COMPETITION AND CORPORATE FRAUD

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Abstract

We examine three information channels through which product market competition in an industry can affect firms' incentives to misreport financial information to investors: the sensitivity of rival firms' product market decisions to information about individual firms; the use of relative performance evaluation in managerial retention decisions; and the extent of information collection about individual firms. Lower average product market sensitivity to individual firms encourages the commission of financial fraud, as does greater use of relative performance evaluation. Less collection of information about individual firms tends to decrease the probability that committed frauds are detected and increase the probability that fraud is committed. All three channels are more likely to be present in more competitive industries, implying that fraud propensity is on average higher in those industries.

We also examine dynamic effects of fraud. Fraud propensity is more cyclical in more competitive industries. Also, in more competitive industries, the consequences of fraud are worse following booms than they are following normal times. The upshot is that poor performance in competitive industries following booms is largely concentrated in firms that are likely to have committed fraud during the booms. These results suggest that fraud can amplify cyclical fluctuations in the real economy, particularly in competitive industries.

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 competition is a natural candidate for investigation. The economics literature has long argued that the nature of product market competition 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 product market pressures and fraud (see Schiesel, 2002).

In this paper we examine the effect of product market competition on firms' incentives to fraudulently report financial information, focusing on three potential channels. 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 incentives to commit. 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

[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.

performance encourages rivals to increase their investment and output, hurting the firm's own product-market position.

The second channel we examine is related to the use of relative performance evaluation (RPE), where managers are evaluated based on their firm's performance relative to that of industry peers. Classic economic theories suggest that RPE is more efficient in more competitive industries, because the existence of a larger number of firms makes the information about industry common shocks more precise. Cheng (2011) theorizes that the existence of RPE can increase managers' incentives to misreport to shareholders. If RPE is more relevant in more competitive industries, then Cheng's theory suggests that corporate fraud propensity should be higher in more competitive industries.

The third channel we examine is related to the amount of information collection about individual firms and stock price efficiency. Firms in more competitive industries tend to focus more on industry common signals and do a worse job of collecting information about their (more numerous) rivals. Moreover, investors in such industries may acquire less firm-specific information as well (Peress, 2010). Firms' failure to gather firm-specific information about rivals can lead to uncoordinated investment by these firms (Dixit and Pindyck 1994, Grenadier 2002, Hoberg and Phillips 2010). Investors' failure to gather firm-specific information leads to less informative stock market prices, reducing the likelihood that fraud is detected; in turn, a lower likelihood of fraud detection can encourage firms to commit fraud.

To test these three potential links between competition and fraud, we construct industry-level proxies for firms' lack of product market sensitivity to other firms' information, for the existence of RPE, and for lack of information collection about individual firms. We measure product market sensitivity by estimating the responsiveness of rival firms' investment to information about each firm's product demand for each three-digit SIC industry. Similarly, we measure the existence of RPE by estimating the responsiveness of managerial turnover to a firm's underperformance relative to its industry peers. Finally, we measure the amount of information collection about individual firms by the degree of stock return comovement and by the number of firms in an industry. We find that more competitive industries (based on industry concentration measures) tend to have lower product market sensitivity, are more likely to use RPE, and have less information collection than more concentrated industries do. This supports the theories that model these aspects of industry competition. However, the correlations between our industry structure proxies and industry concentration measures are far from perfect, suggesting that they do not simply capture the same information.

In our analysis, we have to address the fact that we observe only those frauds that are subsequently detected, rather than all frauds that are ever committed. To the extent detection is imperfect, the true probability of fraud commission is unobservable. Despite this, most research studies on corporate fraud use a probit or logit model, which essentially equates committed frauds with detected frauds. Following Wang (2011) 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 industry competition on fraud commission and fraud detection; this is essential for testing our third channel, the impact of information gathering on fraud.

We find that industries with lower product market sensitivity to individual firm information tend to have a higher fraud propensity. Industries in which managerial turnover is more sensitive to relative performance have a higher fraud propensity. Industries with less information collection about individual firms have a lower probability of fraud detection and a higher probability of fraud commission. All these results hold after controlling for firm characteristics and other industry characteristics that are related to fraud propensity or fraud detection. The economic magnitudes of these effects are also quite meaningful. For example, firms in industries in the bottom tercile of product market sensitivity are on average 7 to 9 percentage points more likely to commit fraud than firms in other industries. 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. Since all three channels are more likely to be present in more competitive industries, our results suggest that fraud propensity is on average higher in those industries.

Our work can also help to explain why Hoberg and Phillips (2010) find evidence of what they call "predictable busts in competitive industries"—that is, firms in competitive industries fare much worse following industry booms than do firms in concentrated industries. We find that fraud incentives are more cyclical in more competitive industries. Also, in competitive industries, the consequences of fraud are worse following booms than they are following normal times. It follows that poor performance in competitive 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, particularly in competitive industries.

As robustness tests, we examine several alternative specifications. Our main analysis does not use industry concentration measures (e.g., Herfindahl-Hirschman Index, or HHI) as proxies for competition because the theories that we test model other aspects of competition rather than concentration per se. Nevertheless, when we use the fitted HHI from Hoberg and Phillips (2010) and the Census HHI for manufacturing industries as competition measures, we find that the probability of fraud detection is lower in less concentrated industries. This is consistent with the third channel discussed above.

We also re-estimate all 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.

Finally, we re-estimate all our baseline results under a specification where all controls in our fraud commission equation are also included in our fraud detection equation. Once again, our results are essentially unchanged.

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 product market competition has important implications for the significant cross-industry variation in corporate fraud propensity. Moreover, the dynamics of fraud can also amplify business cycle fluctuations in competitive industries—an aspect of the real consequences of fraud that has not yet been studied empirically.

Our study also contributes to the ongoing debate about the benefits and costs of product market competition. The common perception is that competition among firms produces many positive social outcomes such as higher firm efficiency and greater consumer surplus. There is empirical evidence supporting this view (e.g., Caves and Barton (1990) on technical efficiency, Nickell (1996) on productivity growth, Blundell, Griffith and Van Reenen (1999) on innovation rates). However, economic theories also suggest that competition can have destructive effects. For example, competitive industries may suffer from a lack of information gathering about individual firms and a consequent lack of investment coordination. Hoberg and Phillips (2010) show that this leads to predictable busts in competitive industries. Our findings that fraud is more prevalent and more cyclical in more competitive industries may help account for Hoberg and Phillips' results.

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 the industry-level determinants of corporate fraud. Since the securities fraud that we examine involves fraudulent disclosure to capital market investors (mainly shareholders), we base our hypotheses on theories that have implications for how product market competition affects firms' disclosure incentives in the capital market. We also discuss the literature that examines the general effects of competition on agency problems within firms and its relationship to our work.

2.1 Product Market Sensitivity and Fraud

One key difference between a competitive industry and an oligopolistic 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, Darrough 1993). 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, over-reporting demand invites entry and competition from rival firms in the product market. The net reporting incentive depends on which effect dominates. In oligopolistic industries, rivals are more responsive to the signal from any one firm, and so there is a strong countervailing force against over-reporting. By contrast, in competitive industries, reports from any one firm have little impact on its rivals' behavior, so capital market effects dominate. Thus, conditional on a firm's external financing needs, fraud propensity should be higher in more competitive industries. Thus, strategic interactions in the product market actually serve to discipline firms' incentives to commit securities fraud.[2] 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 less effect on rival firms' investment decisions (i.e., industries with lower product market sensitivity).

2.2 Relative Performance Evaluation and Fraud

Another strand of theoretical research argues that one benefit of product market competition is that it provides information about industry common shocks that is not available in a monopolistic industry (cf. Hart 1983, Nalebuff and Stiglitz 1983, Meyer and Vickers 1997). The larger the number of firms in an industry, the more precise is this information about common shocks. In turn, more precise information about common shocks helps a firm's owners to make better inferences about how much of firm performance is due to the manager's abilities or efforts. These theories imply that it is more efficient to use a firm's performance relative to industry peers' performance when evaluating managers (relative performance evaluation, or RPE) in industries that have a larger number of competing firms.

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[2] 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).

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, and the theories mentioned earlier suggest that such RPE should be more common in more competitive industries. 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.

