COMPETITION AND CORPORATE FRAUD WAVES

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Abstract

Our paper examines the effect of product market competition on corporate financial misreporting. We find that while firms' propensity for fraud in concentrated industries is relatively insensitive to industry investment booms, firms in competitive industries have a strongly pro-cyclical propensity to commit fraud. As a result, investment booms in competitive industries tend to be accompanied by significant waves of corporate securities fraud. Further analysis suggests that the lack of information gathering about individual firms in the product market and the use of relative performance evaluation in managerial compensation play important roles in generating the cyclical fraud commitment in competitive industries. Our study highlights the potential impact of the destructive forces associated with product market competition, particularly during industry boom-bust periods.

1. INTRODUCTION

Product market competition has both benefits and costs. A common belief is that competition provides discipline and promotes efficiency. Many economists presume that competition spurs a firm to be more efficient by forcing it to reduce its agency problems. Consistent with this view, two recent studies by Giroud and Mueller (2010a, b) find that the usual forms of corporate governance do not matter in competitive industries. On the other hand, competition can lead to destructive forces: competitive industries may suffer from a lack of information gathering about individual firms and a lack of investment coordination (e.g., Grenadier, 2002). Hoberg and Phillips (2010) show that these destructive forces are amplified during industry booms and lead to predictable busts in competitive industries.

Both the benefits and the costs of competition may influence firms' incentives to commit fraud. On the one hand, just as studies have shown that better corporate governance is associated with a lower propensity for fraud, the discipline imposed by competition may have a similar effect. On the other hand, Gigler (1994) theorizes that the lack of strategic interaction and investment coordination in competitive industries may be associated with a higher probability of financial over-reporting. The lack of information gathering may also imply ineffective investor monitoring and thus less fraud detection, which in turn encourages ex ante fraud incentives.

In this paper, we examine how firms' incentives to commit fraud differ in competitive and concentrated industries. Povel, Singh, and Winton (2007) and Wang, Winton, and Yu (2010) show that the fraud dynamic tends to be amplified during industry booms. Since the costs and benefits of competition also tend to be amplified at these times, we use industry boom-bust periods as our research setting to examine and compare fraud dynamics in competitive and concentrated industries. Our results suggest that firms in more competitive industries are significantly more likely to commit fraud during periods of heightened investment. This operates through two channels: one linked to how firms gather information about rivals and incorporate it in their own investment decisions, and the other linked to the use of relative performance evaluation.

We begin by contrasting the prevalence of fraud during investment booms in competitive and concentrated industries. We measure firms' propensity for fraud using the bivariate probit model of Wang (2010) and Wang, Winton, and Yu (2010), which we discuss in Section 2 below.

We measure industry concentration and industry abnormal investment using the methods of Hoberg and Phillips (2010), which we discuss in Section 3 below. We find that, compared to firms in more concentrated industries, firms in more competitive industries are more likely to commit fraud during periods of abnormally high investment. The effects are especially pronounced during the period surrounding an industry's peak abnormal investment: whereas firms in concentrated industries display a relatively constant propensity to commit fraud during this period, firms in competitive industries have a strongly pro-cyclical propensity to commit fraud. The probability of fraud significantly climbs as the competitive industry heads into its investment boom, peaks shortly after the investment peaks, and then falls as the investment falls.

Next, we explore possible mechanisms that create this pattern. We believe that the key lies in how competition affects the way an individual firm's information affects rival firms' decisions. Gigler (1994) predicts that firms in more competitive industries are more likely to commit fraud because such over-reporting has little impact on rival firms' behavior; by contrast, firms in concentrated industries know that reporting strong performance encourages rivals to increase their own investment. For each three-digit SIC industry, we compute the average rival firms' investment sensitivity to a given firm's performance. Not surprisingly, this investment sensitivity measure is negatively but not perfectly correlated with our industry competitiveness measure. We find that firms in low-sensitivity industries are much more likely to commit fraud than those in high-sensitivity industries, consistent with the predictions in Gigler (1994). Such product market sensitivity to some extent explains the differential fraud dynamics in competitive industries and concentrated industries during industry investment booms. Within competitive industries, the documented cyclicality of fraud largely comes from industries with low product market sensitivity.

Hoberg and Phillips (2010) suggest a slightly different way in which industry competition influences the information that firms use in their investment decisions: 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, leading to excessive investment cycles and higher return comovement as in Grenadier (2002) and Chen, Goldstein, and Jiang (2007). We hypothesize that such failure to collect firm-specific information can lead to greater sensitivity of fraud to investment cycles; firms do not take into account any externalities their fraudulent reporting has on rivals, because they know that rivals will not gather and act on such information. We use two proxies for such information coordination failures: the log of the number of firms in an industry and the average comovement of stock returns in an industry. Both proxies have strong positive effects on the sensitivity of fraud to abnormal investment. Moreover, even within competitive industries, the pro-cyclical behavior of fraud in relation to investment is mainly driven by industries with a larger number of firms and industries that exhibit stronger return comovement.

We then turn to a different mechanism for the link between competition and fraud: managerial evaluation policy. Aggarwal and Samwick (1999) show that the use of relative performance evaluation ("RPE")—where a manager's compensation is based on the firm's performance relative to peer firms—can be destructive in more competitive industries because PRE tends to intensify competition. Cheng (2010) examines the use of RPE in managerial firing decisions and shows that it can lead to increased incentives for fraud. For each three-digit SIC industry we estimate the sensitivity of managerial compensation and turnover to peer firm performance and examine how the existence of RPE is linked to firms' propensity to commit fraud in competitive and concentrated industries. We find that the use of RPE in compensation is linked to an increased propensity to commit fraud, with the effects being concentrated in competitive industries. The cyclicality of fraud is particularly strong in competitive industries with RPE in executive compensation. But the existence of RPE does not significantly impact the propensity for fraud in more concentrated industries. We find that the use of RPE in managerial turnover is also linked to a higher fraud propensity, but this form of RPE does not explain the differential fraud dynamics in competitive and concentrated industries. These results provide partial support to the notion that corporate governance practices such as RPE can be destructive in competitive industries.

The remainder of our paper is structured as follows. Section 2 discusses our empirical design. Section 3 describes our model specification and data. Section 4 presents our empirical results. Section 5 concludes.

2. EMPIRICAL DESIGN

2.1 Research Setting

In this paper we use industry boom-bust periods as the research setting to examine the interaction between product market competition and corporate fraud incentives. The reason is twofold.

First, the observed incidences of fraud often cluster in the economic boom-bust periods. Povel, Singh, and Winton (2007) theorize that the effect of business conditions on investor monitoring incentives can explain the observed boom-bust-fraud pattern. Consistent with the implications in Povel et al. (2007), Wang, Winton, and Yu (2010) empirically show that industry business conditions affect the firm's propensity to commit fraud in the IPO process. Both casual observations and these studies suggest that the dynamic of fraud tends to be amplified during industry booms and busts, making these time periods an interesting setting to study corporate fraud incentives.

Second, an interesting recent paper by Hoberg and Phillips (2010) examine how product market competition affects firm performance in industry booms and busts. They show that following an industry boom, firms in competitive industries tend to fare much more poorly than those in concentrated industries. The authors argue that the results are likely due to the lack of information gathering and investment coordination in competitive industries. Information and coordination may both play important roles in determining the firm's incentive to commit fraud. Thus Hoberg and Phillips' findings suggest that the dynamic of fraud during an industry boom-bust period may also significantly differ across competitive and concentrated industries.

2.2 Empirical Methodology

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. If the detection process is not perfect (i.e., the probability of fraud detection is not one), then the probability of detected fraud (what we observe) is different from the probability of fraud (what we want to examine).

Further, the litigation risk (or the risk of fraud detection) could vary systematically across different industry structures and during an industry boom-bust period. For example, Hoberg and Phillips (2010) show that firms in competitive industries tend to fare much more poorly than those in concentrated industries after an industry boom. The litigation literature has linked poor firm performance to high litigation risk. Thus, the litigation risk can be different in these two types of industries around industry booms and busts. It is important to control for the effect of such variation on the observed incidence of fraud when we examine how firms' propensity to commit fraud vary with industry competition and industry conditions.

Poirier (1980) develops a bivariate probit model to address the problem of partial observability. Wang (2010) 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 having been committed. Then consider the following 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. u_i and v_i are zero-mean disturbances with a bivariate normal distribution. Their variances are normalized to unity because the variances 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, where $F_i = 1$ if $F_i^* > 0$, and $F_i = 0$ otherwise. For fraud detection (conditional on occurrence), we transform D_i^* into a binary variable D_i, where $D_i = 1$ if $D_i^* > 0$, and $D_i = 0$ otherwise. However, we do not directly observe the realizations of F_i and D_i. What we observe is

$$Z_i = F_i \times D_i$$

$Z_i = 1$ 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 tries to control for the effect of fraud detection according to the structure of the underlying data generating process.

According to Poirier (1980), 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 (2010), which explores 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 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.

The above model can be estimated using the maximum-likelihood method. The log-likelihood function for the model is

$$L(\beta_F, \beta_D, \rho) = \sum_{z_i=1} \log(P(Z_i = 1)) + \sum_{z_i=0} \log(P(Z_i = 0))$$

$$= \sum_{i=1}^{N} \{z_i \log[\Phi(x_{F,i}\beta_F, x_{D,i}\beta_D, \rho)] + (1 - z_i) \log[1 - \Phi(x_{F,i}\beta_F, x_{D,i}\beta_D, \rho)]\}.$$

3. MODEL SPECIFICATION AND DATA

In this section we specify the left-hand-side variable (Z) and the right-hand-side variables in each of the two latent probit equations. The appendix summarizes the variable definitions. Table 1 provides the summary statistics on all the dependent and independent variables.

3.1 Sample Selection

3.1.1 Detected Accounting Fraud Sample

In this study, we focus on securities frauds that involve deliberate and material misrepresentation of a firm's financial performance. A challenge in empirical studies of fraud is that fraud is not observable until it is discovered. The discovery of an accounting fraud generally leads to a securities lawsuit and often an accounting restatement as well. Thus, the existence of a securities lawsuit and/or the announcement of an accounting restatement have become natural empirical proxies 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 established by Stanford Law School (http://securities.stanford.edu), which provides a comprehensive database of federal private securities class action lawsuits filed since 1996 in the United States.

For both AAERs and class action lawsuits, we examine cases that were filed between 1996 and 2008. The reason for starting at year 1996 is to restrict our attention to the period after the passage of the Private Securities Litigation Reform Act (PSLRA), which was designed to reduce frivolous lawsuits (e.g., Johnson, Kasznik and Nelson, 2000; Choi, 2007). To match the litigation nature of the SEC's AAERs, we identify the nature of fraud allegations in class action lawsuits based on the materials in all the available case documents associated with each lawsuit (i.e., case complaints, press releases, defendant's motion to dismiss, court decisions). Cases that were dismissed by the courts or had settlement value less than $2 million are excluded to further mitigate the possibility of frivolous lawsuits.[1] For firms that had multiple securities lawsuits, we use only the earliest one in the analysis.

We then select frauds that began between 1993 and 2005. The timing of the alleged frauds is determined based on the information in the litigation documents. The average time between the beginning year of fraud and the litigation filing year is about three years in our sample. Thus we require a three-year interval prior to the end of the litigation sample (i.e., year 2005) to make sure that on average frauds that began in the sample period were detected and showed up in our litigation sample.

Lastly, we merge the selected alleged fraudulent companies with the COMPUSTAT-CRSP merged database to make sure that we have firm-level financial information and trading information for the two years before and the two years after fraud commitment. This procedure leads to a final detected accounting fraud sample of 987 lawsuits. Among these cases, 230 cases were subject to both SEC enforcement and private litigation, and 727 were subject only to private litigation. Table 1 Panel A reports the distribution of the detected securities frauds over time.

