CORPORATE FRAUD AND BUSINESS CONDITIONS:

EVIDENCE FROM IPOS*

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Abstract

Using a sample of firms that went public between 1995 and 2005, we examine how a firm's incentive to commit fraud when raising external capital varies with investor beliefs about industry business conditions. Although fraud propensity generally increases with the level of investor beliefs about industry prospects, fraud propensity decreases in the presence of extremely high investor beliefs. Further analysis suggests that two mechanisms are at work: investor monitoring of IPO firms, and the proportion of short-term compensation in total executive compensation, both of which vary with investor beliefs about industry prospects. We also find evidence that venture capitalists and underwriters have different monitoring incentives. When venture capitalists are present, fraud is less likely for low investor beliefs but more likely for high investor beliefs; this suggests that venture capitalists primarily monitor to seek good investments and thus take investor beliefs into account. By contrast, underwriter skill reduces fraud for all investor beliefs; thus, underwriter monitoring seems aimed at preventing fraud per se, though this too is strongest for lower investor beliefs. We also find that fraud propensity is on average higher in industries with high investor uncertainty about business conditions, but this effect disappears once we control for the level of investor beliefs. Our results are consistent with the predictions of several recent models of investor beliefs and corporate fraud, and suggest that regulators and auditors should be especially vigilant for fraud during booms.

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1. INTRODUCTION

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 2 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.

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. In a model of investors' dynamic learning about a firm's financial situation, Kumar and Langberg (2008) predict that greater uncertainty increases the incidence of fraud, regardless of the level of investor beliefs.

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 3, 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.[1] We measure detected fraud with securities lawsuits alleging accounting-related fraud during the period leading up to the IPO. Of course, not all IPO frauds are

[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).

detected, and some lawsuits may be frivolous, so we use the bivariate probit method of Wang (2008) 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, influence managerial compensation contracts, or learn about industry dynamics, 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.

Our first set of tests examines the relationship between the level of 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 affects 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 level of 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. We find that the percentage of compensation that is short-term is increasing in investor beliefs, but at a decreasing rate. This is only partially consistent with Hertzberg's prediction that the relationship should be unambiguously increasing. Next, we find that short-term compensation has a positive and significant impact on a firm's fraud propensity, as predicted by Hertzberg. 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.

Finally, we evaluate the role of investor uncertainty about business conditions. Using two proxies for uncertainty—industry cash flow volatility and the dispersion of investor beliefs for an industry—we find that 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.

Summing up, we find evidence that is consistent with the two fraud mechanisms proposed by Povel et al. (2007) and Hertzberg (2005), whereas our results are only partially consistent with the model of Kumar and Langberg (2008). 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 should be 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 industry clustering and "hot" and "cold" 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. In this respect, our paper is related to Ljungqvist and Wilhelm (2003), who document that the quality of IPOs fell during the 1997-2000 hot IPO market, and to Khanna, Noe and Sonti (2008), who argue that the deterioration in underwriter's screening quality arising from a tight labor market supply during hot IPO markets leads to lower IPO quality. We show that the optimism in investor beliefs contributes to the likelihood of IPO frauds even when a large supply of skilled labor to the investment banking industry mitigates fraud incentives.

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, Efendi, Srivastava, and Swanson, 2007, Peng and Röell, 2008, and Johnson, Ryan, and Tian, 2009), though a recent paper by Armstrong, Jagolinzer, and Larcker (2008) finds evidence to the contrary. 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, Dyck, Morse, and Zingales (2007) examine which monitoring institutions—regulatory-based institutions such as government agencies or market-based institutions such as blockholders and analysts—are more effective in detecting fraud. Li (2008) examines the effect of the SEC's monitoring efforts on firms' incentive to commit fraud. 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 2 discusses the models and empirical hypotheses that we test in the paper. Section 3 discusses the research setting and sets out our model specification. Section 4 describes our sources of data. Section 5 reports our basic results on the impact of the level of investor beliefs on fraud. Section 6 examines monitoring and executive compensation as mechanisms linking investor beliefs to fraud. Section 7 analyzes the impact of uncertainty on the relationship between investor beliefs and fraud. Section 8 discusses extensions and various tests for robustness. Section 9 concludes.

