CORPORATE FRAUD AND BUSINESS CONDITIONS: EVIDENCE FROM IPOS

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ABSTRACT

We examine how a firm's incentive to commit fraud when going public varies with investor beliefs about industry business conditions. Fraud propensity increases with the level of investor beliefs about industry prospects but decreases in the presence of extremely high beliefs. Evidence suggests that two mechanisms are at work: monitoring by investors, and short-term executive compensation, both of which vary with investor beliefs about industry prospects. We also find evidence that monitoring incentives of investors and underwriters differ. Our results are consistent with the predictions of recent models of investor beliefs and corporate fraud, and suggest that regulators and auditors should be especially vigilant for fraud during booms.

Key words: initial public offerings, investor sentiment, corporate fraud, financial intermediations

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The wave of corporate financial fraud cases that came to light in the early 2000s has resulted in a great deal of research into the causes of such fraud. Much of this research has focused on the role of executive compensation and corporate governance structure in promoting or discouraging fraud. In this paper, we take a different approach, examining how the incidence of corporate financial fraud is affected by investor beliefs about industry business conditions and the mechanisms that account for this relationship.

Our starting point is the recent theoretical literature on fraud and investor beliefs about business conditions. As discussed in Section I below, Povel, Singh, and Winton (2007) predict that the incidence of fraud should be a hump-shaped function of investor beliefs about business conditions, peaking when investors believe conditions are good, but not extremely good. By contrast, Hertzberg (2005) predicts that the incidence of fraud should simply increase as investor beliefs improve. These two papers derive their predictions from different mechanisms: in Povel et al. (2007), investor beliefs about business conditions influence investor monitoring intensity, which in turn affects managerial fraud incentives, whereas in Hertzberg (2005), more positive investor beliefs lead to more short-term managerial compensation, which in turn exacerbates managerial fraud incentives.

To test these predictions, we use a sample of U.S. firms that went public during the period from 1995 to 2005. As we discuss in Section II, whereas many factors may influence fraud for established firms, investor beliefs about industry conditions are likely to have a particularly salient influence on fraud in an IPO setting. We measure detected fraud with securities lawsuits alleging accounting-related fraud during the period leading up to the IPO.[1] Of course, not all IPO frauds are detected, and some lawsuits may be frivolous, so we use the bivariate probit method of Wang (2009) to deal with the partial observability of fraud. In measuring investor beliefs about business conditions, we focus on measures that are more likely to reflect the beliefs of institutional investors. As opposed to individual investors, institutional investors are more likely to have the skills and incentives to monitor firms carefully or influence managerial compensation contracts, as assumed by the theory models. We use three proxies for investor beliefs about business conditions: median annual EPS growth forecast for a firm's industry, inverse of the median IPO book-building time by industry, and median Tobin's Q by industry.

[1] In this paper we focus on corporate fraud. There are other actions that firms can take that destroy shareholder value, and value-destruction does not always lead to litigation. For a related discussion, see Graham, Harvey and Rajgopal (2005).

Our first set of tests examines the relationship between investor beliefs and the incidence of fraud. Under both a quadratic specification and a piecewise linear specification, we find that the incidence of fraud is at first increasing in the level of investor beliefs but decreasing once beliefs are sufficiently positive. These results are most consistent with the prediction of Povel et al. (2007). On the other hand, although Hertzberg's (2005) model predicts a strictly increasing relationship between investor beliefs and fraud, it is possible that it could be a partial explanation.

Our next set of tests looks more deeply at the mechanisms linking investor beliefs to the incidence of fraud in these two models. In Povel et al. (2007), the driving force is investor monitoring: lower investors' monitoring costs shift the incidence of fraud towards higher investor beliefs. Using venture capitalists as specialized investors with lower monitoring costs than other institutional investors, we examine how the presence and skill level of venture capitalists affect the incidence of fraud. Our findings are consistent with the predictions of Povel et al. (2007): when venture capitalists are present or when venture capitalists enjoy a high level of industry expertise, fraud is less likely for low investor beliefs but more likely for high investor beliefs.

We also examine the impact of monitoring by underwriters, who are key gatekeepers in the IPO process. If underwriters act purely on behalf of investors, their monitoring incentives should be similar to those of venture capitalists, with an impact that varies with the level of investor beliefs. However, Sherman (1999) predicts that underwriters should generally have incentive to find fraud so as to forestall legal liability and loss of reputation, regardless of investor beliefs. Using two proxies for the role of underwriters' monitoring costs—underwriter's industry specialization and the supply of investment-banking professionals normalized by the number of securities issued—we find that lower underwriter monitoring costs (stronger underwriter expertise or larger supply of skilled labor) are associated with less fraud overall. This differs from the results for venture capitalists, where the sign of the effect depends on investor beliefs. Nevertheless, the impact of underwriter specialization on fraud is strongest for low investor beliefs, so underwriters may be most vigilant in relatively bad times.

In Hertzberg (2005), the driving force linking investor beliefs and fraud propensity is the types of incentive contracts given to managers. We first investigate how firm compensation patterns correlate with investor beliefs about industry business conditions and find that the percentage of compensation that is short-term is increasing in investor beliefs. Next, we document a positive and significant impact of short-term compensation on a firm's fraud propensity and find evidence consistent with beliefs driving part of this compensation effect. These findings are consistent with the predictions in Hertzberg (2005) that executive compensation design plays a role in explaining the relationship between corporate fraud propensity and investor beliefs about business conditions. However, the level of investor beliefs on fraud continues to have an independent, hump-shaped impact on the incidence of fraud, suggesting that the compensation mechanism as highlighted in Hertzberg's model is not the full explanation.

Summing up, we find evidence that is consistent with the two fraud mechanisms proposed by Povel et al. (2007) and Hertzberg (2005). Also, although our evidence on underwriter monitoring generally supports the model of Sherman (1999), the impact of underwriter monitoring on fraud is less pronounced when investor beliefs are relatively high. Our results are robust to alternative proxies for investor beliefs about business conditions, alternative treatments of the internet industry, and various sample restrictions so as to exclude frivolous lawsuits.

Our results suggest that voluntary monitoring by institutional investors or venture capitalists is less effective at reducing fraud when investors are optimistic about an industry's prospects. Thus, relying on investor incentives alone is unlikely to diminish fraud in good times. This matters because increasing fraud can have negative externalities, decreasing investors' trust in financial markets and hurting firms' ability to tap those markets. For IPO firms, this is especially important, because the ability to go public is a key driver of entrepreneurial activity. These problems may be magnified because the volume of IPOs tends to be higher in good times, which is when fraud is most likely. If regulators want to reduce fraud in order to avoid these externalities and negative consequences of fraud, more regulatory vigilance in good times may be needed.

Our paper is related to the IPO literature that studies "hot" and "cold" IPO markets (e.g., Loughran and Ritter 2002, Lowry and Schwert 2002, Ljungqvist and Wilhelm 2003, Lowry 2003, Pastor and Veronesi 2005, and Cornelli, Goldreich, and Ljungqvist 2006). This literature focuses on what factors drive the fluctuations of IPO volumes and underpricing over time, whereas we investigate how investors' beliefs about industry prospects affect investor monitoring and CEO compensation, in turn affecting a firm's incentive to commit fraud when raising external capital.

As noted above, most empirical research on corporate fraud has focused on either the role of executive compensation or corporate governance characteristics. A number of papers link fraud to equity compensation for executives (e.g., Burns and Kedia 2006, Goldman and Slezak 2006, Efendi, Srivastava, and Swanson 2007, Peng and Röell 2008, Armstrong, Jagolinzer, and Larcker 2009, and

Johnson, Ryan, and Tian 2009). Other papers link fraud to corporate boards lacking independence or financial and accounting expertise (e.g., Beasley 1996, Dechow, Sloan, and Sweeney 1996, and Agrawal and Chadha 2005). In addition, Li (2008) and Dyck, Morse, and Zingales (2009) study the effect of monitoring institutions on incidence of fraud and fraud detection. Li (2008) examines SEC monitoring and Dyck et al. examine monitoring by a variety of agents. There is also a large literature in accounting focusing on the role of auditors in preventing and detecting fraud (see, e.g., Francis 2004). By contrast, we emphasize the role of investor beliefs and how these affect fraud through their impact on investor monitoring and on executive compensation.

The structure of our paper is as follows. Section I discusses the models and empirical hypotheses that we test in the paper. Section II discusses the research setting and sets out our model specification. Section III describes our sources of data. Section IV reports our basic results on the impact of the level of investor beliefs on fraud. Section V examines monitoring and executive compensation as mechanisms linking investor beliefs to fraud. Section VI discusses various tests for robustness. Section VII concludes.

I. HYPOTHESIS DEVELOPMENT

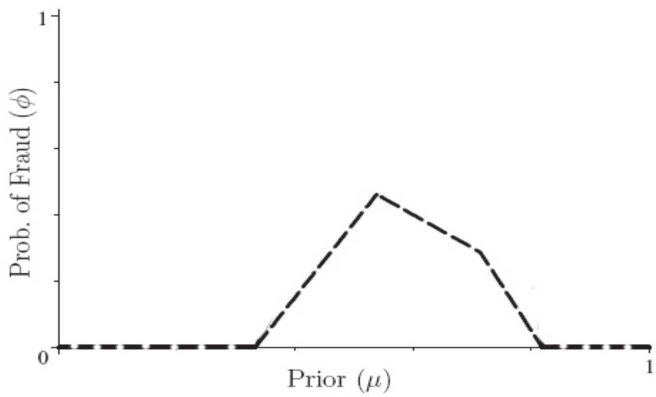
In this section we discuss the theories modeling how investors' beliefs about business conditions affect firms' incentive to commit fraud, as well as these models' direct predictions. We discuss predictions linked to the specific mechanisms of the models, and lay out related empirical hypotheses.

I.A Investor Beliefs and Propensity for Fraud

Our discussion focuses first on Povel et al. (2007) and then on Hertzberg (2005). Povel et al. (2007) model how firms' incentives to commit fraud interact with investors' beliefs and monitoring incentives. In their model, firms seek funding from investors; investors either fund the firm based on its reported results or monitor the firm to get better information before making the funding decision. Firms with poor investment prospects ("bad firms") may fraudulently improve their reported results so as to increase their odds of getting funding. By contrast, firms with good investment prospects ("good firms") do not commit fraud. A critical point of the model is that investors do not monitor so as to find fraud per se; instead, they use monitoring to better decide whether a firm is worth investing in.

When investors believe business conditions are poor or average, they scrutinize even firms with strong reports carefully so as to weed out bad firms which happen to have strong reports. This makes fraud unattractive: a fraudulently strong report will probably be monitored and fail to attract funding. When investors believe business conditions are good, they lessen their scrutiny of firms with strong reports, so incentives for fraud increase. If investors believe business conditions are extremely good, however, they may not be put off even by weak reports because they believe such reports are more likely to represent temporary setbacks rather than poor prospects. Since even weak reports can receive unmonitored funding, incentives for fraud diminish.

Povel et al.'s (2007) prediction about the relationship between the *ex ante* probability of fraud and investor belief is summarized in the following figure (Figure 4 in Povel et al. (2007)).[2]



Whereas Povel et al. (2007) argue that investor beliefs affect fraud propensity by altering investors' monitoring incentives, Hertzberg (2005) argues that investor beliefs about business conditions affect fraud propensity by altering the mix of short- and long-term executive compensation. In his model, investors set managerial compensation based on the firm's (observed) short-term performance and its (true) long-term performance. While executive compensation based on short-term performance is effective at inducing managerial effort, it also increases managers' incentives to manipulate short-term performance. By contrast, long-term compensation deters managers from hiding poor short-term performance. In equilibrium, the optimal contract and the induced fraud propensity depend on the level of investor beliefs.

[2] Povel et al. (2007) assume that the relative numbers of good and bad firms are fixed, given investor beliefs. If entry and exit of bad firms are allowed, then optimistic beliefs may attract the entry of more bad firms; this limits how optimistic rational investor beliefs can be. Similarly, pessimistic beliefs may cause the exit of bad firms, limiting how pessimistic rational investor beliefs can be. Nevertheless, the hump-shaped relationship between investor beliefs and fraud propensity still holds in the presence of free entry and exit by bad firms.

When investor beliefs are high, investors assess that fraud is less likely to occur as only a small fraction of managers find their firm performing poorly. Short-term incentives are optimal, encouraging manipulation (fraud). Conversely, when investor beliefs are low, long-term incentives are optimal, discouraging fraud.

Both Povel et al. (2007) and Hertzberg (2005) focus on business conditions, rather than business cycles per se. Therefore, their implications can be applied to cross-industry analysis as well as time series comparisons within industries. We now summarize the predictions from these two theories.

Hypothesis 1a (Povel et al.): *The likelihood that a firm commits fraud should be a hump-shaped function of investor beliefs about business conditions, first increasing as beliefs improve, but then decreasing once beliefs are sufficiently optimistic (Povel et al. (2007), Proposition 4).*

Hypothesis 1b (Hertzberg): *The likelihood that a firm commits fraud is an increasing function of investor beliefs about business conditions.*

I.B The Underlying Mechanisms

I.B.1 Costs of Monitoring

Several of Povel et al.'s (2007) results can be used to identify whether investor monitoring is in fact linking investor beliefs to fraud propensity. In their model, investors may monitor even firms with strong reported results if they believe that business conditions are poor or average. As monitoring costs decrease, monitoring of firms with strong reports intensifies, reducing incentives to commit fraud. By contrast, in good times, monitoring focuses on firms with weak reports so as to pick out good firms that happen to have weak results. As monitoring costs decrease, monitoring of firms with weak reports intensifies. This increases incentives for bad firms to commit fraud so as to report strong results and avoid being monitored. Thus, how a decrease in monitoring costs affects fraud depends crucially on investor beliefs about business conditions.

Hypothesis 2a (Povel et al.): *The presence of investors with lower monitoring costs decreases the likelihood of fraud when investor beliefs about business conditions are relatively pessimistic and increases the likelihood of fraud when investor beliefs are relatively optimistic (Povel et al. (2007), Propositions 5 and 6).*

The impact of underwriters' monitoring costs on fraud propensity, however, is less clear. On the one hand, if they simply act on behalf of investors and seek out good projects, Hypothesis 2a should apply to them as well. On the other hand, Sherman (1999) proposes a different model of underwriter incentives. In her model, underwriters can certify *ex ante* whether an issuing firm is good, and there is costly *ex post* verification by the courts of the issuer's type. Bad firms may commit fraud (imitate good firms) in order to get more favorable security pricing. Because underwriters face penalties (either legal liability or loss of reputation), they mitigate fraud by certifying new security issues as accurately as they can. In this case, a decrease in underwriter monitoring costs would improve their accuracy, reducing the likelihood of fraud regardless of investor beliefs.

Hypothesis 2b (Sherman): *If fraud is a specific concern of underwriters, a decrease in underwriter monitoring costs will reduce the likelihood of fraud regardless of the level of investor beliefs.*

I.B.2 Managerial Compensation

As with Povel et al. (2007) and monitoring, we can use some of Hertzberg's (2005) results to identify whether managerial compensation is linking investor beliefs to fraud propensity. Hertzberg makes two linked predictions: first, managerial compensation should be more weighted towards short-term incentives when investor beliefs are higher, and second, a greater weight on short-term incentives should lead to more fraud.

Hypothesis 3 (Hertzberg): *The percentage of managerial compensation that is short-term is an increasing function of the level of investor beliefs. The likelihood of fraud is increasing in the percentage of managerial compensation that is short-term.*

II. EMPIRICAL DESIGN

II.A IPOs as the Research Setting

Povel, Singh and Winton (2007) and Sherman (1999) both model a firm's incentive to commit fraud in order to raise external financing. To test the implications of these models, we examine the effect of investor beliefs on a firm's propensity to commit fraud at the IPO stage. This research setting has several advantages. First, the initial public offering is probably the most important financing event in a firm's life. Second, investor beliefs about IPO firms are more strongly influenced by industry conditions because there is relatively little firm-specific information on which investors can condition their beliefs. Third, at the time of the IPO, fraud incentives arising from seeking external financing are relatively more important than those arising from stock-related compensation, insider trading, and pressures from short-term investors; this fits the focus of the three models just mentioned. Of course, Hertzberg (2005) does base his predictions on the role of managerial compensation, so we investigate this as well.

II.B Empirical Methodology

When estimating a firm's probability of committing fraud, an identification problem occurs because such a probability is not directly observable: we only observe frauds that have been committed *and* subsequently detected. This problem has two implications. First, the outcome we observe depends on the outcomes of two distinct but latent economic processes: commitment of fraud and detection of fraud. Second, 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) will be different from the probability of fraud (what we want to estimate). A standard probit model cannot address this partial observability issue.

Following Wang (2009), we use a bivariate probit model to address the problem of partial observability of fraud.[3] For each firm *i*, we denote F_i^* as its incentive to commit fraud and D_i^* as its potential for getting caught conditional on fraud having been committed. We consider the following reduced form model:

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

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.

[3] Poirier (1980) proposes a bivariate probit model to address the problem of partial observability. Feinstein (1990) independently develops a similar model to address the problem of incomplete detection in the analysis of noncompliance. See also the discussion in Wang (2009) about the difference between the bivariate probit approach and the probit approach in analyzing corporate securities frauds.