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[1] Legal studies have established the $2 million threshold level of payment that helps divide frivolous suits from meritorious ones (see, e.g., Choi 2007, Johnson, Nelson, and Pritchard 2005).

3.1.2 Comparison Sample

The partial observability model implies that the appropriate comparison sample should be a random sample of firms that are litigation-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 were sued by the SEC between 1990 and 1993 (immediately before our litigation sample period); (3) firms that were subject to non-accounting related class action lawsuits between 1996 and 2008.

For both the detected fraud sample and the comparison sample, we exclude financial companies (SICs 6000-6999) because COMPUSTAT does not report capital expenditures for these firms, and we will use capital expenditures to define industry investment booms. We further exclude firms with the two-digit SIC code equal to 99 because these firms are shell holding companies and acquisition vehicles whose asset size and other firm characteristics change dramatically in years in which an acquisition takes place, yielding outliers whose economic interpretation can be misleading.

3.2 Fraud Propensity

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

$$F_{i,t}^{*} = \alpha_F + \beta_1 Competitive_{t-1} + \beta_2 Boom_{t-1} + \beta_3 (Competitive_{t-1} \times Boom_{t-1}) + x_{F,i}\gamma_F + x_{D0,i}\delta_F + u_{i,t}.$$

"Competitive" measures the degree of industry competition. "Boom" measures the industry condition. These two variables and their interaction are the key explanatory variables for fraud propensity in this study. x_F contains other variables that that have been found to influence the firm's benefit from committing fraud based on the existing literature. x_{D0} is the set of ex-ante detection variables (will be discussed in Section 3.3). Ex-ante detection factors are included in the fraud propensity equation because they affect the expected cost of committing fraud and their effects can be anticipated when the fraud decision is made (the deterrence of detection).

3.2.1 Key Explanatory Variables

Industry Competition: Hoberg and Phillips (2010) create a fitted Herfindahl-Hirschman Index (HHI) that accounts for both public and private firms and covers all the three-digit SIC industries except the financial companies (SICs 6000-6999) and utilities companies (SICs 4900-4999). The observation unit of the data is industry-year. They combine the COMPUSTAT data with the Herfindahl data from the Commerce Department and the employee data from the Bureau of Labor Statistics when constructing the fitted HHI. The authors show that the fitted HHI is highly correlated with the actually HHI from the Commerce Department on manufacturing industries (correlation=0.54), and is a significant improvement relative to the HHI using only the COMPUSTAT data.

Thus we construct our primary proxy for industry competitiveness based on the fitted HHI from Hoberg and Phillips (2010).[2] We first standardize the fitted HHI so that its value is between zero and one. The standardization effectively ranks our sample industries based on their degree of concentration. The correlation between the standardized fitted HHI and the COMPUSTAT HHI is 0.39. Then we define "*Competitive*" as one minus the standardized fitted HHI. *Competitive* is still between zero and one, with the value of zero meaning the least competitive industry and the value of one meaning the most competitive industry. Table 1 Panel B shows that the average industry competitiveness is 0.82.

Industry Booms/Busts: Hoberg and Phillips (2010) create three measures of industry booms/busts. They use the "*Industry Relative Investment*" to measure industry real booms/busts. This variable is essentially the industry average of the unpredictable firm-level investment in a year.[3] A positive (negative) value means a positive (negative) shock to the investment in an industry-year. The industry is still based on the three-digit SIC. The authors use the "*Industry Relative Valuation*" and "*Industry New Finance*" to measure industry financial booms/busts. Since our study focuses on the impact of product market competition on the firm's fraud incentives, we believe that the investment booms/busts are more meaningful than the financial ones. Thus we use *Industry Relative Investment* as our primary proxy for "*Boom*". We use the financial booms/busts measures for some robustness checks.

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[2] We thank the authors for generously sharing their data with us.

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

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

The relative (unpredicted) 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.

3.2.2 Other Fraud Propensity Factors (x_F)

Profitability, Growth and External Financing Need: Several studies in the accounting literature show that a consistent theme among manipulating firms is that they showed strong financial performance and growth 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 moderating performance.

The second significant fraud motivator is the external financing need. Teoh, Welch and Wong (1998 a, b) find that firms have incentive to engage in earnings management before public equity offers. Several studies in the accounting and litigation literature find that external financing need is a strong determinant of the commission of accounting frauds (e.g., Dechow et al. 2010, Wang 2010).

We use return on assets *ROA* as the profitability measure. For growth and external financing needs, we follow Wang (2010) and use the externally financed growth rate suggested by Demirguc-Kunt and Maksimovic (1998). Specifically, it is a firm's asset growth rate in excess of the maximum internally financeable growth rate (*ROA/(1-ROA)*). This variable captures not only the growth in the firm, but also its projected need for outside financing.[4]

Leverage: Accounting data are often used to help enforce contracts between the firm and its stakeholders. Therefore, these contracts can create incentives for earnings management. One important type of contracts is the debt contract between the firm and its creditors. A number of studies have examined whether firms that are close to debt covenants manage earnings (see Healy and Wahlen (1999) for a review). Following the accounting literture, we use leverage to proxy for closeness to covenants. We define *"Leverage"* as the ratio of long-term and short-term debt to total assets.

Insider Equity Incentives: The recent wave of high-profile corporate frauds has directed a lot of public and academic attention to the role of rapidly increasing executive equity incentives. Goldman and Slezak (2006) theorize that large equity incentives can be a double-edged sword

[4] See Demirguc-Kunt and Maksimovic (1998) for assumptions and justifications for this measure.

because the positive relationship between firm performance and insiders' compensation (or wealth) can induce misreporting.[5]

We use the percentage stock ownership of insiders "*Insider Own*" to proxy for the insider equity incentives. The advantage of using this variable is twofold. First, stock ownership captures a bulk part of the total insider equity incentives and its variation.[6] Second, 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 that use the ExecuComp database for executive equity compensation data may be influenced by selection bias, since ExecuComp does not contain data for the majority of the publicly traded companies in the economy.

3.3 Fraud Detection

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

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

As mentioned in Section 3.2, x_{D0} is the set of ex-ante factors whose effects on the probability of detection can be anticipated when the fraud decision is made. x_{D1} is the set of ex-post factors whose effects on the probability of detection cannot be anticipated at the time of fraud commitment.

3.3.1 Ex-Ante Detection Factors (x_{D0})

Institutional Monitoring: Large and sophisticated institutional investors should have both incentive and power to impose effective monitoring on the management (Shleifer and Vishny

[5] Empirical findings on the link between insider equity incentives and fraud are quite mixed. Several empirical studies find that the sensitivity of executives' option portfolio to stock price is significantly positively related to the propensity to misreport (see, e.g., Peng and Röell (2008) for firms subject to class action lawsuits; Burns and Kedia (2006) for firms with accounting restatements). Johnson, Ryan and Tian (2009), however, find that it is unrestricted stock, not options, that is linked to managerial fraud incentives for a sample of firms subject to AAERs. Erickson, Hanlon and Maydew (2006) and Armstrong, Jagolinzer, and Larcker (2010) find no significant link between equity compensation and fraud.

[6] 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.

1997). Effective monitoring should increase the chance that fraudulent activities get uncovered.

We consider two proxies for the strength of institutional monitoring. The first one is *"Institutional Own"*, a firm's total percentage institutional ownership before fraud begins (i.e., year -1). Chung, Firth and Kim (2002) find that a larger institutional ownership is associated with less earnings management. There is also a non-governance-based reason to control for institutional ownership in the detection equation. The PSLRA passed in December 1995 requires that every class action lawsuit appoint a lead plaintiff. PSLRA encourages large institutional investors to be lead plaintiffs. Therefore, class action lawsuits could be more likely to go through for firms that have large institutional investors.

The second proxy is *"Analyst Coverage"*, which is the number of stock analysts that follow a firm in year -1. Stock analysts have been deemed as important external monitors of firms. Analysts' substantial knowledge about corporate financial statements and their regular interaction with the management provide them with good opportunities to detect fraud. Yu (2008) finds evidence that analyst coverage leads to less earnings management. Dyck, Morse, and Zingales (2010) and Wang (2010) both show evidence of the active role of analysts in corporate fraud detection. In this study, we expect both proxies for institutional monitoring to be positively related to the probability of fraud detection.[7]

Size, Age and Industry: Several studies of financial statement fraud find that firms that get involved in securities litigation tend to be larger firms (e.g., Cox and Thomas 2003; Dechow et al. 2010). There are also clear industry patterns in securities litigation (see Table 1B). Technology firms (software and programming, computer and electronic parts, and biotech), service firms (financial services, business services, utility, and telecommunication services) and the trade industry (wholesale and retail) appear to have high fraud concentration. Since firm size, age, and industry specification influence the probability of detected fraud, these factors should be related to either the fraud propensity or the probability of fraud detection, or both. Thus, we control for firm size (log of total assets), age (as a public company), and the firm's membership in the technology or service or trade sector in year -1.

[7] Of course, analysts tend to follow stocks that have high institutional interest. The correlation between "Analyst Coverage" and "Institutional Own" is 0.5.

3.3.2 Ex-Post Detection Factors (x_{D1})

Fraud detection occurs *after* the commitment of fraud. Therefore, some factors can potentially influence the probability of detection, but they are unpredictable when the fraud decision is made. These ex-post determinants of fraud detection 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, the ex-post fraud detection in this study is closely related to triggers of securities litigation. All ex-post determinants are measured as of one year after fraud begins (i.e., year 1).

Industry Litigation Intensity: Litigation risk can be correlated among firms within the same industry. A fraudulent firm is more likely to get caught when investigators and investors are looking closely into the firm's industry. Thus, besides controlling for industry distribution, we also control for industry securities litigation intensity using the logarithm of the total market value of litigated firms in an industry in year 1. A high total market value of litigated firms can result from either a large number of frauds or the existence of some mega cases.

Some industries may on average have higher litigation risk (e.g., the software programming industry), which is known to corporate insiders when they make the decision to commit fraud. Thus we construct the unexpected industry litigation intensity, "*Abnormal Ind. Litigation*", as the yearly deviation from the average litigation intensity in an industry. Unexpectedly high industry litigation intensity can increase a firm's ex-post litigation risk without affecting its ex-ante incentive to engage in fraud.

Unexpected Performance Shock: Unexpectedly poor stock performance is often an important trigger for fraud investigation. The litigation literature finds that firms that recently experience large negative stock returns are often subject to high litigation risk (e.g., Jones and Weingram 1996, Wang 2010). Following Wang (2010), we construct a dummy variable, "*Disastrous Stock Return*", that 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. We have also used other cutoff points such as the ones for the bottom 25% and bottom 5% of the distribution and the results are qualitatively similar. It is generally difficult, even for corporate insiders, to predict disastrous events in the future. Thus this variable is reasonably exogenous to the ex-ante fraud incentives.

Other Litigation Risk Factors: The litigation literature suggests that a firm's stock return volatility and stock turnover are also related to litigation risk (e.g., Jones and Weingram 1996, Wang 2010). Firms that experience higher return volatility are more likely to be sued because the probability of a big investment loss for the investors is higher. A higher stock turnover implies that more investors are affected by the companies' stock prices and thus it is easier to identify a class of plaintiff investors. Both variables are measured as of year 1. "*Abnormal Return Volatility*" is the standard deviation of monthly stock returns minus the average level for the firm. "*Abnormal Stock Turnover*" is the deviation of the yearly average monthly share turnover from the time-series average level.

