PRODUCT MARKET INTERACTIONS
AND CORPORATE FRAUD

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PRODUCT MARKET INTERACTIONS AND CORPORATE FRAUD

Abstract

We examine three information channels through which product market interactions in an industry can affect firms' incentives to misreport financial information to investors. We find that lower product market sensitivity to individual firm' information and greater use of relative performance evaluation encourage the commission of financial fraud. Less collection of information about individual firms decreases the probability of fraud detection and increases the probability of fraud commission. We also examine dynamic effects of fraud. Our results suggest that, in fragmented industries, fraud can amplify cyclical fluctuations in the real economy.

1. INTRODUCTION

The wave of corporate securities frauds that was discovered early in the last decade boosted interest in understanding what determines firms' incentives to defraud investors. Although much of the research in this area has focused on firm-level determinants, one prominent fact about corporate securities fraud is the importance of industry effects. For example, in the time series, fraud is more likely to occur during industry booms than industry busts.[1] Moreover, in the cross section, the average incidence of fraud varies substantially from one industry to another. Industries such as software and programming and electronics have a persistently higher probability of securities fraud litigation than do industries such as food and textile, and this pattern persists even after controlling for firm characteristics. Nevertheless, little work has been done to understand why such persistent differences exist.

In this regard, product market interactions are a natural candidate for investigation. The economics literature has long argued that the nature of product market interaction is an important force shaping the information environment of an industry and individual firms' disclosure incentives. The way firms interact in the product market affects how an individual firm's information is used by rival firms, which in turn affects each individual firm's disclosure decision. Anecdotal evidence in the business press about frauds at WorldCom and other firms in the telecommunications industry also suggests a link between industry informational interactions and fraud (see Schiesel, 2002).

In this paper we examine three *information* channels through which product market interaction may affect firms' incentives to fraudulently report financial information. The first channel is the product market's sensitivity to information about an individual firm. Gigler (1994) theorizes that when firms compete in both the product market and the capital market, the sensitivity of rival firms' product market behavior to a firm's capital market disclosures can have a disciplining effect on the firm's incentive to commit fraud. Gigler predicts that industries that lack such product market sensitivity have a higher fraud propensity because an individual firm's fraudulent reporting in the capital market has little impact on rival firms' behavior in the product market; by contrast, in industries with high product market sensitivity, each firm knows that reporting strong performance encourages rivals to increase their investment and output, hurting the firm's own product-market position.

[1] For theoretical models of fraud and industry performance, see Povel, Singh, and Winton (2007) and Hertzberg (2005). Wang, Winton, and Yu (2010) study fraud in a sample of IPO firms and find support for these theories.

The second channel through which information about one firm affects other firms is the use of relative performance evaluation (RPE), where managers are evaluated based on their firm's performance relative to that of industry peers. The use of RPE causes feedback between the product market, in which firms compete, and the executive labor market, in which firm managers compete. Cheng (2011) theorizes that the existence of RPE can increase managers' incentives to misreport to shareholders. This theory suggests that corporate fraud propensity should be higher in industries that make more use of RPE.

The third channel we examine is related to the amount of information collection about individual firms and stock price efficiency. In some industries, both rival firms in the product market and investors in the capital market do a worse job of collecting information about individual firms, either because there are many individual firms (e.g., fragmented industries), or some industry common signal is important (e.g., the oil price in the oil industry), or because there is less trading of individual firms' shares and thus less incentive to collect information (e.g., Peress (2010)). The lack of information collection about individual firms implies less effective monitoring by rival firms and investors, reducing the likelihood that fraud is detected; in turn, a lower likelihood of fraud detection can encourage firms to commit fraud.

The above theories suggest that corporate fraud propensity is higher in industries where rivals' investment decisions are less sensitive to an individual firm's information disclosure, where there is little collection of information on individual firms, and where evaluations of executives are based on relative performance. To test these three potential links between product market interaction and fraud, we construct industry-level proxies for each of these factors. We measure product market sensitivity by estimating the average responsiveness of rival firms' investment to information about each firm's product demand for each three-digit SIC industry. We measure the existence of RPE by estimating the average responsiveness of managerial turnover and compensation to a firm's underperformance relative to its industry peers. Finally, we use the number of firms and the degree of stock return comovement in an industry as inverse measures of information collection about individual firms.

In our analysis, we have to address the fact that we observe only frauds that are subsequently detected, not all frauds that are ever committed. To the extent that detection is imperfect, the true probability of fraud commission is unobservable. Following Wang (2013) and Wang et al. (2010), we use a bivariate probit model with partial observability, which models the observed probability of detected fraud as the product of the latent probability of fraud commission and the latent probability of fraud detection conditional on commission. This model not only helps to address the partial observability of fraud, but also allows us to estimate the separate effects of product market informational interaction on fraud commission and fraud detection; this is essential for testing our third channel, the impact of information gathering on fraud detection and fraud commission.

We find that industries with lower product market sensitivity to individual firm information and industries in which managerial turnover and compensation are more sensitive to relative performance have a significantly higher fraud propensity. Industries with less information collection about individual firms have a significantly lower probability of fraud detection and a higher probability of fraud commission. All these results hold after controlling for an extensive list of firm characteristics and other industry characteristics that are related to fraud propensity or fraud detection. The economic magnitudes of these effects are quite meaningful. For example, a one-standard-deviation increase in the product market sensitivity corresponds to a 5-6 percentage-point higher likelihood of firms committing fraud. Similarly, we estimate that only 13% of all industries in our sample use RPE in managerial turnover, but these industries have a fraud propensity that is 12 percentage points higher than that in other industries. If the number of firms in an industry increases by 100, then the probability of fraud detection decreases by 1 percentage point, and the probability of fraud commission increases by 7 percentage points. Our results strongly support the theoretical predictions that these three facets of industry informational interaction affect corporate misreporting incentives.

Although these results are consistent with the theories outlined above, alternative explanations must be addressed. One possible concern is reverse causality: e.g., high fraud propensity in an industry may reduce the product market sensitivity to an individual firm's information or increase the use of RPE in an industry. As discussed in Section 4, our results are generally not consistent with such interpretations. Another potential concern is that omitted variables might drive both the industry characteristics and firms' incentives to commit fraud. For example, we find that fraud propensity varies procyclically with industry conditions, but industry common shocks might also artificially increase rival firms' sensitivity to one firm's information. Accordingly, as discussed in Section 3, we control for industry conditions and shocks in both the construction of the proxies for informational interactions and in the regression analysis.

In fact, our measures of (lack of) information collection about individual firms vary procyclically with business conditions, just as in Hoberg and Phillips (2010). Although this might suggest spurious correlation between information collection and fraud, this is unlikely to be the case: as we discuss in Section 4, this finding is most consistent with the theory of Povel at al. (2007) and the evidence of Wang et al. (2010), where business conditions drive investor monitoring (information collection), which in turn drives fraud incentives.

Hoberg and Phillips also find evidence of what they call “predictable busts in competitive industries”—that is, firms in more fragmented industries fare much worse following industry booms than do firms in more concentrated industries. Because industry comovement tends to increase during booms in more fragmented industries, they suggest that predictable busts could be caused by lack of information collection and lack of coordination in more fragmented industries during booms.

Our work provides an additional explanation for such predictable busts. We find that fraud incentives are more cyclical in more fragmented industries, which is what one would predict given the greater cyclicality of information collection in such industries. Also, in more fragmented industries, the consequences of fraud are worse following booms than they are following normal times. It follows that poor performance in fragmented industries following booms is largely concentrated in firms that are likely to have committed fraud during the booms. These results suggest that the dynamics of fraud can amplify cyclical fluctuations in the real economy, and such amplification is largely concentrated in fragmented industries.[2]

As further robustness tests, we examine several alternative specifications. First, we re-estimate our main results using the simple probit model that is prevalent in the literature. Although the results for measures of product market sensitivity and RPE are basically unchanged, this is not true for our measures of information collection: the probit model suggests that industries with less information collection about individual firms tend to have a *lower* probability of fraud. The bivariate probit model reveals that this is because the lower information collection has a negative direct effect on the probability of fraud detection and a positive indirect effect on the probability of fraud commission; the direct effect on detection dominates, leading to the negative net effect on the probability of detected fraud. Second, we re-estimate all our baseline results under a specification where all the determinants in our fraud commission equation are also included in our fraud detection equation. Once again, our results are essentially unchanged.

[2] Note that our study focuses on the effect of industry informational interactions rather than that of industry concentration per se. However, more fragmented industries are likely to have less information production about individual firms.

By shedding new light on the industry determinants of firms' incentives to commit fraud, our study contributes to the growing literature on corporate securities fraud. Our findings suggest that the nature of informational interactions among firms in a given product market has important implications for the significant cross-industry variation in corporate fraud propensity. Since the nature of industry informational interaction is closely related to industry structure and intra-industry competition, our results also have implications for understanding the effect of industrial organization and competition on firms' incentive to misreport financial information. Moreover, the dynamics of fraud can also amplify business cycle fluctuations, particularly in fragmented industries—an aspect of the real consequences of fraud that has not yet been studied.

The remainder of our paper is structured as follows. Section 2 reviews the literature and develops the main hypotheses. Section 3 describes our empirical model to analyze fraud and discusses the empirical specifications. Section 4 presents our empirical results and discusses robustness issues. Section 5 concludes.

2. HYPOTHESIS DEVELOPMENT

In this section we develop our main hypotheses regarding how industry informational interactions affect the incidence of corporate fraud. The interactions that we focus on relate to how an individual firm's information is used by product market rivals and by capital market investors.

2.1 Product Market Sensitivity and Fraud

One key aspect of how information about one firm affects others in its industry is the degree of interdependence among firms' product market decisions. In an oligopolistic industry, one firm's information disclosure can have a significant effect on rival firms' investment decisions, which in turn affect the firm's own investment. Earlier theoretical work predicts that such interdependence in firms' investment decisions can lead to less informative disclosure policies (cf. Clarke 1983, Gal-Or 1985). Other studies focus on the consequences of disclosing firm-specific information such as product quality or costs and reach similar conclusions (cf. Darrough 1993, Clinch and Verrecchia 1997, Board 2009). Most work in this literature deals with honest disclosure and does not consider the role of the capital market in determining disclosure incentives.

Gigler (1994) incorporates the capital market and allows for fraudulent reporting. He argues that firms' external financing needs create incentives for managers to over-report the demand for their firms' products to investors in the capital market. However, product market interactions may either decrease or increase such incentives, depending on whether over-reporting demand invites or deters entry and competition from rival firms. Conditional on a firm's external financing needs, fraud propensity depends on how sensitive rival firms' product market decisions are to one firm's information disclosure. Thus, strategic interactions in the product market may actually serve to reduce firms' incentives to commit securities fraud.[3] Since Gigler's model explicitly allows for fraudulent reporting in the capital market, we derive our first hypothesis based on Gigler's prediction.

Hypothesis 1: Ceteris paribus, a firm's incentive to commit fraud is higher in industries where one firm's information has a less positive (or more negative) effect on rival firms' investment decisions (i.e., industries with lower product market sensitivity).

2.2 Relative Performance Evaluation and Fraud

Another way in which information about one firm affects others is relative performance evaluation (RPE). The use of RPE causes feedback between the product market, in which firms compete, and the executive labor market, in which firm managers compete. Cheng (2011) models this interaction and its impact on managers' incentives to commit fraud. In his model, a manager is fired if his or her firm's performance lags the rival firm's performance by an amount that exceeds a certain threshold. Cheng shows that the existence of such RPE increases managers' incentives to misreport information to shareholders (who make the firing decision), no matter whether the firm is leading or lagging in performance. The intuition is straightforward: when a manager's job security depends on relative performance, the manager has incentive to manipulate his or her firm's performance relative to that of peer firms. This effect should be stronger in industries where executive firing is more sensitive to a firm's underperformance relative to industry peers. This leads to our second hypothesis.

Hypothesis 2: Ceteris paribus, a firm's incentive to commit fraud is higher in industries where managerial turnover is more sensitive to the firm's performance relative to its industry's.

[3] A broader theoretical literature in finance examines how capital market concerns can affect product market behavior, and vice versa; however, this work does not address incentives to commit fraud. For a review, see Maksimovic (1995).

2.3 Lack of Information Collection and Fraud

Industry structure can affect firms' incentives to gather costly information about individual firms. Collecting information about individual firms is costly, particularly when there are a large number of firms. As a result, fragmented industries may produce less information about individual firms than what is socially optimal and firms in such industries may focus more on industry common signals rather than on costly information about their individual rivals. Such a lack of information collection can lead to product market inefficiencies such as lack of coordination in investment decisions.