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, instead of directly observing the realizations of F_i and D_i, we observe $Z_i = F_i D_i$, where $Z_i = 1$ if firm i has committed fraud and has been detected, and $Z_i = 0$ if firm i has not committed fraud or has committed fraud but has not been detected. Let Φ denote the bivariate standard normal cumulative distribution function. The empirical model for Z_i is

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

Thus, the log-likelihood function for the model is

$$L(\beta,\gamma,\rho) = \sum_{z_i=1} \log(P(Z_i = 1)) + \sum_{z_i=0} \log(P(Z_i = 0))$$
$$= \sum_{i=1}^{N} \{z_i \log[\Phi(x_{F,i}\beta, x_{D,i}\gamma, \rho)] + (1 - z_i)\log[1 - \Phi(x_{F,i}\beta, x_{D,i}\gamma, \rho)]\}.$$

The above model can be estimated using the maximum-likelihood method. The conditions for full identification of the model parameters are: (1) $x_{F,i}$ and $x_{D,i}$ do not contain exactly the same variables; and (2) the explanatory variables exhibit substantial variations in the sample.

In what follows, we specify the left-hand-side variable (Z) and the right-hand-side variables in each of the two probit equations (vectors x_F and x_D, respectively). Detailed variable definitions and proxy constructions are in Appendix I.

II.C Proxies for Detected IPO Fraud

A challenge in empirical studies of fraud is that fraud is not observable until it is discovered. The discovery of a securities fraud generally leads to a securities lawsuit. Thus, the existence of a securities lawsuit becomes a natural empirical proxy for *detected* securities fraud.

There are two types of securities lawsuits: the SEC's Accounting and Auditing Enforcement Releases (AAERs) and the private securities class action lawsuits. We use the filing of a securities lawsuit on an IPO firm for financial misreporting during the IPO process as the proxy for detected IPO fraud. That is, $Z_i = 1$ if there is an SEC enforcement action and/or a private securities lawsuit filed against firm *i*, and $Z_i = 0$ otherwise. We focus on accounting frauds because fraud in these models involves misreporting information to influence investors' beliefs about the financial condition of the firm. We discuss the fraud sample in greater detail in Section III.

A disadvantage of using lawsuits as the proxy for detected frauds is the possibility of false detection. Some lawsuits may be mistaken or frivolous. This problem may be more severe for private class action suits than for AAERs because private securities lawyers are more profit-oriented than the SEC. The model specified in Section II.B cannot directly address this problem. This is because by defining D_i^* conditional on $F_i = 1$, the model assumes away false detection of fraud (type I error) (i.e., $P(F_i = 0, D_i = 1) = 0$). We address the issue of false detection in several ways. First, as discussed in Section II.G, we directly control for factors that are related to frivolous lawsuits in our bivariate probit regressions. Second, as discussed in Section III.A, we select our sample to exclude lawsuits that are most likely to be frivolous. Finally, in Section VI.A.2, we explore alternative sample restrictions that control for frivolous lawsuits.

II.D Proxies for Investor Beliefs

As noted in the introduction, we focus on the beliefs of institutional investors because they have better skills and incentives than individual investors at learning industry dynamics, monitoring, and influencing managerial compensation. Using the Fama-French 49 industry classification, we construct three time-varying measures for institutional investors' prior beliefs about overall industry business conditions. These measures focus on three different dimensions: analyst forecasts, institutional investors' demand for IPO shares, and secondary market prices.

Our first proxy for institutional investor beliefs, "*Ind. EPS Growth*", is based on analyst forecasts of firms' performance. Malmendier and Shanthikumar (2007) and Mikhail, Walther, and Willis (2007) find that, whereas individual investors focus on analyst buy/sell recommendations in a naïve way, institutional investors focus more on earnings forecasts. Accordingly, we focus on the forecast of a firm's annual earnings per share (EPS) growth. This also has the benefit of being the most commonly-issued forecast. We compute the consensus forecast for each firm in an industry and then compute the industry median of firm-level forecasts. The higher the industry median forecasted EPS growth, the more optimistic investors are about the industry's outlook.

Our second belief proxy is based on institutional investors' demand for an industry's IPO shares. "(*Ind. Book-Building*)$^{-1}$" is 100 divided by the industry median of book-building period length, where the length of an IPO firm's book-building period is the number of days between the filing day (when the firm files a preliminary prospectus with the SEC for a public offering) and the pricing day (when the final offer price is set). During an IPO's book-building period, underwriters conduct road-shows about the firm to build and aggregate demand for the shares from outside investors, which are predominantly institutions. A shorter book-building period suggests that it takes less time to market the shares of the issuing firm to institutional investors, which should indicate a stronger demand and thus more optimistic investor beliefs about the issuer. The higher our proxy is, the stronger are investors' beliefs about the industry prospects.

Our last proxy for investor beliefs makes use of market prices. In general, a higher expectation of a firm's growth opportunities is associated with a higher Tobin's Q. Therefore, industry median Tobin's Q ("*Ind. Q*") reflects investors' view about the growth opportunities within an industry. Of course, stock prices aggregate the beliefs from individual investors as well as institutional investors, but the general trend for publicly-held firms has been for institutions to play more of a role in secondary market activity. In any case, industry median Tobin's Q provides a noisy market-based measure of institutional investors' beliefs.

Since all of the theory models mentioned above focus on investor beliefs at the time the firm initiates fraud, we measure our investor belief proxies as of the year when the fraud begins. To mitigate endogeneity concerns, we exclude IPO firms when computing industry median EPS forecasts and industry median Q.[4] (Obviously, we cannot exclude IPO firms from the book-building measure.) Note also that our proxies for investor beliefs are based on industry medians, which are unlikely to be substantially influenced by frauds in a few individual firms.

II.E Proxies for Monitoring Costs

Besides institutional investors, two important types of financial intermediaries are present in the IPO setting: venture capital firms, which provide financing to many firms before their IPOs, and lead underwriters, who serve as the gatekeepers during the IPO process. Their monitoring incentives

[4] The volume of IPOs is unlikely to affect the construction of our industry-specific investor belief measures. For example, the highest annual number of going public events during our sample period occurred in the computer software industry (Fama-French industry 36) in year 1999. But even for that industry, the number of IPO firms in year 1999 was only 26% of all publicly traded firms in that industry.

and quality should affect a firm's incentive to commit fraud during the IPO. Note that Povel et al. (2007) only allow for changes in monitoring cost, keeping monitoring precision fixed. However, greater monitoring expertise should allow an investor to achieve any given level of monitoring quality at a lower cost. Thus, in what follows, we equate greater monitoring expertise with lower monitoring costs.

Compared to other investors, venture capitalists have more expertise in funding start-ups and take larger relative shares of equity. Thus, they should have lower relative monitoring costs than other investors. To capture the variation in industry expertise among VC firms, we construct an industry-specific measure for venture capitalists' expertise. We compute each VC's industry specialty score in a given industry for a given year as the fraction of total proceeds of IPOs that the VC has invested since 1990 that are in that industry. If more than one venture capitalist participates in funding an IPO firm, we take the average of each VC's industry specialty score. If a firm is not backed by VCs then its VC's industry specialty score is zero. Using 1990 instead of the beginning year of our sample alleviates the potential forward-looking bias. A higher "*VC Specialty Score*" indicates lower monitoring costs as the VC has relatively more expertise in investing in that industry.

Besides *VC Specialty Score*, we construct a dummy variable, "*VC Backed*", that equals one if an IPO is backed by venture capital and zero otherwise. This variable is a traditional measure of VC participation in the IPO literature. In our study it captures the presence in a particular issue of investors with lower monitoring costs.

We construct two measures for the monitoring costs of underwriters. Our first measure—"*IB Specialty Score*" focuses on the fact that underwriters' expertise tends to be industry-specific (Benveniste, Busaba and Wilhelm 2002). Similar to *VC Specialty Score*, we compute each underwriter's industry specialty score in a given industry for a given year as the fraction of total IPO proceeds that the underwriter has underwritten since 1990 that are in that industry. If more than one investment bank is involved in underwriting an IPO, we take the average of each bank's industry specialty score. A higher score indicates lower monitoring costs as the underwriter has relatively more expertise in taking firms public in that industry.

Our second measure of underwriter's monitoring costs focuses on the supply side of investment banking labor markets. Khanna, Noe and Sonti (2008) argue that the screening quality of underwriters deteriorates in hot IPO markets due to a strong demand for the limited supply of specialized labor available to the investment banking industry. We compute the fraction of MBA graduates placed in the investment banking industry from Columbia Business School ("*IB Hiring*") from each sample year.[5] To take into account relative need for this labor pool, we normalize this variable by the number of securities offered in the same year (number of IPOs + SEOs + Corporate Debt). We do not argue that new MBAs are as good at monitoring as more experienced underwriters. Still, new MBAs will work under the supervision of more experienced underwriters. A shortage of new MBAs should reduce the effective scope of the experienced underwriters, reducing monitoring efficiency.

Since the supply of MBAs is a noisy measure of the supply of skilled labor in underwriting, we also use the total employment figures for the brokerage and securities industry (NAICS 523110) as provided by the Bureau of Labor Statistics, again normalized by the number of securities offered in the same year ("*IB Employment*"). Since many of these employees may be in brokerage rather than underwriting per se, this too is a noisy measure.

II.F Proxies for Short-Term and Long-Term Executive Compensation

To explore the relationship between executive compensation and fraud propensity as predicted by Hertzberg (2005), we follow Aggarwal and Samwick (1999), Murphy and Sandino (2008), and Faulkender and Yang (2009) to construct proxies for executives' short-term and long-term incentive arrangements. Specifically, for each executive in ExecuComp we calculate "*ST Incentive*" as the sum of an executive's salary, bonus, and other annual (OTHANN) as a fraction of the executive's total expected compensation. "*LT Incentive*" is the sum of the total value of new restricted stock granted (RSTKGRNT) and the total value of new stock options (OPTION_AWARDS_BLK_VALUE) as a fraction of total expected compensation. Then for each firm we compute the average of "*ST Incentive*" and "*LT Incentive*" among the top executives whose compensation figures are publicly reported.

One complication is that most IPO firms are not in the ExecuComp database. Complete pre-IPO compensation data is also not available in firms' SEC filings. Nevertheless, existing literature on executive compensation has documented a significant industry effect in executive compensation design, both in the level of pay and in the structure of pay (e.g., Murphy 1999, and Aggarwal 2008).

[5] Columbia Business School has a long history of placing students in the investment banking industry and maintains a consistent placement record throughout our sample period. On average, 35% of Columbia MBA graduates were placed in the investment banking industry during 1995-2005.

Further, going public implies a substantial change in a firm's governance structure. As IPO firms reset their executive compensation schemes in anticipation of being publicly traded companies, industry norms in executive pay play a pertinent role in this process. Therefore, for each IPO firm in each year, we compute the industry median short- and long-term incentives based on firms in ExecuComp.

II.G Determinants of the Probability of Fraud Detection

Since we use lawsuits as proxies for detected fraud, fraud detection in our study is closely related to triggers of securities litigation. Factors that affect a firm's litigation risk can be firm-specific or industry-related.

The litigation literature (e.g., Jones and Weingram 1996) suggests that stock returns, return volatility, and stock turnover are related to a firm's litigation risk. Firms that experience large negative returns and high return volatility are likely to be sued because shareholders are unhappy about their investment losses. High stock turnover implies that more investors are affected by the company's stock price and thus it is easier to identify a class of plaintiff investors, which is very important in class action lawsuits. Note that these factors can trigger both merited and false fraud detections. Thus, including these variables in the detection equation helps control for the potential bias arising from frivolous lawsuits as discussed in Section II.C.[6] We compute "*Return Volatility*" as the standard deviation of daily stock returns, "*Stock Turnover*" as the annual share turnover, and "*Stock Return*" as the annual buy and hold return.

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 industry that the firm is in. We therefore control for industry securities litigation intensity using the logarithm of the sum of the market values of litigated firms in an industry ("*Ind. Litigation*"). A high total market value can result from either a large number of frauds or the existence of some large cases. High industry litigation intensity should increase firms' litigation risk.

Although a firm's fraud propensity is affected by its anticipated likelihood of fraud detection, fraud detection does not occur at the time when fraud is committed. The majority of IPO frauds (frauds that occurred at the IPO stage) are detected within the first three years following the IPO,

[6] In other words, frivolous lawsuits will have a high probability of detection but a low probability of fraud being committed. In Section VI.A.2 we return to this and use estimated probability of fraud commitment as a further screen to exclude frivolous lawsuits.

including the IPO year. Therefore, for non-fraudulent IPO firms, all of our detection variables are measured at their average levels during the IPO year and the two years following it. For fraudulent IPO firms, all of our detection variables are measured at the year of detection.

II.H Effect of the Sarbanes-Oxley Act

The Sarbanes-Oxley Act (SOX), enacted in 2002, aims at improving corporate governance and combating corporate frauds. Pursuant to the Act, the SEC adopted rules that directed self-regulatory organizations including the NYSE and the NASDAQ to prohibit the listing of any firm that is not in compliance with these rules. All these regulatory changes affect both a firm's incentive to commit fraud during IPO and the probability of fraud detection *ex post*. To control for potential changes in the litigation environment due to this Act and the related mandates, we created a dummy variable, "*After SOX*", which equals one for year 2002 and after.

III. DATA

III.A Sample Selection

We extract a sample of fraudulent firms from two sources: the SEC's Accounting and Auditing Enforcement Releases (AAERs, from http://www.sec.gov/litigation) and the Stanford Law School's Securities Class Action Clearinghouse (SCAC, http://securities.stanford.edu) filed from 1996 to 2007. SCAC provides a comprehensive database of federal private securities class action lawsuits filed since 1996 in the United States. To control for frivolous lawsuits, we first restrict our attention to the period after the passage of the Private Securities Litigation Reform Act (passed in 1995), which was designed to reduce frivolous lawsuits (e.g., Johnson, Kasznik, and Nelson 2000, and Choi 2007). We then follow Dyck, Morse, and Zingales (2009) and exclude all cases where the judicial review process leads to their dismissal. Third, for those class actions that have settled, we exclude those firms where the settlement is less than $2 million, a threshold level of payment that helps divide frivolous suits from meritorious ones (Grundfest 1995, and Choi, Nelson, and Pritchard 2005). As noted in the previous section, in Section VI.A.2 we also examine alternative sample definitions aimed at excluding frivolous lawsuits.

To match the litigation nature of the SEC's AAERs, we identify the nature of the class action allegations based on the materials in all the available case documents associated with each lawsuit (i.e., case complaints, press releases, defendants' motion to dismiss, and court decisions) and single out cases involving allegations of accounting irregularities. This yields 423 SEC AAERs and 1,085 private class action lawsuits, among which 212 suits were subject to both SEC enforcement and private class action litigation.

Since the average time between the beginning year of fraud and the litigation filing year is 2.2 years in our sample, we require a two-year interval prior to the end of our litigation sample—year 2007—when we extract the IPO issues from Thomson Financial's SDC database. After excluding unit offers, rights offers, closed-end mutual funds, REITs, ADRs, and partnerships, our search of the SDC database yielded 3,297 completed IPO issues between January 1995 and December 2005.

We then merge our litigation sample with our IPO sample. Among the 3,297 IPO issuers, 382 have been sued for accounting-related securities fraud between 1996 and 2007. We identify the timing of the alleged frauds based on the information in the litigation documents. Among our 382 frauds, 110 occurred before or in the year of IPO. For frauds that began in their IPO years, we verify that the frauds were committed in order for the issuers to go public. We then label these 110 cases as *IPO Frauds*.

III.B Summary Statistics

Panel A of Table I reports the annual frequency of IPOs and the number of frauds committed by each IPO cohort. We observe that the incidence of fraud related to these firms decreases substantially during the period of the "cold" market (after year 2000).

Panel B indicates that both the commitment and the detection of frauds come in waves. For example, about 47.38% of frauds are committed between 1997 and 2000, and about 31.67% of frauds are detected during 2004 to 2005.

Panel C reports the distributions of frauds from the five most frequently sued Fama-French industries in our sample: computer software, business services, electronic equipment, pharmaceutical, and communication. Despite the overlap between fraud occurrences in these industries and the general stock market boom (see Panel B), we observe variations across different industries. For example, while 83% of frauds in the computer software industry occur during the 1997-2003 period, 73% of frauds in the pharmaceutical industry occur between 2002 and 2004, and 57% of frauds in the communication industry occur between 1999 and 2001.

Table II shows that, compared to other IPO firms, industry median EPS growth is significantly higher for firms that commit fraud at the IPO stage, and the inverse of industry median book-building period and industry median Q are insignificantly higher. This suggests that investor beliefs are weakly more optimistic when fraudulent firms undertake IPOs.

IV. INVESTOR BELIEFS AND THE PROBABILITY OF CORPORATE FRAUD

IV.A Approximating the Hump-Shaped Relationship: Quadratic Specification

To test Hypotheses 1a and 1b in a regression framework, we first examine whether or not the relationship between investor optimism and the incidence of fraud is hump-shaped in a quadratic specification. Specifically, we include the investor belief proxy and its squared term in the fraud propensity equation of our bivariate probit model. Table III reports the results. For each variable, we report both the coefficient estimate and the Huber-White-Sandwich robust standard errors clustered by industry (in square brackets).