4. COMPETITION, INDUSTRY BOOM, AND FRAUD

4.1 Baseline Results

In Table 2 we examine how the competitive structure of an industry interacts with industry investment booms and busts in determining a firm's incentive to commit fraud. We find that the direct effect of *Competitive* on fraud propensity is negative and insignificant. The direct effect of *Boom* is negative and significant (-5.851, p-value=0.04), while the interaction effect of industry competitiveness and industry condition is positive and significant (6.638, p-value=0.03). This implies that for highly competitive industries with competitiveness above 0.88 (about 38% of the industry-year observations), abnormally high industry investment is associated with a higher future probability of fraud. But for less competitive industries, the effect is neutral or even the opposite.

The baseline regression controls for a comprehensive set of firm-level and industry-level determinants of the probability of fraud and the probability of fraud detection. The estimated effects of these factors are generally intuitive and consistent with the findings in the previous literature. Other things equal, high external financing need and high insider equity incentives tend to motivate fraud. High institutional ownership and high analyst coverage tend to increase the probability of fraud detection and therefore decrease a firm's ex ante incentive to commit fraud. After fraud is committed, abnormally high litigation intensity in an industry, disastrous realizations of the firm's stock performance, abnormally high stock return volatility, and abnormally high stock turnovers all tend to increase the probability of fraud being detected.

Controlling for the effect of fraud detection (or the effect of litigation risk) is important in our study. Hoberg and Phillips (2010) show that in competitive industries, high industry investment is associated with lower ex-post firm profitability and stock returns. The accounting literature and the legal literature have shown that poor realizations of profitability and stock performances can trigger securities litigation. Thus the observed incidence of fraud may go up following high industry investment in competitive industries, not because of a higher firm incentive to commit fraud during the boom, but because of higher litigation risk due to the poor post-boom firm performances. This is why we need to control for ex-post firm stock performances and industry litigation intensity in the fraud detection equation in the bivariate probit model.

In an unreported regression, we use the standard probit model instead of the bivariate probit model with partial observability. The coefficient estimate for *Industry Relative Investment* is -3.739 (p-value=0.10). The coefficient estimate for the interaction between industry competitiveness and industry relative investment is 4.737 (p-value=0.05). Thus our baseline result is not driven by the specific structure of the bivariate probit model.

4.1.1 Zooming In: An Event Analysis

To better understand the economic implications of the baseline results, we now zoom into a special "event period"---the period around the largest investment boom in an industry in our sample period. If industry competition interacts with industry conditions to influence the dynamic of fraud commitment, then we expect the effect to be most noticeable and meaningful in this event period.

Specifically, for each three-digit SIC industry we identify the year with the highest industry abnormal investment in our sample period, and call it year 0. This marks the peak of the largest investment boom in an industry. The event window consists of the three years leading to the peak (year -3 to year -1), the peak year (year 0), and the three years after the peak (year 1 to year 3). We group industries into two categories. "Competitive (Concentrated) Industries" are those with the competitive index value in the top (bottom) tercile of the distribution, consistent with the definitions in Hoberg and Phillips (2010).

In Table 3, for each event year we report the median predicted probability of fraud P(F=1) in each industry category. The predicted P(F=1) is generated by the baseline model in

Table 2. Note that the true probability of fraud is not observable. The bivariate probit model with partial observability generates predictions separately for P(F=1) and P(D=1|F=1) based on the information in the observed probability of detected fraud P(Z=1).

Let us start with competitive industries. Under "Competitive Industries", the "All" column shows the predicted probability of fraud in each event year averaged across all the identified industry booms in competitive industries. We can see that in these industries, the probability of a firm committing fraud is around 7% during year -3 and year -2. Then the fraud propensity climbs to 12% in year -1, surges to about 20% as the industry heads into the investment boom (year 0). The fraud propensity continues to climb past the investment peak, peaking around 23% in year 1 before it goes downward. Figure 1(a) illustrates the dynamic of the predicted fraud propensity in competitive industries.

In contrast, both Table 3 and Figure 1(c) show that the predicted probability of fraud stays pretty flat around 15% in the entire event window in concentrated industries. Although the average predicted probability of fraud is not significantly different between competitive industries (14.6%) and concentrated industries (15.2%), the fraud dynamics are very different in these two types of industries. The fraud propensity is sensitive to industry conditions in competitive industries, but not in concentrated industries. Also note that the dynamic of industry abnormal investment is not very different between competitive industries and concentrated industries. Thus the differential fraud dynamics are not driven by the different natures of industry booms and busts across these two types of industries.

Next, we examine how the fraud dynamic depends on the magnitude of the investment boom. If firms' fraud incentives are sensitive to industry conditions, then we expect to see a larger fraud wave following a larger investment boom. We measure the magnitude of the boom-bust as the absolute difference between the year-0 industry abnormal investment and the year-3 abnormal investment.[8] Defining the magnitude of the boom-bust this way also helps to control for the differential litigation risk associated with different magnitudes of industry downturns (we will come back to this point later). "Large (Small) Boom-Bust" means the boom-bust magnitude is in the top (bottom) tercile of the distribution.

[8] We have also used the absolute difference between the year 0 abnormal investment and the year (-3) abnormal investment to measure the magnitude of the investment boom-bust. The results are similar and thus not reported.

The "Large" columns and the "Small" columns in Table 3 report the predicted probability of fraud averaged across large booms and small booms, respectively. In competitive industries, the magnitude of the fraud wave is significantly larger when the industry investment boom-bust is larger (also see Figure 1(b)). The predicted probability of fraud peaks at 36% in year 1 following a large investment boom, while it peaks at 18% following a small investment boom. The predicted P(F=1) around large investment booms during the event window [-3, 3] is on average seven percentage points higher than around small booms, and such difference is statistically significant at 1% confidence level.

The concentrated industries show a quite different picture. The predicted probability of fraud stays fairly flat around 15% throughout the event window, and there is no significant difference when we compare large investment booms and small investment booms (see Figure 1(d)).

A reasonable question to ask is how realistic the predicted levels of fraud propensity are. Since the true probability of fraud commitment is unobservable, there is no way for us to tell whether the predicted 15% fraud propensity (in concentrated industries) is reasonable, or too high, or too low. The average realized probability of *detected* fraud in concentrated industries in the event window is around 3.5%. Thus a 15% probability of fraud implies that the probability of fraud detection is about 23% (close to one in every four). These numbers are not totally unreasonable.[9] But we do not claim that they are necessarily close to the truth. More importantly, what we want to emphasize here is not the absolute level of fraud propensity, but the contrast between competitive industries and concentrated industries. Even if our empirical model tends to overestimate the probability of fraud commitment, there is no clear reason that such bias would lead to systematic differences across different industry structures.

Another reasonable question is whether we are examining waves of fraud commitment or waves of securities litigation. When industry booms turn into busts, firms perform poorly, particularly in competitive industries (Hoberg and Phillips 2010). Investors are upset at their losses and thus are likely to sue the firms. We believe that such a story is unlikely to explain our

[9] A recent working paper by Gerakos and Kovrijnykh (2010) proposes a model of earnings that incorporates the effects of both economic shocks and reporting bias. The model generates a firm-level measure of earnings manipulation that is not conditional on detection. That is, their measure of reporting bias should include all the undetected and detected reporting biases that have occurred. Their model implies that on average 17-20% of the firms with sufficient data on COMPUSTAT exhibit significant earnings manipulation, which is in line with the average 15% predicted probability of fraud based on our model.

results for two reasons. First, if a larger investment boom-bust is associated with larger losses to investors and more securities lawsuits, then we expect to see a larger fraud wave (or essentially litigation wave) following a larger investment boom-bust, regardless of the industry competitive structure. However, Figures 1(b) and 1(d) show that the industry structure clearly matters.

Second, as we have discussed before, we use the bivariate probit model with partial observability precisely to control for the effect of fraud detection (or litigation) in our analysis. Figure 2 shows the dynamics of detected fraud in the two types of industries in our event window. We can see that there is no systematic difference in the realized probability of detected fraud between competitive industries and concentrated industries. Also, in competitive industries the probability of detected fraud is pretty flat before the boom and goes up in the period after the boom, while the predicted probability of fraud tends to go up in the pre-boom period and then go down in the post-boom period. This implies that the likelihood of fraud detection tends to go down as the industry heads into the boom, and then go up in the post-boom period.

4.1.2 Robustness: Different Definitions of Industry Booms

To further understand the implications of our baseline results, we now examine how different natures of the industry shocks affect fraud dynamics in competitive industries and concentrated industries.

We first distinguish between periods of high industry investment and periods of *abnormally* high industry investment. As we have argued before, the normal investment rate can be different in different industries, and it can also vary over time within an industry as the average firm characteristics in the industry gradually change. Thus using the industry relative investment provides a sharper definition of industry real booms and busts. If we examine raw industry investment rather than abnormal investment, then the interaction effect we identified in Table 2 should be weaker. Indeed, in unreported regressions we replace industry relative investment with industry total investment (total capital expenditures divided by total net PPE) or industry average investment (the industry average capital expenditure ratio). We find that the interaction effect between *Competitive* and industry total (or average) investment is positive but insignificant. Thus the regression results suggest that it is the unpredictably high investment that significantly predicts the differential fraud dynamics in competitive industries and concentrated industries.

However, if we look at the event period defined by the highest level of industry total (or average) investment in the sample period (instead of the highest level of unexpected investment), then we still observe a similar difference between competitive industries and concentrated industries as we have seen in Figure 1. Figure 3(a) shows the fraud dynamics in the event window defined by the peak of industry average investment rather than industry abnormal investment. During the event period there is a significant wave of fraud as described by the dynamic of the predicted probability of fraud (based on Table 2) in competitive industries, but not in concentrated industries. The different implications from the regression over the entire sample period and from the event analysis could be due to the fact that the correlation between industry average investment and industry abnormal investment is much higher in the event period (0.45) than in the general sample period (0.27).

Our study focuses on industry investment booms. What about industry financial booms? Do the differential fraud dynamics in competitive and concentrated industries hold when we define industry booms based on financial conditions? Following Hoberg and Phillips (2010), we use the level of industry relative valuation and industry new financing to define industry financial booms and busts.[10] The correlation between industry relative investment and industry relative valuation in our sample period is 0.27, and is 0.19 with industry new financing. Figures 3(b) and 3(c) show the dynamic of the predicted probability of fraud in the event periods defined by the highest level of industry relative valuation and the highest level of industry new financing, respectively. Similar to what we have seen around investment booms, there tends to be a significant surge in the predicted probability of fraud in competitive industries following high industry valuation and new financing. But there is no such pattern in concentrated industries.

In sum, the baseline results so far suggest that the dynamic of fraud incentives around industry booms is quite different in competitive industries and in concentrated industries. Firms' incentives to commit fraud tend to significantly increase during an industry boom in competitive industries, but not in concentrated industries.

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[10] In Hoberg and Philips (2010), a firm's relative valuation is the difference between its actual $\log(M/B)$ and its predicted $\log(M/B)$. The prediction model is described in equation (8) in the paper. Then the industry relative valuation is the average over all firms in each three-digit SIC industry. A firm's new financing in a given year is the sum of a firm's net equity issuing and net debt issuing activity in a given year divided by assets. Industry new financing is the summed total amount of new financing over firms in the industry divided by the total industry assets.

4.2 Underlying Product Market Mechanisms

In this section we examine the underlying mechanisms that drive the contrasting fraud dynamics in competitive and concentrated industries. The existing literature on the benefits and costs of competition has established the lack of information collection about individual firms as a major destructive force associated with product market competition. In competitive industries an individual firm's information does not get fully incorporated into its rival firms' decisions. As a result, there is lack of coordination and failure to internalize externalities among firms in competitive industries. This problem has been argued by economists as the root cause of excessive investment cycles and value destruction during these cycles in competitive industries. Our study finds that the investment cycles are also accompanied by significant corporate fraud waves in competitive industries. Thus we hypothesize that the lack of information gathering about individual firms in competitive industries may explain the contrasting fraud dynamics in competitive and concentrated industries.