2.3 Lack of Information Collection and Fraud

Another key difference between a competitive industry and an oligopolistic one has to do with incentives to gather costly information about individual firms. In a classic perfectly competitive industry, each firm is a price taker and makes its own investment decision independent of rival firms' information. Collecting information about individual firms is costly, particularly when there are a large number of firms. As a result, competitive industries tend to produce less information about individual firms than what is socially optimal and firms tend to focus more on industry common signals rather than on costly information about their individual rivals.

This lack of information collection should in turn exacerbate Grenadier's (2002) results on how competition offsets individual firms' incentives to wait to invest. In Grenadier's model, each firm hastens its individual investment in order to avoid preemption by its rivals, an effect which grows with the total number of firms in the industry. This erodes the value of waiting to invest, and increases the chance that, ex post, industry investment will prove to be excessive. Although Grenadier's results assume firms are fully informed about their rivals, adding costly information should lead this lack of coordination to become more severe as the number of firms increases and their incentive to collect costly information about individual rivals decreases. Indeed, Hoberg and Phillips (2010) find that competitive industries tend to fare much worse than concentrated industries following industry booms. They argue that the lack of costly information gathering and coordination is key to understanding these predictable busts in competitive industries.

Whereas Hoberg and Phillips (2010) focus on how individual firms' information about one another diminishes with increased competition, Peress (2010) focuses on how greater product market competition affects *investors'* incentives to gather information about individual firms. Product market power allows firms to insulate their profits from shocks by passing the shocks onto their consumers. Therefore, profits are less risky for firms with larger 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 less competitive 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. Thus, because there is less information collection about individual firms in more competitive industries, committed fraud should be less likely to be detected in such industries, and fraud should be more likely to be committed. 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 the 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 consequences of the information environment in competitive industries. In Hypothesis 1, product market sensitivity captures how important an individual firm's information is to 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 on how this in turn affects the detection and commitment of fraud.

2.4 Alternative Interpretations

Of course, even if we find evidence that is consistent with one or more of our three hypotheses, concerns of reverse causality or spurious correlation caused by the a third omitted variable may arise. For example, one might argue that fraud affects how rival firms respond to one's reported performance, thus affecting product market sensitivity; or one might argue that the incidence of fraud and the use of relative performance evaluation are jointly caused by some other factor such as CEO entrenchment. Because it is clearest to discuss these concerns in the context of our actual empirical results, we defer a detailed discussion until Section 4; in brief, closer examination suggests that these concerns do not account for our results.

2.5 Competition and Agency Incentives

We have focused on the implications of product market competition for a firm's information environment and its incentives to make fraudulent disclosures to investors. Another strand of literature has examined the effect of competition in mitigating agency incentives. Many economists presume that competition spurs a firm to be more efficient by forcing it to reduce its agency problems. If corporate securities fraud is a reflection of agency problems in a firm, then we would expect the disciplining effect of competition to reduce the incidence of fraud.

The theoretical literature has proposed several channels through which competition may reduce agency incentives. For example, Hermalin (1992) highlights the income effect of competition. If competition lowers the manager's expected income and if agency goods (e.g., slack, perks, empire building) are normal goods, then competition should reduce the manager's consumption of agency goods. Schmidt (1997) argues that, by increasing the probability of bankruptcy following relatively poor performance, competition gives managers more incentive to behave efficiently. Willig (1987) argues that competition reduces profits, making them relatively more sensitive to managerial effort.

Although this literature provides many good insights, it has its limitations. First, it has largely focused on the moral hazard problem, and does not speak to incentives to commit fraud.

Second, as Hermalin (1992) points out, the hypothesized effects of competition on managerial behavior often have ambiguous signs. Finally, as noted by Scharfstein (1988), the predictions are sensitive to the assumptions about managerial preferences.

The empirical literature has examined the effect of competition on corporate performance. Overall, the evidence supports the view that competition promotes efficiency, though, as discussed in the introduction, evidence at the firm level is not overwhelming. Also, note that even clear evidence that competition enhances corporate performance does not prove that this is brought about by reducing managerial agency problems. More recently, Giroud and Mueller (2010a, b) take a different approach by examining how competition interacts with other corporate governance practices in influencing corporate performance. They find that corporate governance rules and practices that mitigate managerial entrenchment have a significant impact on firm value only in noncompetitive industries. This is consistent with the view that competition reduces managerial slack and thus can substitute for the usual forms of corporate governance.

In summary, whether and how competition mitigates agency problems is debatable in theory. Empirical evidence generally supports the view that competition is good. But the evidence does not come from direct tests of theories on competition and agency problems, and it has no direct implications for how competition affects corporate fraud propensity. For these reasons, our tests focus on theories of incentives for fraud rather than theories dealing with general managerial agency problems.

3. EMPIRICAL FRAMEWORK AND SPECIFICATION

In this section we set up the empirical framework for analyzing the effect of competition on a firm's fraud propensity. We first discuss our empirical measures related to product market competition. Then Section 3.2 introduces our empirical model for analyzing fraud, and Sections 3.3-3.5 discuss the empirical specification of major components in the model.

3.1 Empirical Measures Related to Product Market Competition

3.1.1 Product Market Sensitivity

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-code industry, we estimate the following panel regressions:

$$\Delta RivalInv_{t+1} = \alpha_1 + \beta_1 \times \Delta RivalSG_t + \gamma_1 \times \Delta SG_{i,t} + \varepsilon_{t+1} \text{ (1)}$$

$$\Delta RivalInv_{t+1} = \alpha_2 + \beta_2 \times \Delta RivalROA_t + \gamma_2 \times \Delta ROA_{i,t} + \varepsilon_{t+1} \text{ (2)}$$

Here, "Δ" is the first-difference operator. We use the change in sales growth or in ROA to proxy for new information about firm *i*'s product demand. An increase in sales growth rate or profitability should be correlated with stronger demand. Moreover, accounting fraud often involves manipulating sales or profitability numbers (e.g., see Table 1 Panel F in Dechow et al. 2010). "*RivalSG*" ("*RivalROA*") is the weighted-average sales growth rate (ROA) of all firms except firm *i* in a three-digit SIC industry. The weighting factor is a firm's market value of equity. We can think of *RivalSG* and *RivalROA* as capturing the industry common shock in product demand. "*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.[3] The first-difference model also helps to mitigate any firm or industry fixed effects that may not be related to product market sensitivity.

The coefficient γ_1 (γ_2) measures 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*. We construct two sets of product market sensitivity proxies based on the estimate of γ. First, if $|\gamma|$ is close to zero, then the information regarding the demand for firm *i*'s product has little impact on rival firms' investment decisions. To avoid introducing estimation errors in the regressions, we do not directly use the γ estimates. Instead, we construct an indicator variable "*LowPMS_SG*" ("*LowPMS_ROA*") that equals one if $|\gamma_1|$ ($|\gamma_2|$) is in the bottom tercile of the sample distribution, and zero otherwise.

Second, the sign of γ may also affect fraud incentives. In Gigler's theory, the firm's product market concern is that fraudulently disclosing favorable information may invite rivals to enter or increase their existing investment. However, there may be industries in which favorable own-firm information actually *deters* rivals from competing, i.e., γ in equation (1) or (2) is negative. Extending Gigler's insight, firms in a negative-γ industry should have *more* incentive

[3] We have also used an alternative model specification in which all variables in equations (1) and (2) are expressed in levels rather than first-differences. The estimated γ_1 and γ_2 are highly correlated with those in equations (1) and (2). Thus this modification yields similar results.

to commit fraud than those in a positive-γ industry, because fraud both deters rivals and obtains better funding terms in the capital market. To take advantage of the information in the sign of our γ estimates, we construct an indicator variable "*Negative PMS*" that equals one for industries with both γ_1 and γ_2 negative (about 19% of all industries in our sample).

For robustness, we also consider the following two alternative specifications. First, there may be delay in rivals' investment response due to issues such as the time-to-build. We thus consider the cumulative response in the product market by adding one more lag in the change of firm *i*'s ROA in equation (3). Then we define the product market sensitivity based on the summation of γ_3 and γ_4.

$$\Delta RivalInv_{t+1} = \alpha_2 + \beta_2 \times \Delta RivalROA_t + \gamma_3 \times \Delta ROA_{i,t} + \gamma_4 \times \Delta ROA_{i,t-1} + \varepsilon_{t+1} \quad (3)$$

Second, 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 equations (1)-(3) 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 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.