Peress (2010) shows that industry structure can also affect *investors'* incentives to gather information about individual firms, thus affecting stock market efficiency. Product market power allows firms to insulate their profits from shocks by passing the shocks on to their consumers. Therefore, profits are less risky for firms with greater market power, which encourages trading of their stocks. Trading, in turn, motivates information collection and expedites the capitalization of private information into prices. Hence, a more concentrated product market can lead to a more efficient stock market.

A direct consequence of such a failure to collect information is less effective monitoring of individual firms by rival firms and by investors. Moreover, Dyck, Morse, and Zingales (2010) show that external fraud detection (e.g., by capital market participants) has been much more effective than internal fraud detection (e.g., by board members). With less effective external monitoring, fraud is less likely to be detected; in turn, a lower probability of fraud detection can encourage firms to commit fraud. This leads to our third hypothesis.

Hypothesis 3: Ceteris paribus, the probability of fraud detection is lower and the probability of fraud commission is higher in industries where there is less information collection about individual firms.

Note that product market sensitivity as modeled in Gigler (1994) is also related to information gathering about individual firms; after all, if information about one firm's product demand has a meaningful impact on its rivals' capacity decisions, then the rivals must be collecting information about that firm. However, Hypotheses 1 and 3 emphasize distinct aspects of an industry's information environment. In Hypothesis 1, product market sensitivity captures how an individual firm's information affects rival firms' product market decisions. By contrast, in Hypothesis 3, the degree of information gathering proxies for external information production about, and monitoring of, individual firms, and how this in turn affects the detection and commitment of fraud.

3. EMPIRICAL FRAMEWORK AND SPECIFICATION

In this section we set up the empirical framework for analyzing the effect of industry informational interactions on a firm's fraud propensity. We first discuss our empirical measures of these interactions. Then in Section 3.2 we introduce our empirical model for analyzing fraud, and in Sections 3.3-3.5 we discuss the empirical specification of other major components in the model.

3.1 Empirical Measures of Industry Informational Interactions

3.1.1 Product Market Sensitivity to Individual Firm Information

In Gigler's model, a firm's product-market disclosure concerns depend on the sensitivity of the rival firm's investment or output decision to information about the demand for the first firm's products. We construct measures of product market sensitivity as follows. For each three-digit SIC industry, we estimate the following panel regressions:

$$\Delta RivalInv_{t+1} = \alpha_1 + \beta_1 \times RivalROA_t + \gamma_1 \times ROA_{i,t} + \varepsilon_{t+1} \qquad (1)$$

$$RivalInv_{t+1} = \alpha_1 + \beta_1 \times RivalROA_t + \gamma_2 \times ROA_{i,t} + \varepsilon_{t+1} \qquad (2)$$

Here, "Δ" is the first-difference operator. We use ROA, which is operating cash flow before depreciation scaled by the lagged book assets, to proxy for information about firm *i*'s product demand. A higher ROA should be correlated with stronger demand. Moreover, accounting fraud often involves manipulating revenues or costs to inflate profitability numbers (e.g., see Table 1 Panel F in Dechow et al. 2010).

"*RivalROA*" is the weighted-average ROA of all firms except firm *i* in a three-digit SIC industry. The weighting factor is a firm's lagged market share in sales. We can think of *RivalROA* as capturing the industry common shock in product demand, which is important because an industry common shock may artificially increase the sensitivity of rival firms' investment to an individual firm's product demand as both respond to the common shock. "*RivalInv*" is the weighted-average investment rate (capital expenditures to net PPE) of all firms except firm *i* in an industry. The yearly change in rival firms' investment rate captures the rival firms' yearly capacity decision.

The coefficient γ_1 (γ_2) measures an industry's average product market sensitivity: how much impact the information about firm i's product demand at time *t* has on rival firms' investment decision at time *t+1*, after controlling for the information in the rival firms' own product demand at time *t*. The estimation uses annual financial data from COMPUSTAT during 1960 to 1992. Since our fraud sample starts in 1993 (see Section 3.3), using historical data to estimate an industry's product market sensitivity (PMS) helps to mitigate the endogeneity concern. The industry PMS may vary over time, which could bias against finding a significant impact of the historical industry PMS on firms' fraud propensity. To mitigate the estimation errors in the estimated industry PMS, we scale each γ estimate by its estimation standard error. Using alternative specifications to estimate industry PMS provides robustness to our results. Table 1 Panel C reports the summary statistics of these PMS measures.

As a further test, we focus on the sign of γ. A negative γ means that favorable information about a firm's profitability tends to deter rivals from investing. According to Gigler's theory, firms in a negative-γ industry should have *more* incentive to commit fraud than those in a positive-γ industry or zero-γ industry, because fraud both deters rivals and obtains better funding terms in the capital market. We thus construct an indicator variable "*Negative PMS*" that equals one for industries with both γ_1 and γ_2 negative (19% of all industries in our sample).

In robustness tests, we consider three more model specifications. The first is a variant on Equations (1) and (2) that focuses on first differences for both the dependent and the key independent variables:

$$\Delta RivalInv_{t+1} = \alpha_2 + \beta_2 \times \Delta RivalROA_t + \gamma_3 \times \Delta ROA_{i,t} + \varepsilon_{t+1} \quad (3)$$

Second, there may be delay in rivals' investment response due to issues such as time-to-build. We thus consider the cumulative response in the product market by the sum of γ_1 and γ_4 in the following equation:

$$\Delta RivalInv_{t+1} = \alpha_1 + \beta_1 \times RivalROA_t + \gamma_1 \times ROA_{i,t} + \gamma_4 \times ROA_{i,t-1} + \varepsilon_{t+1} \qquad (4)$$

Third, although we have used capital expenditures as our measure of firm investment, R&D expense may also be a form of investment. Furthermore, some industries are more R&D intensive and less capital intensive than others. To the extent that the R&D expenditures of rival firms in these industries respond to firm-*i*'s performance, our measures based on capital expenditures alone may misclassify these industries as having low product market sensitivity. To mitigate this concern, we also estimate equation (1) with $\Delta RivalInv$ replaced by $\Delta RivalRD$, which is the change in the value-weighted rivals' R&D to sales ratio. We then add up the rival's capital investment sensitivity and R&D sensitivity in corresponding equations to define product market sensitivity.

3.1.2 Industry Use of Relative Performance Evaluation

To measure the degree to which RPE affects managerial turnover in an industry, we stay close to the theoretical specification in Cheng (2011). In Cheng's model, the probability of a firm's manager being fired is directly linked to the firm's relative performance, which is the difference between the firm's own performance and the rival firm's performance. The manager is fired if the relative performance is sufficiently negative. Cheng's model implies the following regression.

$$\Pr ob(CEOTO_{i,t+1} = 1) = \alpha + \beta \times RP_{i,t}^{+} + \gamma \times RP_{i,t}^{-} + \varepsilon_{i,t}. \qquad (5)$$

"*CEOTO*" indicates a CEO turnover event in a firm-year. We start with 24,780 firm-year observations from 1992 to 2008 that have identifiable CEOs based on the information in the ExecuComp database. For each firm, we compare the designated CEO in each fiscal year with the one in the previous year to identify CEO turnover events. We exclude turnover events that are associated with mergers and acquisitions (M&A) because the frequency of M&A may differ across industries. But other than M&A, we do not distinguish between causes of turnover (e.g., forced vs. exogenous) because there is no reason to believe that the incidence of exogenous turnovers related to death or retirement depends on the nature of industry informational interactions, and we want the data to indicate how sensitive CEO turnovers are to firms' relative performance in an industry.

"$RP_{i,t}$" is the difference in the two-year average performance between firm i and the weighted-average of its rivals in a three-digit SIC industry in year t. Equation (5) is a spline regression distinguishing outperformance ($R_{i,t}^{+} = RP_{i,t}$ if $RP_{i,t} > 0$, and 0 otherwise) and underperformance ($RP_{i,t}^{-} = RP_{i,t}$ if $RP_{i,t} < 0$, and 0 otherwise) of firm i relative to its industry peers. The parameter γ measures the sensitivity of CEO turnover to relative underperformance. According to Cheng's model, the use of RPE implies that $\gamma < 0$, i.e., the probability of a CEO turnover increases as the firm's underperformance in the industry widens. Although we do not focus on β, we expect it to be negative as well, as outperformance of a firm in the industry should decrease the probability of CEO turnover. We estimate equation (5) for each three-digit

SIC industry using ExecuComp data from 1992 to 2008, and extract the estimate for γ. Then we construct an indicator variable "*RPE_Return (RPE_ROA)*" that equals one if the estimate for γ in an industry is negative using stock return (or ROA) as the performance measure.

For robustness, we also examine the sensitivity of CEO compensation to the firm's relative performance. In this case, the use of RPE implies that CEO compensation is positively related to relative performance. For each three-digit SIC industry, we estimate equation (5) with the probability of CEO turnover replaced with the logarithm of CEO total compensation ("tdc1" in Execucomp) and with stock return as the performance measure. We extract the estimate of γ for each industry, and construct an indicator variable "*RPE_Compensation*" that equals one for industries with positive γ.

3.1.3 Lack of Firm-Specific Information Collection

We construct three proxies to measure the amount of information collection about individual firms in an industry. A simple and intuitive measure is the number of firms in an industry-year. The larger the number of firms, the more difficult it is to collect information about individual firms and to coordinate investment among firms. The next two measures are based on the degree of return comovement in an industry. As pointed out in studies like Durnev, Morck, and Yeung (2004), Barberis, Shleifer, and Wurgler (2005), and Chen, Goldstein, and Jiang (2007), high return comovement is associated with little firm-specific information being impounded into stock prices. When comovement is high, managers have little information outside of common signals, and are likely to make similar investment decisions, leading to inefficient investment.

The comovement measure complements the number of firms because an industry may lack information production about individual firms for reasons other than the existence of a large number of firms. The most important determinant of return comovement in an industry is the correlation of fundamental cash flows among firms. For example, the oil price is a very important industry common signal about profits and investment of all firms in the oil industry, leading to high correlation of cash flows and high return comovement in this industry. Both firms and investors may pay great attention to this common signal and have less incentive to gather costly information about individual firms.

Following previous studies, we measure return comovement in an industry in two ways. The first measure is the correlation of returns in an industry. We compute the correlation between firm i's daily stock return and the weighted average of its rivals' returns in a year. Then we take the average of these correlations within an industry-year, and call it "*Comove*". This measure is simple and free of any parametric specification. The second comovement measure follows the method in Chen, Goldstein, and Jiang (2007). For each year in our sample and each firm in three-digit SIC industry j, we estimate the following regression:

$$r_{i,j,t} = \beta_{i,0} + \beta_{i,m} \times r_{m,t} + \beta_{i,j} \times r_{j,t} + \varepsilon_{i,t}\,. \qquad (6)$$

Here $r_{i,j,t}$ is the day-t return of firm i in industry j, $r_{m,t}$ is the value-weighted market return on day t, and $r_{j,t}$ is the value-weighted return of industry j (excluding firm i) on day t. The regression R^2 measures the degree of comovement between firm i's return and the returns of the market and the industry in that year. Then we compute the market-value weighted average of regression R^2 in that industry-year, and call it "*ComoveRsq*"; this is our third comovement measure.

3.1.4 Summary Statistics and Correlations

Panel A of Table 1 reports the summary statistics of the proxies for the three dimensions of industry informational interactions. Panel B reports the correlation matrix. All these different aspects of product market informational interactions are correlated with each other in an intuitive way. For example, industries with a larger number of firms tend to have lower PMS, and are more likely to use RPE.[4] However, the degrees of correlation are far from perfect, which suggests that these proxies do not capture the same information, but rather distinct aspects of industry informational interactions.

3.2 Empirical Methodology to Analyze Fraud

Empirical research on corporate fraud faces a challenge: frauds are not observable until they are detected. This means that the outcome we observe depends on the outcomes of two distinct but latent economic processes: commitment of fraud and detection of fraud. As long as fraud detection is not perfect, we do not observe all the frauds that have been committed. Poirier (1980) and Feinstein (1990) develop a bivariate probit model to address the problem of partial observability. Wang (2013) and Wang, Winton, and Yu (2010) apply such a model to address the

[4] The economic theory has long established that a key difference between a fragmented industry and an oligopolistic industry is the degree of interdependence among firms' product market decision. Also, a strand of theoretical research argues that RPE is more efficient in industries with a larger number of firms because the information about common shocks is more precise in these industries (e.g., Hart 1983).

unobservability of undetected frauds in the analysis of corporate securities fraud. We adopt the same empirical framework as in these two papers.