Why is there lack of information collection about individual firms in competitive industries? There are two related but different answers. First, in competitive industries firms are numerous and are price takers. They behave non-strategically in the product market. The lack of strategic interaction implies that any one firm's information (or decision) is not important to other firms' decisions. Second, it is also costly to collect individual firm information when there are a large number of firms in an industry. Firms in this kind of industries tend to focus on industry common signals and ignore firm-specific information about their rivals. Therefore, we will explore the implications of these two aspects of the information problem on the firm's incentive to commit fraud.

The analysis in this section is also to some extent an exploration of different definitions of industry competitiveness based on the information structure rather than the concentration of market shares. As long as these two aspects are not perfectly correlated, the analysis here will shed new light on the relationship between industry structure and firms' fraud incentives.

4.2.1 Product Market Sensitivity and Fraud Propensity

The economics literature and the accounting literature have shown that the nature of product market competition can affect a firm's (voluntary) disclosure incentives. Most work in this line of research assumes honest disclosure. Gigler (1994) relaxes such an assumption. He argues that the external financing need creates incentives for managers to over-report the firm's financial conditions (e.g., the demand for the firm's products) in the capital market. However, over-reporting demand tends to invite entry and competition from rival firms in the product market. The net reporting incentive depends on which force dominates. Holding the firm's external financing need constant, the firm's propensity to over-report should decrease in the degree of strategic concerns in the product market. Fraud is more likely in industries where one firm's over-reporting has little impact on rival firms' decisions.

Gigler does not examine how the tradeoff between the two opposing forces evolves around an industry investment boom. We speculate that an industry boom will intensify the tradeoff. External financing needs are generally pro-cyclical. When the industry is heading into an investment boom, the industry-wide expansion creates larger external financing needs, which in turn generates larger corporate incentives for fraud. In concentrated industries, the increase in the fraud propensity is (at least to some extent) offset by concerns of rival reactions in the product market. But in competitive industries, there is no such balancing force. As a result, the cyclicality in external financing needs can generate cyclicality in firms' fraud incentives in competitive industries.

In Gigler's model, the degree of product market concern is reflected in the sensitivity of the rival firm's capacity decision (e.g., investment, output) to the information about the demand for own firm's products. We thus construct a direct measure of product market sensitivity as follows. By each three-digit SIC industry, we run the following regressions:

$$\Delta RivalInv_{t+1} = \alpha_2 + \beta_2 \times \Delta RivalSG_t + \gamma_2 \times \Delta SG_{i,t} + \varepsilon_{t+1} \quad (1)$$

$$\Delta RivalInv_{t+1} = \alpha_1 + \beta_1 \times \Delta RivalROA_t + \gamma_1 \times \Delta ROA_{i,t} + \varepsilon_{t+1} \quad (2)$$

"Δ" is the first-difference operator. We use the change in sales growth and the change in ROA to proxy for new information about a firm's product demand. That is, an increase in sales growth rate or profitability would indicate stronger demand. "*RivalSG*" ("*RivalROA*") is the average sales growth rate (return on assets) of all firms except firm-*i* in an industry. "*RivalInv*" is the 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 proxies for the rival firms' yearly capacity decision.[11] The first-difference model also helps to mitigate any firm or industry fixed effects that may not be related to product market sensitivity. Then the absolute value of coefficient γ_1 (γ_2) measures how much impact the information in firm-*i*'s sales growth (profitability) at time *t* has on the change in rival firms' investment at time *t+1*, after controlling for the information in the rival firms' own sales growth (profitability) at time *t*. If $|\gamma_1|$ ($|\gamma_2|$) is close to zero, then it means that the information in demand for firm-*i*'s product has little impact on rival firms' investment decision. Intuitively, such product market sensitivity should be negatively correlated with the competitiveness of an industry. The correlation between *Competitive* and $|\gamma_1|$ ($|\gamma_2|$) is -0.27 (-0.31).

To avoid introducing estimation errors in the regressions, we do not directly use the γ estimates. Instead, we construct an indicator variable "*LowPMS1*" ("*LowPMS2*") that equals one if $|\gamma_1|$ ($|\gamma_2|$) is in the bottom tercile of the sample distribution, and equals zero otherwise. Table 1 Panel C shows the correlation between *Competitive* and *LowPMS1* (*LowPMS2*) is 0.23 (0.20).

Then in Table 4 Panel A we replace *Competitive* with the product market sensitivity measures in our baseline regression. The interaction effect between *LowPMS1* (*LowPMS2*) and industry relative investment is positive and significant. This implies that given the level of industry relative investment, industries with low product market sensitivity tend to have a high probability of fraud.

Again, we use the event analysis to assess the economic implications for the regression results. The event window is determined as discussed in Section 4.1.1. We put industries into two categories based on the value of *LowPMS1*. Table 4 Panel B reports the median predicted probability of fraud in each event year separately for the two groups of industries. The predicted probability of fraud is again computed based on the baseline regression in Table 2 and thus is not directly related to the product market sensitivity measure. Figure 4A illustrates the patterns in the data. We can see that in industries with high product market sensitivity (*LowPMS1=0*), the fraud propensity stays relatively flat around 14% during the event period. In industries with low product market sensitivity (*LowPMS1=1*), the fraud propensity is about nine percentage points higher on average, and the difference between the two groups is statistically significant at 1% confidence level. The fraud propensity is also more sensitive to industry investment conditions in

[11] 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.

low-sensitivity industries, although not as sensitive as in competitive industries defined by the fitted Herfindahl index.

Next, let us take a closer look at the competitive industries. Figure 4B contrasts the fraud dynamic in competitive and low product market sensitivity industries with that in competitive and high product market sensitivity industries. The fraud incentive is significantly more cyclical in the former group. The predicted probability of fraud goes from about 8% two years before the investment peak up to about 27% in year 1 before it comes down again. In competitive industries with high product market sensitivity, however, the fraud wave is significantly smaller. The predicted probability of fraud peaks around 20% in year 0 and drops back below 9% in year 3. More over, Figure 4B shows that the fraud dynamic in the competitive but high-sensitivity industries is closer to that in concentrated industries.

Overall, the results in Table 4 imply that other things equal, the firm's propensity to commit fraud tends to be higher in industries with low product market sensitivity, consistent with the implications in Gigler (1994). The lack of strategic concerns in the product market implies that one firm's fraudulent reporting has little impact on the rival firms' decisions, making the firm more likely to commit fraud.

4.2.2 Lack of Information Gathering and Fraud Propensity

Hoberg and Phillips (2010) postulate that the role of coordination and costly information gathering is key to understanding why outcomes following industry booms can be very different between competitive industries and concentrated industries. Information about rival firms and optimal investment policy is difficult to gather when there are a large number of firms as in a competitive industry. This is particularly true when valuation uncertainty is high. The lack of information about rivals leads to the inability to coordinate investment among firms (e.g., Grenadier 2002). Interestingly, such problems actually lead to more similarity in firm decisions and more co-movement in firm performances. This is because firms tend to focus on the industry common signals and not gather information about individual firms (see e.g., Chen, Goldstein, and Jiang 2007). Following a positive industry shock, competitive industries are more likely to overinvest and later suffer from poorer outcomes.

If we view the decision to commit fraud as an economic decision, just like investment and financing decisions, then in competitive industries firms may have incentives to raise financing, to invest, and to commit fraud at similar times, i.e., during industry booms, leading to a wave of fraud as illustrated in the previous figures.

We can see that the product market sensitivity as modeled in Gigler (1994) is related to information gathering and coordination in the product market. If rival firms' capacity decisions are sensitive to the information about the demand for own firm's products, then there is information gathering about individual firms, and such information collection helps to coordinate firms' capacity decisions. We have shown that the product market sensitivity can help us understand the difference in fraud dynamics between competitive and concentrated industries around industry investment booms.

In this section we explore two alternative proxies for the lack of information gathering and coordination. A simple and intuitive measure is the number of firms in an industry-year. The larger the number of firms, the more difficult to collect information about individual firms and the more difficult to coordinate investment among firms. Intuitively, the number of firms in an industry is also related to the product market sensitivity in Gigler's model. If there are many firms in an industry, then the demand for any one firm's product should have little impact on the capacity decision of rival firms. But if there are only two firms, then the information about one firm should be very important to the decision of the other firm. To mitigate the effect of skewness in the number of firms, we use the logarithm transformation of the variable. Table 1 Panel C shows that the correlation between *Competitive* and *Ln(# of firms)* is 0.58.

The second measure is based on the degree of return comovement. As pointed out in studies like Durnev, Morck, and Yeung (2004) 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. Hoberg and Phillips (2010) directly link the degree of return comovement to the degree of industry concentration. They show that the return comovement is indeed higher in more competitive industries. Thus we use high return comovement as an alternative proxy for the lack of information gathering about individual firms.

Following the previous studies, we measure return comovement in an industry in two ways. The first measure, and also our main comovement 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' return 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. Table 1 Panel C shows that the correlation between *Competitive* and *Comove* is 0.23. The second comovement measure follows the method in Chen, Goldstein, and Jiang (2007). For each firm in a three-digit SIC industry, we run the regression:

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

Here $r_{i,j,t}$ is the return of firm *i* in industry *j* on date *t*, $r_{m,t}$ is the value-weighted market return on date *t*, and $r_{j,t}$ is the value-weighted return of industry *j* (excluding firm-*i*) on date *t*. The regression R^2 measures the degree of comovement between firm-*i*'s return and the returns of the market and the industry. Then we compute the average of R^2 in an industry-year, and call it "*Comoversq*". Not surprisingly, *Comoversq* and *Comove* are highly correlated with each other (0.84). Table 1 Panel C shows that the correlation between *Comove* and *Competitive* is 0.26.

In Table 5 model (1) we replace *Competitive* with *Ln(# of firms)* in the baseline regression. The results hold. The interaction effect between *Ln(# of firms)* and industry relative investment is positive and significant (0.487, p-value=0.006). This means that in industries with a larger number of firms, firms' fraud propensities tend to increase more following high industry relative investment.

In Figure 5A, we use our event analysis framework to examine the economic implication of such interaction effect. "High (Low) Ln(# of firms)" means industries with *Ln(# of firms)* in the top (bottom) tercile of the sample distribution. The predicted probability of fraud is still based on our baseline regression in Table 2. Figure 5A(a) shows that industries with many firms on average have a much higher probability of fraud around investment booms than industries with a small number of firms. The contrast is even larger than that between competitive and concentrated industries based on the fitted Herfindahl index in Figure 1.

Figure 5A(b) shows that among competitive industries, there is a big difference in the dynamics of fraud commitment across low and high *Ln(# of firms)* categories. The wave of fraud commitment around investment booms, as described by the dynamic of the predicted probability of fraud, is much larger in competitive industries with a larger number of firms than in competitive industries with a smaller number of firms. More over, the difference between concentrated industries and competitive industries with a small number of firms is much smaller.

In Table 5 model (2) we replace *Competitive* with *Comove* in the baseline regression. Again, the interaction effect between *Comove* and industry relative investment is positive and significant (9.723, p-value=0.01). This means that in industries with higher return comovement, firms' fraud propensities tend to increase more following high industry relative investment. Results using *Comoversq* is similar (untabulated). The interaction effect between *Comoversq* and industry relative investment is 21.948 (p-value=0.003).