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

"*CEOTO*" indicates a CEO turnover event in a firm-year. We start with 24,780 firm-year observations from 1992 to 2007 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 between competitive and concentrated 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 is very different across industry competitive structures, 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 two-year average performance between firm *i* and the weighted-average of its rivals in a three-digit SIC industry in year t. Equation (3) 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, 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 (3) for each three-digit SIC industry 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 and significant (p-value<0.1) using stock return (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 (3) 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 and significant γ (p-value < 0.1).

The existence of RPE is not a direct measure of the degree of product market competition. However, theory implies that RPE should be more prevalent in more competitive industries, and later we will show that this is in fact the case in our sample. Given this, RPE captures one way in which competition's effect on an industry's information environment may matter for corporate fraud incentives.

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. To mitigate the effect of skewness in the number of firms, we use the logarithm transformation of the variable.

The next two measures are based on the degree of return comovement. 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. 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-code industry *j*, we run the regression:

$$r_{i,j,t} = \beta_{i,0} + \beta_{i,m} \times r_{m,t} + \beta_{i,j} \times r_{j,t} + \varepsilon_{i,t} \text{ . (4)}$$

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*".

Like our measures for RPE, the degree of return comovement is not a direct measure of the degree of product market compebtition. Instead, it captures a possible consequence of competition, namely lack of information collection about individual firms, which may affect corporate fraud incentives.

3.1.4 Industry Concentration Measures

Empirical tests of theories on product market competition often use some kind of a Herfindahl-Hirschman Index (HHI) that measures how concentrated the sales or assets are in an industry. However, competition often has multiple facets, and the economic theories we test do not model the concentration aspect of competition. Also, the theories we test are about characteristics that are associated with competition, not industry concentration per se. This is why we do not use concentration-based measures in our main hypothesis testing.[4] But it is still useful to compare our measures with the commonly used HHI measures to see how much different aspects of product market competition are correlated with each other.

Many studies construct HHI using only Compustat firms ("*Compustat HHI*"). However, this measure has been criticized because it is based on only publicly traded companies and exhibits low correlation with the actual HHI based on the Department of Commerce data for manufacturing industries that includes all publicly and privately held firms. Hoberg and Phillips (2010) show that the correlation is about 0.34 in their sample. Hoberg and Phillips create *Fitted 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. The authors show that *Fitted HHI* has a correlation of 0.54 with the HHI from the Commerce Department on manufacturing industries in their sample, and is a significant improvement relative to the Compustat HHI.[5]

Finally, we also use the actual HHI from the U.S. Census for manufacturing industries. The data is from the 1992, 1997, and 2002 U.S. Census, and we call it the "*Census HHI*". All the frauds in our sample began during 1993–2005. Thus for years 1993–1995 we use the HHI data from the 1992 Census, for years 1996-2000 we use the HHI data from the 1997 Census, and for the remaining years we use the HHI data from the 2002 Census. In our sample, *Ln(Fitted HHI)* has a correlation of 0.48 with *Compustat HHI*, and 0.49 with *Ln(Census HHI)* for manufacturing industries. The correlation between *Compustat HHI* and *Ln(Census HHI)* is only 0.16.[6]

[4] Similarly, competition may also be reflected in firms' profit margins, entry barriers, probability of failure, etc. However, there are no theories that explicitly link these aspects of competition to firms' fraud propensity. This is why we do not examine these aspects in the paper.
[5] We thank Gerard Hoberg and Gordon Phillips for kindly sharing their data in "Real and Financial Industry Boom and Bust" with us.
[6] Compustat HHI is computed to be between zero and one and thus we do not use any logarithm transformation.

Table 1 Panel C provides the summary statistics of all the industry structure measures. Panel D shows the pair-wise correlation between any two measures. Both *Ln(Fitted HHI)* and *Compustat HHI* are negatively correlated with measures of low product market sensitivity (*LowPMS_SG, LowPMS_ROA*), lack of information collection (*Comove, ComoveRsq, Ln(# of Firms)*), and the existence of RPE (*RPE_Return, RPE_ROA*), but the degrees of correlation are far from perfect. Less concentrated industries tend to have lower product market sensitivity, a larger number of firms, less firm-specific information in stock prices, and are more likely to compare firm performance to industry performance when evaluating managers. All these different aspects of product market competition are correlated with each other in an intuitive way, but they do not simply capture the same information.

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 (2011) and Wang, Winton, and Yu (2010) apply such a model to address the 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

$$Z_i = F_i \times D_i \quad (5)$$

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

$$\begin{aligned} L(\beta_F, \beta_D, \rho) &= \sum_{z_i=1} \log(P(Z_i = 1)) + \sum_{z_i=0} \log(P(Z_i = 0)) \\ &= \sum_{i=1}^{N} \{ z_i \log[\Phi(x_{F,i}\beta_F, x_{D,i}\beta_D, \rho)] + (1 - z_i) \log[1 - \Phi(x_{F,i}\beta_F, x_{D,i}\beta_D, \rho)] \}. \end{aligned} \quad (6)$$

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 (2011), 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.[7]

[7] For further discussion of identification in this model, see Wang (2011).

Hypotheses 1 and 2 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 3 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. There are two types of securities lawsuits: 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.[8] 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.

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

[8] 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.

a settlement value of less than $2 million.[9] 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 the fraud, the ending year of the fraud, and the litigation filing year. The average time between the beginning of the 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 the frauds to be detected and any subsequent lawsuits to appear in our litigation sample.

The variable Z_{it} in equation (5) 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 Section 3.5.[10] Note that identifying the announcement date of fraud is not critical here because we do not do event study analysis.

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

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[9] 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).

[10] 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.

Table 1 Panel A 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 both before and after this period. Panel B 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 many 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 detection's deterrence effect on fraud commission.

Firm-level control variables in x_F include the firm's pre-fraud profitability (ROA), growth and external financing needs, leverage, and insider equity incentives. All these variables are measured as of year -1. We expect that all of these variables will 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*), which is operating cash flow before depreciation scaled by the firm's book assets.

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, 1998b, and Wang 2011). 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 projected need for external financing.

A number of studies have examined whether financially-distressed firms manage earnings. (For a review, see Healy and Wahlen, 1999.) 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. [11] 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 average of the abnormal firm-level investment in a given year for all firms in a 3-digit SIC-code

[11] 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.

industry.[12] 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-code 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 x_F 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 (2011) shows that different types of firm investment have different effects on the probability that fraud will be detected, which leads in turn 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 tend to have no effect. Thus, we separately control for capital expenditures, R&D expenditures, and acquisition expenditures, all scaled by the firm's book assets.

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[12] 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 (2011) 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 (2011) 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, 2011). 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 also suggests that a firm's stock return volatility and stock turnover are related to litigation risk. We measure "*Abnormal Return Volatility*" as the difference between the yearly standard deviation of the firm's stock returns and the firm's average return standard deviation. 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. By definition, one third of the 243 industries are classified as having low product market sensitivity. As already noted, Table 1 Panel D shows that low product market sensitivity is associated with low industry concentration.

We find that industries with low product market sensitivity tend to have a higher fraud propensity. The estimated coefficient for *LowPMS_SG* in model (1) is 0.269, which corresponds to a marginal effect of 0.09 on the probability of fraud commission P(F=1). This implies that ceteris paribus, the probability of committing fraud is 9 percentage points higher in industries with low product market sensitivity than in other industries. Similarly, the estimated coefficient for *LowPMS_ROA* in model (2) is 0.227 (marginal effect 0.07).

As discussed previously, we also examine two alternative measures of product market sensitivity. In untabulated regressions, we use *LowPMS2_ROA* based on the γ_3 and γ_4 estimates from equation (3), which incorporates performance lags. The coefficient estimate for *LowPMS2_ROA* is 0.285 (p-value=0.03) and the marginal effect is 0.10. Similarly, we also use *LowPMS3_ROA* based on the sum of each industry's capital investment sensitivity and R&D sensitivity. The coefficient estimate for *LowPMS3_ROA* is 0.212 (p-value=0.08) and the marginal effect is 0.07. Thus, these results are robust to alternative measures of product market sensitivity.