2. HYPOTHESIS DEVELOPMENT

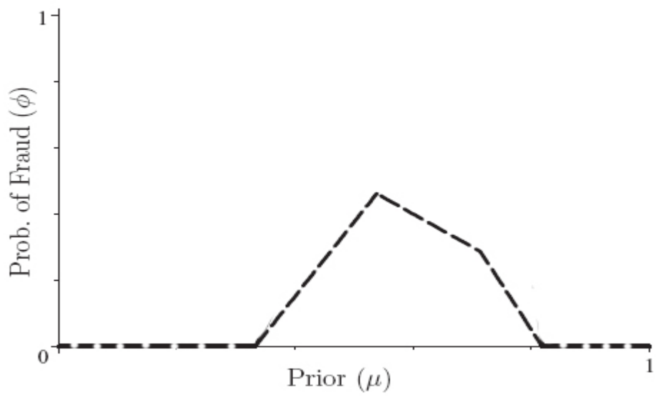
In this section we discuss the theories modeling how investors' beliefs about business conditions affect firms' incentive to commit fraud and lay out related empirical hypotheses. We begin with models linking the *level* of investor beliefs to the incidence of fraud, both in terms of their direct predictions and in terms of predictions linked to the specific mechanisms of the models. We then discuss models linking the *uncertainty* of investor beliefs to the incidence of fraud.

2.1 Level of Investor Beliefs and Propensity for Fraud

Our discussion in this subsection focuses on Povel et al. (2007) and 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 depends on the level of investor beliefs.

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 the cross-industry analysis as well as the time series comparisons within industries. We now summarize the predictions from these two theories.

[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 concave relationship between investor beliefs and fraud propensity still holds in the presence of free entry and exit by bad firms.

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.*

2.2 The Underlying Mechanisms

2.2.1 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 good 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 court 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.*

2.2.2 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.*

2.3 Uncertainty of Investor Belief and Propensity for Fraud

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.

We summarize their predictions below.

Hypothesis 4 (Kumar and Langberg): *The likelihood that a firm commits fraud increases with the uncertainty of investor beliefs.*

3. EMPIRICAL DESIGN

3.1 IPOs as the Research Setting

Kumar and Langberg (2008), Povel, Singh and Winton (2007), and Sherman (1999) all 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.

3.2 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).

Following Wang (2008), 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

[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 (2008) about the difference between the bivariate probit approach and the probit approach in analyzing corporate securities frauds.

disturbances with a bivariate normal distribution. Their variances are normalized to unity because the variances are not estimable. The correlation between u_i and v_i is ρ.

For fraud occurrence, we transform F_i^* into a binary variable F_i, where $F_i = 1$ if $F_i^* > 0$, and $F_i = 0$ otherwise. For fraud detection (conditional on occurrence), we transform D_i^* into a binary variable D_i, where $D_i = 1$ if $D_i^* > 0$, and $D_i = 0$ otherwise.

However, 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 (X_F and X_D, respectively). Detailed variable definitions and proxy constructions are in Appendix I.

3.3 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.[4] 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 Povel et al. (2007)'s model involves misreporting information to influence investors' beliefs about the financial condition of the firm. We discuss the fraud sample in greater detail in Section 4.

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 3.2 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 3.7, we directly control for factors that are related to frivolous lawsuits in our regressions. Second, as discussed in Section 4.1, we select our sample to exclude lawsuits that are most likely to be frivolous. Finally, in Section 8.2, we explore alternative sample restrictions that control for frivolous lawsuits.

3.4 Proxies for Investor Belief

As noted in the introduction, we wish to 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

[4] 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).

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.[5]

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.[6] (Obviously, we cannot exclude IPO firms from the book-

[5] 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.

[6] 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.

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.

3.5 Proxies for Monitoring Costs

In addition to 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 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 of investors with lower monitoring costs in a particular issue.

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 the "*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 fractions of MBA graduates placed in the investment banking industry from Columbia Business School ("*IB Hiring* ") from each sample year.[7] To take into account relative need for this labor pool, we normalize these two variables 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 these measures of the supply of MBAs are noisy measures 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.