Similarly, Figure 5B(a) shows that industries with high return co-movement on average have a much higher probability of fraud around investment booms than industries with low return co-movement. Figure 5B(b) shows that among competitive industries, there is a big difference in the dynamics of fraud commitment across low and high return co-movement categories. Throughout the event period, the predicted probability of fraud is much higher in competitive and high-comovement industries than in competitive and low-comovement industries. The fraud propensity in competitive and low-comovement industries is pretty flat around investment booms, like that in concentrated industries, and is even lower on average.

Overall, the patterns in Figure 5 are similar to those in Figure 4, which examines the effect of the product market sensitivity. The results in Sections 5.2 suggest that the information gathering and coordination in the product market play a role in determining the dynamic of corporate fraud incentives around industry investment booms and busts.

4.3 Competition and Corporate Governance

In the previous section we explore the differential product market interactions in competitive and concentrated industries as an explanation for the differential fraud dynamics in these industries. In this section we explore the impact of corporate governance practices in these two types of industries.

There is a long-time argument that competition provides discipline. This makes many scholars believe that corporate governance matters less in competitive industries. Consistent with this view, a recent study by Giroud and Mueller (2010a) shows that the passage of Business Combination Law has little impact on firm performance in competitive industries, but has significantly negative impact in concentrated industries. Giroud and Mueller (2010b) show that only in noncompetitive industries weak corporate governance is associated with poorer firm performance.

Other scholars believe that corporate governance is important for both types of industries. But the same corporate governance practice can have different performance effect under different industry structures. One governance practice that has been highlighted in this literature is relative performance evaluation (RPE). Aggarwal and Samwich (1999) examine RPE in executive compensation, which means that controlling for own firm performance, the level of own firm executive compensation in decreasing in rival firms' performances. They theorize that RPE is suboptimal for competitive industries because it tends to further toughen the already heated competition. Empirically they show that competitive industries indeed use less RPE.

Cheng (2010) uses a dynamic game theory model to examine the effect of RPE in executive turnover on firms' incentives to misreport financial information. In his model, the manager is fired if the own firm performance lags the rival firm performance by an amount exceeding a certain threshold. Cheng shows that the existence of such RPE tends to increase firms' misreporting incentives, even including firms that are leading in performance. The intuition is straightforward. If relative performance is important to the manager's job security, then this creates an incentive for the manager to manipulate own firm performance relative to rival performance. This effect should be stronger in industries in which executive firing is more frequent and replacement is easier, or put differently in industries with more competitive labor markets. If the competitiveness of the labor market is highly correlated with the competitiveness of the product market, then we expect the effect of RPE on fraud incentives to be stronger in competitive industries.

Both theories suggest that although RPE is generally viewed as a good corporate governance practice, it may have ill effects in competitive industries. By toughening competition among firms, RPE may increase managers' incentives to manipulate financial reporting so that they can obtain high compensation or job security.

4.3.1 Relative Performance Evaluation in CEO Pay

How much does RPE contribute to the formation of fraud waves in competitive industries during industry booms? To answer this question, we first construct proxies for the existence of RPE in an industry. Then we compare fraud dynamics in competitive industries with and without RPE, and in concentrated industries with and without RPE.

To measure the existence of RPE in executive compensation, we run the following panel data regression by each three-digit SIC industry:

$$Ln(TotalComp_{i,t}) = \alpha + \gamma_{pay} \times RivalROA_{i,t} + \beta \times ROA_{i,t} + \delta \times Ln(FirmSize_{i,t}) + \varepsilon_{i.t}, \quad (3)$$

where *"$Ln(TotalComp_{it})$"* is the natural logarithm of the total expected compensation of firm-*i*'s CEO in year *t* (TDC1 in ExecuComp database). *"RivalROA"* is the average ROA of all firms but firm-*i* in the three-digit SIC industry. *"FirmSize"* is measured by total book assets. The standard errors are clustered by firm. Then we construct an indicator variable *"RPE-Pay"* that equals one if the coefficient estimate of γ_{pay} is significantly negative (p-value $\leq$ 10%), and zero otherwise. Table 1 Panel A shows that 25% of the 155 industries with the compensation data exhibit RPE in CEO compensation. Our primary specification uses accounting returns because the frauds in our sample are all accounting-related frauds. The fraud incentive is about misreporting accounting information. We have also used stock returns instead of ROA in (3) for robustness.

In Table 6 we examine the effect of RPE in CEO pay on the firm's incentive to commit fraud, and whether such effect depends on industry competitiveness. We first examine the direct effect of RPE on fraud in model (1). The coefficient estimate for the indicator *RPE-Pay* is positive and significant (0.189, p-value=0.04). This means that other things equal, the average probability of fraud is higher in industries with RPE in CEO compensation. In model (2) we add the interaction effect between RPE and industry competitiveness. The direct effect of the *RPE-Pay* becomes negative and marginally significant (-0.999, p-value=0.09), but the interaction effect is positive and significant (1.304, p-value=0.05). This suggests that the positive effect of RPE on fraud in model (1) largely comes from the more competitive industries. In industries with the competitiveness index greater than 0.77 (about 68% of the industry-year observations), the existence of RPE in pay increases the firm's incentive to commit fraud.[12]

In Figure 6, we use our event analysis framework to examine the economic implication of RPE in CEO pay for the firm's fraud propensity. We first compare the fraud dynamics in industries with RPE and in those without. Panel A shows that during the event window around the industry investment boom, the average predicted probability of fraud in industries with RPE

[12] In unreported regressions, we use stock return in place of ROA in equation (3) and construct the indicator variable *RPE-Pay* in the same fashion as discussed. Then we run the same regression in Table 7 model (1). The results are similar to those reported. The coefficient estimate of *RPE-Pay* is -3.074 with p-value=0.08. The coefficient estimate of the interaction between *RPE-Pay* and *Competitive* is 3.804 with p-value=0.05. We also replace Competitive with the other measures of industry structure (e.g., Log(# of Firms), return comovement, product market sensitivity) in Table 7 model (2). The results are robust to these different measures of competitiveness.

in CEO pay is around 23%, higher than that in industries without RPE (17%). Panel B shows that among competitive industries (the value of competitiveness in the top tercile of the distribution), the fraud wave is substantially larger if there is RPE in CEO pay. But the effect of RPE on the fraud dynamic is much smaller among concentrated industries, as shown in Panel C.

Overall, the results in Table 6 and Figure 6 suggest that the existence of RPE in CEO pay tends to amplify the firm's propensity to engage in fraud, especially in more competitive industries. These results are consistent with the implication in Aggarwal and Samwick (1999) that RPE is suboptimal for competitive industries.

4.3.2 Relative Performance Evaluation in CEO Turnover

We construct two measures for RPE in executive turnover. The first measure parallels our specification in equation (3). We run the following probit regression by each three-digit SIC industry:

$$\Pr ob(CEOTO_{i,t} = 1) = \alpha + \gamma_{to1} \times RivalROA_{i,t-1} + \beta \times ROA_{i,t-1} + \delta \times Ln(FirmSize_{i,t-1}) + \varepsilon_{i,t}\ , \ (4)$$

where $CEOTO_{i,t}=1$ indicates a CEO turnover event in firm-*i* in year *t*. This variable is constructed based on the information in ExecuComp database. We set $CEOTO_{i,t}=0$ if the turnover is associated with a merger/acquisition event or a possible retirement (the CEO leaving office is more than 65 years old).

In this specification, RPE means that controlling for own firm performance, the probability of the CEO being fired is increasing in rival firms' performance. That is, $\gamma_{to1}>0$. Thus we construct an indicator variable *"RPE-TO1"* that equals one if the coefficient estimate of γ_{to1} is significantly positive (p-value $\leq$ 10%), and zero otherwise. Again we have also used stock returns instead of ROA in (4) for robustness. According to Jenter and Kanaan (2010), equation (4) tests the existence of the so-called *weak-form* RPE.

Our second proxy for RPE in CEO turnover is closer to the theoretical specification in Cheng (2010) and the empirical specification in Jenter and Kanaan (2010). In Cheng's model, the probability of the manager being fired is directly linked to the relative performance, which is the difference between own firm ROA and rival firm ROA. The manager is fired if the relative performance is sufficiently negative. Cheng's model implies the following regression.

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

"*RP*" is the relative performance as defined above. According to Cheng's model, RPE means that γ <0. Jenter and Kanaan (2010) decompose own-firm performance into two parts, the firm-specific performance ($\hat{v}_{i,t-1}$) and the industry-induced performance ($\hat{r}_{i,t-1}$). Then they use the following empirical model to identify RPE.

$$\Pr ob(CEOTO_{i,t} = 1) = \alpha + \gamma \times \hat{v}_{i,t-1} + \beta \times \hat{r}_{i,t-1} + \varepsilon_{i,t} \,. \quad (6)$$

The authors argue that the *strong-form* RPE implies that γ <0 and β=0. We can view *RP* as one proxy for the firm-specific performance because the industry performance is subtracted out. Since Cheng's model assumes that only *RP* drives the CEO firing decision, we can interpret Cheng's model as assuming that β=0.

Thus we combine the insights in equations (5) and (6), and run the following probit regression by each three-digit SIC industry:

$$\Pr ob(CEOTO_{i,t-1} = 1) = \alpha + \gamma_{to2} \times RP_{i,t-1} + \beta \times RivalROA_{i,t-1} + \delta \times Ln(FirmSize_{i,t-1}) + \varepsilon_{i,t-1} \,. \quad (7)$$

We then define the indicator variable *"RPE-TO2"* that equals one if the coefficient estimate for γ_{to2} is significantly negative and the coefficient estimate for β is insignificantly different from zero. Table 1 Panel A shows that 15% of the 155 industries with the executive turnover data exhibit RPE in CEO turnover.

Table 7 reports the effect of RPE in CEO turnover on the firm's fraud propensity. In both models (1) and (3), the direct effects of the two RPE indicators are positive and significant. Thus other things equal, the average probability of fraud is higher in industries with RPE in CEO turnover decisions. This is consistent with the effect of *RPE-Pay* in Table 6. In models (2) and (4) we add the interaction effect between RPE and industry competitiveness. Both the direct effect of RPE and the interaction effect are statistically insignificant. Results using stock returns in place of ROA in equations (4) and (7) are similar and thus not reported.

The results in Table 7 suggest that RPE in CEO turnover cannot help us understand the contrasting fraud dynamics in competitive industries and concentrated industries. Cheng's model implies that the effect of RPE on the firm's fraud propensity is stronger in industries with more competitive labor market. The competitiveness variable in our study measures the competitiveness of the product market, which may not be highly correlated with the competitiveness of the labor market.

In sum, the results in this section suggest that the existence of RPE in CEO compensation or in CEO turnover tends to increase the firm's propensity to commit fraud. RPE in CEO pay can significantly amplify fraud waves in competitive industries during an industry investment boom. But it has a much weaker effect on the fraud dynamics in concentrated industries. Thus the adverse effect of RPE on firms' fraud incentives in competitive industries can to some extent explain the differential fraud dynamics in competitive industries versus concentrated industries in our baseline results.

5. CONCLUSION

Our paper examines the effect of industry competition on financial misreporting. We find that more competitive industries have significantly more fraud than concentrated industries during times of abnormally high investment. Further tests find that these effects are concentrated on firms whose performance has less impact on their rivals' investment decisions, consistent with the theory of Gigler (1994). We also find evidence that, consistent with the ideas of Grenadier (2002) and Chen, Goldstein, and Jiang (2007), poor information gathering and investment coordination in competitive industries account for part of these effects. Finally, we find that, consistent with Aggarwal and Samwick (1999) and Cheng (2010), the use of relative performance evaluation exacerbates firms' incentives to commit fraud, particularly in competitive industries.