In model (3) we include both *LowPMS_SG* and *Negative PMS*. The estimated coefficient for *Negative PMS* is 0.694 (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 industries. The larger marginal effect of *Negative PMS* relative to *Low PMS* is intuitive: low PMS means that fraudulent reporting in the capital market does not hurt the firm's position in its product market, whereas 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 misreporting 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 ignore rivals' information due to prevalent fraud, then a firm will be unable to deter rival competition by fraudulent disclosure—and so negative PMS should not encourage fraud.

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 industry use of RPE by whether CEO turnover in the industry is positively and significantly linked to poor relative accounting profitability (*RPE_ROA* equals one). According to Table 1 Panel C, 13% of the 243 industries exhibit this form of RPE. This implies that, consistent with earlier findings in the literature, RPE is not a frequently observed practice. As noted before, Table 1 Panel D shows that industries with this form of RPE tend to be less concentrated, have lower product market sensitivity, higher return comovement, and a larger number of firms, all of which are consistent with the theoretical argument that RPE is more relevant in more competitive industries. 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 quite substantial.

In model (2), we measure industry use of RPE with *RPE_Return*, which equals one for industries in which the CEO is significantly more likely to be fired when the firm's stock return underperforms those of industry peers. According to Table 1 Panel B, this form of RPE is even less common than that which uses 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). Thus, firms in industries that practice RPE based on stock performance are 16 percentage points more likely to commit fraud than are firms in other industries.

Finally, in model (3) we measure industry use of RPE with *RPE_Compensation*, which equals one in industries in which CEO compensation is significantly sensitive to relative underperformance in the stock return. According to Table 1 Panel B, this form of RPE is observed in 23% of the industries. The coefficient estimate for *RPE_Compensation* is 0.24 (marginal effect 0.08). Thus, RPE in executive compensation is more frequently observed than RPE in executive turnover, but it has a weaker effect on managerial fraud incentives.

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 now be noisier. 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.

Our results are also unlikely to be due to a third variable that affects both the use of RPE and incentives to commit fraud. For example, Jenter and Kanaan (2010) find that RPE is more commonly used during industry downturns rather 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. Similarly, one might be concerned that RPE is driven by (lack of) CEO power, 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 also unlikely to be the omitted variable that drives our results.

In summary, the results in Table 3 support Hypothesis 2: greater use of RPE is associated with higher managerial incentives to commit fraud. Since RPE is more common in more competitive industries, this is consistent with fraud propensity being higher in such industries.

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.

In model (1) we measure lack of firm-specific information collection with *Comove*, the average return correlation in an industry-year. Higher return comovement implies that less firm-specific information is being incorporated in stock prices, so that monitoring by the capital market is less effective. We find that *Comove* has a negative and significant effect on the probability of fraud detection: its estimated coefficient is -1.196, which corresponds to a marginal effect of -0.13 on P(D=1|F=1), which is the probability that fraud is detected given that fraud has been committed. Thus, as the industry return comovement increases from 0.12 (25th percentile) to 0.27 (75th percentile), the probability of fraud detection decreases by 2% (= -0.13*(0.27-0.12)). The estimated effect of *Comove* on fraud propensity is positive, implying that higher return comovement is associated with a higher fraud propensity. The marginal effect of *Comove* on P(F=1) is 0.11, which is economically meaningful even though the coefficient estimate is not statistically significant.

In models (2) and (3) we use our two alternative measures for lack of firm-specific information collections, *ComoveRsq* and *Ln(# of Firms)*. Both measures have a significantly negative effect on the probability of fraud detection and a positive but insignificant effect on the probability of fraud commission. Both *Comove* and *ComoveRsq* exhibit an upward trend during our sample period. In unreported robustness tests, we use the detrended comovement variables, and find that the results are similar to those reported in Table 4.

Overall, the results in Table 4 are broadly consistent with Hypothesis 3. Industries with less firm-specific information collection have a lower probability of fraud detection, and an economically (but not statistically) higher probability of committing fraud.

As noted earlier, all of our proxies for competition are correlated, which opens up the possibility that one of our three channels is driving the apparent significance of the others. To address this, in Table 5 we include all three dimensions of industry competition in one regression. Our main results continue to hold. Low product market sensitivity, negative product market sensitivity, and use of RPE still have positive effects on the probability of fraud commission, and greater return comovement still has a negative effect on 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 variables capture three correlated yet distinct dimensions of industry competition.

4.4 Fraud and Predictable Bust in Competitive Industries

Povel et al. (2007) theorize that fraud is more likely to occur during booms and then be detected during busts. Consistent with their theory, *Industry Relative Investment* has strongly positive effects on fraud propensity in all models, suggesting that fraud propensity is cyclical. The existence of fraud generally predicts performance reversal in future years either because of the impact of fraud detection or because fraudulently good performance 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) also find that fraudulent firms increase investment and employment during the fraudulent period and then shed assets and labor after fraud is detected. If firms 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.

Hoberg and Phillips (2010) find that firms in competitive industries tend to fare much worse than those in concentrated industries following industry booms. They call this finding "the predictable bust in competitive industries." If either fraud propensity is more cyclical in competitive industries or the consequences of fraud in competitive industries are worse following booms than in normal times, then the dynamic of fraud may help us understand the predictable bust in competitive industries.

Hoberg and Phillips (2010) show that the firm-level return comovement (*ComoveRsq*) significantly increases following industry booms in competitive industries, but does not significantly increase in concentrated industries. In Table 6 Panel A we show that similar results hold in our sample. Return comovement in an industry is higher following abnormally high industry investment (model 1) or industry valuation (model 3). In models (2) and (4) we include the interaction effect between industry conditions and the number of firms in an industry. We find that the direct effect of industry condition on return comovement becomes insignificant, but the interaction effect is positive and significant. This implies that return comovement is more cyclical in industries with more firms, which tend to be more competitive industries. The lack of information collection and coordination problem gets worse during booms in those industries. Since this problem affects firms' fraud detection risk and fraud incentives, the stronger cyclicality of return comovement in competitive 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 (2) 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 order to mitigate the error-in-regressor problem, we do not directly use the original predicted P(F=1) in our analysis, but our results are not specific to this transformation.)

In Table 6 Panel B we examine whether the sensitivity of firms' fraud propensity to industry conditions depends on the degree of industry competition. In model (1) we use *Ln(# of Firms)* to measure industry competition. As before, the direct effect of *Ln(# of Firms)* is positive, implying that the average fraud propensity is higher in more competitive industries. In addition, the interaction between industry condition and *Ln(# of Firms)* has a positive and significant effect on fraud propensity, implying that the cyclicality of fraud is stronger in more competitive industries. In model (2) we use the fitted HHI from Hoberg and Phillips (2010) to measure lack of industry competition. The results are consistent with those in model (1): in particular, the interaction between industry condition and *Ln(Fitted HHI)* has a negative and significant effect on fraud propensity, implying that the cyclicality of fraud is stronger in more competitive (less concentrated) industries.

Next we examine whether the dynamics of fraud can explain predictable busts in competitive 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 6 we first replicate Hoberg and Phillips' results by regressing *"Δ(Op. CF) 2 years"* on *Industry Relative Investment* at time t for two subsamples, competitive industries and concentrated industries. We define competitive industries (concentrated industries) to be those with the fitted HHI in the bottom (top) tercile of the sample distribution, as in Hoberg

[13] Our estimates are consistent with those in Dyck, Morse, and Zingales (2011), who estimate conservatively that in any given year the probability of a large US company committing fraud is between 11 and 13 percent.

and Phillips (2010). 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 (e.g., Grenadier 2002). 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 competitive 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 competitive 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 competitive industries are largely concentrated in firms that are likely to 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 competitive 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.

Model (5) performs the same analysis for firms in concentrated industries. The direct effect of fraud propensity on future performance is negative and significant. 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 competitive industries, industry condition's power to predict future firm performance is not completely captured by fraud propensity and its interaction with industry condition, but the magnitude of the direct effect of industry condition is substantially reduced, from −0.125 to −0.07. For concentrated industries, the direct effect of fraud is very similar to that for competitive industries, but the effect of the interaction between fraud propensity and industry condition is positive and insignificant.