3.6 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 Faulkender and Yang (2008) and Murphy and Sandino (2008) to construct proxies for executives' short-term and long-term incentive arrangements. Specifically, for each firm 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

[7] We also obtain the MBA placement data from the Wharton School. These two schools have a long history of placing students in the investment banking industry and maintain a consistent placement record throughout our sample period. On average, 35% of Columbia MBA graduate seek investment banking jobs, and 24% of Wharton graduate do. We report the result using the data from Columbia. Results using the Wharton data are similar and thus not reported.

(RSTKGRNT) and the total value of new stock options (OPTION_AWARDS_BLK_VALUE) as a fraction of total expected compensation. We then compute the average of "*ST Incentive*" and "*LT Incentive*" among the tope 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). Further, going public implies a substantial change in a firm's governance structure. As IPO firms reset their executive compensation schemes as publicly traded companies, industry norms in executive pay play a pertinent role in this process. Therefore, for each IPO firm and in the IPO year, we compute the industry median short- and long-term incentives based on firms in ExecuComp.

3.7 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 3.2.[8] We compute return volatility as the standard deviation of daily stock returns. Stock turnover is the annual share turnover.

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. A high total market value can result

[8] In other words, frivolous lawsuits will have a high probability of detection but a low probability of fraud being committed. In Section 8.2.3 we return to this and use estimated probability of fraud commitment as a further screen to exclude frivolous lawsuits.

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

3.8 Effect of the Sarbanes-Oxley Act

The Sarbanes-Oxley Act (SOX), enacted in July 2002, aims at improving corporate governance and combating corporate frauds. Pursuant to the Act, the Securities and Exchange Commission adopted rules that directed self-regulatory organizations (SRO) 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.

4. DATA

4.1 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) filed from 1996 to 2007, and the Securities Class Action Clearinghouse (SCAC) established by Stanford Law School (http://securities.stanford.edu). 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 (2007) 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 8.2 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 1085 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*. We label the remaining 272 cases occurred after the year of IPO as *Post-IPO Frauds*.

4.2 Summary Statistics

Panel A of Table 1 reports the annual frequency of IPOs and the number of frauds committed by each IPO cohort. We observe that the probability of a fraudulent IPO decreases substantially during the period of the "cold" market (after year 2000).

Panel B indicates that the majority of frauds (75%) last at least two years and that both the commitment and the detection of IPO frauds come in waves. For example, about 38% of frauds are committed during 1999 and 2000, and about 43% of frauds are detected during 2000 to 2002.

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 communications. Despite the overlap between fraud occurrences in these industries and the general stock market boom (see Panel B), we do 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.

5. INVESTOR BELIEFS AND THE PROBABILITY OF CORPORATE FRAUD

The descriptive statistics of Table 2 show that, compared to other IPO firms, industry median EPS growth is significantly higher, and both the inverse of industry median book-building period and industry median Q are insignificantly higher for firms that commit fraud at the IPO stage. This suggests that investor beliefs are weakly more optimistic when fraudulent firms undertake IPOs.

To test Hypotheses 2a and 2b 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. Models 1 through 3 of Table 3 report bivariate probit results. For each variable, we report both the coefficient estimate and the Huber-White-Sandwich robust standard errors clustered by industry (in parentheses).

Model 1 of Table 3 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 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, $(\textit{Ind. EPS Growth})^2$. This indicates that while a firm is more likely to commit fraud given a more optimistic industry-specific investor belief, this likelihood increases at a decreasing rate. To illustrate, the average probability of fraud for the bottom decile of investor beliefs is 4.8%. It rises to 9.7% for the 5th decile and peaks for 11.4% at the 8th decile. The fraud propensity then drops to 10.1% once investor beliefs reach the top (10th) decile, a 13% decrease.

We estimate the inflection point for the industry median EPS growth forecast to be 0.67. That is, for any industry median EPS growth forecast level exceeding 0.67, a higher level of investor beliefs is associated with a lower probability of fraud. This turning point reflects the top 1% of the distribution of the investor beliefs variable.[9]

Figure 1 graphs each firm's predicted probability of fraud based on Model 1 of Table 3 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 3 confirm the results of Model 1 for different measures of investor beliefs, the inverse of the industry median book-building period and industry median Q. The positive coefficient estimates for (*Ind. Book-Building*)$^{-1}$ and *Ind.* Q suggests that an increase in investor optimism 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 is diminished at higher levels of beliefs.

