. Results are depicted in table 12 following the same specification presented in column 1 of table 10.

Column 1 of table 12 shows that restricting our sample to frauds that last 3 quarters or more do not qualitatively change our results compared to the ones presented for the unrestricted sample in table 10. Likewise, the results for the trimmed sample, presented in column 2, are also quite similar to the ones presented in table 10. There are just a few distinctions. First, the level dummy indicating 4^{th} Quarter is not statistically significant in either columns, while in column 1 of table 10 this coefficient is significant at the 10% level. In any case, the coefficients for the interaction between the 4^{th} Quarter dummy and the presence of explanatory language is still highly significant, corroborating the importance of auditors' oversight. Second, the coefficients for the 4^{th} and 5^{th} quintiles of the analyst distribution are now negative and statistically significant at the 5% level. This is in line with the results presented in columns 4 and 5 in table 8 that added coverage may reduce the fraud termination hazard, as shown theoretically in appendix A.4. Finally, the results for the subsamples of large and small firms, presented in columns 3 and 4 of table 12, respectively, are also fairly consistent with the ones obtained for the overall sample, although statistical significance goes down for many variables, as the sample size decreases significantly.

In summary, the results discussed here show that our findings are robust to removing very short frauds and to differences in initial firm size.

I.C.2: Robustness Test - Extended Sample

Our main analysis focuses on AAERs that involve charges of financial misrepresentation under Section 13(b) of the Exchange Act, and that also involve charges of misconduct related to anti-fraud provisions of the Securities Act or the Exchange Act as suggested in (Karpoff, Koester, Lee, and Martin [2017]). However, the SEC also investigates and brings charges against firms that engage in other forms of misreporting. In this section, we extend our sample to include these additional cases of alleged accounting misrepresentation that trigger the SEC to issue a AAER. Our goal is to evaluate if the results obtained for the anti-fraud provisions violations extend for the larger group of financial misrepresentation observed in the AAERs. Hence, we expand the sample to include all financial misrepresentation that triggered the issuance of an AAER, conditional on having available information on our core controls. Our extended sample includes 299 financial misconduct spells. Results are shown in table 13 following the same specifications as in table 10.

The results in table 13 are qualitatively similar to the ones obtained in our main analysis – recall table 10. The few deviations that we observe are that the effort variable log(Number of Areas) becomes statistically significant at the 10% level in the specification with total accruals and auditor switch becomes significant at the 5% level. Overall, table 13 indicates that the results obtained from the sub-sample of violations of the anti-fraud provisions of the Securities Act can be extended to the sample of overall financial misrepresentation that are the SEC focus. Moreover, even the magnitudes of the coefficients are very similar to the ones obtained in table 10.

TABLE 12

Robustness Tests - Trimmed Samples

	(1)	(2)	(3)	(4)
	End of Fraud	**End of fraud**	**End of Fraud**	**End of fraud**
Gross Profit Related Indicator	0.339	0.415*	0.715**	0.443
	(0.262)	(0.241)	(0.315)	(0.332)
1^{st} Quarter Start	-1.558***	-1.250***	-1.483***	-1.338***
	(0.277)	(0.220)	(0.313)	(0.319)
log(Number of Areas)	-0.534**	-0.474**	-0.310	-0.589**
	(0.220)	(0.186)	(0.252)	(0.267)
4^{th} Quarter	0.228	0.188	0.370	0.197
	(0.262)	(0.226)	(0.271)	(0.324)
4^{th} Quarter x Audit Explanation	1.229***	1.066***	0.773*	1.304***
	(0.318)	(0.304)	(0.413)	(0.383)
Auditor Switch 2	1.042***	0.123	1.022**	-0.446
	(0.356)	(0.315)	(0.401)	(0.598)
Analysts $1^{st.}$ Quintile	0.874***	0.267	-0.255	1.030*
	(0.316)	(0.284)	(0.350)	(0.606)
Analysts $2^{nd.}$ Quintile	-0.541	-0.607*	-0.468	-0.909*
	(0.352)	(0.327)	(0.468)	(0.522)
Analysts $3^{rd.}$ Quintile	-0.419	-0.649*	-1.345	-0.493
	(0.390)	(0.381)	(0.825)	(0.555)
Analysts $4^{th.}$ Quintile	-1.203***	-0.889*		-0.254
	(0.455)	(0.471)		(0.516)
Analysts $5^{th.}$ Quintile	-1.635***	-1.314**		-0.340
	(0.542)	(0.622)		(0.575)
log(Period)	2.050***	0.698***	0.887***	0.987***
	(0.240)	(0.146)	(0.202)	(0.211)
Control Variables	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES
Time Period Dummies	YES	YES	YES	YES
N	1,280	1,056	549	816

The table reports the results of implementing a random effects panel complementary log-log regression of the quarterly fraud termination hazard rate using different subsamples based on our sample of SEC AAERs over the 1982 to 2010 period. Column 1 restricts the sample to the subsample of frauds that last longer than 2 quarters. Column 2 restricts the sample to a trimmed subsample in which we eliminate both firms at the $1^{st.}$ and $9^{th.}$ deciles in terms of log(Total Assets) at the fraud's onset. Finally, columns 3 and 4 restrict the sample to the subsamples of fraudulent firms below and above the median log(Total Assets) at the fraud's onset, respectively. The full set of variables used in column 2 of table 4 is included but not reported. Full estimation results are available from the authors upon request. The definitions of all variables are presented in appendix B. Standard errors are reported in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

TABLE 13

Extended Sample of Financial Misconduct

	(1)	(2)
	End of Fraud	**End of Fraud**
Gross Profit Related Indicator	0.361**	0.382**
	(0.147)	(0.161)
1^{st} Quarter Start	-1.039***	-0.976***
	(0.140)	(0.154)
log(Number of Areas)	-0.251**	-0.229*
	(0.119)	(0.132)
Total Accruals		-1.789***
		(0.368)
4^{th} Quarter	0.257	0.417**
	(0.156)	(0.172)
4^{th} Quarter x Audit Explanation	0.752***	0.881***
	(0.205)	(0.216)
Auditor Switch 2	0.479**	0.581**
	(0.212)	(0.239)
Analysts $1^{st\cdot}$ Quintile	0.478**	0.563***
	(0.187)	(0.204)
Analysts $2^{nd\cdot}$ Quintile	-0.253	-0.010
	(0.224)	(0.240)
Analysts $3^{rd\cdot}$ Quintile	-0.132	-0.047
	(0.272)	(0.283)
Analysts $4^{th\cdot}$ Quintile	-0.128	-0.029
	(0.259)	(0.265)
Analysts $5^{th\cdot}$ Quintile	-0.599*	-0.526*
	(0.309)	(0.316)
log(Period)	0.548***	0.559***
	(0.090)	(0.099)
Control Variables	YES	YES
Industry Dummies	YES	YES
Time Period Dummies	YES	YES
N	2,307	2,141

The table reports the results of implementing a random effects panel complementary log-log regression of the quarterly fraud termination hazard rate using a sample of SEC AAERs over the 1982 to 2010 period. The full set of variables used in column 2 of table 4 is included but not reported. Full estimation results are available from the authors upon request. The definitions of all variables are presented in appendix B. Standard errors are reported in parentheses.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

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