Model 1 of Table III measures investor beliefs with industry median EPS growth forecasts. We observe the concave relation between investor beliefs and fraud propensity as predicted in Povel et al. (2007). Controlling for firm size, the passage of the SOX and related mandates, and the probability of fraud detection, the probability of fraud at the time of IPO is significantly positively related to the level of investor optimism, but significantly negatively related with the squared term, (*Ind. EPS Growth*)^2.

This result indicates that while a firm is at first more likely to commit fraud given a more optimistic industry-specific investor belief, this likelihood increases at a decreasing rate and eventually decreases. To illustrate, the average predicted probability of fraud for the bottom decile of investor beliefs is 4.8%. It rises to 9.7% for the fifth decile and peaks for 11.4% at the 8th decile. The fraud propensity then drops to 10.1% once investor beliefs reach the top (tenth) decile, a 13% decrease.

We estimate the point of an industry median EPS growth forecast at which the predicted probability of fraud peaks to be 0.34. That is, for any industry median EPS growth forecast level exceeding 0.34—corresponding to the top 6% of the distribution of the investor beliefs variable—a higher level of investor beliefs is associated with a lower probability of fraud. The top 6% includes 14 unique industries and 9 unique years (see details in the internet appendix).[7]

Figure 1 graphs each firm's predicted probability of fraud based on Model 1 of Table III against investor beliefs about the firm's industry. We observe a hump-shaped relationship: the probability of fraud is close to zero when investor beliefs are extremely low or extremely high. The probability peaks for the intermediate level of investor optimism.

Models 2 and 3 of Table III confirm the results of Model 1 using different measures of investor beliefs, the inverse of the industry median book-building period and industry median respectively. The positive coefficient estimates for (*Ind. Book-Building*)$^{-1}$ and *Ind. Q* suggest that an increase in investor optimism (a shorter industry median book-building period or a higher industry median Tobin's Q) leads to an increase in the fraud propensity. The negative and significant coefficient estimate for the squares of these two measures again suggests that this increasing effect diminishes and eventually reverses at higher levels of beliefs.

IV.B Approximating the Hump-Shaped Relationship: Piecewise Linear Specification

While the quadratic specification captures the general trend of the relationship between fraud propensity and investor beliefs, it imposes a smooth functional form. Instead of parametric form, we now test for the hump-shaped effect of investor optimism on the probability of corporate fraud using a piecewise linear specification—a spline. A spline specification allows the slope coefficient to vary with different levels of investor beliefs. We choose the spline cutoff points based on the quintiles of investor belief variables (for example, the cutoff points for *Ind. EPS Growth* are 10%, 15%, 19%, and 25%). We then drop the square of EPS growth but examine the slope coefficient of the measure at each of the five different regions defined by the four cutoff points just given.

The spline-regression results in Table IV are consistent with the results using the quadratic specification: when the level of investor beliefs is relatively low, the coefficient is positive, suggesting that a more optimistic investor belief about the firm's industry prospect is associated with a higher incidence of fraud. However, as investor optimism rises further (the top quintile), the

[7] Additional discussions, extensions, and robustness results are available in the internet version of this paper: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1024229. [OR, GIVE JF's SITE ADDRESS]

relationship between fraud propensity and investor beliefs becomes negative: a firm's incentive to commit fraud decreases when investor beliefs become too optimistic.

Both the results from quadratic and piecewise linear regressions suggest that investor beliefs about industry prospects affect the probability of corporate fraud in the manner that is more consistent with the predictions of Povel et al. (2007) than those of Hertzberg (2005). A firm's incentive to commit fraud in the event of raising external capital is higher when investors are more optimistic about the prospects of the firm's industry. Nevertheless, the probability of fraud becomes lower in the presence of extreme investor optimism, as the firm can obtain external financing without misrepresenting information to outside investors.

Tables III and IV also reveal that the factors affecting the probability of fraud detection have the predicted signs. Detection is more likely if the industry is more likely to be sued, if there is a sharp decline in stock prices, more aggressive trading activity, and more volatile returns. Frauds from large firms are also more likely to be caught than frauds from small firms.

V. UNDERLYING MECHANISMS: MONITORING VS. EXECUTIVE COMPENSATION

In Povel et al. (2007), the driving force behind the relationship between investor beliefs and fraud propensity is investor monitoring: investor beliefs about business conditions influence their monitoring intensity, which in turn affects managerial fraud incentives. In Hertzberg (2005), the driving force is executive compensation design: more positive investor beliefs lead to more short-term managerial compensation, which in turn exacerbates managerial fraud incentives. In this section, we investigate the roles of the underlying mechanisms highlighted by these two theories.

V.A Monitoring

Povel et al. (2007) predict that if investors' monitoring costs are lower, then the incidence of fraud should be shifted towards higher investor beliefs. When attempting an IPO, a firm is involved with not only institutional investors, but also two distinct and important financial intermediaries: investment banks (underwriters) and, sometimes, venture capitalists. Therefore, we examine and compare the effects of their monitoring costs on a firm's propensity to commit fraud at the IPO stage.

V.A.1 Venture Capitalists

Venture capitalists may provide major funding for a firm at its start-up stage. They are actively involved in the firm's business operations before it files for an IPO. On the one hand, to obtain repeated rounds of financing, the firm is subject to extensive screening and monitoring by the venture capitalists. On the other hand, being an investor seeking returns on its capital, a venture capitalist may have incentives like those of an investor in the Povel et al. (2007) model; that is, its goal in screening and monitoring the firm may be to find a good investment rather than to prevent fraud per se. Compared to other investors, the venture capitalist's combination of specialized expertise and privileged access to the firm's management should give it a lower cost of monitoring.

To examine how venture capitalists affect the probability of fraud at the IPO stage, we first repeat the tests in Table III with the addition of a VC specialty score. The results are reported in Model 1 of Table V. We find that our previous results about the effect of investor beliefs on fraud propensity do not change. In addition, after controlling for investor beliefs, there is no significant difference in fraud propensity between firms backed by VCs of higher industry expertise and those of lower industry expertise. We find similar results when we replace VC specialty score with the VC-backing dummy (Model 3 of Table V): having VC backing does not significantly impact an IPO firm's fraud propensity.

Nevertheless, the lack of significance of the coefficient for *VC Specialty Score* and for VC-backing dummy is not conclusive. This is because the analysis so far does not allow the monitoring impact of venture capitalists to vary with the degree of investor optimism, as described in Hypothesis 2a. To allow for the impact of venture capitalists to vary across different level of investor beliefs, in a spline-like framework, we interact the indicator variable for each investor belief quintile with one of the two VC variables, and include these interaction terms in the fraud propensity equation. The first (fifth) quintile corresponds to the lowest (highest) level of investor beliefs. In addition, we control for the level of investor beliefs.

The results of the above specification are reported in Models 2 and 4 of Table V. Consistent with Hypothesis 2a, the fraud incentive of firms varies with the degree of industry-specific investor optimism. When investor optimism is low, VC-backed firms, or firms backed by VCs of high industry specialty, are less likely to commit fraud than non-VC-backed firms or firms backed by VCs of low industry expertise. At higher levels of investor optimism, however, there is a shift in this relationship; now, firms backed by VCs of higher industry expertise are more likely to commit fraud than VCs of lower industry expertise, and VC-backed firms are more likely to commit fraud than non-VC-backed firms.

To summarize, compared to other pre-IPO investors, venture capitalists have expertise and management access which should translate into lower monitoring costs. Povel et al. (2007) predict that this will shift the incidence of fraud towards states with more optimistic beliefs. This is exactly what we find: in the presence of VC monitoring, the probability of fraud declines for low investor beliefs and rises for high investor beliefs.

V.A.2 Investment Banks

A large literature has established the gate-keeping role of investment banks when taking a firm public (e.g., Beatty and Ritter 1986, Carter and Manaster 1990, Chemmanur and Fulghieri 1994, and Fang 2005). Unlike venture capitalists, investment banks enter shortly before a firm's IPO decision. Investment banks usually are not investors in the firm, but they may act on behalf of the institutional investors that they market the firm's securities to. If this is their only concern, then underwriters may behave like venture capitalists—lower underwriter monitoring costs will affect the propensity for fraud as per Hypothesis 2a. However, as argued by Sherman (1999), taking a fraudulent firm public may have a very negative impact on an underwriter's reputation, in which case underwriters may try to catch fraud whenever possible. If so, lower underwriter monitoring costs may reduce the propensity for fraud regardless of investor beliefs (Hypothesis 2b).

As we did for venture capitalists, we first repeat the tests of Table III while adding measures of underwriters' monitoring costs. The results are reported in Table VI. Model 1 of Table VI indicates that the previously documented concave effect of investor beliefs on the probability of fraud is robust after controlling for lead underwriter's industry specialty score. More importantly, unlike the case of venture capitalists, we find that underwriter's industry specialty is negatively and significantly associated with the probability of fraud.

Models 2 and 3 show that in addition to the industry-specific expertise of investment banks, the supply of skilled human capital to the investment banking industry helps to mitigate a firm's fraud incentive when it attempts an IPO. The labor market condition in the investment banking industry, as captured by *IB Hiring* and *IB Employment* variables, is negatively and significantly related to the probability of fraud at the stage of IPO. A decrease in labor supply (per deal) to the investment banking industry reduces the quality of gate-keeping and deal-screening, increasing the issuing firm's incentive to commit fraud. Including underwriter ranking—a traditional measure of underwriter's overall market share and hence reputation—does not significantly affect an issuing firm's propensity to commit fraud. The effect of underwriter ranking appears to be subsumed by underwriter's industry-specific expertise and labor market conditions.

The significant and negative coefficients for the underwriter variables in Models 1 to 3 suggest that, unlike venture capitalists, underwriters' monitoring impact does not vary significantly with the degree of investor optimism. We now explicitly explore this effect in Model 4 by interacting *IB Specialty Score* with the indicator variable for each quintile of investor belief proxy. In contrast to venture capitalists (Table V), the coefficient estimates of the interaction terms in Model 4 of Table VI are consistently negative in all quintiles, though not always significant.

Overall, the results in Table VI are consistent with the implication of Sherman (1999) that underwriters care about their reputation as gatekeepers and thus try to detect fraud regardless of the level of investor beliefs. Nevertheless, we do observe that the effect of *IB Specialty Score* tends to be stronger in the lower level of investor belief quintiles. A possible explanation is that, in boom times, both current and expected investment banking profits are high. Underwriters are likely to look less hard so as not to irritate clients (firms) who may have significant expected future business with the underwriters. Thus, even underwriters seem to be relatively more vigilant when investor beliefs are less optimistic.[8]

V.B Executive Compensation

Hertzberg (2005) argues that executive compensation design can explain the link between investor beliefs and firms' fraud incentives. More optimistic beliefs about business conditions lead to more short-term compensation and less long-term compensation, encouraging fraud (Hypothesis 3). Moreover, if compensation is the dominating underlying mechanism, then after controlling for compensation, we should not expect a significant relationship between investor beliefs and fraud.

We first examine the relationship between investor beliefs about business conditions and the structure of executive pay in a panel regression analysis, using firm-level compensation data in the entire ExecuComp database between 1993 and 2005. Our results are reported in Table VII Panel A. After controlling for firm-specific factors known to affect executive compensation structure as well as the firm fixed effect and the time trend effect, we observe that more optimistic beliefs are

[8] We thank a referee for raising this point.

associated with more short-term compensation (Model 1) and less long-term compensation (Model 2). These findings are consistent with Hypothesis 3.

Next, we investigate whether executive pay structure is the underlying mechanism affecting the relationship between fraud propensity and investor beliefs as predicted by Hertzberg (2005). We utilize a two-stage regression approach. In the first stage, we regress firm-level short- and long-term executive compensation against investor beliefs (industry EPS growth forecast) for the entire ExecuComp database, respectively, and compute the predicted firm-level short- and long-term compensation. This gives us compensation driven by the variation in investor beliefs. We then calculate "*Ind. Predicted ST Incentive*" and "*Ind. Predicted LT Incentive*", which are industry median of the predicted values of short- and long-term incentives. In the second stage, we include the industry median predicted compensation in the fraud propensity equation of the bivariate probit analysis for our IPO sample.

Models 1 and 2 of Table VII Panel B report the results. We find that *Ind. Predicted ST Incentive* is positively associated with the probability of fraud (Model 1), and *Ind. Predicted LT Incentive* is negatively associated with the fraud propensity (Model 2). While the signs of the coefficient estimates for the compensation effect are consistent with the predictions in Hertzberg (2005), neither of the coefficients is statistically significant.[9]

Next, we examine whether compensation structure, rather than just the part of compensation structure driven by investor beliefs, affects fraud propensity. We compute the industry median *actual* short- and long-term compensation for each industry and each year based on the ExecuComp database. We then replace the industry median predicted value of compensation with the industry median actual value of compensation in the fraud propensity equation. Models 3 and 4 of Table VII Panel B show that the actual short-term compensation is significantly positively related to the probability of fraud, and the actual long-term compensation is significantly negatively related to the probability of fraud.

In Models 5 and 6 of Table VII Panel B, we control for the direct effect of investor beliefs by including the level of belief variable and its squared term in the fraud propensity equation. We

[9] However, we acknowledge a caveat when interpreting the results here. When using predicted values rather than actual values in the second-stage regression, the standard errors of the coefficient estimate for the predicted variable need to be corrected (see Greene 1997). But since Table VII Panel B is based on our IPO sample rather than the entire ExecuComp database, and the predicted values of executive pay structure variables are aggregated at industry level instead of being firm-specific, we are unable to correct for the variance-covariance matrix for the predicted variable. With this said, the fact that the compensation coefficient estimates are highly insignificant suggests that standard error correction is unlikely to overturn the inference.

find that investor beliefs continue to have an independent hump-shaped impact on fraud propensity, even after controlling for the effect of compensation structure. This effect is consistent with Povel et al (2007) but not Hertzberg (2005), and suggests that investor beliefs do not affect fraud just through executive compensation design.

Taken together, the results in Table VII Panel B convey two messages. First, while executive compensation structure affects a firm's fraud propensity, the evidence is only weakly consistent with Hertzberg's (2005) claim that compensation is the mechanism that drives the relationship between investor beliefs and fraud. Second, the investor monitoring mechanism is still at work in affecting a firm's incentive to commit fraud during its IPO, even after controlling for the compensation effect.

VI. ROBUSTNESS

VI.A Alternative Sample Specifications

VI.A.1 Internet IPO Firms As a Separate Industry

Our IPO sample period of 1995-2005 overlaps with the dot com bubble period and contains a significant number of internet IPO firms. As a robustness check, we identify 483 internet companies using the reference list from Loughran and Ritter (2004). As reported in the internet appendix, our results remain unchanged if we exclude the internet companies from the IPO sample, or if we re-group them into a 50th industry—the internet industry.

VI.A.2 False Detection

A disadvantage of using lawsuits as the proxy for detected frauds is that the lawsuits may be frivolous, especially for private class action suits. In our main analyses, we address the issue of false detection by imposing a series of filters on our fraud sample and by controlling for factors that are related to frivolous lawsuits in the regressions.

To further check the robustness of our results with respect to frivolous lawsuits, we re-estimate our results by excluding all firms that were subject to class action lawsuits but not AAERs. The AAER-only sub-sample thus contains 30 IPO frauds and 3,005 non-fraudulent IPOs. We observe the same concave relationship between investor beliefs and the propensity of fraud.

Finally, frivolous lawsuits, by definition, are lawsuits associated with low probabilities of fraud being actually committed. As another robustness test of our results, we first use Model 1 in

Table III to predict the fraud propensity at the IPO stage for each sample firm. We then exclude firms in our IPO fraud sample (i.e., Z=1) that have low predicted fraud propensities (i.e., in the bottom 10% of the distribution), as they are most likely to be wrongly sued according to our model. Next, we re-run the base models in Table III. Our results are robust to this sample restriction. Our results also remain unchanged when we use the alternative cutoff of the bottom 25%.

VI.B Fundamental Industry Differences and Time Effects

It is possible that average EPS growth rates vary across different industries due to fundamental differences such as financial leverage, or that there are economy-wide effects that affect all industries in certain years. Either is consistent with the theories we examine, since both Povel et al. (2007) and Hertzberg (2005) model business conditions rather than business cycles per se. Therefore, their implications can be applied to cross-industry analysis as well as time-series comparisons with industries. In the internet appendix, we further explore this issue and find that both the time-series and the cross-sectional effects are present.

VI.C Investor Belief Uncertainty and Fraud

In addition to links between the level of investor beliefs and fraud, some of the literature makes predictions about how investor uncertainty about business conditions affects fraud incentives. Kumar and Langberg (2008) predict that greater uncertainty increases the incidence of fraud, regardless of the level of investor beliefs. Using two proxies for uncertainty—industry cash flow volatility and the dispersion of investor beliefs for an industry—we find that controlling for investor belief uncertainty does not alter our main findings. Fraud propensity continues to be concave in investor beliefs, for the whole sample as well as the low-uncertainty industries and the high-uncertainty industries. The *average* incidence of fraud is higher when uncertainty is higher, as predicted by Kumar and Langberg (2008). Nevertheless, after controlling for the level of investor beliefs, the *marginal* impact of uncertainty on fraud propensity is not significant.