In summary, if we focus on the predictability of future firm performance based on current industry condition, then the significant negative interaction effect in competitive 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 competitive 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 competitive 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 competitive industries.

Why then is the consequence of fraud particularly bad following industry booms in competitive 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 competitive 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 Robustness

4.5.1 Industry Concentration and Fraud

Empirical tests of theories on product market competition often use a Herfindahl-Hirschman Index (HHI) that measures how concentrated firm sales or assets are in an industry. However, there is no specific theory that directly links the degree of product market concentration to either the probability of fraud or the probability of fraud detection. Of course, as shown in Table 1 Panel D, industry concentration is correlated with other aspects of competition. As a robustness test, in Table 7 we examine how industry concentration affects corporate fraud incentives. Since we have no theoretical guidance, we test two models: in the first model, industry concentration affects only the fraud propensity, and in the second, it affects both the probability of fraud detection and the probability of fraud commission.

We use three industry concentration measures: the fitted HHI from Hoberg and Phillips (2010) along with Compustat HHI in Panel A, and the Census Bureau HHI in Panel B. In Panel A, *Ln(Fitted HHI)* has a positive but insignificant effect on the probability of fraud commission in model (1), and a negative but insignificant effect in model (2). However, in model (2), *Ln(Fitted HHI)* has a positive and significant effect on the probability of fraud detection, so that, on average, more concentrated industries have a higher probability of fraud detection. In model (3), *Compustat HHI* is positively and significantly related to the probability of fraud, so that more competitive industries are *less* likely to commit fraud; however, in model (4), when we put *Compustat HHI* in both the fraud detection and the fraud commission equations, it is not significant in either. In Panel B we use *Ln*(*Census HHI)*, which restricts our sample to manufacturing industries. In both models (1) and (2), *Ln*(*Census HHI)* has a positive but insignificant effect on the probability of fraud commission, but model (2) shows that it has a positive and weakly significant effect on the probability of fraud detection. These results are consistent with those in Panel A based on *Ln(Fitted HHI)*.

In summary, there is no theory that directly links the degree of industry concentration to corporate fraud incentives. Empirical results using different concentration measures yield mixed results. The findings using the fitted HHI and the Census HHI are consistent with each other, with both suggesting that the probability of fraud detection is lower in less concentrated industries. This is most consistent with our results based on proxies for lower firm-specific information collection in industries, since this leads to less fraud detection in those industries. By contrast, industry concentration does not seem to be a good proxy for our first two channels, product market sensitivity and relative performance evaluation.

4.5.2 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 8, we use probit models to test our main hypotheses. In Panel A we examine Hypotheses 1 and 2, in which measures of industry competition (low product market sensitivity, RPE) affect only fraud propensity and not detection. We find that the probit models generate 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. In Panel B, the probit models show that all proxies for lack of firm-specific information collection have a *negative* effect on the observed incidence of fraud. However, this does not mean that lack of firm-specific information collection decreases firms' incentives to commit fraud. On the contrary, the bivariate probit model with partial observability shows that 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 3.

4.5.3 Robustness of Model Specification

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 possible fraud detectors can anticipate all the factors that may affect a firm's incentives to commit fraud, and so they can take these factors into account in choosing their fraud detection efforts. Wang (2011) 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 9 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 regarding 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. (In fact, use of RPE weakly *lowers* the probability of detection.) Comovement still affects fraud detection but not fraud commission. 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.

5. CONCLUSION

Our paper examines the effect of industry competition on firms' incentives to misreport financial information. The theoretical foundation for our empirical analysis lies in the economic

[14] For example, in Povel et al. (2007) investors monitoring is not to detect fraud per se, but 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) develops 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.

literature on how the nature of product market competition shapes the information environment of an industry and individual firms' incentives to disclose information to investors. We examine three specific channels. We find that lack of strategic concerns in the product market tend to encourage fraud, as does the use of relative performance evaluation. By contrast, lack of firm-specific information collection tends to decrease the probability of fraud detection, and there is weak evidence that this in turn increases the probability of fraud commission. All three aspects are more likely to be present in industries that are more competitive, implying that fraud propensity should be higher in those industries.

We also show that the dynamics of fraud can help explain the predictable busts in competitive 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 tend to be more cyclical in industries that are more competitive. Second, the consequences of fraud tend to be worse following booms than in normal times in competitive industries.

The upshot is that fraud can have significant real effects. Because competition tends to exacerbate both the level and the cyclicality of fraud, our work highlights a possible destructive aspect of competition. 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 industries, particularly during industry booms.

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Appendix A: Variable Definitions

Industry Characteristics	
LowPMS_SG	=1 if sensitivity of the change in rival firms' investment to change in own-firm sales growth is in the bottom tercile of the sample distribution.
LowPMS_ROA	=1 if sensitivity of the change in rival firms' investment to change in own-firm profitability is in the bottom tercile of the sample distribution.
Negative PMS	=1 for industries in which both γ_1 and γ_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
Ln(# of Firms)	Natural logarithm of the number of firms in an industry-year
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)
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: Corporate Securities Fraud

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 B: 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

Panel C: Explanatory Variables

	# of Obs.	Mean (Median)	Std. Deviation
Industry Characteristics (by industry-year or by industry)			
LowPMS_SG	243	0.33 (0.00)	0.47
LowPMS_ROA	243	0.33 (0.00)	0.47
Negative PMS	243	0.19 (0.00)	0.39
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
Ln(# of Firms)	3083	2.37 (2.40)	1.23
Ln(Fitted HHI)	2085	6.51 (6.46)	0.38
Compustat HHI	2890	0.27 (0.19)	0.23
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 D: Correlation Matrix

	Ln(Fitted HHI)	Compustat HHI	LowPMS (SG)	LowPMS (ROA)	Comove	Comove Rsq	Ln(# of Firms)	RPE (Return)	RPE (ROA)
Ln(Fitted HHI)	1.00								
Compustat HHI	0.48	1.00							
LowPMS_ SG	-0.34	-0.19	1.00						
LowPMS_ ROA	-0.31	-0.14	0.41	1.00					
Comove	-0.40	-0.39	0.17	0.22	1.00				
Comove Rsq	-0.09	-0.22	0.08	0.04	0.74	1.00			
Ln(# of Firms)	-0.63	-0.59	0.31	0.27	0.58	0.41	1.00		
RPE_Ret	-0.31	-0.11	0.35	0.29	0.36	0.13	0.35	1.00	
RPE_ROA	-0.11	-0.04	0.27	0.31	0.15	0.04	0.20	0.60	1.00

Note: All pair-wise correlation coefficients are significant at 1% confidence level.