Let F_i^* denote firm *i*'s incentive to commit fraud, and D_i^* denote the firm's potential for getting caught conditional on fraud being committed. Then consider the reduced form model:

$$F_i^* = x_{F,i}\beta_F + u_i;$$
$$D_i^* = x_{D,i}\beta_D + v_i,$$

where $x_{F,i}$ is a row vector with elements that explain firm *i*'s incentive to commit fraud, and $x_{D,i}$ contains variables that explain the firm's potential for getting caught. The variables u_i and v_i are zero-mean disturbances with a bivariate normal distribution. Their variances are normalized to unity because they are not estimable. The correlation between u_i and v_i is ρ. For fraud occurrence, we transform F_i^* into a binary variable F_i, which equals one if $F_i^* > 0$, and zero otherwise. For fraud detection (conditional on occurrence), we transform D_i^* into a binary variable D_i, which equals one if $D_i^* > 0$, and zero otherwise. However, we do not directly observe the realizations of F_i and D_i. What we observe is

$$Z_i = F_i \times D_i \qquad (7)$$

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

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

In essence, the above model aims to control for the effect of fraud detection according to the structure of the underlying data generating process. This model can be estimated using the maximum-likelihood method. The log-likelihood function for the model is

$$\begin{aligned} L(\beta_F, \beta_D, \rho) &= \sum_{z_i=1} \log(P(Z_i = 1)) + \sum_{z_i=0} \log(P(Z_i = 0)) \\ &= \sum_{i=1}^{N} \{z_i \log[\Phi(x_{F,i}\beta_F, x_{D,i}\beta_D, \rho)] + (1 - z_i)\log[1 - \Phi(x_{F,i}\beta_F, x_{D,i}\beta_D, \rho)]\}. \end{aligned} \qquad (8)$$

According to Poirier (1980) and Feinstein (1990), the conditions for full identification of the model parameters are twofold. First, $x_{F,i}$ and $x_{D,i}$ do not contain exactly the same variables. We use the identification strategy in Wang (2013), which exploits both the implications of existing economic theories and a special feature in the context of fraud. The fact that the detection of fraud occurs *after* the commission of fraud implies that there are factors that may affect a firm's ex-post likelihood of being detected but not the firm's ex-ante incentive to commit fraud. These ex-post determinants of fraud detection provide a natural set of variables for identification. The second condition for identification is that the explanatory variables exhibit substantial variations in the sample. In particular, the condition for identification is strong when $x_{F,I}$ and $x_{D,i}$ contain continuous variables.[5]

Hypotheses 1 and 3 state that low product market sensitivity and the existence of RPE can increase a firm's incentive to commit fraud. Thus measures of low product market sensitivity and RPE will be in the fraud commission equation (F^*) only. Hypothesis 2 states that the lack of information collection about individual firms decreases the likelihood of fraud detection and increases the incentive to commit fraud through the deterrence of detection. Thus the measures of the lack of information collection will enter both the fraud commission equation and the fraud detection equation (D^*), and the direct effect is in the detection equation.

3.3 Sample Selection

In this study, we focus on securities frauds that involve deliberate and material misrepresentation of a firm's financial performance. The discovery of an accounting fraud generally leads to a securities lawsuit. Thus, the existence of a securities lawsuit has become a natural empirical proxy for *detected* accounting fraud. Two types of securities lawsuits are relevant: the SEC's Accounting and Auditing Enforcement Releases (AAERs) and the private securities class action lawsuits. Information about the SEC's AAERs is extracted from the SEC's litigation database (http://www.sec.gov/litigation). Private securities class action lawsuits are extracted from the Securities Class Action Clearinghouse (http://securities.stanford.edu). We then combine these two databases. As Karpoff et al. (2012) points out, combining AAERs and class action lawsuits can mitigate errors of omission in the AAER database.[6] We start with cases that were filed between 1996 and 2008. To match the nature of the SEC's AAERs, we only include class action lawsuits related to accounting fraud. The nature of fraud allegations in class action lawsuits is identified based on the available case materials.

[5] For further discussion of identification in this model, see Wang (2013).

[6] Case omission is less of a problem for our analysis because the starting point of our empirical model is that the control sample includes undetected frauds. Thus, omitted cases are treated as undetected frauds in the model, which may lead to underestimation of the probability of fraud detection. But as long as case omission is not systematically related to the variables of interest in our study, it should not bias our main findings.

Karpoff et al. (2012) show that databases used in fraud studies usually contain a significant fraction of cases that most likely do not involve material financial misconduct. To mitigate this problem, we apply several screens. First, by starting our sample in 1996, we restrict our attention to the period after the passage of the Private Securities Litigation Reform Act (PSLRA), which was designed to reduce frivolous lawsuits (cf. Johnson, Kasznik and Nelson, 2000, and Choi, 2007). Second, we exclude cases that either were dismissed by the courts or had a settlement value of less than \$2 million.[7] Third, we personally read all the available case documents associated with each lawsuit (i.e., case complaints, press releases, defendant motions to dismiss, court decisions, SEC decisions), because we need to collect information such as the nature of the allegation, the timing of the fraud (beginning year, ending year, etc.), and the case outcome (settlement, court decision, etc.). This data collection effort also allows us to make judgments in choosing appropriate cases for our analysis, mitigating the chances of including frivolous cases and duplicated cases.

We then select frauds that begin between 1993 and 2005. For each case, we collect the beginning year of fraud, the ending year of fraud, and the litigation filing year. The average time between the beginning of fraud and the litigation filing is about three years in our sample. Thus, we require frauds that begin at least three years before the end of the litigation sample in 2008 so as to allow a reasonable amount of time for frauds to be detected and any subsequent lawsuits to appear in our litigation sample.

The variable Z_{it} in equation (7) equals one if firm *i* begins to commit the alleged fraud in year t. This beginning year (year 0) is critical because we want to use pre-fraud firm characteristics (from year -1) to predict the probability of fraud commission. If the AAER and the class action lawsuit identify different beginning years of fraud for the same case, then we use the earlier of the two. We treat the fraud ending year as the detection year. However, the exact timing of detection is not used in the empirical estimation. Since the average duration of fraud is less than 3 years in our sample, fraud that begins in year t will on average end by year t+2. Thus, we use the information from year t-1 to t+1 to predict the probability of fraud being detected by year t+2. We discuss this issue further in Section 3.5.[8]

Lastly, we merge the selected fraudulent companies with the Compustat-CRSP merged

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[7] Legal studies have established that the \$2 million threshold level of payment helps divide frivolous suits from meritorious ones; cf. Choi (2007) and Johnson, Nelson, and Pritchard (2007).

[8] As a robustness test, we also use information up to the detection year for fraudulent firms and up to t+1 for the rest of the firms. The results are similar.

database to obtain firm-level financial and trading information for the two years before and the two years after fraud commitment. The entire sample selection procedure leads to a detected accounting fraud sample of 987 lawsuits. Among these cases, 260 cases were subject to both SEC enforcement and private litigation, and 727 were subject only to private litigation. Table 1 Panel C reports the distribution of these securities frauds over time. Although frauds are most common in 1999-2000, there are significant numbers of frauds in many years before and after this period. Panel D reports the top five industries in terms of the number of alleged frauds. They are software and programming, pharmaceuticals, computers, electronics, and medical instrument industries, which is consistent with the findings in earlier studies.

The partial observability model implies that the appropriate comparison sample should be a random sample of firms that are litigation-free but not necessarily fraud-free. We therefore start with all the firms in the Compustat-CRSP merged database. We then exclude (1) firms that are in our detected fraud sample; (2) firms that have litigation records but are excluded from our final fraud sample (e.g., firms subject to non-accounting-related class action lawsuits between 1996 and 2008); (3) firms that were sued by the SEC between 1990 and 1995 (immediately before our litigation sample period); and (4) firms with two-digit SIC code equal to 99 because these firms are shell holding companies.

3.4 Fraud Commission Equation

Our baseline specification for the latent fraud commission equation is as follows.

$$F_{i,t}^{*} = \alpha_F + x_{F,i}\beta_F + x_{D0,i}\gamma_F + u_{i,t}.$$

The vector x_F contains firm and industry characteristics that the previous literature has found to be key influences on the firm's incentives to commit fraud. The vector x_{D0} is the set of ex-ante detection variables, which we discuss in Section 3.5. Ex-ante detection factors are included in the fraud commission equation because they affect the expected cost of committing fraud and their effects can be anticipated at the time that the decision to commit fraud is made. This incorporates the deterrence effect of detection on fraud commission.

Firm-level control variables in x_F include the firm's pre-fraud profitability, external financing needs, leverage, and insider equity incentives. All these variables are measured as of year -1. We expect that all of these variables be positively related to the firm's fraud propensity, as we now discuss.

Several studies in the accounting literature show that a consistent theme among manipulating firms is that they had strong financial performance prior to the manipulations (e.g., Dechow, Ge, Larson and Sloan 2010, Crutchley, Jensen and Marshall 2007). These findings suggest that manipulations can be motivated by management's desire to disguise a weakening performance. Following this literature, we measure performance by return on assets (*ROA*).

The literature has also found that high external financing needs are a strong determinant of the commission of accounting frauds (cf. Teoh, Welch and Wong 1998a,b, and Wang 2013). We measure external financing needs with the externally-financed growth rate suggested by Demirguc-Kunt and Maksimovic (1998), which is a firm's asset growth rate in excess of the maximum internally-financeable growth rate, *ROA/(1-ROA)*. This excess captures the firm's potential need for external financing.

A number of studies have examined whether financially-distressed firms manage earnings (see Healy and Wahlen (1999) for a review.) Following the accounting literature, we use the firm's book-value leverage ratio as a proxy for the degree of financial distress, where leverage is defined as the ratio of long-term and short-term debt to total assets.

Goldman and Slezak (2006) theorize that large equity incentives can be a double-edged sword because a positive relationship between firm performance and insiders' compensation (or wealth) can induce misreporting. Empirical tests of this theory have generated mixed results. Our proxy for insider equity incentives is the percentage of stock owned by insiders. [9] The advantage of using this variable is that stock ownership information is available for a large number of firms via the Compact Disclosure database. As Armstrong et al. (2010) point out, prior studies on the relationship between fraud and executive compensation based solely on the ExecuComp database may be influenced by selection bias, because ExecuComp does not contain data for the majority of publicly traded companies in the economy.

At the industry level, Povel et al. (2007) and Wang et al. (2010) show that a firm's incentive to commit fraud is sensitive to business conditions in its industry. Our proxies for industry conditions are taken from Hoberg and Phillips (2010). Their first measure of whether an industry is in a boom or bust is "*Industry Relative Investment*". This variable is essentially the

[9] The insider equity ownership includes equity shares held by officers and directors, underlying shares in their vested stock options, and underlying shares in their stock options exercisable within 60 days of the reporting date. Although this variable does not include the full incentive effect of stock options, we believe that it captures the bulk part of total equity incentives provided to executive officers and directors. For example, for firms covered by the ExecuComp database the average executive stock ownership is 5.2% and the average executive option sensitivity is 3%. Stock ownership also captures 60% of the variation in the total equity incentives.

average of the abnormal firm-level investment in a given year for all firms in a 3-digit SIC industry.[10] A positive (negative) value indicates a positive (negative) shock to investment in an industry-year. Hoberg and Phillips also use similar techniques to construct "*Industry Relative Valuation*", which measures financial booms or busts within each 3-digit SIC industry. We use Hoberg and Phillips' measures as proxies for industry business conditions because later we will use our findings to explain some of their main results.

3.5 Fraud Detection

Our baseline specification for the latent fraud detection equation is as follows.

$$D_i^* = \alpha_D + x_{D0,i}\delta_D + x_{D1,i}\lambda_D + v_i.$$

The vector x_{D0} is the set of ex-ante factors whose effects on the probability of detection can be anticipated at the time that the decision to commit fraud is made. The vector x_{D1} is the set of ex-post factors whose effects on the probability of detection cannot be anticipated at the time fraud is committed. The ex-ante detection variables are measured as of year -1, and the ex-post detection variables are measured as of year 1. All variable definitions are listed in Appendix A. One may argue that if those seeking to detect fraud can anticipate all the variables that affect fraud commission, then they will also take those factors into account. If so, the variables in x_F should also be included in the fraud detection equation. We examine this alternative specification in Section 4.5.3.