VI.D Other Robustness Tests

As described in detail in the internet appendix of this paper, our results are also robust to alternative proxies for investor beliefs, alternative definitions of the presence of venture capitalists in IPO firms, additional control variables such as the SEC's monitoring capacity, sales growth and accounting accruals, to alternative specification of the timing of investor beliefs, and to a standard probit specification. In addition, our findings are not driven by alternative hypotheses such as variation in underwriters' exposure to litigation. In an extension to the analysis of IPO frauds, we also analyze post-IPO frauds, which provide additional supporting evidence for the theory of Povel et al. (2007).

VII. CONCLUSIONS

In this paper we use a sample of firms that went public between 1995 and 2005 to test a set of theories modeling how a firm's incentive to commit fraud when raising external capital varies with investor beliefs. Instead of a strictly increasing relationship between investor beliefs and fraud propensity as highlighted in Hertzberg (2005), we find evidence more consistent with the predictions of Povel, Singh, and Winton (2007): a firm is more likely to commit fraud when investors are more optimistic about the firm's industry's prospects, but in the presence of extreme investor optimism, the probability of fraud becomes lower as the firm is able to obtain funding without misrepresenting information to outside investors.

Further analysis suggests that both investor monitoring and executive pay structure play a role in the relationship between investor beliefs and fraud. Using venture capitalists as specialized investors with lower monitoring costs than other institutional investors, we find evidence supporting the prediction of Povel et al. Fraud is less likely for low investor beliefs but more likely for high investor beliefs for firms backed by venture capitalists than non-VC-backed firms, and for firms backed by venture capitalists of a higher level of industry expertise. Also, investor beliefs about business conditions have a positive impact on short-term compensation, which in turn has a positive impact on a firm's fraud propensity, consistent with the predictions in Hertzberg. Nevertheless, the level of investor beliefs continues to have an independent, hump-shaped impact on the incidence of fraud even after controlling for executive compensation. This suggests that the mechanisms in both Hertzberg and Povel et al. are relevant for IPO fraud.

We also find that the monitoring incentives of underwriters differ from those of venture capitalists. Lower underwriter monitoring costs reduce fraud for all levels of investor beliefs about business conditions, though more so for low beliefs; thus, underwriters' monitoring choices appear to be more concerned with preventing fraud per se so as to protect their reputations. We interpret this as evidence in support of Sherman (1999).

Our findings suggest that the monitoring mechanism modeled in Povel et al. (2007) help better understand the effect of investor beliefs on firms' fraud propensity, and thus have implications for regulators and auditors concerned with rooting out fraud. As we noted before, corporate fraud is likely to have negative externalities, particularly in the IPO market; widespread fraud can turn investors off from IPOs, depriving young firms of a critical source of funding. Although some have argued that it should be up to investors to prevent fraud, our findings support Povel et al. (2007)'s argument that investors are focused on finding good investments rather than preventing fraud per se. Since fraud seems to peak in relatively good times, and even underwriter expertise is least effective in preventing fraud in such times, this suggests that regulators and auditors should be especially vigilant during booms.

REFERENCES

Aggarwal, Rajesh K., and Andrew A. Samwick, 1999, Executive compensation, strategic competition, and relative performance evaluation: Theory and evidence. *Journal of Finance* 54, 1999-2043.

Aggarwal, Rajesh K., 2008. Executive compensation and incentives, in Espen Eckbo (eds.), *Handbook of Empirical Corporate Finance* Vol. 2, Elsevier Science North Holland, Chapter 17: 498-534.

Agrawal, Anup, and Sahiba Chadha, 2005. Corporate governance and accounting scandals, *Journal of Law and Economics* 48, 371-406.

Armstrong, Christopher S., Alan D. Jagolinzer, and David F. Larcker, 2009. Chief executive officer equity incentives and accounting irregularities, Working Paper, University of Pennsylvania.

Beasley, Mark S., 1996. An empirical analysis of the relation between the board of director composition and financial statement fraud, *The Accounting Review* 71, 443-465.

Beatty, Randolph P. and Jay R. Ritter, 1986. Investment banking, reputation, and the underpricing of initial public offerings, *Journal of Financial Economics* 15, 213-232.

Benveniste, Lawrence M., Walid Y. Busaba, and William J. Wilhelm, Jr., 2002. Information externalities and the role of underwriters in primary equity markets, *Journal of Financial Intermediation* 11, 61-86.

Burns, Natasha, and Simi Kedia, 2006. The impact of performance-based compensation on misreporting, *Journal of Financial Economics* 79, 35-67.

Carter, Richard B., and Steven Manaster, 1990. Initial public offerings and underwriter reputation, *Journal of Finance* 45, 1045-1068.

Chemmanur, Thomas J., and Paolo Fulghieri, 1994. Investment bank reputation, information production, and financial intermediation, *Journal of Finance* 49, 57-79.

Choi, Stephen J., Karen K. Nelson, and A.C. Pritchard, 2005. The screening effect of the Securities Litigation Reform Act, Working Paper, New York University.

Choi, Stephen J., 2007. Do the merits matter less after the Private Securities Litigation Reform Act? *Journal of Law, Economics, and Organization* 23, Issue 3, 598-626.

Cornelli, Francesca, David Goldreich, and Alexander Ljungqvist, 2006. Investor sentiment and pre-IPO markets, *Journal of Finance* 61, 1187-1216.

Dechow, Patricia M., Richard G. Sloan, and Amy Sweeney, 1996. Causes and consequences of earnings manipulation, *Contemporary Accounting Research* 13, 1-36.

Dyck, Alexander, Adair Morse, and Luigi Zingales, 2009. Who blows the whistle on corporate fraud?, *Journal of Finance* forthcoming.

Efendi, Jap, Anup Srivastava, and Edward P. Swanson, 2007. Why do corporate managers misstate financial statements? The role of option compensation and other factors, *Journal of Financial Economics* 85, 667-708.

Fang, Lily H., 2005. Investment bank reputation and the price and quality of underwriting services, *Journal of Finance* 60, 2729-2761.

Faulkender, Michael and Jun Yang, 2009. Inside the black box: The role and composition of compensation peer groups, *Journal of Financial Economics* forthcoming.

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

Francis, Jere R., 2004. What do we know about audit quality? *British Accounting Review* 34, 345-368.

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

Graham, John R., Cam Harvey and Shiva Rajgopal, 2005, The economic implications of corporate financial reporting, *Journal of Accounting and Economics* 40, 3-73.

Greene, William H. 1997, Econometric Analysis, 3rd Edition, Prentice-Hall International, Inc.

Grundfest, Joseph A., 1995. Why disimply? *Harvard Law Review* 108, 740-741.

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

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

Johnson, Shane A., Harley E. Ryan, and Yisong S. Tian, 2009. Managerial incentives and corporate fraud: the sources of incentives matter, *Review of Finance* 13, 115 - 145.

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

Khanna, Naveen, Thomas H. Noe, and Ramana Sonti, 2008. Good IPOs draw in bad: Inelastic banking capacity in the primary issue market, *Review of Financial Studies* 21, 1873-1906.

Kumar, Praveen, and Nisan Langberg, 2008. Innovation, self-fulfilling optimism, and aggregate investment, Working Paper, University of Houston.

Li, Si, 2008. Corporate fraud: An application of detection controlled estimation, Working Paper, Wilfrid Laurier University.

Ljungqvist, Alexander P., and William J. Wilhelm, 2003. IPO pricing and the dot-com bubble, *Journal of Finance* 58, 723–752.

Lowry, Michelle, 2003. Why does IPO volume fluctuate so much? *Journal of Financial Economics* 67, 3-40.

Lowry, Michelle, and G. William Schwert, 2002. IPO market cycles: Bubbles or sequential learning? *Journal of Finance* 57, 1171-1198.

Loughran, Tim, and Jay R. Ritter, 2002. Why don't issuers get upset about leaving money on the table in IPOs? *Review of Financial Studies* 15, 413–443.

Loughran, Tim, and Jay R. Ritter, 2004. Why has IPO underpricing changed over time? *Financial Management* 33, 5-37.

Malmendier, Ulrike, and Devin Shanthikumar, 2007. Do security analysts speak in two tongues? NBER Working Paper No. W13124.

Mikhail, Michael, Beverly Walther, and Richard Willis, 2007. When security analysts talk, who listens? *Accounting Review*, forthcoming.

Murphy, Kevin J., 1999. Executive compensation, in Orley Ashenfelter and David Card (eds.), *Handbook of Labor Economics*, Vol. 3b, Elsevier Science North Holland, Chapter 38: 2485-2563.

Murphy, Kevin J. and Tatiana Sandino, 2008. Executive pay and "independent" compensation consultants, Working Paper, University of Southern California.

Pastor, Lubos, and Pietro Veronesi, 2005. Rational IPO waves, *Journal of Finance* 60, 1713-1757.

Peng, Lin, and Ailsa Röell, 2008. Executive pay and shareholder litigation, *Review of Finance* 12, 141-184.

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

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

Sherman, Ann E., 1999. Underwriter certification and the effect of shelf registration on due diligence, *Financial Management* 28, 5-19.

Wang, Tracy Y., 2009. Real investment and corporate securities fraud, Working Paper, University of Minnesota.

APPENDIX I: Variable Definitions

Panel A. Variables of Interest: Measuring Investor Beliefs

For the fraud sample, all investor belief variables are measured as of the beginning year of fraud. For the non-fraud sample, these variables are measured as of the IPO year.

Belief Based on	Main Proxy	Definition	Data Source	Robustness Alternatives
Analyst forecasts	Ind. EPS Growth	Industry median forecasted EPS growth. EPS growth is the forecasted annual EPS divided by the prior year realized EPS and then minus one. Industries are defined based on the Fama-French 49 industry classification.	IBES database	Industry median forecasted long-term growth
Institutional investors' demand for IPO shares	$(\text{Ind. Book-Building})^{-1}$	100 divided by the median length of IPO book-building period in a given industry, where the length of an IPO's book-building period is the number of days between the filing day (when a company files a preliminary prospectus with the SEC) and the pricing day (when the final offer price is set).	SDC Platinum database	Industry overallotment options (the ratio of the industry total number of shares under the over-allotment options for issuing firms to the industry total number of shares offered by issuing firms, multiplied by 100)
Secondary market prices	Ind. Q	The median of Tobin's Q in a given industry, where a firm's Tobin's Q is calculated as (book value of assets + market value of equity – book value of equity) divided by book value of assets. Firms with negative book value of equity are excluded.	COMPUSTAT	Industry median equity market to book ratio

Panel B: Other Variables

Variables	Definition	Data Source	Measured as of Year
Assets	Book value of total assets.	COMPUSTAT	For the fraud sample, this variable is measured as of the year before the beginning year of fraud. For the non-fraud sample, this is measured as of the year before the IPO year.
After SOX	A dummy variable equal to one if the year is in or after 2002, and zero otherwise.		
Ind. Litigation	Log of total market value of all litigated firms in an industry in a year.	Our Litigation Sample	For the fraud sample, this variable is measured as of the year of detection. For the non-fraud sample, this variable is measured at the average of the information in the IPO year and in the two years after IPO.
Stock Return	Annual buy-and-hold stock return.	COMPUSTAT	
Return Volatility	Standard deviation of daily stock returns.	CRSP	
Stock Turnover	Number of shares traded in a year divided by the number of shares outstanding.	CRSP	
Ind. ST Incentive	Industry median short-term incentive. Short-term incentive = (salary + bonus + other annual compensation)/(Total expected compensation). "Total expected compensation" is the sum of the following items from ExecuComp database: salary, bonus, other annual (OTHANN), value of restricted stock granted (RSTKGRNT), value of stock option grants (OPTION_AWARDS_BLK_VALUE), long-term incentive payouts (LTIP), and all other total (ALLOTHTOT).	ExecuComp	For the fraud sample, this variable is measured as of the beginning year of fraud. For the non-fraud sample, it is measured as of the IPO year.
Ind. LT Incentive	Industry median long-term incentive. Long-term incentive = (RSTKGRNT + OPTION_AWARDS_BLK_VALUE)/(Total expected compensation).	ExecuComp	

VC Specialty Score	The industry specialty score of venture capital firms. For each year, a VC's industry specialty score in a given industry is the fraction of total proceeds of IPOs that the VC has invested since 1990 that are in that industry. If more than one venture capitalist participates in funding an IPO firm, we take the average of each VC's industry specialty score. If a firm is not backed by VCs, then its VC Specialty Score is zero.	SDC	
VC Backed	Dummy variable that equals one if an IPO firm is backed by venture capitals, and zero otherwise.	SDC	
IB Specialty Score	The industry specialty score of lead underwriter(s). For each year, an investment bank's industry specialty score in a given industry is defined as the fraction of total IPO proceeds that the investment bank has underwritten since 1990 that are in that industry. If more than one investment banks underwrite an IPO, we take the average of each bank's industry specialty score.	SDC	
IB Hiring	The fraction of MBA graduates in a year from Columbia Business School that gets offer from the investment banking industry divided by the total number of IPOs, SEOs and corporate debt issued in that year.	MBA placement office of the Columbia Business School	
IB Employment	The number of investment banking professionals divided by the total number of IPOs, SEOs and corporate debt issued in that year.	Bureau of Labor Statistics, U.S. Department of Labor	
IB Ranking	Underwriter ranking is based on Loughran-Ritter (2004)'s updates of Carter-Manaster (1990) tomestone measures.	Jay Ritter's website	

Table I: Summary Statistics of Corporate Securities Frauds

Panel A: Time Trend of IPOs and Securities Frauds

"IPO Fraud" means that the beginning year of fraud is either before or in the year of IPO. "Post-IPO Fraud" means that the beginning year of fraud is after the year of IPO. "# of IPO Frauds" is the number of IPO firms in a given year that committed fraud at the IPO stage. "# of Post-IPO Frauds" is the number of firms that went public in a given year and committed fraud after the IPO year. The percentages in the last column are total number of frauds as the fractions of the IPO volume in that year.

Year	# of IPOs	# of IPO Frauds	# of Post-IPO Frauds	% of Total
1995	435	9	38	12.30%
1996	668	17	80	25.39%
1997	476	18	28	12.04%
1998	319	9	25	8.90%
1999	478	17	46	16.49%
2000	333	9	34	11.26%
2001	78	4	4	2.09%
2002	73	3	3	1.57%
2003	74	7	6	3.40%
2004	190	10	7	4.45%
2005	173	7	1	2.09%
Total	3,297	110	272	11.59%

Panel B: Timing of Frauds

"Beginning Year" of fraud is the first fiscal year in which the financial statements were misreported. "Ending Year" of fraud is the last fiscal year in which the financial statements were misreported. The information is retrieved from the litigation documents.

	Ending Year												
Beginning Year	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Total
1995	7	5	0	0	0	0	0	0	0	0	0	0	12
1996	4	14	9	0	0	0	0	0	0	0	0	0	27
1997	0	6	26	8	2	0	1	1	0	2	0	0	46
1998	0	0	4	10	9	1	4	1	1	1	0	0	31
1999	0	0	0	6	22	8	8	4	1	0	1	0	50
2000	0	0	0	0	11	22	9	1	6	5	0	0	54
2001	0	0	0	0	0	3	14	5	2	0	0	0	24
2002	0	0	0	0	0	0	1	7	11	2	1	0	22
2003	0	0	0	0	0	0	0	1	38	11	1	0	51
2004	0	0	0	0	0	0	0	0	10	21	5	0	36
2005	0	0	0	0	0	0	0	0	0	10	5	2	17
2006	0	0	0	0	0	0	0	0	0	0	1	11	12
Total	11	25	39	24	44	34	37	20	69	52	14	13	382

Panel C: Top 5 Most Frequently Sued Industries

This table lists the five most frequently sued industries for accounting-related securities fraud in our sample. The industries are defined according to the Fama-French 49 industry classification: Computer Software (36), Business Services (34), Electronic Equipment (37), Pharmaceutical (13), and Communication (32).

Fraud Beginning Year	Computer Software	Business Services	Electronic Equipment	Pharmaceutical	Communication	Total
1995	3	0	1	0	1	5
1996	5	7	1	0	0	13
1997	11	5	4	0	1	21
1998	8	3	2	1	0	14
1999	16	5	4	2	8	35
2000	20	6	9	0	3	38
2001	7	6	3	1	1	18
2002	7	3	4	2	0	16
2003	10	3	7	7	2	29
2004	7	1	3	7	3	21
2005	1	1	1	1	1	5
2006	0	1	1	1	1	4
Total	95	41	40	22	21	219

Table II: Univariate Comparisons

This table reports the median and mean (in parentheses) of variables for the IPO fraud sample and the non-IPO-fraud sample. It also reports the *z* statistics for the Wilcoxon tests that compare characteristics of the two samples. **, * and + indicate significance at 1%, 5% and 10% levels, respectively.