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)
LowPMS_SG	0.269**				0.370***	
	(0.135)				(0.133)	
LowPMS_ROA			0.227*			
			(0.132)			
Negative PMS					0.694**	
					(0.308)	
Ind. Rel. Investment	3.488***		3.486***		3.272***	
	(1.013)		(1.001)		(0.961)	
ROA	0.895**		0.859**		0.992***	
	(0.391)		(0.400)		(0.369)	
Ext. Fin. Need	2.454***		2.460***		2.579***	
	(0.489)		(0.506)		(0.497)	
Leverage	0.012		0.011		-0.018	
	(0.357)		(0.354)		(0.342)	
Insider Ownership	1.292***		1.219***		1.378***	
	(0.477)		(0.462)		(0.479)	
CAPEX	-3.530***	0.609	-3.243**	0.591	-3.275**	0.595
	(1.324)	(0.536)	(1.276)	(0.535)	(1.361)	(0.524)
R&D	5.302**	-1.081***	5.532**	-1.078***	4.699*	-0.934**
	(2.581)	(0.409)	(2.682)	(0.407)	(2.415)	(0.379)
M&A	-0.347	0.734***	-0.338	0.735***	-0.408	0.712***
	(0.592)	(0.248)	(0.601)	(0.249)	(0.557)	(0.231)
Institution Ownership	-0.333	0.373*	-0.333	0.376*	-0.237	0.330*
	(0.449)	(0.203)	(0.449)	(0.203)	(0.417)	(0.181)
Analyst Coverage	-0.028**	0.028***	-0.026*	0.027***	-0.032***	0.028***
	(0.013)	(0.006)	(0.013)	(0.006)	(0.012)	(0.006)
Ln(Assets)	0.308***	-0.039	0.287***	-0.035	0.356***	-0.050*
	(0.092)	(0.030)	(0.094)	(0.032)	(0.086)	(0.027)
Firm Age	-0.001	0.001	-0.000	0.001	-0.007	0.003
	(0.008)	(0.004)	(0.008)	(0.004)	(0.007)	(0.004)
Technology	0.262	0.173	0.240	0.153	0.275	0.195*
	(0.272)	(0.112)	(0.271)	(0.110)	(0.259)	(0.105)
Service	0.364	0.015	0.342	0.007	0.317	0.031
	(0.314)	(0.134)	(0.317)	(0.135)	(0.318)	(0.125)
Trade	-0.236	0.231	-0.189	0.232	-0.518	0.330*
	(0.332)	(0.193)	(0.330)	(0.192)	(0.338)	(0.187)
Abnormal Ind. Litigation		0.965**		0.941**		0.935**
		(0.433)		(0.430)		(0.418)
Disastrous Stock Return		0.503***		0.497***		0.520***
		(0.062)		(0.062)		(0.060)
Abnormal Return Volatility		4.594***		4.558***		4.768***
		(0.840)		(0.871)		(0.783)
Abnormal Stock Turnover		0.037***		0.036***		0.039***
		(0.007)		(0.007)		(0.007)
Constant	-2.286***	-1.844***	-2.154***	-1.839***	-2.547***	-1.840***
	(0.657)	(0.154)	(0.667)	(0.158)	(0.627)	(0.142)

χ^2 (d.f.)	276(30)	267(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)
Technology	0.249	0.153	0.160	0.170	0.172	0.171
	(0.258)	(0.107)	(0.289)	(0.104)	(0.300)	(0.115)
Service	0.326	0.005	0.310	0.030	0.275	0.017
	(0.319)	(0.130)	(0.331)	(0.128)	(0.324)	(0.137)
Trade	-0.260	0.190	-0.260	0.210	-0.349	0.257
	(0.322)	(0.184)	(0.350)	(0.185)	(0.353)	(0.201)
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)
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. ***, **, 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)
Comove	0.321	-1.196***				
	(0.867)	(0.445)				
ComoveRsq			0.715	-0.976***		
			(0.663)	(0.344)		
Ln(# of Firms)					0.106	-0.115**
					(0.111)	(0.055)
Ind. Rel. Investment	3.230***		2.928***		3.238***	
	(0.966)		(0.995)		(1.024)	
ROA	0.808**		0.942**		0.794*	
	(0.404)		(0.413)		(0.406)	
Ext. Fin. Need	2.501***		2.631***		2.473***	
	(0.481)		(0.517)		(0.489)	
Leverage	-0.011		-0.089		-0.038	
	(0.358)		(0.372)		(0.353)	
Insider Ownership	1.162***		1.222**		1.192***	
	(0.442)		(0.480)		(0.441)	
CAPEX	-3.150**	0.622	-2.957**	0.527	-2.925**	0.491
	(1.266)	(0.535)	(1.370)	(0.548)	(1.321)	(0.551)
R&D	5.311**	-1.093***	4.853	-0.891*	5.705*	-1.034**
	(2.674)	(0.412)	(3.122)	(0.463)	(2.944)	(0.406)
M&A	-0.279	0.739***	-0.276	0.704***	-0.340	0.764***
	(0.613)	(0.256)	(0.638)	(0.257)	(0.595)	(0.249)
Institution Ownership	-0.323	0.385**	-0.282	0.347*	-0.334	0.364*
	(0.427)	(0.195)	(0.439)	(0.194)	(0.457)	(0.209)
Analyst Coverage	-0.026**	0.028***	-0.027*	0.027***	-0.028**	0.030***
	(0.013)	(0.006)	(0.014)	(0.006)	(0.013)	(0.006)
Ln(Assets)	0.289***	-0.025	0.307***	-0.031	0.290***	-0.039
	(0.096)	(0.032)	(0.099)	(0.032)	(0.095)	(0.032)
Firm Age	0.001	0.000	-0.001	0.001	0.002	-0.001
	(0.008)	(0.004)	(0.009)	(0.005)	(0.008)	(0.004)
Technology	0.334	0.191*	0.330	0.237**	0.061	0.353**
	(0.267)	(0.111)	(0.284)	(0.119)	(0.365)	(0.171)
Service	0.308	-0.012	0.245	-0.022	0.329	-0.017

	(0.314)	(0.134)	(0.318)	(0.135)	(0.314)	(0.137)
Trade	-0.234	0.175	-0.181	0.161	-0.219	0.174
	(0.312)	(0.185)	(0.355)	(0.197)	(0.316)	(0.187)
Abnormal Ind. Litigation		1.035**		0.926**		1.226***
		(0.433)		(0.439)		(0.458)
Disastrous Stock Return		0.504***		0.525***		0.503***
		(0.062)		(0.064)		(0.063)
Abnormal Return Vola.		5.042***		5.047***		4.657***
		(0.881)		(0.930)		(0.901)
Abnormal Stock Turnover		0.033***		0.036***		0.036***
		(0.007)		(0.007)		(0.007)
Constant	-2.223***	-1.663***	-2.491***	-1.637***	-2.488***	-1.398***
	(0.567)	(0.166)	(0.555)	(0.176)	(0.803)	(0.260)
Log Likelihood		-1850		-1928		-1854
χ^2 (d.f.)		304(31)		329(31)		273(31)
Observations		18086		18086		18086

Table 5: Combined Analysis

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)
LowPMS_SG	0.235*	
	(0.138)	
Negative PMS	0.734**	
	(0.315)	
RPE_Return	0.656**	
	(0.303)	
Comove	0.827	-1.685***
	(1.075)	(0.605)
Ind. Rel. Investment	3.551***	
	(1.084)	
ROA	0.997**	
	(0.423)	
Ext. Fin. Need	2.968***	
	(0.547)	
Leverage	0.054	
	(0.363)	
Insider Ownership	1.507***	
	(0.577)	
CAPEX	-3.203**	0.646
	(1.395)	(0.497)
R&D	4.708*	-0.865**

	(2.562)	(0.359)
M&A	-0.716	0.766***
	(0.612)	(0.225)
Institution Ownership	-0.216	0.322**
	(0.400)	(0.164)
Analyst Coverage	-0.037***	0.028***
	(0.013)	(0.005)
Ln(Assets)	0.390***	-0.038
	(0.095)	(0.025)
Firm Age	-0.004	0.003
	(0.008)	(0.004)
Technology	0.189	0.189*
	(0.264)	(0.099)
Service	0.319	0.010
	(0.336)	(0.121)
Trade	-0.533	0.271
	(0.330)	(0.170)
Abnormal Ind. Litigation		0.796**
		(0.402)
Disastrous Stock Return		0.516***
		(0.059)
Abnormal Return Vola.		5.008***
		(0.803)
Abnormal Stock Turnover		0.036***
		(0.006)
Constant	-2.816***	-1.746***
	(0.655)	(0.144)
χ^2 (d.f.)		372(33)
Observations		18086

Table 6: Fraud and Predictable Bust in Competitive Industries

Panel A: Cyclicality of Lack of Information Gathering

Dependent Variable: ComoveRsq	(1)	(2)	(3)	(4)
Ind. Rel. Investment	0.038**	0.014		
	(0.019)	(0.036)		
Ind. Rel. Inv. X Ln(# of Firms)		0.032*		
		(0.018)		
Ind. Rel. Valuation			0.038***	0.016
			(0.009)	(0.014)
Ind. Rel. Val. X Ln(# of Firms)				0.011*
				(0.006)
Ln(# of Firms)		0.009***		0.007**
		(0.003)		(0.003)
Constant	0.053***	0.033***	0.047***	0.031***
	(0.004)	(0.007)	(0.003)	(0.007)
Year Fixed Effects	Yes	Yes	Yes	Yes
Adj. R-sq	0.377	0.401	0.373	0.404
Obs.	1883	1883	2053	2053

Panel B: Industry Structure and Cyclicality of Fraud

Dependent Variable: Relative Fraud Propensity	(1)	(2)
Ind. Rel. Investment	-0.048	1.160***
	(0.031)	(0.194)
Ind. Rel. Inv. X Ln(# of Firms)	0.047***	
	(0.007)	
Ln(# of Firms)	0.065***	
	(0.003)	
Ind. Rel. Inv. X Ln(Fitted HHI)		-0.156***
		(0.031)
Ln(Fitted HHI)		-0.124***
		(0.011)
Constant	0.265***	1.255***
	(0.012)	(0.070)
Year Fixed Effects	Yes	Yes
Adj. R-sq	0.107	0.043
Obs.	19958	19634

Panel C: Fraud and Predictable Bust in Competitive Industries

"Relative Fraud Propensity" is constructed from the predicted probability of fraud commission (P(F=1)) based on model (2) in Table 4. 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:	Competitive 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 7: Industry Concentration and Fraud

Fitted HHI is from Hoberg and Phillips (2010). Compustat HHI is computed based on only firms covered by COMPUSTAT. 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.