Besides the quadratic specification, Model 4 of Table 3 tests for the hump-shaped effect of investor optimism on the probability of corporate fraud using a piecewise linear specification—a spline.[10] 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 industry median forecasted EPS growth, *Ind. EPS Growth*: 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.[11]

Model 4 shows that when the level of investor beliefs is relatively low (the bottom three quintiles), 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 fourth and top quintiles), the relationship between fraud propensity and investor beliefs becomes negative: a firm's incentive to commit fraud decreases when investor beliefs become too optimistic.

These results suggest that investor beliefs about industry prospects affect the probability of corporate fraud in the manner that is predicted by Povel et al. (2007). A firm's incentive to commit fraud in the event of raising external capital is higher when investors are more optimistic about the

[9] The top 1% includes the coal industry in year 2004 and 2005, the petroleum and natural gas industry in year 1996 and 2000, and the electronic equipment industry in year 2004.
[10] For a detailed description of spline regression, see Garber and Poirier (1974) and Poirier (1974).
[11] Alternative cutoff points based on quartiles and terciles as well as alternative proxies for investor beliefs yield results consistent with those reported in Model 4. Therefore, these results are not reported.

prospects of the firm's industry. Nevertheless, the probability of fraud becomes lower in the presence of extreme investor optimism, as the firm is able to obtain external financing without misrepresenting information to outside investors.

Table 3 also reveals 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. [12]

6. 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.

6.1. 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.

6.1.1 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

[12] Controls for market conditions in addition to firm-specific conditions in the detection model (such as economic downturns, market returns, and the cascading effect that a major scandal has on subsequent monitoring and fraud detection) do not change our results. As expected, in our detection analysis, firm-specific conditions subsume the effect of market conditions.

venture capitalist. 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 3 with the addition of a VC specialty score. The results are reported in Model 1 of Table 4.[13] 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 4): having VC backing does not significantly impact an IPO firm's fraud propensity.

Nevertheless, the lack of significance of the coefficient for the VC-backing dummy and for VC Specialty Score is not conclusive. This is because the analysis so far does not allow the monitoring incentives 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, for all three proxies, we interact the average level of 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 4. 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.

[13] For brevity, only the results with respect to industry EPS growth proxy are tabulated. The results with respect to the other two belief proxies are similar and thus not reported.

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.

6.1.2 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 3 while adding measures of underwriters' monitoring costs. The results are reported in Table 5. Model 1 of Table 5 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 quality 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 quintiles of investor belief proxy. In contrast to venture capitalists (Table 4), the coefficient estimates of the interaction terms in Model 4 of Table 5 are consistently negative in all quintiles. This suggests that firms underwritten by more experienced investment banks are less likely to commit fraud, regardless of the level of investor optimism.

Overall, the results in Table 5 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, profits and expected profits are high. Underwriters are likely to look less hard so as not to irritate clients (firms) who may have expected future business with the underwriters. Thus, even underwriters seem to be relatively more vigilant when investor beliefs are less optimistic.[14]

6.2 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.

Table 6 Panel A establishes the relationship between investor beliefs about business conditions and the structure of executive pay, using firm-level compensation data in ExecuComp database. Consistent with Hypothesis 3, we find that more optimistic beliefs are associated with more short-term compensation (Model 1) and less long-term compensation (Model 2). But the relationship between beliefs and pay is nonlinear. As beliefs become more optimistic, short-term compensation increases at a decreasing rate, as reflected by the significant negative coefficient on

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

the square term of *Ind. EPS Growth* in Model 1. Results using the other two investor belief proxies are similar; in the interests of space, we do not report these here.

In Table 6 Panel B we include the industry median short- and long-term compensation as well as investor beliefs in the fraud propensity equation. We find that short-term compensation is significantly positively related to the probability of fraud, while long-term compensation is significantly negatively related to the probability of fraud. Overall, these findings support the predictions in Hertzberg (2005).