	IPO Frauds		Non IPO Frauds		
Variables	**# of Obs.**	**Median (Mean)**	**# of Obs.**	**Median (Mean)**	**Wilcoxon Z**
Ind. EPS Growth	110	0.194 (0.193)	3,005	0.153 (0.176)	2.652**
(Ind. Book-Building)$^{-1}$	110	1.408 (1.445)	3,005	1.399 (1.402)	1.179
Ind. Q	110	2.074 (2.357)	3,005	2.041 (2.264)	0.689
Assets (Millions)	110	103.9 (5,436)	2,766	89.06 (711.4)	1.263
Ind. Litigation	110	66.20 (132.13)	3,005	49.72 (108.8)	2.418*
Stock Return	110	-0.234 (-0.151)	3,005	0.046 (0.006)	-5.604**
Return Volatility	110	0.049 (0.055)	3,005	0.046 (0.051)	1.769^{+}
Stock Turnover	110	1.464 (1.817)	3,005	1.194 (3.014)	2.962**
Ind. ST Incentive	110	0.610 (0.607)	3,005	0.621 (0.615)	-0.981
Ind. LT Incentive	110	0.332 (0.325)	3,005	0.315 (0.321)	1.326
VC Backed	110	1.000 (0.528)	3,005	0.000 (0.452)	1.548
VC Specialty Score	107	0.029 (0.206)	2,930	0.000 (0.198)	0.974
IB Specialty Score	110	0.083 (0.137)	3,005	0.111 (0.196)	-3.384**
IB Hiring	110	0.554 (0.933)	3,005	0.554 (0.788)	1.414
IB Employment	110	3.454 (6.483)	3,005	3.454 (5.430)	1.279
IB Ranking	110	8.501 (7.989)	3,000	8.100 (7.512)	1.993*

Table III: Investor Beliefs and Firms' Propensity to Commit Fraud at IPO—Quadratic Specification

The dependent variable is a dummy variable Z=1 if a firm committed fraud at IPO stage and then got caught later, and Z=0 otherwise. Estimation of fraud propensity is indicated by P(F=1), and the estimation of fraud detection likelihood is indicated by P(D=1|F=1). Coefficient estimates and the Huber-White-Sandwich robust standard errors clustered by industry (in square brackets) are reported. **, * and + indicate significance at 1%, 5% and 10% levels respectively.

P(F=1)	(1)	(2)	(3)
Ind. EPS Growth	3.752**		
	[1.096]		
(Ind. EPS Growth)^2	-5.563**		
	[1.753]		
(Ind. Book-Building)$^{-1}$		0.882**	
		[0.220]	
((Ind. Book-Building)$^{-1}$)^2		-0.161**	
		[0.040]	
Ind. Q			0.722**
			[0.188]
(Ind. Q)^2			-0.128**
			[0.036]
Log(Assets)	0.133**	0.087**	0.109**
	[0.051]	[0.028]	[0.030]
After SOX	1.397	0.254	0.154
	[0.816]	[0.135]	[0.119]
Constant	-4.113**	-3.891**	-4.213**
	[1.020]	[0.559]	[0.608]
P(D=1|F=1)			
Ind. Litigation	0.002**	0.001**	0.001**
	[0.001]	[0.0003]	[0.0004]
Stock Return	-0.861*	-0.739**	-0.708**
	[0.352]	[0.199]	[0.178]
Return Volatility	16.257	3.575**	4.092**
	[13.717]	[1.205]	[0.979]
Stock Turnover	0.070	0.252**	0.208**
	[0.064]	[0.070]	[0.048]
Log(Assets)	0.109	0.134**	0.129**
	[0.063]	[0.034]	[0.033]
After SOX	-0.470	0.269*	0.277*
	[0.517]	[0.118]	[0.124]
Constant	-3.694*	-4.902**	-4.804**
	[1.711]	[0.742]	[0.714]
Observations	2,876	2,876	2,876
Pseudo-likelihood	-433	-430	-431

Table IV: Investor Beliefs and Firms' Propensity to Commit Fraud at IPO—Piecewise Linear Specification

The dependent variable is a dummy variable Z=1 if a firm committed fraud at IPO stage and then got caught later, and Z=0 otherwise. Estimation of fraud propensity is indicated by P(F=1), and the estimation of fraud detection likelihood is indicated by P(D=1|F=1). The spline regression is based on the quintile cutoff points of *Ind. EPS Growth* in Model (1), (*Ind. Book-Building*)$^{-1}$ in Model (2), and *Ind. Q* in Model (3). Coefficient estimates and the Huber-White-Sandwich robust standard errors clustered by industry (in square brackets) are reported. **, * and + indicate significance at 1%, 5% and 10% levels respectively.

P(F=1)	(1)	(2)	(3)
Spline 1 (lowest belief)	3.048*	0.519**	1.765**
	[1.428]	[0.112]	[0.444]
Spline 2	7.602	0.753*	0.198*
	[6.739]	[0.359]	[0.094]
Spline 3	21.380*	1.180	0.030
	[8.647]	[1.251]	[0.044]
Spline 4	-2.022	2.961**	0.240**
	[2.133]	[1.148]	[0.056]
Spline 5 (highest belief)	-1.418+	-0.212**	-0.150**
	[0.808]	[0.049]	[0.052]
Log(Assets)	0.128**	0.102**	0.110**
	[0.046]	[0.028]	[0.031]
After SOX	1.085	0.371**	0.227
	[0.821]	[0.142]	[0.124]
Constant	-3.883**	-4.081**	-5.693**
	[0.904]	[0.543]	[0.899]
P(D=1|F=1)			
Ind. Litigation	0.002**	0.001**	0.002**
	[0.001]	[0.000]	[0.000]
Stock Return	-0.848*	-0.744**	-0.747**
	[0.352]	[0.203]	[0.187]
Return Volatility	16.158	5.950**	2.820**
	[11.428]	[1.667]	[0.661]
Stock Turnover	0.086	0.202**	0.215**
	[0.084]	[0.042]	[0.051]
Log(Assets)	0.078	0.136**	0.127**
	[0.073]	[0.035]	[0.033]
After SOX	-0.673	0.286*	0.246*
	[0.475]	[0.129]	[0.122]
Constant	-2.480	-4.956**	-4.722**
	[1.978]	[0.762]	[0.697]
Observations	2,876	2,876	2,876
Pseudo-likelihood	-428	-430	-430

Table V: Investor Belief, Incentive of Venture Capitalist and IPO Fraud

The dependent variable is a dummy variable Z=1 if a firm committed fraud at IPO stage and then got caught later, and Z=0 otherwise. Estimation of fraud propensity is indicated by P(F=1), and the estimation of fraud detection likelihood is indicated by P(D=1|F=1). In Models (2) and (4) we interact *VC Specialty Score* and *VC Backed* dummy variable with *Q#_EPS*, the indicator variable for each quintile of *Ind. EPS Growth*. Coefficient estimates and the Huber-White-Sandwich robust standard errors clustered by industry (in square brackets) are reported. **, * and + indicate significance at 1%, 5% and 10% levels respectively.

	VC=VC Specialty Score		VC=VC Backed	
P(F=1)	(1)	(2)	(3)	(4)
VC	-0.290		0.018	
	[0.244]		[0.144]	
Q1_EPS × VC		-0.096		0.197
		[0.283]		[0.191]
Q2_EPS × VC		-3.186**		-0.561**
		[0.866]		[0.117]
Q3_EPS × VC		-0.191		-0.015
		[0.353]		[0.135]
Q4_EPS × VC		0.500**		0.299
		[0.155]		[0.185]
Q5_EPS × VC		7.850**		3.486**
		[1.709]		[1.267]
Ind. EPS Growth	3.439**	3.904**	3.783**	6.190**
	[1.136]	[0.957]	[1.142]	[1.484]
$(\text{Ind. EPS Growth})^2$	-4.966**	-11.553**	-5.624**	-17.979**
	[1.820]	[3.072]	[1.811]	[4.816]
Log(Assets)	0.124*	0.112**	0.133**	0.124**
	[0.051]	[0.036]	[0.051]	[0.032]
After SOX	1.174	1.725**	1.403	0.654**
	[0.782]	[0.611]	[0.823]	[0.128]
Constant	-3.834**	-3.798**	-4.135**	-4.121**
	[1.015]	[0.607]	[0.991]	[0.577]
P(D=1|F=1)				
Ind. Litigation	0.002*	0.001**	0.002**	0.001**
	[0.001]	[0.0004]	[0.001]	[0.0004]
Stock Return	-0.844*	-0.660**	-0.860*	-0.687**
	[0.361]	[0.187]	[0.350]	[0.214]
Return Volatility	18.005	11.696**	16.181	7.875*
	[15.068]	[2.127]	[13.884]	[3.232]
Stock Turnover	0.084	0.049	0.069	0.056
	[0.085]	[0.033]	[0.064]	[0.032]
Log(Assets)	0.095	0.131**	0.110	0.131**
	[0.076]	[0.034]	[0.063]	[0.032]
After SOX	-0.484	0.295*	-0.468	0.290**
	[0.524]	[0.117]	[0.520]	[0.100]
Constant	-3.299	-4.837**	-3.715*	-4.724**
	[2.129]	[0.704]	[1.717]	[0.666]
Observations	2,801	2,801	2,876	2,876
Log pseudo-likelihood	-421	-413	-433	-430

Table VI: Investor Belief, Incentive of Underwriters and IPO Fraud

The dependent variable is a dummy variable Z=1 if a firm committed fraud at IPO stage and then got caught later, and Z=0 otherwise. Estimation of fraud propensity is indicated by P(F=1), and the estimation of fraud detection likelihood is indicated by P(D=1|F=1). In Model (4) we interact *IB Specialty Score* with *Q#_EPS*, the indicator variable for each quintile of *Ind. EPS Growth*. Coefficient estimates and the Huber-White-Sandwich robust standard errors clustered by industry (in square brackets) are reported. **, * and + indicate significance at 1%, 5% and 10% levels respectively.

P(F=1)	(1)	(2)	(3)	(4)
IB Specialty Score	-1.147**	-0.687*	-0.390*	
	[0.342]	[0.298]	[0.152]	
IB Hiring		-2.585*		
		[1.074]		
IB Employment			-0.594**	
			[0.227]	
Q1_EPS × IB Specialty				-4.061**
				[1.018]
Q2_EPS × IB Specialty				-1.977
				[1.372]
Q3_EPS × IB Specialty				-0.915**
				[0.286]
Q4_EPS × IB Specialty				-0.054
				[0.432]
Q5_EPS × IB Specialty				-0.014
				[0.261]
IB Ranking	-0.003	0.049	0.051	-0.014
	[0.046]	[0.027]	[0.044]	[0.030]
Ind. EPS Growth	4.051**	2.082**	2.075**	0.386
	[1.377]	[0.625]	[0.768]	[0.919]
$(\text{Ind. EPS Growth})^2$	-6.052**	-3.185**	-3.082*	-1.389
	[2.104]	[1.169]	[1.240]	[1.320]
Log(Assets)	0.113*	0.127*	0.139**	0.116*
	[0.049]	[0.058]	[0.050]	[0.049]
After SOX	1.508*	0.752**	1.126**	0.959
	[0.698]	[0.233]	[0.341]	[0.760]
Constant	-3.564**	-3.681**	-3.933**	-3.071**
	[0.958]	[0.823]	[0.727]	[0.907]
P(D=1|F=1)				
Ind. Litigation	0.002**	0.002**	0.002**	0.002**
	[0.001]	[0.001]	[0.001]	[0.001]
Stock Return	-0.855**	-0.704*	-0.621**	-0.843*
	[0.330]	[0.285]	[0.233]	[0.343]
Return Volatility	14.438	18.689**	19.597**	12.273
	[11.137]	[4.193]	[5.389]	[11.432]
Stock Turnover	0.064	0.080	0.046	0.080
	[0.058]	[0.051]	[0.046]	[0.091]
Log(Assets)	0.118*	0.150**	0.147**	0.058
	[0.060]	[0.041]	[0.038]	[0.062]
After SOX	-0.418	0.390**	0.405**	-0.718
	[0.601]	[0.102]	[0.122]	[0.531]
Constant	-3.907*	-5.560**	-5.508**	-1.578
	[1.675]	[0.894]	[0.886]	[1.570]
Observations	2,872	2,872	2,872	2,872
Log pseudo-likelihood	-437	-435	-401	-401

Table VII: Investor Beliefs, CEO Compensation, and IPO Fraud

"Total expected compensation" is the sum of the following items from ExecuComp database: Salary, Bonus, Other Annual (OTHANN), Value of Restricted Stock Granted (RSTKGRNT), Value of Stock Options (OPTION_AWARDS_BLK_VALUE), Long-Term Incentive Payouts (LTIP), and All Other Total (ALLOTHTOT). "*ST Incentive*" = (Salary + Bonus + OTHANN)/(Total expected compensation). "*LT Incentive*" = (RSTKGRNT + OPTION_AWARDS_BLK_VALUE)/(Total expected compensation). For each firm each year we compute the average "*ST Incentive*" and "*LT Incentive*" for all executives. For each industry each year, we compute "*Ind. ST Incentive*" and "*Ind. LT Incentive*" as the median levels of firms' *ST Incentive* and *LT Incentive* within that industry.

Panel A

This table reports panel regression results of executive compensation on contemporaneous investor beliefs about business conditions (the industry median EPS growth forecast). The analysis is based on the entire sample of ExecuComp database over the period of 1993-2005. The dependent variables are firm-level annual short- and long-term incentives, respectively. "*Time Trend*" ranges from 1 to 13, where *Time Trend* = 1 for year 1993 and 13 for year 2005. All firm characteristics are lagged. The Huber-White-Sandwich robust standard errors clustered by firm are reported.

	(1) ST Incentive	(2) LT Incentive
Ind. EPS Growth	0.028**	-0.036**
	[0.010]	[0.011]
Sales Growth	-0.033**	0.028*
	[0.011]	[0.011]
ROA	-0.143**	0.124**
	[0.032]	[0.040]
Stock Return	-0.0002	-0.003
	[0.004]	[0.005]
Tobin's Q	-0.019**	0.024**
	[0.004]	[0.004]
Log(Assets)	-0.031**	0.044**
	[0.007]	[0.007]
Time Trend	-0.010**	0.011**
	[0.001]	[0.001]
Constant	1.318**	-0.664**
	[0.140]	[0.142]
Firm fixed effect	Yes	Yes
Observations	18,565	18,565
Number of Firms	2,683	2,683
R-squared	0.075	0.055

Table VII continued.

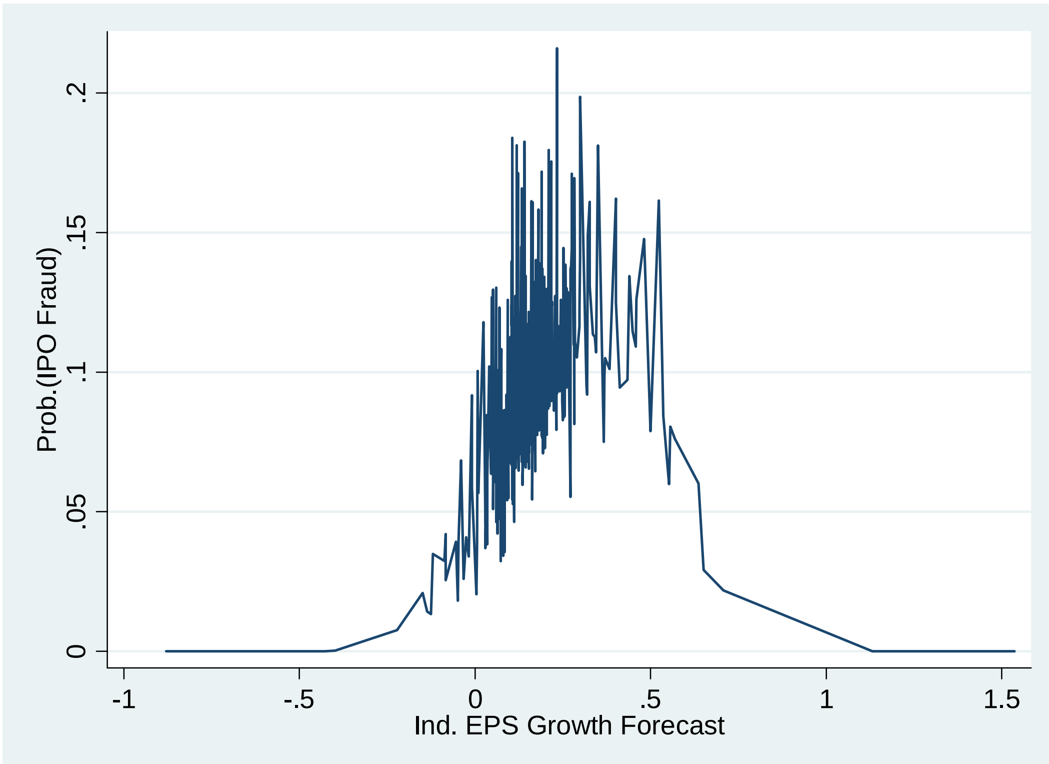
Panel B

This table reports bivariate probit regression results based on our sample firms that went public from 1995 to 2005. The dependent variable is a dummy variable Z=1 if a firm committed fraud at IPO stage and then got caught later, and Z=0 otherwise. Estimation of fraud propensity is indicated by P(F=1), and the estimation of fraud detection likelihood is indicated by P(D=1|F=1). "*Ind. Predicted ST Incentive*" is the industry median of the predicted value of *ST Incentive* when we regress firm-level *ST Incentive* on *Ind. EPS Growth*. "*Ind. Predicted LT Incentive*" is the industry median of the predicted value of *LT Incentive* when we regress firm-level *LT Incentive* on *Ind. EPS Growth*. Coefficient estimates and the Huber-White-Sandwich robust standard errors clustered by industry (in square brackets) are reported. **, * and + indicate significance at 1%, 5% and 10% levels respectively.