The ex-ante detection controls in x_{D0} include firm investment measures, institutional monitoring proxies, firm size, firm age, and industry membership. Wang (2013) shows that different types of firm investment have different effects on the probability that fraud will be detected, which in turn leads to different effects on the probability that the firm will commit fraud. Specifically, R&D investment tends to decrease the probability of fraud detection, mergers and acquisitions tend to increase the probability of fraud detection, and capital expenditures have no effect. Thus, we separately control for capital expenditures, R&D expenditures, and acquisition expenditures, all scaled by the firm's book assets.

[10] Specifically, Hoberg and Phillips estimate the following regression for each 3-digit SIC industry.

$$\log(\frac{Invest_{i,t}}{PPE_{i,t-1}}) = a + bQ_{i,t-1} + cROE_{i,t} + dDD_{i,t} + eAGE_{i,t} + fLEV_{i,t} + gVOLP_{i,t} + h\log(SIZE_{i,t}).$$

The relative (abormal) investment for each firm is the actual firm investment less the predicted investment. Then *Industry Relative Investment* is the average relative investment in each industry.

We have two proxies for the strength of institutional monitoring, both of which should increase the probability that fraud is detected. Our first proxy is "*Institutional Ownership*", which is a firm's total percentage institutional ownership before the fraud begins (i.e., year -1). Large and sophisticated institutional investors should have both the incentive and the power to impose effective monitoring on a firm's management, which should increase the chance that fraud gets uncovered. Our second proxy is *"Analyst Coverage"*, which is the number of stock analysts that follow a firm in year -1. Stock analysts are deemed to be important external monitors of firms. Their substantial knowledge about corporate financial statements and regular interaction with the management provide them with good opportunities to detect fraud (cf. Dyck et al., 2010).

We also control for the firm's size (logarithm of total book assets), age as a publicly traded company, and whether the firm belongs to a technology industry (software and programming, computer and electronic parts, biotech, and pharmaceuticals), service industry (financial services, business services, and telecommunication services), or trade industry (wholesale and retail trade). Wang (2013) documents that these industries tend to have high fraud concentration.

Because fraud detection occurs *after* fraud is committed, some factors that are unpredictable when the fraud decision is made can influence the probability of detection ex post. These ex-post determinants of fraud detection, x_{D1}, are important in our analysis because they provide a natural set of variables for identification between the fraud commission equation and the fraud detection equation. Since we use lawsuits to proxy for detected fraud, our ex-post fraud detection controls are closely related to triggers of securities litigation. Following Wang (2013) and Wang et al. (2010), these variables include abnormal industry litigation intensity, unexpected firm performance shocks, abnormal stock return volatility, and abnormal turnover, all of which are measured as of one year after fraud begins (i.e., year 1) and are expected to increase a firm's *ex post* litigation risk without affecting its *ex ante* incentives to engage in fraud.

Firms' litigation risk is often correlated within an industry, as lawyers and SEC regulators develop industry expertise that makes fraud detection at similar firms easier. We measure industry securities litigation intensity using the logarithm of the total market value of litigated firms in an industry-year. "*Abnormal Industry Litigation*" is the yearly deviation from the industry average litigation intensity.

Unexpectedly poor stock performance is often an important trigger for fraud investigation (cf. Jones and Weingram, 1996, and Wang, 2013). We construct an indicator variable, "*Disastrous Stock Return*", which equals one if the firm's stock return in year 1 is in the bottom 10% of all the firm-year return observations in the COMPUSTAT database. Other cutoff points such as the bottom 25% or bottom 5% yield similar results. It is generally difficult, even for corporate insiders, to predict disastrous events in the future. Thus, this variable is reasonably exogenous to ex-ante fraud incentives.

The litigation literature suggests that a firm's stock return volatility and stock turnover affect its litigation risk. We measure "*Abnormal Return Volatility*" as the difference between the yearly standard deviation of the firm's stock returns and its time-series average. Similarly, "*Abnormal Stock Turnover*" is the deviation of the monthly share turnover from the firm's time-series average.

4. RESULTS

4.1 Product Market Sensitivity and Fraud

In Table 2 we test Hypothesis 1, which predicts that a firm's incentive to commit fraud is higher in industries with lower product market sensitivity. We find that industries with low product market sensitivity tend to have a higher fraud propensity. The estimated coefficient for *PMS1* in model (1) is −0.077, which corresponds to a marginal effect of −0.029 on the probability of fraud commission P(F=1). This implies that ceteris paribus, a one-standard-deviation increase in the industry average product market sensitivity corresponds to a 5.5 percentage-point increase in firms' probability of committing fraud. Similarly, the estimated coefficient for *PMS2* in model (2) is −0.051 (marginal effect −0.019), which means that a one-standard-deviation increase in PMS2 corresponds to a 4.9 percentage-point increase in firms' fraud propensity.[11]

In model (3) the estimated coefficient for *Negative PMS* is 0.692 (marginal effect is 0.21), which means that firms in industries in which favorable information disclosure deters rivals are on average 21 percentage points more likely to commit fraud than those in other

[11] As discussed previously, we also examine three alternative measures of PMS. First, the coefficient estimate of *PMS3* (from Equation (3)) is −0.075 (p-value=0.09). Second, we use *PMS* that incorporates delayed responses. The coefficient estimate for *PMS* is −7.325 (p-value=0.04). Finally, we use *PMS* based on the sum of each industry's capital investment sensitivity and R&D sensitivity. The coefficient estimate for *PMS* is −7.718 (p-value=0.02). Note that for the last two estimated PMS, we do not scale them by the standard deviation of the estimates because each is constructed by summation of two coefficient estimates. For brevity, we do not report these results, but in all cases our results are robust to these alternative ways to measure product market sensitivity.

industries. The large marginal effect of *Negative PMS* is intuitive: negative PMS means that by committing fraud, the firm would benefit in both the capital market *and* the product market.

Overall, the results in Table 2 are consistent with Gigler's (1994) theory. Firms do internalize how committing fraud is likely to affect rival firms' product market decisions. Fraud is more likely when misreported information either deters or has little impact on product market competition, and is less likely when misreporting increases product market competition.

One might argue that high fraud propensity in an industry could cause firms to ignore rivals' information disclosure, thus causing low PMS. However, such reverse causality cannot explain the positive relationship between negative PMS and fraud propensity. If firms ignored rivals' information due to prevalent fraud, then a firm would be unable to deter rival competition by fraudulent disclosure—and so high fraud would not lead to negative PMS. Also note that our estimate of industry PMS is based on historical data from before our main sample period, which helps to address concerns arising from any contemporaneous relation between PMS and fraud.

One may also be concerned that our results are driven by industry common shocks affecting both the PMS and firms' incentive to commit fraud. However, as we have discussed before, we already control for industry conditions when we construct the PMS measures. We also control for industry conditions in the fraud commission equation.

Our other control variables all have the expected effects. A firm's incentive to commit fraud is higher during industry booms, and it is higher when the firm has stronger performance, larger external financing needs, or higher insider equity incentives. Firms with higher R&D intensity tend to have a lower likelihood of fraud detection and a higher propensity to commit fraud. High intensity of M&A, high institutional ownership, and high analyst coverage also tend to increase the probability of fraud detection and decrease the probability of fraud commission. Finally, all four of the ex post deception variables (abnormally high industry litigation intensity, disastrous firm stock return, abnormally high return volatility, and abnormally high stock turnover) have the predicted positive effects on fraud detection.

4.2 RPE and Fraud

In Table 3 we examine Hypothesis 2, which predicts that an industry's use of RPE is positively related to the firm's fraud propensity. In Model (1), we measure the industry use of RPE by whether CEO turnover in the industry is sensitive to poor relative accounting performance (*RPE_ROA* equals one). According to Table 1 Panel A, 13% of the 243 industries exhibit this form of RPE. This implies that RPE is not a frequently observed practice, consistent with earlier findings in the literature. The coefficient estimate for *RPE_ROA* in the fraud commission equation is 0.388, which corresponds to a marginal effect of 0.12. Thus, ceteris paribus, industries in which CEO turnover is sensitive to relative underperformance to industry peers on average have a 12 percentage-point higher probability of committing fraud than do other industries. The economic impact of RPE on fraud incentive is clearly nontrivial.

In model (2), we measure the industry use of RPE with *RPE_Return*, which equals one for industries in which the CEO is more likely to be fired when the firm's stock return underperforms those of industry peers. According to Table 1 Panel A, this form of RPE is even less common than that using accounting performance, being observed in only 6% of the 243 industries. The coefficient estimate for *RPE_Return* in the fraud propensity equation is 0.651 (marginal effect 0.16). In model (3), we measure the industry use of RPE with *RPE_Compensation*, which equals one in industries in which CEO compensation is sensitive to relative underperformance in the stock return (observed in 23% of the industries). The coefficient estimate for *RPE_Compensation* is 0.24 (marginal effect 0.08).

Our results are unlikely to be driven by reverse causality. If more prevalent fraud affected the industry's sensitivity of CEO turnover to poor relative performance, then we would expect the effect to be negative rather than positive, because relative underperformance measures would be noisier in the presence of fraud. Indeed, Hazarika et al. (2011) show that aggressive earnings management increases the probability of forced CEO turnover, but this result is insensitive to firm performance. Thus, their results imply that more prevalent earnings management *decreases* the sensitivity of (forced) CEO turnover to firm performance, which is the opposite of the relationship we find.

Of course, one may wonder why some industries are more likely to use RPE than others. Jenter and Kanaan (2010) offer good insights on this question. First, they find that RPE is more commonly used during economic downturns than during booms. Our measure of RPE captures an industry's average tendency to use RPE, which is not time-varying; thus, one might be concerned that our RPE measure captures cross-sectional variation in average industry conditions, which also affects fraud incentives. However, fraud is more likely to occur during industry booms (see the positive coefficient estimates on *Industry Relative Investment* in the P(F) equations, as well as the findings in Wang et al. 2010). Thus, the counter-cyclicality in RPE and the pro-cyclicality in fraud commission imply that industry conditions cannot be the cause of the positive relationship between RPE and fraud. Second, one might be concerned that RPE is driven by (lack of) CEO power in an industry, which might also affect fraud incentives. However, Jenter and Kanaan find that CEO tenure and CEO power do not affect the use of RPE, which suggests that CEO entrenchment is unlikely to be the omitted variable that drives our results.

There may also be determinants of RPE that are not studied in Jenter and Kanaan (2010), which may also affect firms' fraud propensity. Thus, we cannot completely rule out the possibility of an omitted variable problem for this specification. Further understanding of the determinants of RPE, particularly at the industry level, can advance the understanding of our results here. However, we do think that this result, even without exact identification, is interesting and can shed light on cross-industry differences in firms' fraud propensity.

4.3 Lack of Information Collection and Fraud

In Table 4 we examine Hypothesis 3, which predicts that the probability of fraud detection is lower in industries where there is less information collection about individual firms, and that this lower detection risk leads to higher managerial incentives to commit fraud. This hypothesis implies that measures of the lack of information collection should be in both the fraud detection equation and the fraud commission equation.

We begin in Panel A by using one-year lagged proxies for information gathering and fraud. In model (1) we measure lack of firm-specific information collection with the number of firms (in 100s) in an industry-year. A larger number of firms implies that collecting individual firm information is more costly, so that monitoring by the product market as well as the capital market is less effective. We find that the number of firms has a negative and significant effect on the probability of fraud detection: the estimated coefficient is −0.095, which corresponds to a marginal effect of −0.01 on $P(D=1|F=1)$, which means that if the number of firms in an industry increases by 100, then the probability that a committed fraud is detected decreases by one percentage point. The estimated effect of the number of firms on fraud propensity is positive and significant, with a marginal effect of 0.075. This means that if the number of firms in an industry increases by 100, then the probability of fraud increases by 7.5 percentage points.

In models (2) and (3) we use the return comovement based measures to proxy for the lack of firm-specific information collections. Both comovement measures have a negative and significant effect on the probability of fraud detection and a positive but insignificant effect on the probability of fraud commission. The consistent effects of the number of firms and industry return comovement on the fraud detection likelihood are very interesting, as the two variables tend to capture different reasons for the lack of information collection at individual firm level.

Overall, the results in Table 4, Panel A, are broadly consistent with Hypothesis 3: industries with less firm-specific information collection have a lower probability of fraud detection, and a higher probability of committing fraud. However, as mentioned in the introduction, our measures of information gathering are likely to be subject to cyclical forces; return comovement may be higher in booms, and firm entry and exit may lead to more firms in booms than in downturns. We also know that, in all of our tests, business conditions (*Industry Relative* Investment) have a positive impact on fraud propensity. This means that joint cyclicality of information collection and fraud needs further investigation.