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Appendix: Variable Definitions

Industry Characteristics	
Boom	The average unpredicted investment in an industry-year as in Hoberg and Phillips (2010).
Competitive	=1-(standardized Fitted HHI). Fitted HHI is the industry concentration index created by Hoberg and Phillips (2010). We standardize the Fitted HHI so that its value is between 0 and 1.
Ln(# of Firms)	Natural logarithm of the number of firms in an industry-year
Comove	The industry-year average correlation between one firm's return and the rival firms' value-weighted returns.
LowPMS1	=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.
LowPMS2	=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.
RPE-Pay	=1 if the industry exhibits relative performance evaluation in CEO pay, =0 otherwise.
RPE-TO1	=1 if the industry exhibits the weak-form relative performance evaluation in CEO turnover decisions, =0 otherwise.
RPE-TO2	=1 if the industry exhibits the strong-form relative performance evaluation in CEO turnover decisions, =0 otherwise.
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
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: Explanatory Variables

	# of Obs.	Mean (Median)	Std. Deviation
Industry Characteristics (by industry-year or by industry)			
Boom	1889	-0.01 (-0.02)	0.10
Competitive	1889	0.82 (0.86)	0.14
Ln(# of Firms)	1889	4.85 (4.85)	1.13
Comove	1863	0.13 (0.11)	0.10
LowPMS1	180	0.34 (0.00)	0.48
LowPMS2	180	0.33 (0.00)	0.47
RPE-Pay	155	0.28 (0.00)	0.45
RPE-TO1	155	0.15 (0.00)	0.38
RPE-TO2	155	0.15 (0.00)	0.35
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 Own	18931	0.18 (0.10)	0.20
Institutional Own	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 C: Correlations between alternative proxies of industry structure

	Competitive	LowPMS1	LowPMS2	Ln(# of Firms)	Comove
Competitive	1.00***				
LowPMS1	0.23***	1.00***			
LowPMS2	0.20***	0.23***	1.00***		
Ln(# of Firms)	0.58***	0.42***	0.42***	1.00***	
Comove	0.26***	0.18***	0.30***	0.52***	1.00***

Table 2: Industry Competition, Investment Booms, and Corporate 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.

	P(F)	P(D|F)
Competitive	-0.126	
	(0.202)	
Boom	-5.851**	
	(2.809)	
Competitive*Boom	6.638**	
	(3.126)	
ROA	0.117	
	(0.150)	
Ext. Fin. Need	0.723***	
	(0.275)	
Leverage	0.041	
	(0.123)	
Insider Ownership	0.416**	
	(0.191)	
Institution Ownership	-0.871***	0.735***
	(0.337)	(0.241)
Analyst Coverage	-0.030***	0.030***
	(0.009)	(0.007)
Log(Assets)	0.039	0.006
	(0.077)	(0.040)
Firm Age	0.015**	-0.009*
	(0.007)	(0.005)
Technology	0.402	-0.049
	(0.249)	(0.150)
Service	-0.118	0.110
	(0.275)	(0.180)
Trade	-0.807***	0.597***
	(0.267)	(0.199)
Abnormal Ind. Litigation		1.004***
		(0.266)
Disastrous Stock Return		0.321***
		(0.058)
Abnormal Return Volatility		2.121***
		(0.328)
Abnormal Stock Turnover		0.022***
		(0.006)
Constant	1.468***	-1.939***
	(0.427)	(0.149)
Log Likelihood		-1963
χ^2 (d.f.)		207 (25)
Observations		18839

Table 3: Largest Investment Boom-Bust, Industry Competition, and Fraud

For each industry we identify the year with the highest unpredictable investment, and call it year 0. This is the peak of the investment boom in an industry. Then we measure the magnitude of the boom-bust as the absolute difference between the year-0 abnormal investment and the year-4 abnormal investment. "Large (Small) Boom-Bust" means the boom-bust magnitude is in the top (bottom) tercile of the distribution. "Competitive (Concentrated) Industries" are those with the competitive index value in the top (bottom) tercile of the distribution. For each event year, we report the median predicted P(F=1) in each category defined by industry competitiveness and the magnitude of the boom-bust. The predicted probability of fraud is generated by the baseline model in Table 2. In the last row we report the difference in the median predicted P(F=1) between large and small boom-bust for competitive and concentrated industries, respectively. *** means significance at 1% confidence level.

	Competitive Industries			Concentrated Industries		
Event Year	All	Large	Small	All	Large	Small
-3	0.07	0.08	0.07	0.14	0.14	0.13
-2	0.07	0.07	0.05	0.15	0.15	0.12
-1	0.12	0.13	0.11	0.14	0.15	0.14
0	0.20	0.22	0.18	0.12	0.12	0.14
1	0.23	0.36	0.17	0.18	0.18	0.18
2	0.18	0.26	0.15	0.16	0.18	0.18
3	0.15	0.21	0.14	0.16	0.17	0.17
Difference in P(F=1) btw. Large and Small, [-3, 3]	0.07***			0.01		

Table 4: Product Market Sensitivity, Investment Booms 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.

Panel A

	(1)		(2)	
	P(F)	P(D|F)	P(F)	P(D|F)
LowPMS1	0.114			
	(0.145)			
LowPMS1*Boom	3.019***			
	(1.087)			
LowPMS2			-0.247	
			(0.155)	
LowPMS2*Boom			2.620**	
			(1.144)	
Boom	-0.173		-0.561	
	(0.830)		(0.878)	
ROA	0.400		0.393	
	(0.317)		(0.329)	
Ext. Fin. Need	2.047***		2.154***	
	(0.396)		(0.431)	
Leverage	-0.109		-0.057	
	(0.309)		(0.317)	
Insider Ownership	1.107***		1.084***	
	(0.390)		(0.411)	
Institution Ownership	-0.218	0.442**	-0.300	0.451**
	(0.431)	(0.201)	(0.413)	(0.193)
Analyst Coverage	-0.023	0.027***	-0.024*	0.029***
	(0.014)	(0.007)	(0.013)	(0.007)
Log(Assets)	0.237**	-0.030	0.238**	-0.032
	(0.106)	(0.037)	(0.100)	(0.035)
Firm Age	0.004	-0.001	0.005	-0.001
	(0.009)	(0.005)	(0.009)	(0.005)
Technology	0.627*	0.067	0.777**	0.052
	(0.341)	(0.145)	(0.313)	(0.134)
Service	0.041	0.105	-0.027	0.117
	(0.326)	(0.153)	(0.300)	(0.142)
Trade	-0.704**	0.473**	-0.676**	0.420**
	(0.319)	(0.199)	(0.317)	(0.196)
Abnormal Ind. Litigation		1.164***		1.128***
		(0.436)		(0.432)
Disastrous Stock Return		0.482***		0.483***
		(0.062)		(0.061)
Abnormal Return Volatility		4.458***		4.362***
		(1.147)		(1.136)
Abnormal Stock Turnover		0.039***		0.039***
		(0.007)		(0.007)
Constant	-1.869**	-1.869***	-1.685**	-1.872***
	(0.794)	(0.141)	(0.788)	(0.137)
Log Likelihood		-1947		-1945
χ^2 (d.f.)		239 (25)		230 (25)
Observations		18764		18764

Panel B: During the Largest Industry Investment Boom-Bust

"LowPMS" is an indicator variable that equals one for industries with | γ_1 | in equation (1) in the bottom tercile of the sample distribution, and equals zero otherwise. The event years are defined as in Table 3. The predicted P(F=1) is from the baseline model in Table 2.

Event Year	LowPMS=1	LowPMS=0
-3	0.16	0.14
-2	0.20	0.12
-1	0.23	0.13
0	0.24	0.15
1	0.27	0.15
2	0.26	0.14
3	0.23	0.12
Difference in P(F) during [-3, 3]	0.09***	

Table 5: The Role of Coordination and Information Gathering

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)	
	P(F)	P(D|F)	P(F)	P(D|F)
Log(# of Firms)	-0.108			
	(0.071)			
Log(# of Firms)*Boom	0.487***			
	(0.178)			
Comove			-1.333	
			(0.913)	
Comove*Boom			9.723***	
			(3.833)	
Boom	-0.525		-0.657	
	(0.848)		(0.851)	
ROA	0.402		0.332	
	(0.338)		(0.319)	
Ext. Fin. Need	2.060***		2.027***	
	(0.500)		(0.389)	
Leverage	-0.049		-0.036	
	(0.314)		(0.302)	
Insider Ownership	1.021***		0.980***	
	(0.383)		(0.380)	
Institution Ownership	-0.339	0.462**	-0.050	0.387*
	(0.487)	(0.211)	(0.411)	(0.200)
Analyst Coverage	-0.023	0.029***	-0.020	0.028***
	(0.015)	(0.007)	(0.013)	(0.007)
Log(Assets)	0.207*	-0.025	0.215**	-0.021
	(0.116)	(0.039)	(0.097)	(0.038)
Firm Age	0.008	-0.003	0.005	-0.001
	(0.010)	(0.005)	(0.008)	(0.005)
Technology	1.001**	-0.004	0.771***	0.057
	(0.421)	(0.163)	(0.295)	(0.131)
Service	0.044	0.081	0.026	0.113
	(0.312)	(0.149)	(0.301)	(0.149)
Trade	-0.704**	0.434**	-0.669**	0.432**
	(0.324)	(0.197)	(0.315)	(0.201)
Abnormal Ind. Litigation		1.195***		1.139***
		(0.421)		(0.435)
Disastrous Stock Return		0.475***		0.490***
		(0.067)		(0.061)
Abnormal Return Volatility		4.164**		4.797***
		(1.725)		(0.998)
Abnormal Stock Turnover		0.038***		0.038***
		(0.009)		(0.007)
Constant	-1.135	-1.855***	-1.627***	-1.877***
	(1.425)	(0.141)	(0.607)	(0.143)
Log Likelihood		-1944		-1937
χ^2 (d.f.)		207 (25)		225 (25)
Observations		18931		18759

Table 6: RPE in CEO Pay, Industry Competition, 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)	
	P(F)	P(D|F)	P(F)	P(D|F)
Competition	-0.517*		-0.657**	
	(0.270)		(0.291)	
RPE-Pay	0.189**		-0.999*	
	(0.092)		(0.601)	
Competition*RPE-Pay			1.304**	
			(0.648)	
ROA	0.361		0.360	
	(0.225)		(0.220)	
Ext. Fin. Need	1.026***		1.017***	
	(0.398)		(0.372)	
Leverage	0.413**		0.410**	
	(0.181)		(0.171)	
Insider Ownership	0.583**		0.581**	
	(0.246)		(0.231)	
Institution Ownership	-0.131	0.331	-0.171	0.353
	(0.444)	(0.237)	(0.407)	(0.225)
Analyst Coverage	-0.022*	0.027***	-0.022*	0.027***
	(0.012)	(0.009)	(0.011)	(0.008)
Log(Assets)	0.065	-0.009	0.055	-0.004
	(0.054)	(0.027)	(0.052)	(0.027)
Technology	0.238	0.051	0.265	0.027
	(0.334)	(0.174)	(0.307)	(0.159)
Service	-0.533	0.338*	-0.495	0.319*
	(0.366)	(0.198)	(0.335)	(0.188)
Trade	-0.936***	0.615***	-0.899***	0.598***
	(0.343)	(0.222)	(0.325)	(0.219)
Abnormal Ind. Litigation		1.361***		1.335***
		(0.282)		(0.274)
Disastrous Stock Return		0.392***		0.392***
		(0.067)		(0.065)
Abnormal Return Volatility		1.656***		1.638***
		(0.293)		(0.282)
Abnormal Stock Turnover		0.035***		0.035***
		(0.007)		(0.006)
Constant	1.212**	-1.998***	1.370**	-2.011***
	(0.588)	(0.152)	(0.545)	(0.148)
Log Likelihood		-2579		-2579
χ^2 (d.f.)		223 (23)		223 (23)
Observations		18931		18931

Table 7: RPE in CEO Turnover, Industry Competition, and Fraud

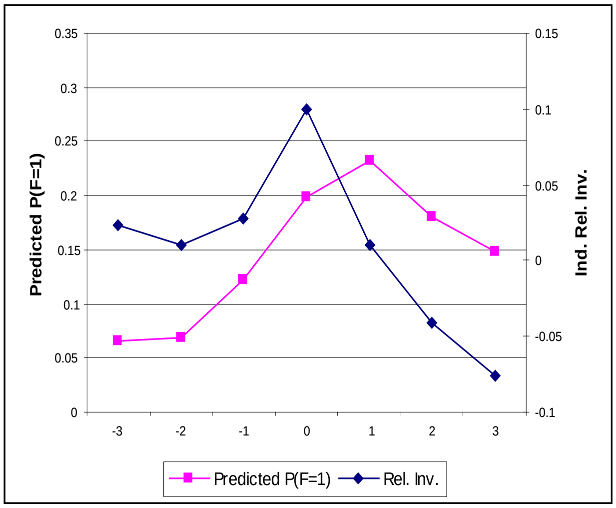
P(F) is the probability of fraud, and P(D|F) is the probability of detection conditional on fraud occurrence. Robust standard errors (in parentheses) are clustered by firm. ***, **, and * indicate significance at 1, 5, and 10% confidence levels respectively.