P(F=1)	(1)	(2)	(3)	(4)	(5)	(6)
Ind. Predicted ST Incentive	2.546					
	[2.393]					
Ind. Predicted LT Incentive		-1.444				
		[1.393]				
Ind. ST Incentive			2.353**		1.368**	
			[0.809]		[0.366]	
Ind. LT Incentive				-2.449**		-1.373**
				[0.645]		[0.340]
Ind. EPS Growth					1.913**	2.324**
					[0.457]	[0.521]
$(\text{Ind. EPS Growth})^2$					-2.771**	-3.290**
					[0.665]	[0.722]
Log(Assets)	0.116^{+}	0.116^{+}	0.077*	0.073**	0.090**	0.090**
	[0.063]	[0.063]	[0.031]	[0.026]	[0.035]	[0.031]
After SOX	1.107	1.108	0.382*	0.265*	0.353**	0.342**
	[0.802]	[0.803]	[0.169]	[0.120]	[0.119]	[0.117]
Constant	-17.132	2.185	-4.186**	-1.862**	-4.087**	-2.829**
	[13.703]	[4.722]	[0.848]	[0.465]	[0.743]	[0.498]
P(D=1|F=1)						
Ind. Litigation	0.003**	0.003**	0.002**	0.002**	0.002**	0.002**
	[0.001]	[0.001]	[0.000]	[0.000]	[0.0004]	[0.0004]
Stock Return	-0.897*	-0.896*	-0.749**	-0.748**	-0.694**	-0.705**
	[0.454]	[0.453]	[0.206]	[0.200]	[0.180]	[0.176]
Return Volatility	20.784	20.733	6.236**	7.405**	5.195**	5.843**
	[36.190]	[35.907]	[1.568]	[1.888]	[1.343]	[1.523]
Stock Turnover	0.066	0.066	0.136**	0.156**	0.142**	0.148**
	[0.126]	[0.125]	[0.043]	[0.039]	[0.037]	[0.042]
Log(Assets)	0.102	0.102	0.145**	0.146**	0.113**	0.116**
	[0.111]	[0.110]	[0.036]	[0.037]	[0.039]	[0.035]
After SOX	-0.550	-0.552	0.263*	0.291*	0.262*	0.269*
	[1.060]	[1.052]	[0.116]	[0.121]	[0.110]	[0.112]
Constant	-3.408	-3.411	-5.090**	-5.182**	-4.437**	-4.523**
	[4.180]	[4.138]	[0.790]	[0.821]	[0.815]	[0.754]
Observations	2,866	2,866	2,866	2,866	2,866	2,866
Log pseudo-likelihood	-437	-437	-430	-430	-433	-433

Figure 1: Predicted Probability of Fraud and Industry EPS Growth

In the following figure, the variable on the *y*-axis is the predicted probability of a firm committing fraud at IPO stage based on Model 1 in Table 3. The variable on the *x*-axis is the industry median EPS growth forecast (*Ind. EPS Growth*).



INTERNET APPENDIX FOR

CORPORATE FRAUD AND BUSINESS CONDITIONS: EVIDENCE FROM IPOS

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* Wang, Tracy, Y., Andrew Winton, and Xiaoyun Yu, 2009, Internet Appendix to "Corporate Fraud and Business Conditions: Evidence from IPOs," Journal of Finance [vol #], [pages], http://www.afajof.org/IA/[year].asp. Wang and Winton are at the Carlson School of Management, University of Minnesota. Yu is at the Kelley School of Business, Indiana University and the Shanghai Advanced Institute of Finance, Shanghai Jiaotong University.

This internet appendix contains a detailed description of various robustness tests and extensions of the paper.

VI. ROBUSTNESS

VI.A Alternative Sample Specifications

VI.A.1 Internet IPO Firms As a Separate Industry

Our IPO sample period of 1995-2005 overlaps with the dot com bubble period and contains a significant number of internet IPO firms. If those internet firms differ in nature from the rest of the sample firms, the Fama-French 49-industry specification may not fully capture this distinction. As a robustness check, we identify 483 internet companies using the reference list from Loughran and Ritter (2004) and exclude them from the IPO sample. We then re-estimate our models in Tables III and IV. Our results remain unchanged.

In a separate robustness test, we re-group these internet firms into a 50th industry—the internet industry. Thus, the remaining 49 industries do not contain any internet IPO firms. We then re-calculate the book-building measure of investor beliefs for each of the 50 industries and re-estimate Model 2 in Table III.[1] Our results hold. The coefficient of (*Ind. Book-Building*)$^{-1}$ is 2.325 (p = 0.01), and that of the squared term is -0.522 (p = 0.03). These robustness analyses suggest that industry classification about internet firms does not affect our results.

VI.A.2 False Detection

Many papers have used lawsuits to proxy for the presence of corporate financial fraud (e.g., Beasley 1996, Beasley, Carcello, and Hermanson 1999, and Li 2008 use AAERs; Helland 2004, Srinivasan 2005, Fich and Shivdasani 2007, and Peng and Röell 2008 use class-action lawsuits). A disadvantage of using lawsuits as the proxy for detected frauds is that the lawsuits may be frivolous, especially for private class action suits. In our main analyses, we address the issue of false detection by imposing a series of filters on our fraud sample and by controlling for factors that are related to frivolous lawsuits in the regressions.

To further check the robustness of our results with respect to frivolous lawsuits, we re-estimate our results by excluding all firms that were subject to class action lawsuits but not

[1] We do not do this exercise for the other two investor beliefs measures. Since we classify internet firms into one separate industry, and all the sample internet firms went public during our sample period, the measures of *Ind. EPS Growth* and *Ind. Q*, which exclude IPO firms in a given industry, are no longer valid for the internet industry.

AAERs. The AAER-only sub-sample thus contains 30 IPO frauds and 3,005 non-fraudulent IPOs. We observe the same concave relationship between investor beliefs and the propensity of fraud. The coefficient associated with *Ind. EPS Growth* in Model 1 of Table III is 3.775 (p = 0.06), and coefficient for the squared term is -10.804 (p = 0.02).

Finally, frivolous lawsuits, by definition, are lawsuits associated with low probabilities of fraud being actually committed. As another robustness test of our results, we first use Model 1 in Table III to predict the fraud propensity at the IPO stage for each sample firm. We then exclude firms in our IPO fraud sample (i.e., Z=1) that have low predicted fraud propensities (i.e., in the bottom 10% of the distribution), as they are most likely to be wrongly sued according to our model. Next, we re-run the base models in Table III. Our results are robust to this sample restriction. For example, for Model 1 in Table III, the coefficient on *Ind. EPS Growth* is 3.695 (p = 0.00), and the coefficient on $(\textit{Ind. EPS Growth})^2$ is -5.10 (p = 0.00). Our results also remain unchanged when we use the alternative cutoff of the bottom 25%.

VI.A.3 Accounting-Related vs. Non-Accounting-Related Frauds

The theories we focus on argue that firms may misreport information in order to raise external capital or increase executive compensation. Accordingly, we focus on accounting-related frauds at the time of IPO in our empirical analysis. There were 248 issuers that were sued for non-accounting-related frauds during our sample period and have been classified as non-fraudulent firms. To check the robustness of our results, we re-estimate our models by excluding those 248 firms from the sample. Our results remain unchanged. For example, the coefficient of *Ind. EPS Growth* is 3.381 (p = 0.01), and that of $(\textit{Ind. EPS Growth})^2$ is -4.657 (p = 0.03) for Model 1 of Table III.

VI.A.4 Sub-sample Analysis

The Sarbanes-Oxley Act (SOX) and the related mandates represent a major change in the litigation decisions and in the regulatory landscape during our sample period that affects all the firms in the economy. In our main analyses we control the effect of SOX and the related mandates on both the incentive to commit fraud ex ante and the probability of detecting fraud ex post. However, there is an emerging debate among researchers and mixed empirical evidence with respect to the economic impact of SOX and related mandates.

In an alternative setting, we restrict our IPO sample to 1995-2002 and fraud sample to 1996-2005 only. Among the 2,860 completed IPO issues between January 1995 and December 2002, 251 have been sued for accounting-related securities fraud between 1996 and 2005, 78 of which are IPO frauds, and 173 of which are post-IPO frauds. We then re-estimate our main regressions, with the *After SOX* dummy being removed from both the fraud equation and the detection equation of our bivariate probit analysis.

Our findings are similar. For example, for Table III Model 1, the coefficient associated with *Ind. EPS Growth* is 5.284 and is significant at 1% level, and the coefficient for (*Ind. EPS Growth*)^2 is -9.410 and is significant at 5% level. For Table V Model 2, the coefficient for Q1_EPS × VC, the interaction term between the lowest quintile of investor belief and *VC Specialty Score*, is -1.384 (significant at 5% level), but for Q5_EPS × VC, the interaction term between the highest quintile of investor belief and VC specialty score, becomes 0.721 (significant at 1% level). Lastly, for Table VI Model 1, the coefficient associated with *IB Specialty Score* is -1.335 and is significant at 1% level.

VI.B Fundamental Industry Differences and Time Effects

It is possible that average EPS growth rates vary across different industries due to fundamental differences such as financial leverage, or that there are economy-wide effects that affect all industries in certain years. Either is consistent with the theories we examine, since both Povel et al. (2007) and Hertzberg (2005) model business conditions rather than business cycles per se. Therefore, their implications can be applied to cross-industry analysis as well as time-series comparisons within industries.

To see whether our results are solely driven by cross-sectional differences among industries, we construct a measure of industry "abnormal" EPS growth rate by computing the deviation of *Ind. EPS Growth* from the sample period mean for each industry. This approach takes out the cross-sectional differences in *Ind. EPS Growth*. We re-estimate our bivariate probit model and report the results in Model 1 of Table A1 attached with this internet appendix. We observe a similar result as before: fraud propensity is positively related to abnormal investor beliefs about industry conditions, and negatively related to the squared terms. This suggests that our previous findings are not only driven by the cross-sectional difference industry growth rates.

To see whether our results are solely driven by an economy-wide effect, we construct another measure of industry "abnormal" EPS growth rate by computing the deviation of *Ind. EPS Growth* from the yearly cross-sectional mean for all industries. This approach takes out the time-varying differences in *Ind. EPS Growth*. As a variation to the above specification, we retain the original *Ind. EPS Growth* specification but include year fixed effects. As Models 2 and 3 of Table A1 indicate, our main results hold under these alternative specifications. Therefore, our findings are not just driven by time series effects.

VI.C Monitoring by the SEC

During the IPO process, the SEC also serves as an important gatekeeper. However, unlike venture capitalists (and perhaps underwriters), who are more likely to monitor to look for good investment opportunities as modeled by Povel et al. (2007), the SEC monitors to find fraud. Nevertheless, the SEC's monitoring capacity can be affected by its available resources, and it is possible that this capacity constraint affects the fraud propensity of IPO firms.

As a robustness check, we explicitly take into account the impact of the SEC being constrained with its ability to deter fraud by including the annual SEC budget, normalized by the number of securities issued in a given year in our regression. The number of securities issued includes IPOs, SEOs and corporate debt, all of which are subject to the SEC's supervision.

In addition, we recognize the role of SEC in both preventing fraud from occurring and investigating fraud when it occurs. We include this variable in both the fraud equation and the detection equation of our bivariate probit analysis. We then re-run our regression for all three proxies for investor beliefs.[2] The results are reported in Table A2 of this internet appendix.

Table A2 reveals that, after controlling for the SEC's resources, the hump-shaped relationship between fraud propensity and investor beliefs holds. The impact of SEC monitoring on fraud propensity is not significant.

VI.D Alternative Proxies for Investor Beliefs

To capture the varying level of institutional investors' optimism, we have used three proxies: the industry median analyst forecast of EPS growth, the inverse of the industry median

[2] We find that the SEC's budget is highly correlated with the dummy variable for SOX. To avoid multicollinearity, we drop the After SOX dummy from our bivariate probit analyses when we include the SEC budget variable.

length of the book-building period, and the industry median Tobin's Q. As a robustness check, we re-estimate our basic models in Tables III and IV using several alternative proxies.

We replace the measures of analyst forecasted EPS growth with analyst forecasted long-term growth based on information from IBES. Results using industry median forecasted long-term growth are similar and slightly weaker compared to those using EPS growth. This may reflect the fact that long-term forecasts are likely to be noisier than short-term ones. For the base model in Table III, the coefficient of industry median long-term growth forecast is 6.957 (p = 0.06), and is -18.587 (p = 0.01) for the squared term, $(\textit{Ind. Long-Term Growth})^2$.

Next, we use an alternative proxy for investor beliefs that is based on institutional investors' demand for IPO shares in an industry. Under the over-allotment option, underwriters can issue additional shares at the final offer price in the case of over-subscription driven by a strong demand from their network of investors. We compute "*OAL*" as the ratio of the industry total number of shares under the over-allotment options for issuing firms to the industry total number of shares offered by issuing firms, multiplied by 100. We then replace $(\textit{Ind. Book-Building})^{-1}$ with *OAL* and re-estimate our results. Our findings remain unchanged. For example, in Table III the coefficient for *OAL* is 0.372 (p = 0.00) and for the squared term of *OAL* is -0.017 (p = 0.00).[3]

Lastly, instead of Tobin's Q, we use industry median equity market-to-book ratio as an alternative proxy for investor beliefs. Again, our main results hold. For example, in the base model in Table III, the coefficient estimate for the industry median market-to-book ratio is 0.605 (p = 0.00), and the coefficient estimate for the squared term of this variable is -0.078 (p = 0.01).

In two other separate robustness checks, we find similar results when we use alternative specification of the timing of investor beliefs, or if the cutoff points of investor belief variables are based on quartiles and terciles instead of quintiles as those reported in Table IV.

VI.E Other Robustness Tests

VI.E.1 Additional Control Variables

Since we use class action lawsuits and SEC litigations instead of earnings irregularities as proxies for detected fraud, fraud detection in our study is closely related to triggers of securities

[3] We do not use underpricing as a measure of institutional investor beliefs, because the degree of underpricing is heavily dependent on the beliefs of individual investors in the aftermarket.

litigation. In our detection equation of the bivariate probit model, we include firm-specific and industry-related time-varying factors that are known to affect a firm's litigation risk. Furthermore, the time-varying firm-specific and industry-specific variables in our detection equation should be correlated with accounting measures identified in the accounting literature.

As a robustness check, we include the key accounting variables studied in Beneish (1999) that are shown to affect fraud detection. Namely, we construct the following five accounting variables:

- Days Sales in Receivables Index: $DSRI = \dfrac{(receivables/sales)_t}{(receivables/sales)_{t-1}}$
- Gross Margin Index: $GMI = \dfrac{((sales - COGS)/sales)_{t-1}}{((sales - COGS)/sales)_t}$
- Asset Quality Index: $AQI = \dfrac{(1 - (CurrentAssets - NetPPE)/TotalAssets)_t}{(1 - (CurrentAssets - NetPPE)/TotalAssets)_{t-1}}$
- Sales Growth Index: $SGI = \dfrac{sales_t}{sales_{t-1}}$
- Accruals to Total Assets: $TATA = \dfrac{TotalAccruals_t}{TotalAssets_t}$, where Total Accruals is defined as Current Assets – Cash – Current Liabilities – Current Maturities of Long-Term Debt – Income Taxes – Depreciation and Amortization.

As Table A3 of this internet appendix indicates, our main results are robust to the inclusion of these accounting measures.

In another robustness analysis, we control for market conditions in addition to firm-specific conditions in the detection equation (such as economic downturns, market returns, and cascading effect on monitoring and fraud detection due to the surfaces of major scandals). This does not change our results. As expected, in our detection analysis, firm-specific conditions subsume the effect of market conditions.

As another robustness check, we also control for secondary shares offered as a fraction of the total shares offered in both the fraud propensity equation and the detection equation. The secondary offering variable has a positive and weakly significant coefficient in the propensity equation, and a positive and insignificant coefficient in the detection equation. Our main results remain unchanged.

VI.E.2 Alternative Regression Specification

In our main analyses we estimate a bivariate probit regression in attempt to disentangle the effect of a variable on the propensity to commit fraud as opposed to its effect on the probability of detecting fraud. As we observe only detected fraud, using a logit or probit to estimate fraud propensity is only able to capture the aggregate impact of both these effects.

As a robustness check, we fit a standard probit model instead of a bivariate probit model and report the results in Table A4 of the internet version of this paper. We find a similar hump-shaped relationship. Fraud propensity continues to be positively related to investor beliefs and negatively related to their squared terms. This suggests that our findings are not caused by a specific bivariate specification.

VI.E.3 Alternative Definition of the Presence of Venture Capitalists

In Povel et al. (2007), investors monitor to find and fund good investment opportunities. Therefore, their incentives to monitor firms who seek external capital vary with their beliefs about industry prospects. In our main analysis, we show that the presence of venture capitalists—a key type of investor with relatively low monitoring costs—affects the propensity of fraud.