As a first step to addressing this issue, we re-estimate our fraud commission and detection equations using the sample averages of each industry's number of firms and return comovement. If baseline industry characteristics drive information-gathering, then these long-term sample averages should have a positive impact on fraud commission and a negative impact on fraud detection.

The results are reported in Panel B of Table 4. Consistent with Panel A, industry long-run average return comovement still has a negative and significant effect on fraud detection and a positive but insignificant effect on fraud commission. By contrast, the average number of firms in an industry has insignificant effects on both fraud commission and detection. This suggests that some, though not all, of the relationship between our information-gathering proxies and fraud may reflect cyclicality in both. The long-run determinants of industry return comovement (e.g., the fundamental correlation of cash flows among firms) seem to matter for firms' fraud detection risk, while the long-run determinants of the number of firms in an industry (e.g., the entry cost, the long-run profitability) do not, suggesting that it is not industry competition per se that affects fraud detection and commission.

Table 5, Panel A presents further evidence on the cyclicality of information collection. Our proxies for the lack of information collection on individual firms, return comovement (*ComoveRsq*) and the number of firms in an industry, are both higher following abnormally high industry investment (models 1 and 3).[12] Our finding that both fraud propensity and lack of information collection are procyclical is consistent with the theory of Povel et al. (2007), where

[12] In unreported robustness tests, we show that results are similar if industry conditions are proxied by industry relative valuation rather than industry relative investment.

fraud is more likely to occur during booms because booms reduce monitoring (information collection) incentives for investors, which in turn makes fraud more attractive. By contrast, it is unlikely that business conditions directly and independently drive both firm's incentive to commit fraud and investors' incentive to collection information, and thus cause a spurious relation between the two. Such an argument would need an alternative mechanism through which business conditions affect fraud propensity. The only alternative we are aware of is that of Hertzberg (2005), which argues that booms increase the amount of short-term compensation for executives, which in turn increases their incentives to commit fraud; however, Wang et al. (2010) find little support for this mechanism as opposed to that of Povel et al. (2007).

4.4 Fraud and Predictable Bust in Fragmented Industries

Hoberg and Phillips (2010) find that firms in fragmented industries tend to fare much worse than those in concentrated industries following industry booms, a finding which they call "the predictable bust in competitive industries." In this subsection, we ask whether this pattern may in part be caused by differences in fraud dynamics across fragmented and concentrated industries.

First, note that the existence of fraud generally predicts performance reversal in future years, either because fraud detection has a negative impact on the firm's real performance or because the fraudulently good performance itself is unsustainable. Karpoff, Lee, and Martin (2008) show that the loss of firm value (in terms of the present value of the loss of future cash flow) upon fraud detection is substantial. According to their estimate, for each dollar of value inflation the firm on average loses $4.08 when the misconduct is revealed. Kedia and Phillipon (2009) find that fraudulent firms increase investment and employment during the fraudulent period and then shed assets and labor after fraud is detected. If firms in fragmented industries are more likely to commit fraud during booms and experience subsequent performance deterioration and restructuring, then the cyclicality of fraud can contribute to the cyclical fluctuations in the real economy, helping to explain Hoberg and Phillips' findings.

As we show below, our measures of lack of information collection are more procyclical in fragmented industries than in concentrated industries. Following Povel et al.'s (2007) theory, this suggests fraud incentives should be more procyclical in fragmented industries than in concentrated industries; we find that this is in fact the case. Furthermore, we find that the consequences of fraud in fragmented industries are worse following booms than in normal times.

All together, our evidence suggests that the dynamics of fraud can help to explain predictable busts in fragmented industries.

We have already shown that firm-level return comovement and number of firms in an industry are procyclical. Hoberg and Phillips (2010) show that firm-level return comovement significantly increases during industry booms in fragmented industries, but does not significantly increase in concentrated industries. In models (2) and (4) of Table 5 Panel A, we show that similar results hold in our sample by adding the interaction effect between industry relative investment and Hoberg and Phillips' measure of industry concentration, fitted HHI. The direct effect of industry condition on our two proxies for lack of information collection becomes larger, while the interaction effect is negative and significant. This implies that return comovement and the number of firms are more cyclical in industries with lower fitted HHI, which tend to be more fragmented industries, and so the lack of information collection and resulting coordination problem should be worse during booms in those industries. Since this problem affects firms' fraud detection risk and fraud incentives, the stronger cyclicality of the lack of information production on individual firms in fragmented industries implies that fraud incentives should be more cyclical in those industries.

To see whether this hypothesis is true, we do the following analysis. We first generate the predicted probability of fraud commission (P(F=1)) based on model (3) in Table 4. The median predicted P(F=1) is 9% and the average is 15%.[13] Then we create a variable called "*Relative Fraud Propensity*", which is a yearly ranking of the predicted P(F=1) from the lowest to the highest. We scale the ranking by the number of firms in a year so that *Relative Fraud Propensity* lies between 0 and 1.

In Table 5 Panel B we examine whether the sensitivity of firms' fraud propensity to industry conditions depends on our measures of (lack of) information collection. In model (1) we use *ComoveRsq* to measure lack of information collection; in model (2), we use *# of firms*. As before, the direct effect of each information proxy is positive, implying that average fraud propensity is higher in industries with less information collection. In addition, the interaction between industry condition and lack of information collection has a positive and significant effect on fraud propensity, implying that the cyclicality of fraud is stronger in industries with less

[13] Our estimates are consistent with those in Dyck, Morse, and Zingales (2013), who estimate that in any given year the probability of a large US company committing fraud is about 14.5 percent. Although this may seem high, it is consistent with a situation where frauds are started to cover a downturn in firm performance, but many are quietly unwound once true performance subsequently recovers.

information collection. By contrast, the direct impact of industry condition and fraud propensity becomes negative in model (1) and insignificant in model (2).

Next we examine whether the dynamics of fraud can explain predictable busts in fragmented industries. Following Hoberg and Phillips (2010), we construct the two-year change in a firm's operating cash flow, *"Δ(Op. CF) 2 years*", which is the change in operating cash flow before depreciation (scaled by book assets) from year t to t+2. In our sample, the average duration between the fraud beginning year and the fraud ending year is roughly 2.5 years, so fraud that begins at year t should on average end in year t+2 or later. This is why we do not examine shorter-term changes in profitability. Results using changes in operating cash flow over longer horizons (e.g., three years) yield similar results and are not reported.

In Panel C of Table 5 we first replicate Hoberg and Phillips' results by regressing *"Δ(Op. CF) 2 years"* on *Industry Relative Investment* at time t for two subsamples, fragmented industries and concentrated industries. We define fragmented industries (concentrated industries) to be those with the fitted HHI in the bottom (top) tercile of the sample distribution, as in Hoberg and Phillips (2010). In unreported robustness checks, we find similar results if we use the number of firms to measure industry fragmentation. We also control for the firm-level return comovement because the lack of information collection may affect both the firm's fraud propensity (as we have shown) and its future profitability. We also control for firm-level lagged profitability, investment, size, and year fixed effects; in models (3) and (6), we add firm fixed effects. We cluster standard errors by firm. We find that *Industry Relative Investment* significantly and negatively predicts future firm cash flow changes in fragmented industries (model 1), but not in concentrated industries (model 4).

In model (2), we add *Relative Fraud Propensity* and its interaction with *Industry Relative Investment* into the fragmented industry regression. Model (2) shows that the direct effect of *Industry Relative Investment* becomes positive and insignificant, whereas the interaction term's effect is negative and significant. This suggests that the post-boom poor outcomes in fragmented industries are largely concentrated in firms that likely have committed fraud during the boom. The direct impact of *Relative Fraud Propensity* is negative and significant, implying that, in general, fraudulent performance is not sustainable. The economic magnitudes of the effects are also meaningful. If a firm in a fragmented industry commits fraud (e.g., *Relative Fraud Propensity* = 1) in a normal year (*Industry Relative Investment* = 0), then this firm tends to experience a 4-percentage-point decrease in profitability over the next two years. But if this firm commits fraud during an investment boom such that *Industry Relative Investment* = 0.1, then the firm tends to experience a 6.3-percentage-point decrease in profitability following the boom ($-0.226*0.1 - 0.040= -0.063$). Thus, the consequences of fraud are worse following an industry boom than they are in normal times.

In model (3) we control for firm fixed effects. The interaction effect becomes even more negative and significant. However, the direct effect of *Relative Fraud Propensity* becomes insignificant, suggesting that the direct effect is largely a cross-sectional effect.

Models (4)-(6) performs the same analysis for firms in concentrated industries. The direct effect of fraud propensity on future performance is negative. But the predictive power of fraud for future performance does not depend on whether fraud occurs during an industry boom or not, because the interaction effect between fraud propensity and *Industry Relative Investment* is insignificant. Thus, in concentrated industries, booms are not followed by predictable busts, even for firms with high fraud propensity. In the lower part of Panel C we show that our results are similar if we use *Industry Relative Valuation* to capture industry booms and busts.

In summary, if we focus on the predictability of future firm performance based on current industry condition, then the negative interaction effect in fragmented industries suggests that predictable busts are largely concentrated in firms that are more likely to have committed fraud during booms. If we focus on the predictability of future firm performance based on current fraud propensity, then the negative interaction effect in fragmented industries suggests that the consequences of fraud are worse following industry booms than they are under normal industry conditions. By contrast, with the exception of the direct effect of fraud propensity, these predictive effects do not exist in concentrated industries.

One might argue that our model is more likely to predict a high probability of fraud for firms that subsequently perform poorly because these firms are more likely to be sued for securities fraud. If so, the negative direct effect of fraud propensity on future performance could be mechanical. Nevertheless, this argument cannot explain why the interaction effect differs between fragmented and concentrated industries. In an untabulated test, we replace the predicted probability of fraud with the realized probability of detected fraud in model (2) of Panel C. The idea is that, because poor performance increases the probability of ex post detection, the ex post probability of detected fraud should have an even stronger direct relationship with ex post firm performance. However, we find that the direct effect of detected fraud is −0.027 (p-value = 0.08), which is *weaker* than the direct effect of predicted fraud propensity. This is probably due to the fact that detected fraud is rare. The direct effect of industry relative investment is −0.137 (p-value < 0.001), and the interaction effect is −0.022 (p-value = 0.87). Thus, the realized probability of detected fraud cannot explain predictable busts in fragmented industries.

Why then is the consequence of fraud particularly bad following industry booms in fragmented industries? One possibility is that high fraud propensity during the boom can introduce significant biases in industry-level common signals, making the coordination problem even worse. In fragmented industries, firms tend to focus on industry-level common signals. When the common signal is (fraudulently) positive, firms rush to invest and expand, as in Grenadier (2002); this overinvestment sows the seeds for future collapse. What happened to the telecommunications industry around the WorldCom fraud is certainly consistent with this argument (see Sidak, 2003).

4.5 Alternative Model Specifications

4.5.1 Probit Model Estimation

The probit model that has been used in the existing literature essentially treats the probability of detected fraud (P(Z=F*D=1)) as the probability of fraud commission (P(F = 1)). Thus, it cannot address the partial observability of fraud. It also cannot separately estimate the effects of a factor on fraud commission and fraud detection because detection is assumed to be perfect. It follows that the probit model and the bivariate probit model with partial observability can lead to very different inferences for determinants that affect fraud detection and fraud commission in opposite directions.

In Table 6 model (1), we use a probit model to test our main hypotheses. For Hypotheses 1 and 3 (product market sensitivity and RPE), the probit model generates results that are qualitatively consistent with those obtained from the bivariate probit models with partial observability, which implies that these industry characteristics do not have strong opposing effects on fraud detection. For Hypothesis 2, the probit model shows that two of our proxies for lack of firm-specific information collection (*# of Firms* and *Comove*) have a *negative* effect on the observed incidence of fraud. However, the bivariate probit model with partial observability shows that this is because lack of information collection has opposite effects on the probability of fraud detection and the probability of fraud commission. The negative direct effect on fraud detection dominates the positive indirect effect on fraud commission, leading to the negative net effect on the probability of detected fraud. Thus, the bivariate probit model is particularly meaningful for testing Hypothesis 2.