Panel A: Fitted HHI and COMPUSTAT HHI

	(1)		(2)		(3)		(4)	
	P(F)	P(D|F)	P(F)	P(D|F)	P(F)	P(D|F)	P(F)	P(D|F)
Ln(Fitted HHI)	0.173		-0.324	0.309**				
	(0.188)		(0.312)	(0.155)				
Compustat HHI					1.280**		0.014	0.658
					(0.612)		(1.168)	(0.629)
Ind. Rel. Investment	3.491***		3.467***		3.187***		3.197***	
	(1.012)		(1.023)		(0.977)		(0.982)	
ROA	0.901**		0.866**		0.859**		0.836**	
	(0.411)		(0.409)		(0.410)		(0.412)	
Ext. Fin. Need	2.493***		2.477***		2.410***		2.472***	
	(0.513)		(0.510)		(0.526)		(0.513)	
Leverage	0.014		-0.021		0.056		0.027	
	(0.370)		(0.355)		(0.360)		(0.361)	
Insider Own.	1.192***		1.209***		1.130***		1.185***	
	(0.455)		(0.449)		(0.436)		(0.451)	
CAPX	-3.319***	0.561	-3.033**	0.417	-3.069**	0.563	-3.048**	0.529
	(1.285)	(0.536)	(1.299)	(0.545)	(1.302)	(0.539)	(1.296)	(0.544)
R&D	5.765**	-1.081***	5.882*	-1.074***	5.838**	-1.086***	5.923**	-1.043**
	(2.818)	(0.409)	(3.005)	(0.408)	(2.665)	(0.406)	(2.880)	(0.407)
M&A	-0.355	0.774***	-0.298	0.748***	-0.380	0.752***	-0.323	0.732***
	(0.603)	(0.251)	(0.609)	(0.250)	(0.601)	(0.251)	(0.629)	(0.254)
Institution Own.	-0.373	0.384*	-0.313	0.358*	-0.499	0.429**	-0.410	0.398*
	(0.448)	(0.200)	(0.446)	(0.200)	(0.440)	(0.199)	(0.478)	(0.210)
Analyst Coverage	-0.024*	0.027***	-0.028**	0.029***	-0.027**	0.028***	-0.028**	0.029***
	(0.014)	(0.006)	(0.014)	(0.006)	(0.013)	(0.006)	(0.014)	(0.006)
Ln(Assets)	0.275***	-0.032	0.290***	-0.040	0.292***	-0.039	0.280***	-0.034
	(0.106)	(0.033)	(0.106)	(0.034)	(0.096)	(0.032)	(0.102)	(0.035)
Technology	0.001	-0.001	0.002	-0.001	-0.000	0.000	0.002	-0.000
	(0.008)	(0.005)	(0.008)	(0.005)	(0.008)	(0.004)	(0.009)	(0.005)
Service	0.406	0.136	0.240	0.198	0.440	0.118	0.335	0.162
	(0.276)	(0.114)	(0.302)	(0.123)	(0.279)	(0.112)	(0.301)	(0.123)
Trade	0.460	-0.032	0.312	0.020	0.379	-0.025	0.306	0.007
	(0.335)	(0.139)	(0.341)	(0.144)	(0.313)	(0.134)	(0.322)	(0.139)
Ab. Ind. Litigation		0.209		0.272		0.209		0.237
		(0.196)		(0.193)		(0.207)		(0.192)
Disastrous Return		0.914**		1.055**		0.964**		0.992**
		(0.435)		(0.439)		(0.422)		(0.425)
Ab. Ret. Volatility		0.499***		0.494***		0.493***		0.493***
		(0.062)		(0.061)		(0.062)		(0.062)
Ab. Turnover		4.667***		4.595***		4.466***		4.454***
		(0.874)		(0.844)		(0.910)		(0.929)
Constant	-3.221***	-1.833***	-0.055	-3.738***	-2.159***	-1.809***	-1.989***	-1.930***

	(1.224)	(0.157)	(2.082)	(1.048)	(0.744)	(0.158)	(0.745)	(0.207)
Log Likelihood		-1826		-1824		-1855		-1854
χ^2 (d.f.)		278(30)		272(31)		256(30)		260(31)
Observations		17675		17675		18086		18086

Panel B: Census HHI for Manufacturing Industries

	(1)		(2)	
	P(F)	P(D|F)	P(F)	P(D|F)
Ln(Census HHI)	0.138		0.042	0.146*
	(0.099)		(0.135)	(0.080)
Ind. Rel. Investment	4.172***		3.937**	
	(1.595)		(1.745)	
ROA	0.142		0.155	
	(0.497)		(0.526)	
Ext. Fin. Need	2.357***		2.522***	
	(0.791)		(0.930)	
Leverage	0.181		0.100	
	(0.522)		(0.552)	
Insider Ownership	0.653		0.579	
	(0.576)		(0.584)	
CAPEX	-1.765	1.912**	-1.752	1.788*
	(2.030)	(0.862)	(2.382)	(0.968)
R&D	3.896	-1.286**	4.698	-1.391**
	(3.159)	(0.501)	(4.765)	(0.547)
M&A	-0.507	0.299	-0.278	0.154
	(1.099)	(0.497)	(1.530)	(0.597)
Institution Ownership	0.257	0.086	0.127	0.168
	(0.905)	(0.477)	(1.459)	(0.688)
Analyst Coverage	0.006	0.027	0.003	0.026
	(0.052)	(0.025)	(0.082)	(0.037)
Ln(Assets)	0.191	-0.046	0.178	-0.038
	(0.224)	(0.078)	(0.324)	(0.114)
Firm Age	-0.009	0.006	-0.004	0.003
	(0.016)	(0.011)	(0.027)	(0.016)
Abnormal Ind. Litigation		3.246**		2.757*
		(1.401)		(1.498)
Disastrous Stock Return		0.566***		0.521***
		(0.128)		(0.141)
Abnormal Return Volatility		5.450***		4.981**
		(1.828)		(2.520)
Abnormal Stock Turnover		0.029**		0.027**
		(0.012)		(0.013)
Constant	-3.484***	-1.777***	-2.587*	-2.697***
	(1.047)	(0.238)	(1.506)	(0.658)
χ^2 (d.f.)		210(24)		230(25)
Observations		9826		9826