	(1)		(2)		(3)		(4)	
	P(F)	P(D|F)	P(F)	P(D|F)	P(F)	P(D|F)	P(F)	P(D|F)
Competitive	-0.387		-0.091		-0.238		-0.269	
	(0.275)		(0.294)		(0.207)		(0.206)	
RPE-TO1	0.310**		-0.339					
	(0.151)		(0.419)					
Comp.*RPE-TO1			0.732					
			(0.516)					
RPE-TO2					0.265**		-0.267	
					(0.122)		(0.776)	
Comp.*RPE-TO2							0.638	
							(0.948)	
ROA	0.411		0.405		0.339*		0.335*	
	(0.250)		(0.249)		(0.193)		(0.190)	
Ext. Fin. Need	1.122**		1.120**		0.893***		0.877***	
	(0.490)		(0.491)		(0.331)		(0.323)	
Leverage	0.421**		0.430**		0.388**		0.382**	
	(0.198)		(0.199)		(0.155)		(0.153)	
Insider Own.	0.594**		0.585**		0.488**		0.478**	
	(0.272)		(0.268)		(0.201)		(0.196)	
Institution Own.	-0.183	0.330	-0.198	0.336	-0.300	0.389	-0.300	0.384
	(0.398)	(0.211)	(0.390)	(0.208)	(0.408)	(0.248)	(0.402)	(0.246)
Analyst Coverage	-0.022**	0.028***	-0.023**	0.028***	-0.021*	0.028***	-0.021**	0.028***
	(0.011)	(0.006)	(0.011)	(0.006)	(0.011)	(0.008)	(0.011)	(0.008)
Log(Assets)	0.081	-0.012	0.081	-0.012	0.051	-0.009	0.051	-0.010
	(0.059)	(0.026)	(0.059)	(0.026)	(0.049)	(0.026)	(0.048)	(0.026)
Technology	0.443	-0.030	0.429	-0.031	0.422	-0.015	0.407	-0.010
	(0.290)	(0.141)	(0.285)	(0.138)	(0.328)	(0.184)	(0.328)	(0.184)
Service	-0.392	0.256	-0.384	0.255	-0.469	0.320	-0.481	0.327
	(0.320)	(0.176)	(0.314)	(0.173)	(0.407)	(0.238)	(0.404)	(0.237)
Trade	-0.849***	0.567***	-0.845***	0.560***	-0.897**	0.628***	-0.924**	0.645***
	(0.312)	(0.213)	(0.307)	(0.214)	(0.366)	(0.237)	(0.373)	(0.242)
Ab. Ind. Litigation		1.376***		1.374***		1.277***		1.271***
		(0.298)		(0.297)		(0.257)		(0.255)
Disastrous Return		0.404***		0.402***		0.371***		0.368***
		(0.079)		(0.079)		(0.065)		(0.064)
Ab. Ret. Volatility		1.735***		1.735***		1.607***		1.595***
		(0.358)		(0.355)		(0.272)		(0.267)
Ab. Turnover		0.037***		0.037***		0.034***		0.034***
		(0.007)		(0.007)		(0.006)		(0.006)
Constant	0.897	-1.936***	0.646	-1.937***	1.167**	-1.960***	1.232**	-1.961***
	(0.803)	(0.127)	(0.888)	(0.127)	(0.536)	(0.146)	(0.523)	(0.147)
Log Likelihood		-2575		-2575		-2536		-2579
χ^2 (d.f.)		214 (23)		214 (23)		231 (22)		251 (23)
Observations		18931		18931		18931		18931

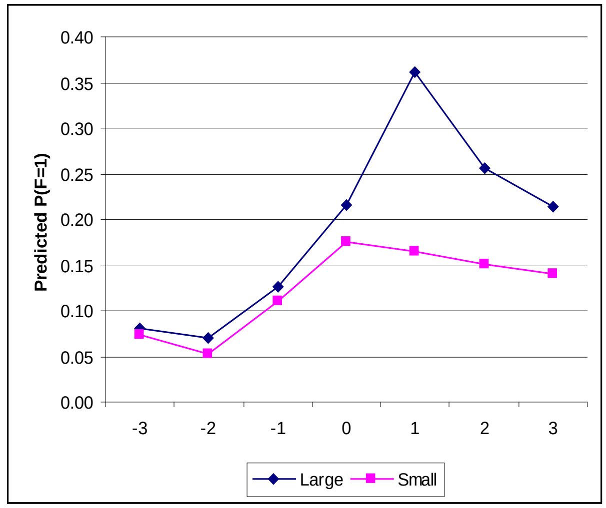
Figure 1: Investment Boom-Bust, Industry Competition, and Fraud

Panel A: Competitive Industries

(a)

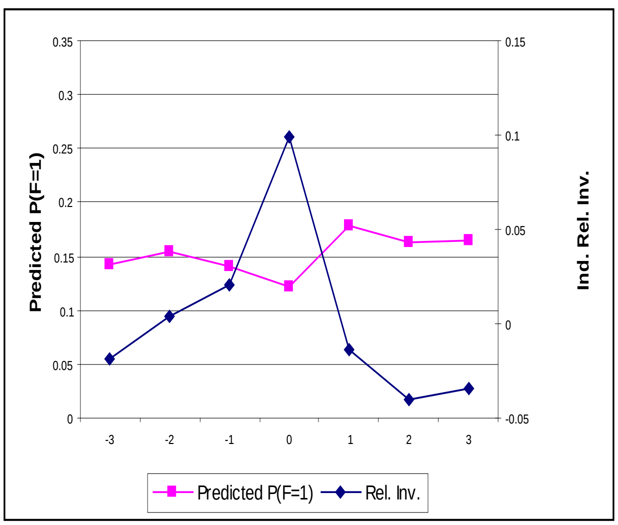


(b)



Panel B: Concentrated Industries

(c)



(d)

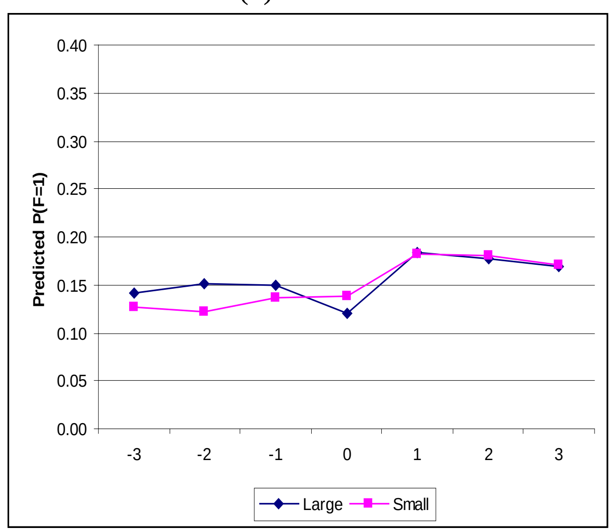


Figure 2: Realized Probability of Detected Fraud

The realized probability of detected fraud is the number of litigated firms divided by the total number of firms in an industry-year.

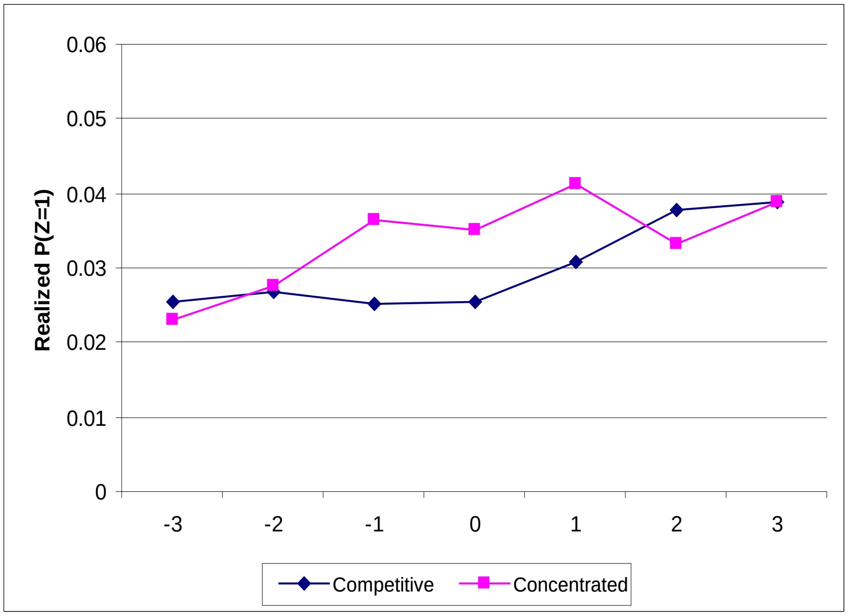
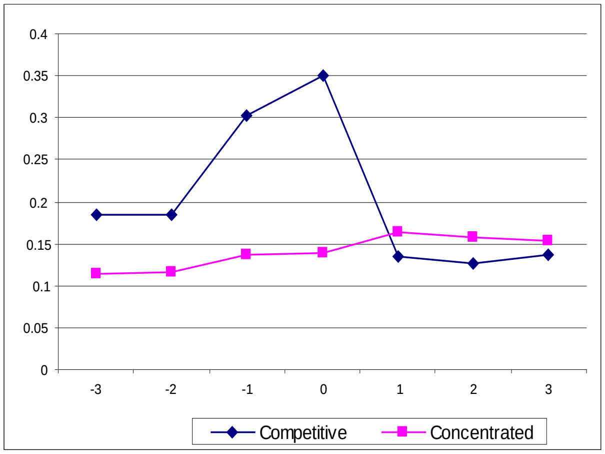
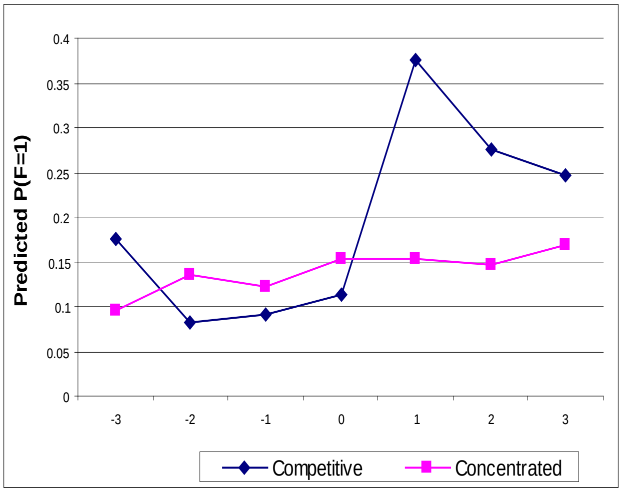