4.5.2 Alternative Specification for the Bivariate Probit Model

As noted in Section 3.5, it is reasonable to ask whether all the variables that affect the probability of fraud commission could also affect the probability of fraud detection in the same direction. The underlying assumption is that fraud detecting parties can anticipate all the factors that may affect a firm's incentives to commit fraud, and so they can take these factors into account when choosing their fraud detection efforts. Wang (2013) Section 4.3 discusses this question in detail. First, because there are theoretical arguments for why this assumption may *not* hold, it must be tested empirically.[14] Second, when we put all the variables in the P(F) equation into the P(D|F) equation, model identification relies solely on the ex post detection variables. The system can still be identified as long as the ex post detection variables have strong predictive power for fraud detection but have no effect on fraud commission.

In Table 6 model (2), we do robustness tests on our three main hypotheses using this alternative model specification. All variables that are included in the P(F) equation are also included in the P(D|F) equation. The main results on the effects of industry competition still hold under the alternative specification. Firms in industries with low product market sensitivity or industries that use RPE have higher fraud propensity, but these industry characteristics do not seem to increase the probability of detection. The number of firms in an industry and the industry return comovement still negatively affect fraud detection. Also, other powerful predictors of fraud commission such as external financing needs and industry relative investment still have a positive and significant effect on P(F), but no significant effect on P(D|F). Overall, our main findings are robust to this alternative model specification, but there is no evidence for significant feedback from fraud commission to the intensity of fraud detection.

4.5.3 Joint Tests of Hypotheses 1 through 3

[14] For example, in Povel et al. (2007), investors monitor not to detect fraud per se, but rather to find good investment opportunities. In this case, firm characteristics such as high externally financed growth and high insider ownership may signal good project quality rather than high fraud propensity. Qiu and Slezak (2010) develop an agency model of fraud in which there is a strategic interaction between the fraud commission strategy of managers and the fraud detection strategy of a centralized regulatory authority. They show that in the equilibrium in which fraud investigation occurs, the regulatory authority rationally chooses a random selection process to monitor.

As we have already noted, all of our proxies for product market informational interactions are correlated, which opens up the possibility that one of the three channels is driving the apparent significance of the others. To address this, in Table 7 we include all three dimensions of industry informational interactions in one regression. Our main results for all three dimensions continue to hold. Lower product market sensitivity and use of RPE tend to encourage fraud commission, and less information collection about individual firms proxied by greater number of firms in an industry and greater return comovement tend to decrease the probability of fraud detection. Furthermore, most of the relevant coefficients have values close to those in Tables 2-4. This finding suggests that these three sets of variables capture three correlated yet distinct dimensions of information interactions between firms within an industry.

5. CONCLUSION

Our paper examines how information interactions between firms within an industry affect firms' incentives to misreport financial information. The theoretical foundation for our empirical analysis lies in the economic literature on how product market interactions shapes a firm's information environment and its incentives to manipulate the information it discloses to investors. We examine three specific channels. We find that lack of strategic concerns in the product market tends to encourage fraud, as does the use of relative performance evaluation. Furthermore, lack of firm-specific information collection tends to decrease the probability of fraud detection, and this in turn increases the probability of fraud commission. The findings in this paper strongly support the theoretical predictions on how these aspects of industry informational interaction affect corporate fraud incentives.

We also show that the dynamics of fraud can help explain the predictable busts in fragmented industries documented by Hoberg and Philips (2010). Poor post-boom performance is largely concentrated in firms that are likely to have committed fraud during the booms. There are two potential reasons for this. First, fraud incentives are more cyclical in more fragmented industries. Second, in fragmented industries, the consequences of fraud tend to be worse following booms than in normal times. The upshot is that fraud can have significant real effects.

Many of the features of product market interaction that we use are also linked to notions of what constitutes a "competitive" industry. Indeed, all of our informational interaction measures are correlated with industry concentration, a traditional measure of (lack of) competition. Thus, our work suggests that some aspects of competition may exacerbate both the level and the cyclicality of fraud. Given that much other work suggests that increased competition has many positive effects, our findings do not argue for reducing competition so as to reduce fraud, but they do argue for increased monitoring for fraud in “competitive” (fragmented) industries, particularly during industry booms.

REFERENCES

Armstrong, Christopher S., Alan D. Jagolinzer, and David F. Larcker, 2010. Chief executive officer equity incentives and accounting irregularities. *Journal of Accounting Research* 48, 225-271.

Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler, 2005. Comovement. *Journal of Financial Economics* 75, 283-317.

Board, Oliver J., 2009. Competition and disclosure. *Journal of Industrial Economics* 57, 197-213.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2007. Price informativeness and investment sensitivity to stock prices. *Review of Financial Studies* 20, 619-650.

Cheng, Ing-Haw, 2011. Corporate governance spillover. Working paper, University of Michigan.

Choi, Stephen J., 2007, Do the merits matter less after the Private Securities Litigation Reform Act? *Journal of Law, Economics, and Organization* 23, 598-626.

Clarke, Richard, 1983. Collusion and the incentives for information sharing. *Bell Journal of Economics* 14, 383-394.

Clinch, G. and R. E. Verrecchia, 1997. Competitive disadvantage and discretionary disclosure in industries. *Australian Journal of Management* 22, 125-138.

Crutchley, C. E., Jensen, M., Marshall, B. B., 2007. Climate for Scandal: Corporate Environments that contribute to accounting fraud. *Financial Review* 42, 53-73.

Darrough, Masako N., 1993. Disclosure policy and competition: Cournot vs. Bertrand. *The Accounting Review* 68, 534-561.

Dechow, P. M., Ge, W., Larson, C. R., Sloan, R. G., 2010. Predicting material accounting manipulations. *Contemporary Accounting Research* forthcoming.

Demirguc-Kunt, A., Maksimovic, V., 1998. Law, finance, and firm growth. *Journal of Finance* 53, 2107-2137.

Durnev, Art, Randall Morck, and Bernard Yeung, 2004. Value enhancing capital budgeting and firm-specific stock return variation. *Journal of Finance* 59, 65-105.

Dyck, Alexander, Adair Morse, and Luigi Zingales, 2010. Who blows the whistle on corporate fraud? *Journal of Finance* 65, 2213-2253.

Dyck, Alexander, Adair Morse, and Luigi Zingales, 2013. How pervasive is corporate fraud? Working paper, University of Chicago.

Feinstein, Jonathan S., 1990. Detection controlled estimation. *Journal of Law and Economics* 33, 233-276.

Gal-Or, Esther, 1985. Information sharing in oligopoly. *Econometrica* 53, 329-343.

Gigler, Frank, 1994. Self-enforcing voluntary disclosures. *Journal of Accounting Research* 32, 224-240.

Goldman, Eitan, and Steve Slezak, 2006, An equilibrium model of incentive contracts in the presence of information manipulation, *Journal of Financial Economics* 80, 603-626.

Grenadier, Steve R., 2002. Option exercise games: An application to the equilibrium investment strategies of firms. *Review of Financial Studies* 15, 691-721.

Hart, Oliver, 1983. The market mechanism as an incentive scheme. *Bell Journal of Economics* 14, 366-382.

Hazarika, Sonali, Jonathan Karpoff, and Rajarishi Nahata, 2011. Internal corporate governance, CEO turnover, and earnings management. *Journal of Financial Economics* forthcoming.

Healy, P. M., Wahlen, J. M., 1999. A review of the earnings management literature and its implications for standard setting. *Accounting Horizons* 13, 365-383.

Hertzberg, Andrew, 2005, Managerial incentives, misreporting, and the timing of social learning: A theory of slow booms and rapid recessions, Working paper, Northwestern University.

Hoberg, Gerard, and Gordon Phillips, 2010. Real and financial industry booms and busts. *Journal of Finance* 65, 45-86.

Jenter, Dirk, and Fadi Kanaan, 2010. CEO turnover and relative performance evaluation. *Journal of Finance* forthcoming.

Johnson, Marilyn, Ron Kasznik, Karen Nelson, 2000, Shareholder wealth effects of the Private Securities Litigation Reform Act of 1995, *Review of Accounting Studies* 5, 217-233.

Johnson, M. F., Nelson, K. K., and Pritchard, A.C., 2007. Do the merits matter more? Class action under the Private Securities Litigation Reform Act. *Journal of Law, Economics, & Organization* 23 (3), 627-652.

Jones, Christopher, and Seth Weingram, 1996, The determinants of 10b-5 litigation risk, Working paper, Stanford Law School.

Karpoff, Jonathan M., D. Scott Lee, and Gerald S. Martin, 2008. The cost to firms of cooking the books. *Journal of Financial and Quantitative Analysis* 43, 581-612.

Karpoff, Jonathan M., Allison Koester, D. Scott Lee, and Gerald S. Martin, 2012. An analysis of database challenges in financial misconduct research. Working paper, University of Washington.

Kedia, Simi and Thomas Phillipon, 2009. The economics of fraudulent accounting, *Review of Financial Studies* 22, 2169-2199.

Maksimovic, Vojislav, 1995. “Financial structure and product market competition,” in Finance, Handbooks in Operations Research and Management Science, Vol. 9, North-Holland, Amsterdam, 887-920.

Peress, Joel, 2010. Product market competition, insider trading and stock market efficiency. *Journal of Finance* 65, 1-43.

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

Povel, Paul, Raj Singh, and Andrew Winton, 2007. Booms, busts, and fraud. *Review of Financial Studies* 20, 1219-1254.

Qiu, B., and Slezak, S. L., 2010. A theory of growth, productivity, and the commission and detection of fraudulent misreporting. University of Cincinnati, working paper.

Schiesel, Seth, 2002. Trying to catch WorldCom’s mirage. *New York Times*, June 30, 2002, 3.1.

Sidak, J. Gregory, 2003. The failure of good intentions: The WorldCom fraud and the collapse of American telecommunications after deregulation. *Yale Journal on Regulation* 20, 207-267.

Teoh, S. H., Welch, I., and Wong, T. J., 1998a. Earnings management and the underperformance of seasoned equity offerings. *Journal of Financial Economics* 50, 66-99.

Teoh, S. H., Welch, I., and Wong, T. J., 1998b. Earnings management and the long-term market performance of initial public offerings. *Journal of Finance* 53, 1935-1974.

Wang, Tracy Yue, 2013. “Corporate securities fraud: Insights from a new empirical framework,” *Journal of Law, Economics and Organization* 29 (3), 535-568.

Wang, Tracy Yue, Andrew Winton, and Xiaoyun Yu, 2010. Business conditions and corporate securities fraud: Evidence from IPOs. *Journal of Finance* 65, 2255-2292.

Appendix A: Variable Definitions

Industry Characteristics	
PMS1(2)	The estimate of the γ coefficient in Equation (1) (2), scaled by the standard error of the estimate.
Negative PMS	=1 for industries in which both PMS_1 and PMS_2 are negative.
RPE_ROA	=1 if CEO turnovers in an industry are sensitive to firm underperformance (in terms of ROA) relative to industry peers, =0 otherwise.
RPE_Return	=1 if CEO turnovers in an industry are sensitive to firm underperformance (in terms of stock return) relative to industry peers, =0 otherwise.
RPE_Compensation	=1 if CEO compensation in an industry is sensitive to firm underperformance (in terms of stock return) relative to industry peers.
Comove	The industry-year average correlation between one firm's return and the rival firms' value-weighted returns.
ComoveRsq	The average regression R-squared from equation (3) in an industry-year
# of Firms	The number of firms in an industry-year (in 100s).
Ind. Rel. Investment	Average abnormal investment in an industry-year (Hoberg and Phillips 2010)
Ind. Rel. Valuation	Average abnormal valuation in an industry-year (Hoberg and Phillips 2010)
Fitted HHI	The industry concentration measure from Hoberg and Phillips (2010). The authors create the HHI that accounts for both public and private firms and covers all the three-digit SIC industries except the financial industries (SICs 6000-6999) and utilities industries (SICs 4900-4999). They combine the Compustat data with the HHI data from the Commerce Department and the employee data from the Bureau of Labor Statistics to construct the fitted HHI.
Ex-ante Information	
ROA	(Operating income after depreciation)/Assets
Ext. Fin. Need	Asset growth rate – ROA2/(1-ROA2) ROA2 = (income before extraordinary items)/Assets
Leverage	(Long-term debt)/Assets
Insider Own	% of equity ownership of all officers
CAPX	Capital expenditures scaled by book assets
R&D	R&D expenditures scaled by book assets
M&A	acquisition expenditures scaled by book assets
Institutional Own	% of equity ownership of all institutional investors
Analyst Coverage	# of analyst following the firm
Log (Assets)	Log (total book assets)
Age	# of years since IPO
Technology	=1 for SIC industries 2833-2836, 3570-3577, 3600-3695, 7370-7377, = 0 otherwise
Service	=1 for SIC industries 4812-4899, 4900-4991, 6021-6799, 7000-7361,7380-7997, 8111-8744, 8000-8093, = 0 otherwise
Trade	=1 for SIC industries 5000-5190, 5200-5990, = 0 otherwise
Ex-post Information	
Abnormal Ind. Litigation	Litigation intensity is measured as Log (total market value of all the litigated firms in an industry-year). Abnormal Ind. Litigation is the yearly deviation from the average litigation intensity in an industry.
Disastrous Stock Return	=1 if stock return is below -53%, =0 otherwise
Abnormal Return Volatility	The demeaned standard deviation of monthly stock returns in a year
Abnormal Stock Turnover	The demeaned average monthly turnover in a year