Table 8: Probit Estimation

Panel A: Low Product Market Sensitivity, RPE, and Incentive to Commit Fraud

	(1)	(2)	(3)	(4)
LowPMS_SG	0.100*			
	(0.051)			
LowPMS_ROA		0.123**		
		(0.059)		
RPE_ROA			0.104**	
			(0.054)	
RPE_Return				0.112*
				(0.067)
Ind. Rel. Investment	1.369***	1.414***	1.361***	1.391***
	(0.298)	(0.301)	(0.298)	(0.295)
ROA	0.223*	0.214*	0.200*	0.202*
	(0.119)	(0.118)	(0.117)	(0.117)
Ext. Fin. Need	0.097***	0.097***	0.097***	0.096***
	(0.015)	(0.014)	(0.015)	(0.015)
Leverage	0.081	0.084	0.080	0.080
	(0.123)	(0.123)	(0.123)	(0.123)
Insider Ownership	0.323***	0.315***	0.313***	0.307***
	(0.113)	(0.114)	(0.114)	(0.114)
CAPEX	-0.572	-0.497	-0.481	-0.516
	(0.380)	(0.384)	(0.382)	(0.381)
R&D	0.050	0.073	0.120	0.101
	(0.223)	(0.221)	(0.222)	(0.222)
M&A	0.601***	0.611***	0.599***	0.594***
	(0.134)	(0.134)	(0.134)	(0.134)
Institution Ownership	0.230**	0.229**	0.235**	0.233**
	(0.107)	(0.107)	(0.107)	(0.107)
Analyst Coverage	0.017***	0.017***	0.017***	0.017***
	(0.004)	(0.004)	(0.004)	(0.004)
Ln(Assets)	0.041**	0.040**	0.040**	0.039**
	(0.017)	(0.017)	(0.017)	(0.017)
Firm Age	-0.004	-0.004	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Technology	0.304***	0.275***	0.281***	0.283***
	(0.066)	(0.069)	(0.070)	(0.070)
Service	0.187***	0.179**	0.159**	0.163**
	(0.072)	(0.071)	(0.070)	(0.070)
Trade	0.076	0.109	0.047	0.067
	(0.079)	(0.082)	(0.080)	(0.079)
Abnormal Ind. Litigation	1.145***	1.123***	1.056***	1.074***
	(0.373)	(0.374)	(0.376)	(0.376)
Disastrous Stock Return	0.542***	0.541***	0.534***	0.536***
	(0.052)	(0.052)	(0.052)	(0.052)
Abnormal Return Volatility	2.635***	2.631***	2.647***	2.634***
	(0.371)	(0.376)	(0.372)	(0.372)
Abnormal Stock Turnover	0.035***	0.035***	0.035***	0.035***
	(0.006)	(0.006)	(0.006)	(0.006)
Constant	-2.776***	-2.784***	-2.740***	-2.726***
	(0.116)	(0.117)	(0.112)	(0.111)
Observations	18086	18086	18086	18086

Panel B: Lack of Information Collection and Fraud

	(1)	(2)	(3)
Comove	-0.823***		
	(0.259)		
ComoveRsq		-1.168***	
		(0.437)	
Ln(# of Firms)			-0.034
			(0.026)
Ind. Rel. Investment	1.295***	1.310***	1.282***
	(0.300)	(0.301)	(0.303)
ROA	0.186	0.185	0.204*
	(0.117)	(0.117)	(0.118)
Ext. Fin. Need	0.099***	0.098***	0.099***
	(0.014)	(0.014)	(0.014)
Leverage	0.072	0.074	0.058
	(0.123)	(0.123)	(0.123)
Insider Ownership	0.314***	0.311***	0.321***
	(0.114)	(0.114)	(0.113)
CAPEX	-0.456	-0.475	-0.504
	(0.384)	(0.384)	(0.385)
R&D	0.057	0.058	0.118
	(0.221)	(0.221)	(0.220)
M&A	0.621***	0.611***	0.624***
	(0.134)	(0.134)	(0.134)
Institution Ownership	0.250**	0.250**	0.225**
	(0.108)	(0.108)	(0.108)
Analyst Coverage	0.017***	0.017***	0.018***
	(0.004)	(0.004)	(0.004)
Ln(Assets)	0.047***	0.048***	0.038**
	(0.017)	(0.017)	(0.017)
Firm Age	-0.004	-0.004	-0.004
	(0.003)	(0.003)	(0.003)
Technology	0.348***	0.330***	0.364***
	(0.067)	(0.066)	(0.073)
Service	0.147**	0.137**	0.150**
	(0.070)	(0.070)	(0.070)
Trade	0.032	0.034	0.042
	(0.080)	(0.079)	(0.080)
Abnormal Ind. Litigation	1.200***	1.144***	1.246***
	(0.366)	(0.366)	(0.382)
Disastrous Stock Return	0.541***	0.541***	0.539***
	(0.052)	(0.052)	(0.052)
Abnormal Return Volatility	2.853***	2.836***	2.665***
	(0.397)	(0.397)	(0.376)
Abnormal Stock Turnover	0.033***	0.033***	0.035***
	(0.006)	(0.006)	(0.006)
Constant	-2.626***	-2.653***	-2.590***
	(0.113)	(0.112)	(0.143)
χ^2 (d.f.)	473(20)	470(20)	474(20)
Observations	18086	18086	18086

Table 9: Robustness of Model Specification

	(1)		(2)		(3)	
	P(F)	P(D|F)	P(F)	P(D|F)	P(F)	P(D|F)
LowPMS_SG	0.488*	-0.119				
	(0.287)	(0.218)				
RPE_Ret			1.182***	-0.188*		
			(0.443)	(0.100)		
Comove					-0.015	-0.124**
					(0.981)	(0.490)
Ind. Rel. Investment	2.792***	0.232	3.649***	0.313	2.778***	0.143
	(1.058)	(0.304)	(1.242)	(0.310)	(0.978)	(0.324)
ROA	0.178	0.370*	0.396	0.332**	0.298	0.301
	(0.701)	(0.208)	(0.594)	(0.163)	(0.593)	(0.189)
Ext. Fin. Need	2.090*	0.014	2.933***	0.011	2.428***	0.002
	(1.126)	(0.042)	(0.614)	(0.022)	(0.726)	(0.028)
Leverage	-0.158	0.071	0.063	0.007	-0.145	0.050
	(0.461)	(0.224)	(0.546)	(0.205)	(0.525)	(0.232)
Insider Ownership	1.245	-0.100	1.732*	-0.100	1.149	-0.051
	(0.944)	(0.256)	(0.929)	(0.208)	(0.857)	(0.256)
CAPEX	-2.604	0.421	-3.181**	0.445	-2.686*	0.523
	(2.207)	(0.711)	(1.477)	(0.533)	(1.523)	(0.587)
R&D	2.863	-0.659	4.139	-0.644	3.521	-0.717
	(2.357)	(0.404)	(2.877)	(0.453)	(2.628)	(0.501)
M&A	-0.305	0.710**	-1.013	0.865***	-0.228	0.696**
	(0.579)	(0.276)	(0.685)	(0.236)	(0.628)	(0.272)
Institution Ownership	-0.144	0.279	-0.203	0.270	-0.171	0.305
	(0.424)	(0.212)	(0.422)	(0.175)	(0.424)	(0.201)
Analyst Coverage	-0.026	0.028***	-0.036***	0.028***	-0.026*	0.028***
	(0.016)	(0.007)	(0.014)	(0.006)	(0.014)	(0.007)
Ln(Assets)	0.361***	-0.084*	0.427***	-0.070**	0.347***	-0.058
	(0.086)	(0.047)	(0.093)	(0.034)	(0.093)	(0.043)
Firm Age	-0.009	0.005	-0.004	0.003	-0.005	0.004
	(0.008)	(0.006)	(0.009)	(0.005)	(0.010)	(0.006)
Technology	0.090	0.284	-0.007	0.286**	0.302	0.239*
	(0.429)	(0.212)	(0.285)	(0.114)	(0.303)	(0.132)
Service	0.209	0.063	0.154	0.084	0.128	0.065
	(0.309)	(0.144)	(0.356)	(0.133)	(0.336)	(0.148)
Trade	-0.293	0.276	-0.339	0.248	-0.305	0.226
	(0.381)	(0.232)	(0.362)	(0.179)	(0.355)	(0.206)
Abnormal Ind. Litigation		1.043**		0.928**		1.038**
		(0.472)		(0.445)		(0.467)
Disastrous Stock Return		0.535***		0.516***		0.530***
		(0.066)		(0.063)		(0.067)
Abnormal Return Vola.		5.029***		4.812***		5.465***
		(0.848)		(0.838)		(0.948)
Abnormal Stock Turnover		0.039***		0.037***		0.034***
		(0.007)		(0.007)		(0.007)
Constant	-2.541***	-1.560***	-2.786***	-1.745***	-2.388***	-1.553***
	(0.714)	(0.410)	(0.679)	(0.196)	(0.601)	(0.220)
χ^2 (d.f.)		325(36)		335(36)		328(36)
Observations		18086		18086		18086