However, it can be argued that venture capitalists may be involved with the start-up firms long before their IPOs, so that their incentives are no longer those of investors looking for good investments, but instead are those of investors looking to unload existing investments.

As a robustness check, we use our 1995-2002 IPO sub-sample and distinguish between firms who receive funding from venture capitalists up until their public offerings, and firms who receive funding only at their early start-up stages. The intuition is that venture capitalists who invest in firms shortly before the IPO are still acting as investors seeking good investments, whereas those who only invested in firms long before the IPO are now playing the role of investors seeking to unload their existing investments at a profit. In the latter case, one could argue that venture capitalists may not monitor firms when investor beliefs are high because they know they can sell out via an IPO at a good price, whereas when investor beliefs are low and IPOs are more difficult they have incentive to monitor and prevent fraud.

We construct a *LateVC* dummy variable that equals one if an IPO firm received new (round of) venture capital financing within one year of its final offer date and zero otherwise. We also construct an *EarlyVC* dummy variable that equals one if an IPO firm received early rounds of venture capitals but no funding within one year of its final offer date and zero otherwise.[4] Among the 1,139 venture-capital-backed IPO firms in our sample, 792 firms (or 70%) received new rounds of venture capitals within one year of their IPOs, and 347 firms only received venture capitals at their early stages. We then interact both the *LateVC* dummy and the *EarlyVC* dummy with the terciles of investor beliefs.[5]

We find that, consistent with our previous results, both *LateVC* and *EarlyVC* are associated with lower fraud propensity in the lowest belief tercile and higher fraud propensity in the highest belief tercile. Interestingly, in the middle tercile, firms funded by venture capitalists until their IPOs have lower incentive to commit fraud while firms funded by venture capitalists only at their early stage have higher probability to commit fraud. This second finding is consistent with early-stage venture capitalists not monitoring and seeking to exit even in somewhat good times.

VI.E.4 Alternative Explanation for the Role of Venture Capitalists in IPO Frauds

Gompers (1996) suggests that the age of the venture capitalist plays a role in VC monitoring: young VCs have little incentive to discourage fraud because they prefer to bring the firms public so that they can raise more money later.

For VC age to explain our results would require two conditions to hold: (1) young VCs encourage fraud (even relative to the non-VC group) whereas old VCs discourage fraud; (2) young VCs dominate in good times, and old VCs dominate in bad times.

We follow the VC literature and calculate *VC Age* as the difference between the founding year of a venture capitalist and the IPO year. If more than one venture capitalist participates in funding an IPO firm, we take the average of each VC's age. The data on VC's founding year is obtained from VentureXpert.

We find from Table A5 that neither the fraction of IPOs backed by VC nor the VC Specialty Score change monotonically as investor beliefs rise. In addition, the distribution of VC-backed IPOs across investor belief quintiles indicates that our regression results are not driven by a few observations with unique characteristics or extreme values.

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[4] Of course, the *EarlyVC* dummy is only a noisy proxy for venture capitalists who seek to unload existing investment. An IPO firm may not need any additional funding within one year of its IPO. Nevertheless, this should work against us finding meaningful distinctions between late VCs and early VCs.

[5] We use terciles rather than quintiles because using quintiles generates too many interaction terms. Given that we only have a few IPO fraud observations, the number of interaction terms makes the estimation difficult to converge.

More importantly, unlike VC expertise, VC age in general increases from the lowest to highest investor belief levels. Table A6 Model 1 shows that VC age is positively correlated with incidence for fraud. However, controlling for VC age does not alter our previous findings. Table A6 Model 2 shows that when interacting *VC Age* with investor belief quintile variables, the coefficient is uniformly positive (though generally insignificant) across all belief quintiles.

These results indicate that our findings with respect to VC are not driven by the presence of young VCs, suggesting that mechanisms other than monitoring costs are unlikely to explain our findings.

VI.E.5 Underwriter's Monitoring Incentives

Li and Masulis (2007) document a substantial increase in investment banks' venture equity holdings in IPOs since the early 1990s, implying that the underwriters' incentives should have become more aligned with those of the venture capital funds. This should work against us finding any difference between the effect of underwriter monitoring and that of VC monitoring on IPO firms' incentive to commit fraud. Nevertheless, as a robustness check, we include both the VC dummy and the underwriter variables in the regressions for our 1995-2002 IPO sub-sample. Our results for Tables V and VI do not change.

Underwriters themselves can be subject to lawsuits alleging fraud in the IPO process. Can our results about *IB Specialty Score* be caused by private securities lawyers' incentive to chase the "deep pockets" of large underwriters? We explore this possible alternative interpretation in three ways. First, we include in regressions in Table VI only IPO firms with lead underwriters whose market share ranks greater than the sample mean of 7.5 (i.e., large underwriters with potentially "deep pockets"). *IB Specialty Score* is still negatively (-0.466) and significantly (p = 0.01) related to the fraud propensity.

Second, as noted in Section VI.A.2 of this internet appendix, we focus on SEC AAER lawsuits, which are less likely to have the "deep pockets" concern. We find that the impact of investment bank specialty on fraud is again significant: more skilled investment banks reduce the probability of fraud (coefficient is 1.952 and p = 0.00). In addition, in the sub-sample analysis (the 1995-2002 IPOs), 31 out of 78 IPO fraud cases named the lead underwriters as codefendants. We find that *IB Specialty Score* between these 31 cases and the rest of the IPO fraud cases are not significantly different, implying that *IB Specialty Score* is not strongly correlated with the probability of underwriters being sued. These results seem to confirm our view that greater investment bank specialization leads to lower fraud.

In our main analyses we use the MBA placement data from the Columbia Business School as one of the proxies to capture the supply side of investment banking labor markets. To check the robustness of our results, we also obtain the MBA placement data from the Wharton School. On average, 24% of Wharton graduates were placed in the investment banking industry during 1995-2005. We find similar results using the Wharton data.

VI.E.6 Robustness of the Hump-Shaped Relationship between Fraud and Investor Beliefs

To check the robustness of the hump-shaped relationship between fraud propensity and investor beliefs as predicted in Povel et al. (2007), we report the characteristics of IPOs and frauds within each quintile of investor belief variables in the raw dataset. To ensure that this hump-shaped relationship is not driven by a few observations with extreme values within a particular quintile, Table A7 of this internet appendix reports the number of IPOs, number of unique industries and number of unique years in addition to the fraction of IPOs being fraudulent for each quintile.

The descriptive statistics in Table A7 reveals that in the absence of any functional forms, there is evidence in the raw data that the detected incidence of fraud and the investor belief variables exhibit a hump-shaped relationship: In general, the fraction of IPOs being fraudulent initially increases, but eventually decreases, as investor beliefs rise from the bottom to top quintiles. We observe this general pattern for all three proxies for investor beliefs.

Furthermore, when discussing the results from the quadratic specification (Table III), we show that the inflexion point of *Ind. EPS Growth* at which the predicted fraud propensity peaks is 0.34, corresponding to the top 6% of *Ind. EPS Growth* distribution.

The top 6% includes 14 unique industries and 9 unique years: Agriculture (1996), Healthcare (2002), Steel Works (1995), Fabricated Products (1996), Machinery (2004), Shipbuilding and Railroad Equipment (1998, 2004, 2005), Coal (2001, 2004, 2005), Petroleum and Natural Gas (1996, 2000, 2003, 2004, 2005), Communication (2003), Computer Software (2004), Electronic Equipment (1995, 2000, 2004), Measuring and Control Equipment (1995, 2000, 2004), Insurance (2002), Real Estate (1998, 2004, 2005). Thus, the hump shape is pronounced with a declining relationship over a relatively large fraction of investor beliefs.

We further confirm this result via a numerical approximation as follows. We first compute the predicted probability of fraud for each firm based on Model (1) of Table III. We then partition the range of *Ind. EPS Growth* variable into 50 equal intervals and calculate the average predicted probability of fraud and the average *Ind. EPS Growth* in each interval. We identify the peak value of the predicted probability of fraud and the corresponding level of *Ind. EPS Growth*. We repeat the estimations for finer and finer intervals (up to 100) until the difference in the value of predicted probability of fraud and the corresponding level of investor belief variable between various interval cuts is no longer significant. The predicted probability of fraud peaks at a value of 17.2%, corresponding to *Ind. EPS Growth* of 0.34.

VII. EXTENSIONS

VII.A Uncertainty of Investor Beliefs and Propensity for Fraud

In addition to links between the level of investor beliefs and fraud, some of the literature makes predictions about how investor uncertainty about business conditions affects fraud incentives. Kumar and Langberg (2008) use a dynamic setting with managerial empire-building to argue that the relationship between fraud propensity and investor beliefs about business conditions varies with investor uncertainty about the industry's productivity. They show that, for any level of investor beliefs, greater uncertainty exacerbates incentives for fraud. The intuition is as follows. The empire-building manager always wishes to control a larger firm. Investors are willing to invest more in the good state, creating an incentive for the manager to inflate earnings so as to attract more investment. The fraud incentive is particularly high when uncertainty is high, i.e., when the difference between the good state and the bad state is large. In sum, their model predicts that a firm's propensity to commit fraud increases with the uncertainty of investor beliefs.

To investigate the above prediction, we use two proxies for uncertainty of investor beliefs about the industry prospects. Our first variable "*Ind. CF Uncertainty*", calculated as the industry median standard deviation of operating cash flow (scaled by total book assets) in the previous 10 years, captures uncertainties arising from industry characteristics. Our second variable "*Ind. Belief Dispersion*", calculated as industry median dispersion of analyst EPS growth forecasts, captures uncertainties arising from investor beliefs about business conditions. Both proxies are measured at the year when the fraud is committed. Results are reported in Table A8 of this internet appendix.

Panel A of Table A8 reports results using the cash flow volatility variable. Model 1 of Panel A reveals that, inconsistent with Kumar and Langberg (2008), the coefficient associated with the uncertainty variable is negative and insignificant. This suggests that after controlling for the level of investor beliefs, industry uncertainty itself does not significantly impact fraud propensity.

In Models 2 and 3 we classify industries into low/high uncertainty groups based on the sample median of the industry cash flow volatility. We then re-run our bivariate probit regression for each sub-sample. Consistent with Kumar and Langberg (2008), the *average* predicted probability of fraud is higher in high-uncertainty industries (8.09% in low-uncertainty industries vs. 8.4% in high-uncertainty industries), although the difference is not statistically significant.

Nevertheless, including industry cash flow volatility does not alter our main findings. Fraud propensity continues to be concave in investor beliefs, for the whole sample as well as the low-uncertainty industries and the high-uncertainty industries.

Cash flow volatility may not be as good a measure of the investor uncertainty about business conditions as the dispersion in EPS growth forecasts, so in Panel B we capture industry uncertainty using the latter measure. Our findings are similar to those in Panel A: controlling for uncertainty does not change the concave relationship between investor beliefs and propensity for fraud. However, the predicted fraud probability is on average higher for firms in high-uncertainty industries. The difference in the predicted fraud probabilities is statistically significant between the two sub-samples.

These findings provide limited support for the predictions of Kumar and Langberg (2008). The average probability of fraud is higher in high-uncertainty industries, but once we control for the impact of the level of investor beliefs, the marginal effect of uncertainty is insignificant.

VII.B Consequences of IPO Frauds

VII.B.1 Failure Rates of IPO Frauds

Povel et al. (2007) argue that firms that commit fraud tend to have worse prospects than those that don't commit fraud. If this is true, fraudulent firms should have higher failure rates than other firms.[6] Table A9 of this internet appendix shows that fraudulent firms do in fact have a higher average failure rate than non-fraudulent firms (39.05% vs. 24.15%, and $p \leq 0.001$), indicating that fraudulent firms are more likely to be poorly-performing firms.

In addition, firms committing fraud at the IPO stage have a higher failure rate than firms committing fraud post-IPO: 47.44% vs. 35.26% ($p = 0.068$). This suggests that firms committing fraud at their IPO stages are more vulnerable and are worse economic performers than those that commit fraud later on; IPO fraud seems to be associated with more serious economic consequences than does post-IPO fraud.

VII.B.2 Post-IPO Frauds

Povel et al. (2007) hypothesize that when investor beliefs are extremely high, bad firms can raise external funding without committing fraud. By contrast, when investor beliefs are not as high, bad firms are either monitored or commit fraud to avoid being monitored. A natural extended prediction is that firms that went public during a time of high investor optimism are more likely to turn out to be bad firms than those that went public during a time of lower investor optimism. Since these firms have bad prospects, they should be more likely to commit fraud subsequently than firms that go public in more pessimistic times.

We now extend our analysis to the effect of investor optimism on post-IPO fraud. We repeat the tests of Table III for the sample of firms that committed fraud after their IPO. We include a dummy variable to distinguish whether a firm went public during a period of high investor optimism. To be consistent with our measures of investor beliefs, we construct *Hot IPO Industry 1*, a dummy variable equal to 1 if a firm went public during the period when the inverse of the industry median IPO book-building period falls in the top two quintiles. As a robustness check, we also use an alternative measure, *Hot IPO Industry 2*, a dummy variable equal to 1 if a firm went public during the time when the industry median EPS growth forecast falls in the highest two quintiles.

Note also that the information environment changes once a firm goes public. Unlike the pre-IPO stage where information about the firm is relatively limited, more firm-specific information is available in the post-IPO stage. To take into account the change of information

[6] The extended analyses in Sections VII.B.1 and VII.B.2 are based on the IPO sub-sample during the period of 1995-2002, and the subsequent fraud sub-sample of 1996-2005.

environment once a firm goes public, in addition to the industry-specific measure used in Table III we include *Firm EPS Growth*, the consensus EPS growth forecast at the firm level, as a measure of firm-specific investor beliefs.

Results are reported in Table A10 of this internet appendix. We observe that the coefficient for the hot IPO industry dummy is positive and significant. This indicates that firms going public during periods of high investor beliefs have a higher likelihood of committing frauds post-IPO. Our result thus provides evidence consistent with Povel et al. (2007): a higher portion of bad firms raised capital through their IPO without committing fraud during the period of high investor beliefs than during the period of low investor beliefs.[7]

In addition, we find that the effect of industry-specific investor beliefs is subsumed by firm-specific investor beliefs, as the coefficient of *Firm EPS Growth* is significant at least at 5% level while the coefficient of industry median EPS growth is no longer significant. Also, similar to our results in the case of IPO fraud, the coefficient associated with the squared term of firm EPS growth rate is negative, albeit statistically insignificant for both models.

[7] We also defined the hot IPO industry dummy based on the industry median Q. The coefficient estimate for this dummy variable is positive but statistically insignificant (0.07, $p = 0.62$).

ADDITIONAL REFERENCES

Beasley, Mark S., Joseph V. Carcello, Dana R. Hermanson, 1999. Fraudulent financial reporting: 1989-1997, Research commissioned by the Treadway Commission.

Beneish, Messod D., 1999. The detection of earnings manipulation, *Financial Analysts' Journal* 55 (5), 24-36.

Fich, Eliezer, and Anil Shivdasani, 2007. Financial fraud, director reputation, and shareholder wealth, *Journal of Financial Economics* 86, 306-336.

Helland, Eric, 2004. A secondary market test of the merits of class-action securities litigation: Evidence from the reputation of corporate officers, *Journal of Law and Economics* forthcoming.

Gompers, Paul A., 1996, Grandstanding in the venture capital industry, *Journal of Financial Economics* 42, 133-156.

Li, Xi, and Ronald W. Masulis, 2007. How do venture investments by different classes of financial institutions affect the equity underwriting process? Working Paper, Vanderbilt University.

Srinivasan, Suraj, 2005. Consequences of financial reporting failure for outside directors: Evidence from accounting restatements, *Journal of Accounting Research* 43, 291-334.

Table A1: Abnormal Investor Beliefs

In Model (1), "Abnormal Ind. EPS Growth 1" is computed as the deviation of "Ind. EPS Growth" from the sample period mean for each industry. By doing this we take out the differences in "Ind EPS Growth" in the cross section. In Model (2), "Abnormal Ind. EPS Growth 2" is computed as the deviation of "Ind. EPS Growth" from the annual cross-sectional mean for all industries. By doing this we take out the differences in "Ind. EPS Growth" over time. In Model (3), year fixed effect is included to control for the time effect. **, * and + indicate significance at 1%, 5% and 10% levels respectively.