Table 1: Summary Statistics

Panel A: Summary Statistics of Explanatory Variables

	# of Obs.	Mean (Median)	Std. Deviation
Industry Characteristics (by industry or by industry-year)			
PMS_1	243	0.77 (0.80)	1.91
PMS_2	243	-.27 (0.38)	2.58
Negative PMS	243	0.19 (0.00)	0.40
RPE_ROA	243	0.13 (0.00)	0.33
RPE_Return	243	0.06 (0.00)	0.22
RPE_Compensation	200	0.23 (0.00)	0.42
Comove	2934	0.18 (0.16)	0.12
ComoveRsq	3021	0.21 (0.18)	0.15
# of Firms (in 100s)	3083	0.25 (0.11)	0.53
Ind. Rel. Investment	1889	-0.01 (-0.02)	0.10
Ind. Rel. Valuation	1889	-0.02 (-0.001)	0.25
Ex-Ante Information (by firm-year)			
ROA	18931	0.06 (0.12)	0.28
Ext. Fin. Need	18931	0.36 (0.07)	1.11
Leverage	18931	0.21 (0.170	0.20
Insider Ownership	18931	0.18 (0.10)	0.20
CAPX	18931	0.06 (0.04)	0.07
R&D	18931	0.05 (0.001)	0.12
M&A	18931	0.04 (0.00)	0.11
Institutional Ownership	18931	0.32 (0.27)	0.26
Analyst Coverage	18931	5.01 (2.00)	7.24
Log (Assets)	18931	5.04 (4.87)	2.05
Age	18931	9.99 (7.68)	8.49
Technology	18931	0.29 (0.00)	0.46
Service	18931	0.15 (0.00)	0.35
Trade	18931	0.12 (0.00)	0.33
Ex-Post Information (by firm-year)			
Abnormal Ind. Litigation	18931	0.04 (0.03)	0.05
Disastrous Stock Return	18931	0.10 (0.00)	0.33
Abnormal Return Volatility	18931	-0.01 (-0.02)	0.05
Abnormal Stock Turnover	18931	0.15 (-0.16)	3.45

Panel B: Correlation Matrix of Proxies for Industry Informational Interactions

	PMS1	PMS2	# of Firms	Comove	Comove Rsq	RPE_Ret	RPE_ROA
PMS1	1.00						
PMS2	0.10	1.00					
# of Firms	-0.17	-0.13	1.00				
Comove	0.11	0.06	0.17	1.00			
ComoveRsq	0.08	0.07	0.10	0.92	1.00		
RPE_Ret	0.08	-0.03	0.34	0.14	0.12	1.00	
RPE_ROA	0.05	0.09	0.13	0.06	0.02	0.10	1.00

Panel C: Corporate Securities Fraud by Beginning Year

Year	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	Total
# of Frauds	14	19	50	90	107	101	123	127	80	47	101	89	39	987

Panel D: Top Five Industries with Alleged Fraud

Ranking	3-Digit SIC Industry	# of Lawsuits
1	737-Software & Programming	153
2	283-Pharmaceuticals	61
3	357-Computers	47
4	367-Electronics	40
5	384-Medical Instruments	30

Table 2: Product Market Sensitivity and Fraud

P(F) is the probability of fraud, and P(D|F) is the probability of detection conditional on fraud occurrence. Robust standard errors (in parentheses) are clustered by firm. ***, **, and * indicate significance at 1, 5, and 10% confidence levels respectively.

	(1)		(2)		(3)	
	P(F)	P(D|F)	P(F)	P(D|F)	P(F)	P(D|F)
PMS1	-0.077**					
	(0.031)					
PMS2			-0.051**			
			(0.022)			
Negative PMS					0.692**	
					(0.261)	
Ind. Rel. Investment	3.500***		3.298***		3.561***	
	(0.992)		(0.932)		(1.013)	
ROA	0.778*		0.789**		0.900**	
	(0.402)		(0.385)		(0.400)	
Ext. Fin. Need	2.318***		2.268***		2.533***	
	(0.489)		(0.505)		(0.487)	
Leverage	0.033		0.012		0.014	
	(0.360)		(0.347)		(0.355)	
Insider Ownership	1.113**		1.139***		1.164***	
	(0.436)		(0.412)		(0.419)	
CAPEX	-2.863**	0.710	-2.888**	0.531	-3.569***	0.656
	(1.236)	(0.536)	(1.283)	(0.558)	(1.263)	(0.521)
R&D	5.649**	-1.131***	5.189**	-1.154***	5.558**	-1.067***
	(2.719)	(0.417)	(2.483)	(0.430)	(2.565)	(0.397)
M&A	-0.352	0.763***	-0.211	0.689***	-0.338	0.745***
	(0.598)	(0.255)	(0.627)	(0.267)	(0.585)	(0.245)
Institution Ownership	-0.423	0.409*	-0.441	0.430**	-0.253	0.345*
	(0.459)	(0.209)	(0.450)	(0.211)	(0.443)	(0.197)
Analyst Coverage	-0.022**	0.027***	-0.022*	0.026***	-0.022**	0.027***
	(0.010)	(0.006)	(0.012)	(0.007)	(0.011)	(0.006)
Ln(Assets)	0.265***	-0.032	0.272***	-0.032	0.259***	-0.025
	(0.102)	(0.035)	(0.097)	(0.034)	(0.097)	(0.034)
Firm Age	0.001	0.001	0.000	0.001	0.002	0.000
	(0.008)	(0.004)	(0.008)	(0.004)	(0.007)	(0.004)
Technology	0.360	0.146	0.261	0.168	0.437*	0.122
	(0.268)	(0.114)	(0.283)	(0.118)	(0.263)	(0.107)
Service	0.316	-0.034	0.286	-0.000	0.268	-0.029
	(0.314)	(0.139)	(0.312)	(0.138)	(0.312)	(0.135)
Trade	-0.236	0.208	-0.243	0.241	-0.094	0.125
	(0.323)	(0.197)	(0.325)	(0.197)	(0.336)	(0.193)
Abnormal Ind. Litigation		0.942**		1.098**		0.922**
		(0.435)		(0.448)		(0.429)
Disastrous Stock Return		0.500***		0.497***		0.501***
		(0.063)		(0.063)		(0.062)
Abnormal Return Volatility		4.612***		4.465***		4.693***
		(0.897)		(0.900)		(0.841)
Abnormal Stock Turnover		0.036***		0.036***		0.036***
		(0.007)		(0.007)		(0.007)
Constant	-1.957***	-1.844***	-1.916***	-1.838***	-2.164***	-1.848***
	(0.647)	(0.162)	(0.697)	(0.158)	(0.591)	(0.154)
χ^2 (d.f.)		271(30)		263(30)		295(30)
Observations		18086		18086		18086

Table 3: Relative Performance Evaluation and Fraud Propensity

P(F) is the probability of fraud, and P(D|F) is the probability of detection conditional on fraud occurrence. Robust standard errors (in parentheses) are clustered by firm. ***, **, and * indicate significance at 1, 5, and 10% confidence levels respectively.

	(1)		(2)		(3)	
	P(F)	P(D|F)	P(F)	P(D|F)	P(F)	P(D|F)
RPE_ROA	0.388**					
	(0.192)					
RPE_Return			0.651**			
			(0.316)			
RPE_Compensation					0.240**	
					(0.125)	
Ind. Rel. Investment	3.621***		4.003***		3.328***	
	(1.074)		(1.183)		(0.962)	
ROA	0.950**		0.964**		0.867**	
	(0.422)		(0.445)		(0.389)	
Ext. Fin. Need	2.648***		2.837***		2.394***	
	(0.496)		(0.549)		(0.488)	
Leverage	0.073		0.064		0.013	
	(0.389)		(0.385)		(0.354)	
Insider Ownership	1.348**		1.417**		1.234***	
	(0.527)		(0.572)		(0.457)	
CAPEX	-3.307**	0.600	-3.614***	0.612	-3.233***	0.589
	(1.286)	(0.519)	(1.368)	(0.509)	(1.244)	(0.531)
R&D	5.571**	-1.023**	5.735*	-1.015**	5.646**	-1.107***
	(2.781)	(0.398)	(3.072)	(0.395)	(2.625)	(0.408)
M&A	-0.484	0.781***	-0.749	0.821***	-0.408	0.745***
	(0.595)	(0.242)	(0.643)	(0.234)	(0.589)	(0.247)
Institution Ownership	-0.298	0.348*	-0.371	0.361*	-0.385	0.388*
	(0.437)	(0.194)	(0.446)	(0.187)	(0.442)	(0.200)
Analyst Coverage	-0.031**	0.030***	-0.033**	0.028***	-0.029**	0.029***
	(0.013)	(0.006)	(0.014)	(0.006)	(0.013)	(0.006)
Ln(Assets)	0.322***	-0.041	0.350***	-0.043	0.301***	-0.040
	(0.096)	(0.030)	(0.100)	(0.028)	(0.096)	(0.032)
Firm Age	-0.000	0.001	0.000	0.001	0.000	0.001
	(0.008)	(0.004)	(0.008)	(0.004)	(0.008)	(0.004)
Abnormal Ind. Litigation		0.860**		0.835**		0.974**
		(0.434)		(0.422)		(0.425)
Disastrous Stock Return		0.504***		0.493***		0.493***
		(0.062)		(0.060)		(0.062)
Abnormal Return Vola.		4.735***		4.495***		4.477***
		(0.787)		(0.858)		(0.879)
Abnormal Turnover		0.037***		0.036***		0.036***
		(0.007)		(0.007)		(0.007)
Constant	-2.472***	-1.839***	-2.348***	-1.854***	-2.045***	-1.832***
	(0.635)	(0.154)	(0.716)	(0.152)	(0.693)	(0.154)
Sector Dummies	Yes	Yes	Yes	Yes	Yes	Yes
χ^2 (d.f.)		267(30)		276(30)		265(30)
Observations		18086		18086		18086

Table 4: Lack of Information Gathering and Fraud

P(F) is the probability of fraud, and P(D|F) is the probability of detection conditional on fraud occurrence. Robust standard errors (in parentheses) are clustered by firm. Sector dummies include dummies for the technology, service, and trade sectors, respectively. ***, **, and * indicate significance at 1, 5, and 10% confidence levels respectively.

Panel A

	(1)		(2)		(3)	
	P(F)	P(D|F)	P(F)	P(D|F)	P(F)	P(D|F)
# of Firms (in 100s)	0.203*	-0.095**				
	(0.110)	(0.038)				
Comove			0.321	-1.196***		
			(0.867)	(0.445)		
ComoveRsq					0.711	-1.612**
					(1.082)	(0.651)
Ind. Rel. Investment	3.763***		3.230***		3.129***	
	(1.146)		(0.966)		(0.975)	
ROA	0.817*		0.808**		0.836**	
	(0.437)		(0.404)		(0.404)	
Ext. Fin. Need	2.548***		2.501***		2.503***	
	(0.546)		(0.481)		(0.473)	
Leverage	-0.058		-0.011		-0.032	
	(0.358)		(0.358)		(0.358)	
Insider Ownership	1.320***		1.162***		1.186***	
	(0.512)		(0.442)		(0.449)	
CAPEX	-3.150**	0.494	-3.150**	0.622	-3.165**	0.556
	(1.330)	(0.541)	(1.266)	(0.535)	(1.275)	(0.542)
R&D	5.569**	-1.065***	5.311**	-1.093***	5.317**	-1.067***
	(2.584)	(0.389)	(2.674)	(0.412)	(2.649)	(0.408)
M&A	-0.623	0.854***	-0.279	0.739***	-0.294	0.721***
	(0.591)	(0.243)	(0.613)	(0.256)	(0.605)	(0.255)
Institution Ownership	-0.249	0.339*	-0.323	0.385**	-0.398	0.415**
	(0.444)	(0.198)	(0.427)	(0.195)	(0.447)	(0.204)
Analyst Coverage	-0.031**	0.031***	-0.026**	0.028***	-0.027**	0.028***
	(0.014)	(0.006)	(0.013)	(0.006)	(0.013)	(0.006)
Ln(Assets)	0.317***	-0.042	0.289***	-0.025	0.291***	-0.027
	(0.096)	(0.030)	(0.096)	(0.032)	(0.096)	(0.032)
Firm Age	0.001	-0.000	0.001	0.000	0.001	0.000
	(0.007)	(0.004)	(0.008)	(0.004)	(0.008)	(0.004)
Abnormal Ind. Litigation		1.323***		1.035**		0.965**
		(0.492)		(0.433)		(0.432)
Disastrous Stock Return		0.517***		0.504***		0.507***
		(0.063)		(0.062)		(0.062)
Abnormal Return Vol.		4.659***		5.042***		5.010***
		(0.826)		(0.881)		(0.901)
Abnormal Stock Turnover		0.036***		0.033***		0.034***
		(0.007)		(0.007)		(0.007)
Constant	-2.445***	-1.776***	-2.223***	-1.663***	-2.227***	-1.735***
	(0.657)	(0.156)	(0.567)	(0.166)	(0.571)	(0.160)
Sector Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood		-1854		-1850		-1853
χ^2 (d.f.)		271(31)		304(31)		317(31)
Observations		18086		18086		18086

Panel B: Long-run Average Industry Information Production

The long-run average # of Firms is the industry average number of firms per year during our sample period (1993-2008). The long-run average Comove is the industry average yearly return comovement during our sample period.