Figure 3: Different Definitions of Industry Booms and Busts

(a) Industry Average Investment



(b) Industry Relative Valuation



(c) Industry Net New Financing

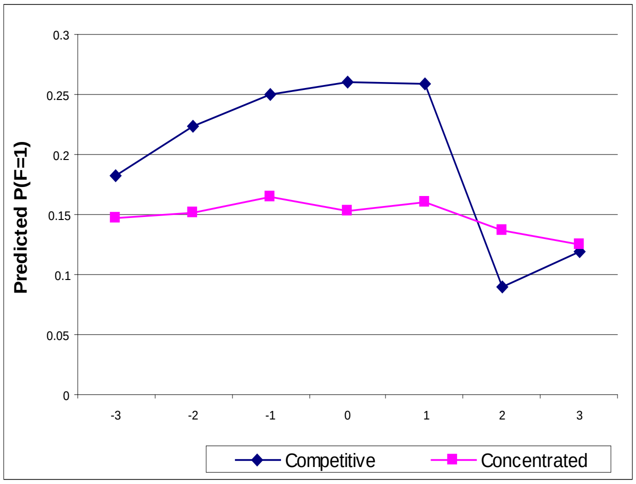
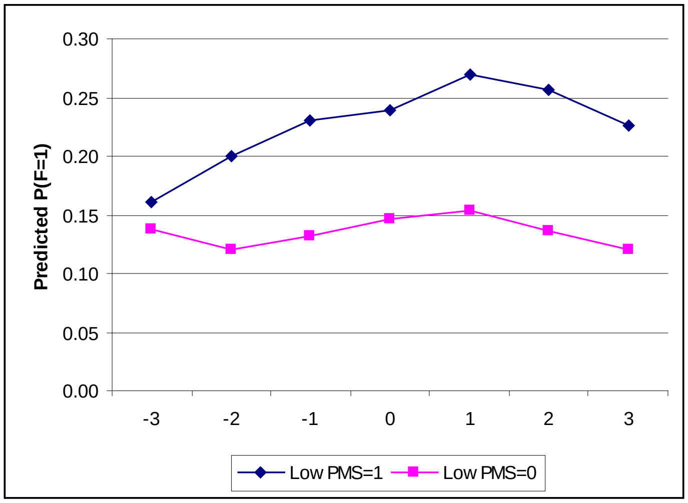


Figure 4: Product Market Sensitivity, Investment Booms and Fraud

Panel A: Lower Sensitivity versus Higher Sensitivity



Panel B: Among Competitiveness Industries

"Competitive & LowPMS=1" means the value of Competitive is in the top tercile of the sample distribution, while the value of $|\gamma_1|$ (in equation (1)) is in the bottom tercile of the sample distribution. "Competitive & LowPMS=0" means the value of Competitive is in the top tercile of the distribution, while the value of $|\gamma_1|$ is not in the bottom tercile of the distribution. "Concentrated" means the value of Competitive is in the bottom tercile of the distribution.

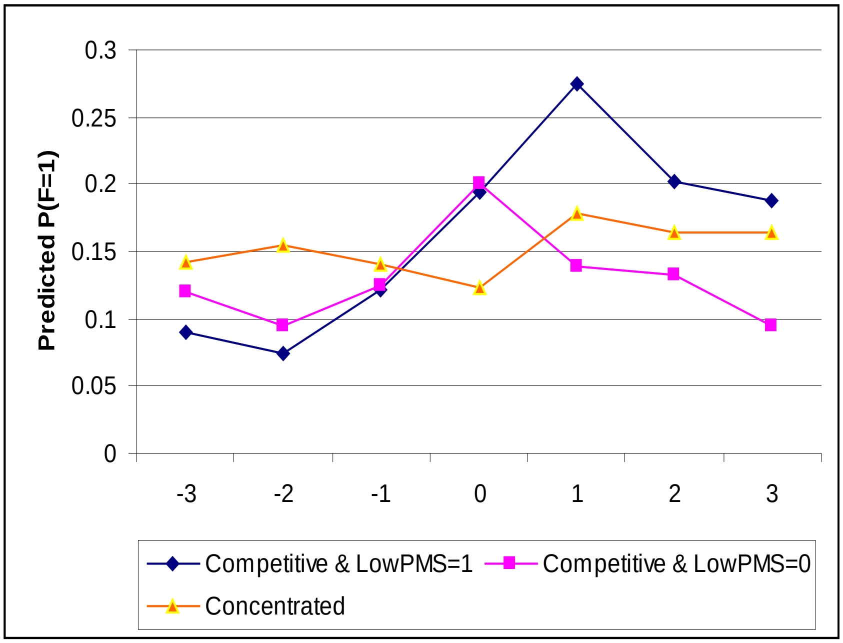
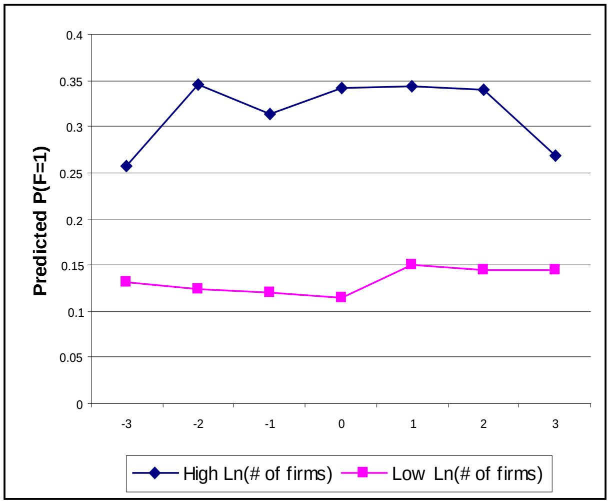


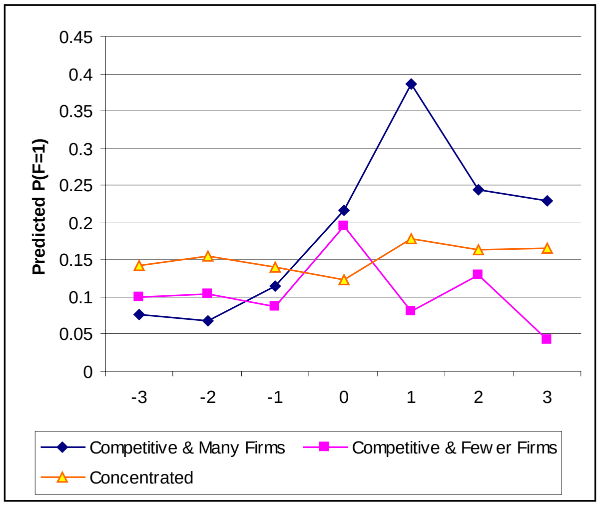
Figure 5: Coordination and Information Gathering

Panel A: Number of Firms

(a)

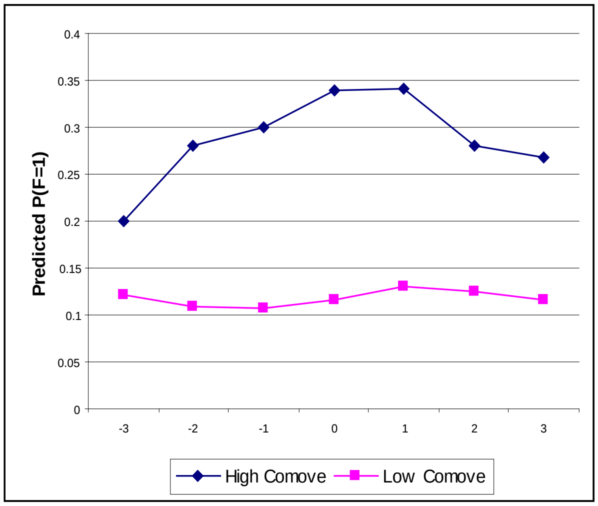


(b)

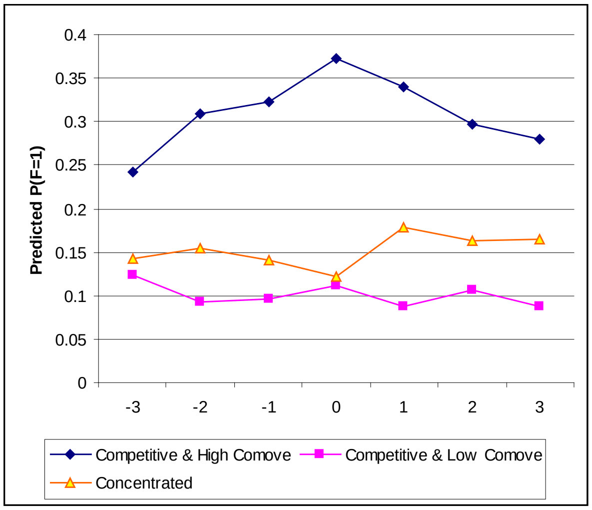


Panel B: Return Co-movement

(a)



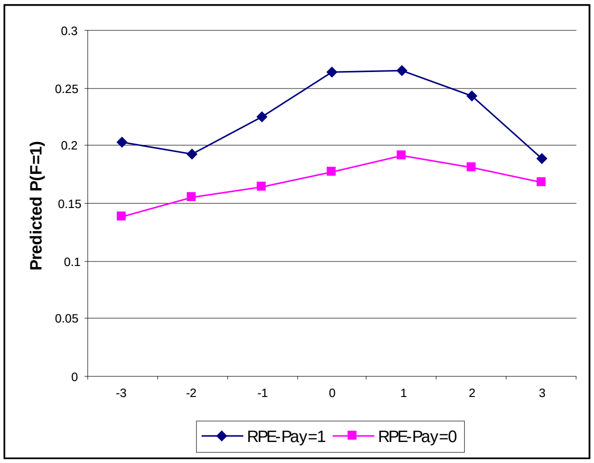
(b)



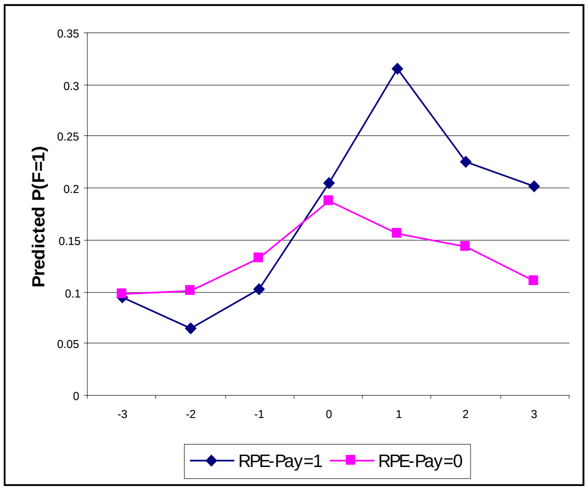
Note: “Low (High) Comove” means the value of the return comovement is in the bottom (top) tercile of the distribution. “Competitive & High Comove” means the value of Competitive is in the top tercile of the distribution, while the value of Comove is in the top tercile of the distribution. “Competitive & Low Comove” means the value of Competitive is in the top tercile of the distribution, while the value of Comove is in the bottom tercile of the distribution. “Concentrated” means the value of Competitive is in the bottom tercile of the distribution.

Figure 6: RPE in CEO Pay, Competition, and Fraud

Panel A: Effect of RPE on Fraud



Panel B: Competitive Industries



Panel C: Concentrated Industries