P(F=1)	(1)	(2)	(3)
Abnormal Ind. EPS Growth 1	2.007**		
	[0.472]		
(Abnormal Ind. EPS Growth 1)^2	-6.487**		
	[1.953]		
Abnormal Ind. EPS Growth 2		1.911**	
		[0.562]	
(Abnormal Ind. EPS Growth 2)^2		-6.413**	
		[1.731]	
Ind. EPS Growth			1.963**
			[0.549]
(Ind. EPS Growth)^2			-1.572*
			[0.654]
Log(Assets)	0.090*	0.095*	0.062*
	[0.038]	[0.039]	[0.031]
After SOX	1.097	1.576*	
	[0.875]	[0.714]	
Constant	-2.784**	-2.975**	-0.704
	[0.713]	[0.738]	[0.603]
Year Fixed Effect			Included
P(D=1|F=1)			
Ind. Litigation	0.002**	0.002*	0.004**
	[0.001]	[0.001]	[0.001]
Stock Return	-0.850**	-0.872**	-2.895**
	[0.314]	[0.314]	[0.461]
Return Volatility	10.105	11.342	33.745**
	[9.375]	[10.273]	[9.043]
Stock Turnover	0.088	0.071	0.266**
	[0.078]	[0.060]	[0.088]
Log(Assets)	0.091	0.081	0.327**
	[0.048]	[0.053]	[0.071]
After SOX	-0.316	-0.714	
	[0.637]	[0.473]	
Constant	-3.329*	-2.712*	-9.396**
	[1.343]	[1.322]	[1.679]
Year Fixed Effect			Included
Observations	2,876	2,876	2,876
Log pseudo-likelihood	-437	-413	

Table A2: Controlling for the SEC's Capacity

"SEC Budget" is the SEC's annual dollar budget normalized by the number of securities (IPOs + SEOs + nonconvertible debt) issued in that year. **, * and + indicate significance at 1%, 5% and 10% levels respectively.

P(F=1)	(1)	(2)	(3)
Ind. EPS Growth	4.295**		
	[1.499]		
(Ind. EPS Growth)^2	-6.226**		
	[2.057]		
(Ind. Book-Building)$^{-1}$		0.822**	
		[0.191]	
((Ind. Book-Building)$^{-1}$)^2		-0.139**	
		[0.032]	
Ind. Q			0.651**
			[0.175]
(Ind. Q)^2			-0.121**
			[0.035]
SEC Budget	2.052	0.449	0.058
	[1.640]	[0.367]	[0.327]
Log(Assets)	0.122*	0.088**	0.102**
	[0.058]	[0.028]	[0.031]
Constant	-4.233**	-3.930**	-3.966**
	[1.081]	[0.538]	[0.548]
P(D=1|F=1)			
SEC Budget	-0.621	0.438	0.464
	[1.566]	[0.316]	[0.308]
Ind. Litigation	0.002	0.001**	0.001**
	[0.001]	[0.000]	[0.000]
Stock Return	-0.860*	-0.731**	-0.699**
	[0.426]	[0.190]	[0.179]
Return Volatility	10.871	2.982**	3.901**
	[14.703]	[0.723]	[1.369]
Stock Turnover	0.116	0.251**	0.198**
	[0.113]	[0.064]	[0.048]
Log(Assets)	0.114*	0.135**	0.127**
	[0.058]	[0.034]	[0.034]
Constant	-3.762	-4.914**	-4.773**
	[2.074]	[0.727]	[0.708]
Observations	2,876	2,876	2,876
Pseudo-likelihood	-435	-432	-436

Table A3: More Controls in Fraud Detection Equation

The following accounting variables are included as additional control in the fraud detection equation. Days Sales in Receivables Index "DSRI" = $(\text{Receivables/Sales})_t$ / $(\text{Receivables/Sales})_{t-1}$. Gross Margin Index "GMI" = $[(\text{Sales} - \text{Cost of Goods Sold})/\text{Sales}]_{t-1}$ / $[(\text{Sales} - \text{Cost of Goods Sold})/\text{Sales}]_t$. Asset Quality Index "AQI" = $[1- (\text{Current Assets} + \text{Net PPE})/\text{Total Assets}]_t$ / $[1- (\text{Current Assets} + \text{Net PPE})/\text{Total Assets}]_{t-1}$. Sales Growth Index "SGI" = Sales_t / Sales_{t-1}. Accruals to Total Assets "TATA" = $(\text{Current Assets} - \text{Cash} - \text{Current Liabilities} - \text{Current Maturities of Long-Term Debt} - \text{Income Taxes} - \text{Depreciation and Amortization})_t$ / Total Assets_t. **, * and + indicate significance at 1%, 5% and 10% levels respectively.

P(F=1)	(1)
Ind. EPS Growth	4.562**
	[1.317]
$(\text{Ind. EPS Growth})^2$	-7.438**
	[2.166]
Log(Assets)	0.121*
	[0.049]
After SOX	4.161**
	[0.665]
Constant	-3.859**
	[0.964]
P(D=1|F=1)	
Ind. Litigation	0.002**
	[0.001]
Stock Return	-0.735**
	[0.266]
Return Volatility	14.615*
	[6.894]
Stock Turnover	-0.000*
	[0.000]
Log(Assets)	0.109
	[0.058]
After SOX	-0.760*
	[0.373]
DSRI	0.155
	[0.133]
GMI	-0.105
	[0.057]
AQI	-0.007
	[0.006]
SGI	-0.089
	[0.135]
TATA	-0.432
	[0.574]
Constant	-3.429*
	[1.343]
Observations	2,876
Pseudo-likelihood	-430

Table A4: Probit Specification

This table reports results using standard probit models. The dependent variable is a dummy variable that equals one if a firm has committed IPO fraud and has been detected, and zero otherwise. **, * and + indicate significance at 1%, 5% and 10% levels respectively.

	(1)	(2)	(3)
Ind. EPS Growth	3.543**		
	[1.312]		
$(\text{Ind. EPS Growth})^2$	-5.616**		
	[2.112]		
$(\text{Ind. Book Building})^{-1}$		0.551*	
		[0.281]	
$((\text{Ind. Book Building})^{-1})^2$		-0.073*	
		[0.034]	
Ind. Q			0.507**
			[0.195]
$(\text{Ind. Q})^2$			-0.099**
			[0.038]
Log(Assets)	0.082*	0.070*	0.072*
	[0.037]	[0.034]	[0.034]
After SOX	0.338**	0.481**	0.341**
	[0.126]	[0.156]	[0.120]
Ind. Litigation	0.001**	0.001**	0.001*
	[0.000]	[0.000]	[0.000]
Stock Return	-0.579**	-0.543**	-0.536**
	[0.191]	[0.206]	[0.198]
Return Volatility	2.979	2.466	2.051
	[2.393]	[2.499]	[2.394]
Stock Turnover	-0.000*	-0.000*	-0.000*
	[0.000]	[0.000]	[0.000]
Constant	-3.985**	-4.002**	-3.918**
	[0.819]	[0.803]	[0.765]
Observations	2,876	2,876	2,876
Log pseudo-likelihood	-420	-416	-426

Table A5: Summary Statistics of VC-backing by Investor Beliefs Quintiles

This panel reports in each quintile of *Ind. EPS Growth* the mean value of investor beliefs, the fraction of IPOs fraudulent, the fraction of IPOs backed by venture capital, the mean value of VC specialty score and VC age. VC age is defined as the number of years between a VC firm's founding year and the IPO year. If more than one VC firm participate in funding an IPO firm, we take the average of all VCs' ages.

	1st Q	2nd Q	3rd Q	4th Q	5th Q	Top 6%
Ind. EPS Growth (mean)	0.034	0.129	0.162	0.220	0.351	0.495
% of IPOs fraudulent	2.24%	2.67%	3.60%	5.14%	4.01%	3.59%
% of IPOs backed by VC	41.4%	36.3%	54.4%	44.6%	52.4%	59.0%
VC Specialty Score (mean)	0.183	0.149	0.263	0.177	0.233	0.240
VC Age (mean)	17.11	18.24	18.57	19.26	18.49	19.77

Table A6: Controlling for VC Firm's Age at IPO

In Model (1), we include one more control variable in the fraud equation—Ln(VC Age)—in Table 5 Panel B Model 2. "VC Age" is the average VC firms' age in a firm's IPO year, and is zero for non-VC-backed IPOs. In Model (2), we examine the VC-backed IPOs only and interact Ln(VC Age) with the quintiles of investor beliefs (Ind. EPS Growth). ** and * indicate significance at 1% and 5% levels respectively.

P(F=1)	VC=VC Specialty Score (1)	VC=Ln(VC Age) (VC-backed IPO only) (2)
Q1_EPS × VC	-1.747**	1.260
	[0.583]	[0.851]
Q2_EPS × VC	-5.390**	1.029
	[1.548]	[0.635]
Q3_EPS × VC	-2.101**	1.393*
	[0.610]	[0.703]
Q4_EPS × VC	-1.013**	1.641
	[0.386]	[0.890]
Q5_EPS × VC	4.381*	1.655
	[1.749]	[0.845]
Ln(VC Age)	0.374**	
	[0.102]	
Ind. EPS Growth	6.010*	0.250
	[2.443]	[4.657]
(Ind. EPS Growth)^2	-16.759**	-2.375
	[5.793]	[6.997]
Log(Assets)	0.100**	0.129
	[0.029]	[0.149]
After SOX	1.965*	0.597
	[0.879]	[1.446]
Constant	-3.782**	-7.565**
	[0.604]	[1.708]
P(D=1|F=1)		
Ind. Litigation	0.002**	0.003
	[0.000]	[0.001]
Stock Return	-0.660**	-1.509**
	[0.205]	[0.451]
Return Volatility	7.353	3.324
	[10.068]	[7.902]
Stock Turnover	0.045	0.113
	[0.031]	[0.100]
Log(Assets)	0.128**	0.207*
	[0.030]	[0.082]
After SOX	0.265*	0.212
	[0.120]	[0.398]
Constant	-4.631**	-5.858**
	[0.578]	[1.706]
Observations	2,778	1,299
Log pseudo-likelihood	-407	-192

Table A7: Investor Beliefs and Incidence of IPO Fraud

This table reports the summary statistics by quintiles as well as the top 6% of the investor beliefs distribution. In each group we report the mean value of investor beliefs, the number of IPOs, the number of unique industries associated with those IPOs, the number of unique calendar years associated with those IPOs, and the fraction that is fraudulent.

	Investor beliefs	# of IPOs	# of unique industries	# of unique years	% of IPOs fraudulent
Ind. EPS Growth					
Q1	0.034	625	43	11	2.24%
Q2	0.129	675	33	10	2.67%
Q3	0.162	583	30	11	3.60%
Q4	0.220	662	27	11	5.14%
Q5	0.351	574	26	11	4.01%
Top 6%	0.495	195	14	9	3.59%
(Ind. Book-Building)$^{-1}$					
Q1	0.926	628	43	11	3.98%
Q2	1.253	635	29	11	3.62%
Q3	1.410	658	29	10	4.10%
Q4	1.555	583	36	8	3.43%
Q5	1.888	615	38	11	2.44%
Top 6%	2.160	172	21	7	3.35%
Ind. Q					
Q1	1.123	624	34	11	3.37%
Q2	1.363	624	34	11	2.88%
Q3	1.617	650	29	10	3.54%
Q4	2.141	625	15	11	4.48%
Q5	3.221	596	5	10	3.36%
Top 6%	4.075	164	2	2	3.40%

Table A8: Investor Beliefs, Uncertainty and Fraud

The dependent variable is a dummy variable Z=1 if a firm committed fraud at IPO stage and then got caught later, and Z=0 otherwise. Estimation of fraud propensity is indicated by P(F=1), and the estimation of fraud detection likelihood is indicated by P(D=1|F=1). Coefficient estimates and the Huber-White-Sandwich robust standard errors clustered by industry (in square brackets) are reported. **, * and + indicate significance at 1%, 5% and 10% levels respectively.

Panel A: Industry Cash Flow Uncertainty

For each year and each industry, *Ind. CF Uncertainty* is the industry median standard deviation of operating cash flow (scaled by total book assets) in the previous 10 years. We group industries into Low/High Uncertainty groups based on the overall sample median industry cash flow uncertainty.

P(F=1)	(1) All Industries	(2) Low Uncertainty	(3) High Uncertainty
Ind. CF Uncertainty	-2.587		
	[2.216]		
Ind. EPS Growth	3.722**	4.151**	1.905*
	[0.834]	[1.470]	[0.907]
(Ind. EPS Growth)^2	-5.525**	-8.350*	-2.518$^+$
	[1.389]	[3.659]	[1.333]
Log(Assets)	0.109	0.085	0.018
	[0.059]	[0.077]	[0.095]
After SOX	1.185	3.580**	0.012
	[0.817]	[1.012]	[0.212]
Constant	-3.184*	4.151**	-1.947
	[1.502]	[1.470]	[1.611]
P(D=1|F=1)			
Ind. Litigation	0.003**	0.004	0.002**
	[0.001]	[0.005]	[0.0004]
Stock Return	-0.855*	-0.442	-1.053**
	[0.339]	[0.409]	[0.291]
Return Volatility	13.727	15.116	-10.087**
	[14.051]	[13.692]	[3.580]
Stock Turnover	0.083	-0.012	0.310**
	[0.081]	[0.023]	[0.095]
Log(Assets)	0.116	0.134	0.011
	[0.066]	[0.070]	[0.174]
After SOX	-0.236	-0.495	0.267
	[0.763]	[0.469]	[0.336]
Constant	-4.027*	-4.221*	1.290
	[1.939]	[1.794]	[2.850]
Observations	2,876	1,370	1,506
Median Predicted P(F=1)		8.09%	8.40%
Wilcoxon Z-score for difference between (2) and (3)		-0.793	

Table A8 continued.

Panel B: Industry EPS Growth Forecast Dispersion

For each year and each industry, *Ind. Belief Dispersion* is the industry median of analysts' EPS growth forecast dispersion. We group industries into Low/High Uncertainty groups based on the overall sample median industry EPS growth forecast dispersion.

P(F=1)	(1) All Industries	(2) Low Dispersion	(3) High Dispersion
Ind. Belief Dispersion	0.040		
	[0.075]		
Ind. EPS Growth	4.186*	6.596*	4.034**
	[1.836]	[3.137]	[1.222]
(Ind. EPS Growth)^2	-6.471*	-14.337*	-6.659**
	[3.080]	[6.229]	[2.000]
Log(Assets)	0.142*	0.189**	0.080
	[0.068]	[0.070]	[0.051]
After SOX	1.413	-0.209	4.757**
	[0.891]	[0.434]	[0.629]
Constant	-4.440**	-5.329**	-3.227**
	[1.592]	[1.612]	[0.944]
P(D=1|F=1)			
Ind. Litigation	0.002*	-0.001	0.002**
	[0.001]	[0.001]	[0.001]
Stock Return	-0.818	-0.586	-1.038**
	[0.446]	[1.096]	[0.369]
Return Volatility	15.717	13.592	19.415
	[14.298]	[20.057]	[12.287]
Stock Turnover	0.064	0.576	0.067
	[0.059]	[0.441]	[0.056]
Log(Assets)	0.117	-0.008	0.126
	[0.067]	[0.158]	[0.077]
After SOX	-0.240	0.563	-1.367**
	[1.324]	[0.735]	[0.500]
Constant	-4.131	-0.842	-3.289
	[2.540]	[3.624]	[1.904]
Observations	2,876	1,423	1,453
Median Predicted P(F=1)		6.97%	8.31%
Wilcoxon Z-score for difference between (2) and (3)		-8.137**	

Table A9: Status of Alleged Fraudulent Firms

The IPO sample period is 1995-2002. The fraud sample period is 1996-2005. "Still Trading" means the CRSP delisting code equals 100. "Being Bought" means the CRSP delisting code is in 200s (merger) or in 300s (stock exchange). "Failed" means the CRSP delisting code is in 400s (liquidation) or in 500s (involuntary delisting) or the firm filed for bankruptcy protection.

	Total	Still Trading	Being Bought	Failed
Entire IPO Sample	2,860	35.56%	39.44%	25.45%
Firms not alleged fraudulent	2,609	35.07%	41.21%	24.15%
Firms alleged fraudulent	251	40.64%	21.11%	39.05%
IPO Frauds	78	32.05%	21.79%	47.44%
Post-IPO Frauds	173	44.51%	20.81%	35.26%

Table A10: Investor Belief and Firms' Propensity to Commit Fraud after IPO

The IPO sample period is 1995-2002. The fraud sample period is 1996-2005. The dependent variable is a dummy variable Z=1 if a firm committed fraud after the IPO year and got caught later, and Z=0 otherwise. "Firm EPS Growth" is the consensus EPS growth forecast at firm level. All the industry-wide and firm-specific investor belief proxies are measured as of the beginning year of fraud. Coefficient estimates and robust standard errors (in square brackets) are reported. **, * and + indicate significance at 1%, 5% and 10% levels respectively.

	(1)	(2)
P(F=1)		
Hot IPO Industry 1	0.249*	
	[0.100]	
Hot IPO Industry 2		0.313*
		[0.155]
Ind. EPS Growth	0.036	-0.816
	[0.362]	[1.240]
(Ind. EPS Growth)^2	-0.125	3.239
	[0.176]	[4.311]
Firm EPS Growth	0.133**	0.184*
	[0.046]	[0.078]
(Firm EPS Growth)^2	-0.008	-0.014
	[0.006]	[0.016]
Log(Assets)	0.092	0.083
	[0.077]	[0.060]
Constant	-1.869**	-1.914**
	[0.445]	[0.353]
P(D=1|F=1)		
Ind. Litigation	0.001	0.001
	[0.001]	[0.001]
Stock Return	-0.682*	-0.561
	[0.325]	[0.427]
Return Volatility	2.312	1.927
	[4.535]	[5.337]
Stock Turnover	0.648*	0.605$^+$
	[0.333]	[0.343]
Log(Assets)	0.018	0.071
	[0.147]	[0.054]
Constant	-0.941	-3.163**
	[2.154]	[0.412]
Observations	3,809	3,813
Pseudo-likelihood	-525	-540