	(1)	
	P(F)	P(D|F)
Long-run Avg. # of Firms	0.070	-0.004
	(0.124)	(0.042)
Long-run Avg. Comove	0.701	-2.413***
	(2.145)	(0.937)
Ind. Rel. Investment	3.303***	
	(1.055)	
ROA	0.837**	
	(0.423)	
Ext. Fin. Need	2.556***	
	(0.541)	
Leverage	0.032	
	(0.364)	
Insider Ownership	1.222**	
	(0.485)	
CAPEX	-3.102**	0.732
	(1.307)	(0.526)
R&D	6.748**	-1.103***
	(3.043)	(0.378)
M&A	-0.601	0.822***
	(0.641)	(0.255)
Institution Ownership	-0.345	0.345*
	(0.442)	(0.198)
Analyst Coverage	-0.029**	0.029***
	(0.015)	(0.006)
Ln(Assets)	0.290***	-0.026
	(0.100)	(0.032)
Firm Age	0.002	-0.001
	(0.008)	(0.004)
Abnormal Ind. Litigation		0.915**
		(0.434)
Disastrous Stock Return		0.496***
		(0.062)
Abnormal Return Volatility		4.368***
		(0.907)
Abnormal Stock Turnover		0.035***
		(0.007)
Constant	-2.254***	-1.143***
	(0.843)	(0.309)
Sector Dummies	Yes	Yes
Observations		18086

Table 5: Fraud and Predictable Bust in Fragmented Industries

The dependent variables in Panel A are measured at the industry-year level. "Ln(Fitted HHI)" is the industry concentration measure from Hoberg and Phillips (2010). The authors create the HHI that accounts for both public and private firms and covers all the three-digit SIC industries except the financial industries (SICs 6000-6999) and utilities industries (SICs 4900-4999). They combine the Compustat data with the HHI data from the Commerce Department and the employee data from the Bureau of Labor Statistics to construct the fitted HHI. Robust standard errors (in parentheses) are clustered by industry. In Panel B, the dependent variable is the firm-year predicted relative fraud propensity based on model (3) of Table 4. The explanatory variables are lagged by a year. Robust standard errors (in parentheses) are clustered by firm. In each regression there is a constant term, which is not reported for brevity. ***, **, and * indicate significance at 1, 5, and 10% confidence levels, respectively.

Panel A: Cyclicality of Lack of Information Gathering

	ComoveRsq		# of Firms	
	(1)	(2)	(3)	(4)
Ind. Rel. Investment	0.038**	0.236**	0.219**	2.949**
	(0.019)	(0.111)	(0.105)	(1.302)
Ind. Rel. Inv. * Ln(Fitted HHI)		-0.030*		-0.425**
		(0.017)		(0.189)
Ln(Fitted HHI)		0.010		-0.843***
		(0.011)		(0.257)
Year Fixed Effects	Yes	Yes	Yes	Yes
Adj. R-sq	0.373	0.375	0.030	0.103
Obs.	1883	1883	2023	2023

Panel B: Lack of Information Collection and Cyclicality of Fraud

Dependent Variable: Relative Fraud Propensity	(1)	(2)
Ind. Rel. Investment	-0.121***	0.060
	(0.059)	(0.043)
Ind. Rel. Inv. * ComoveRsq	0.985***	
	(0.018)	
ComoveRsq	0.322***	
	(0.058)	
Ind. Rel. Inv. * # of Firms		0.030***
		(0.011)
# of Firms		0.032***
		(0.001)
Year Fixed Effects	Yes	Yes
Adj. R-sq	0.043	0.088
Obs.	19958	19958

Panel C: Fraud and Predictable Bust in Fragmented Industries

"Relative Fraud Propensity" is constructed from the predicted probability of fraud commission (P(F=1)) based on model (2) in Table 3. It is the yearly ranking of the predicted P(F=1) from the lowest to the highest. We scale the ranking by the number of firms in a year so that *Relative Fraud Propensity* lies between 0 and 1.

Dependent Variable:	Fragmented Industries (bottom tercile of fitted HHI)			Concentrated Industries (top tercile of fitted HHI)		
Δ(Op. CF) 2 years	(1)	(2)	(3)	(4)	(5)	(6)
Ind. Rel. Investment	-0.125***	0.011	0.049	-0.012	-0.037	-0.050
	(0.042)	(0.071)	(0.090)	(0.022)	(0.049)	(0.048)
Ind. Rel. Inv. X Rel. Fraud Propensity		-0.226**	-0.403**		0.078	0.037
		(0.115)	(0.161)		(0.084)	(0.073)
Rel. Fraud Propensity		-0.040***	-0.029		-0.018**	-0.003
		(0.012)	(0.019)		(0.008)	(0.011)
Firm ComoveRsq	-0.046**	-0.043**	-0.110***	0.049***	0.048***	0.033**
	(0.020)	(0.021)	(0.039)	(0.011)	(0.011)	(0.016)
ROA	-0.043**	-0.046**	-0.295***	-0.100***	-0.103***	-0.526***
	(0.020)	(0.020)	(0.064)	(0.037)	(0.038)	(0.057)
CAPX	0.240***	0.219***	0.255***	0.107***	0.108***	0.079*
	(0.033)	(0.034)	(0.095)	(0.034)	(0.034)	(0.047)
R&D	-0.042	-0.024	-0.161	-0.176*	-0.160	-0.788***
	(0.040)	(0.042)	(0.099)	(0.101)	(0.102)	(0.235)
M&A	0.040*	0.059**	0.004	0.043***	0.060***	0.039**
	(0.021)	(0.023)	(0.037)	(0.014)	(0.015)	(0.019)
Ln(Assets)	0.009***	0.010***	-0.003	-0.002**	-0.001	-0.071***
	(0.002)	(0.002)	(0.011)	(0.001)	(0.001)	(0.006)
Constant	0.017	0.030**	0.091**	0.051***	0.054***	0.498***
	(0.012)	(0.012)	(0.046)	(0.009)	(0.009)	(0.034)
Firm Fixed Effects			x			x
Year Fixed Effects	x	x	x	x	x	x
Adj. R-sq	0.04	0.06	0.30	0.05	0.05	0.45
Obs.	5854	5854	5854	6802	6802	6802
	(1)	(2)	(3)	(4)	(5)	(6)
Ind. Rel. Valuation	-0.126***	-0.086***	-0.070**	0.020**	0.015	0.030**
	(0.019)	(0.030)	(0.033)	(0.009)	(0.013)	(0.014)
Ind. Rel. Val. X Rel. Fraud Propensity		-0.065*	-0.075*		0.014	-0.013
		(0.037)	(0.040)		(0.026)	(0.027)
Rel. Fraud Propensity		-0.024**	-0.012		-0.020**	-0.007
		(0.012)	(0.014)		(0.008)	(0.011)
Firm ComoveRsq	-0.013	-0.010	-0.074*	0.048***	0.047***	0.030*
	(0.020)	(0.021)	(0.039)	(0.011)	(0.011)	(0.015)
Controls	x	x	x	x	x	x
Adj. R-sq	0.05	0.06	0.31	0.05	0.05	0.45
Obs.	5854	5854	5854	6785	6785	6785

Table 6: Alternative Model Specifications

	(1) Probit	(2) Alternative specification for bivariate-probit	
	P(Z=1)	P(F)	P(D|F)
PMS1	-0.038***	-0.149*	0.017
	(0.013)	(0.080)	(0.047)
RPE_ROA	0.135**	1.035*	-0.156
	(0.057)	(0.610)	(0.159)
# of Firms (in 100s)	-0.031	0.265	-0.095***
	(0.019)	(0.189)	(0.034)
Comove	-0.699***	0.917	-1.230***
	(0.261)	(1.071)	(0.418)
Ind. Rel. Investment	1.236***	3.552**	0.567
	(0.306)	(1.541)	(0.426)
ROA	0.170	0.366	0.254*
	(0.117)	(0.575)	(0.150)
Ext. Fin. Need	0.098***	2.674***	0.036
	(0.014)	(0.546)	(0.030)
Leverage	0.082	-0.021	0.069
	(0.124)	(0.576)	(0.201)
Insider Ownership	0.307***	1.474*	0.020
	(0.115)	(0.795)	(0.247)
CAPEX	-0.144	-1.862	0.395
	(0.401)	(1.475)	(0.556)
R&D	0.055	4.418	-0.718*
	(0.223)	(2.856)	(0.408)
M&A	0.626***	-0.873	0.919***
	(0.134)	(0.656)	(0.214)
Institution Ownership	0.237**	0.021	0.216
	(0.109)	(0.394)	(0.158)
Analyst Coverage	0.019***	-0.042**	0.035***
	(0.004)	(0.020)	(0.006)
Ln(Assets)	0.045***	0.420**	-0.045
	(0.017)	(0.136)	(0.030)
Firm Age	-0.004	-0.002	0.000
	(0.003)	(0.009)	(0.005)
Abnormal Ind. Litigation	1.312***		1.524***
	(0.381)		(0.514)
Disastrous Stock Return	0.539***		0.561***
	(0.052)		(0.070)
Abnormal Return Volatility	2.875***		5.181***
	(0.401)		(0.804)
Abnormal Stock Turnover	0.032***		0.038***
	(0.006)		(0.008)
Constant	-2.622***	-3.648***	-1.693***
	(0.114)	(0.993)	(0.282)
Observations	18086	18086	18086

Table 7: All Dimensions of Informational Interactions Together

P(F) is the probability of fraud, and P(D|F) is the probability of detection conditional on fraud occurrence. Robust standard errors (in parentheses) are clustered by firm. ***, **, and * indicate significance at 1, 5, and 10% confidence levels respectively.

	(1)	
	P(F)	P(D|F)
PMS1	-0.081**	
	(0.037)	
RPE_ROA	0.530**	
	(0.259)	
# of Firms (in 100s)	0.231*	-0.106***
	(0.128)	(0.037)
Comove	0.712	-1.230***
	(0.807)	(0.413)
Ind. Rel. Investment	3.899***	
	(1.227)	
ROA	0.733	
	(0.447)	
Ext. Fin. Need	2.656***	
	(0.508)	
Leverage	0.032	
	(0.399)	
Insider Ownership	1.391**	
	(0.598)	
CAPEX	-2.502**	0.681
	(1.234)	(0.521)
R&D	5.012**	-1.001***
	(2.343)	(0.374)
M&A	-0.783	0.931***
	(0.622)	(0.236)
Institution Ownership	-0.097	0.278
	(0.428)	(0.182)
Analyst Coverage	-0.035**	0.033***
	(0.015)	(0.006)
Ln(Assets)	0.352***	-0.037
	(0.113)	(0.029)
Firm Age	0.001	-0.001
	(0.008)	(0.004)
Abnormal Ind. Litigation		1.407***
		(0.493)
Disastrous Stock Return		0.537***
		(0.065)
Abnormal Return Vola.		5.170***
		(0.787)
Abnormal Stock Turnover		0.035***
		(0.007)
Constant	-3.086***	-1.609***
	(0.751)	(0.164)
Sector Dummies	Yes	Yes
χ^2 (d.f.)		319 (33)
Observations		18086