Nevertheless, investor beliefs about business conditions continue to be concave in fraud propensity after controlling for compensation structure. This suggests that monitoring and compensation mechanisms are both at work when a firm has its IPO.[15]

7. THE IMPACT OF UNCERTAINTY

Kumar and Langberg (2008) predict that fraud is more likely in industries of high uncertainty, regardless of the level of investor beliefs (Hypothesis 4). In this section we investigate the impact of industry-specific uncertainty on the relationship between fraud and investor beliefs highlighted by Kumar and Langberg (2008). 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 forecasts, captures

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[15] Several recent papers have found that firms with high pay-for-performance sensitivities (PPS) are more likely to commit fraud (e.g., Burns and Kedia, 2006, and Peng and Röell, 2008); however, Armstrong, Jagolinzer and Larcker (2008) find evidence that equity incentives reduce fraudulent reporting. As a robustness check (not tabulated), we also examine the effect of PPS in our IPO fraud context by including in the fraud propensity equation the industry median PPS from *new* option grants and equity compensation, as well as the industry median PPS from *new and past* option grants and equity compensation, respectively. While PPS from *new and past* equity compensation is less appropriate in this set of tests because past equity compensation should not be affected by current investor beliefs about business conditions, neither of the two PPS variables is statistically significant. This discrepancy between our finding and those in the earlier literature may arise for several reasons. First, industry median PPS is only a noisy proxy for firm-level PPS; on the other hand, we do find significant effects of industry short- and long-term compensation as predicted by Hertzberg (2005). Second, PPS may be less important in determining a firm's fraud propensity during its IPO, which is consistent with the findings of Lowry and Murphy (2007). In addition, using hand-collected compensation data from the first available proxy statement after the IPO for 78 fraudulent IPOs and 78 industry- and size-matched non-fraudulent IPOs, we find that compared to the industry median firm, IPO firms tend to have a higher fraction of short-term (cash) compensation, a lower fraction of long-term (equity) compensation, but no significant difference in the pay-for-performance sensitivity. The lower fraction of long-term (equity) compensation may be due to the fact that managers of an IPO firm still hold a substantial amount of the firm's equity right after IPO. There is no significant difference in the level of pay or the structure of pay between the fraudulent IPO sample and the control sample. Finally, our findings may be evidence in support of the findings in Armstrong, Jagolinzer, and Larcker (2008).

uncertainties arising from investors' beliefs about business conditions. Both proxies are measured at the year when the fraud is committed. Results are reported in Table 7.

Panel A of Table 7 reports results using the cash flow volatility variable. Model 1 of Panel A reveals that, inconsistent with Hypothesis 4, 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. The concavity is weaker in the low-uncertainty group, which is probably because industries with low cash flow uncertainty do not have extremely high investor beliefs.

Cash flow volatility may not be as good a measure of the investor uncertainty about business conditions as the dispersion in EPS 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, uncertainty's effect is insignificant.

8. ROBUSTNESS

8.1 Alternative Sample Specifications

8.2.1 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 Table 3. 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 3.[16] Our results hold. These robustness analyses suggest that industry classification about internet firms does not affect our results.

8.2.2 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 3005 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 3 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 3. Our results are robust to this sample restriction. Our results also remain unchanged when we use the alternative cutoff of the bottom 25%.

8.2.3 Accounting-Related vs. Non-Accounting-Related Frauds

[16] 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.

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.

8.2 Fundamental Industry Differences and Time Effects

It is possible that industries have different average industry EPS growth rates due to fundamental differences in financial leverage. To check the robustness of our results, 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 bi-probit model. 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 less likely to be driven by the cross-sectional differences in industry growth rates.

It is also possible that there are economy-wide effects that affect all industries in certain years. This is fine with our study, 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. Nevertheless, to control for the 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 year effect in "Ind. EPS Growth" over time. As a variation to the above specification, we retain the original "Ind. EPS Growth" specification but include year fixed effects. Our main results hold under these alternative specifications.

8.3 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 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.

In unreported regressions, we include the annual SEC budget normalized by the number of securities issued in a given year to control for the constraint of SEC's resources. We find that after controlling for the SEC's resources, the hump-shape relationship between fraud propensity and investor beliefs holds. The impact of SEC monitoring on fraud propensity is not significant.

8.4 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 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 3 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 to those using EPS growth. This may reflect the fact that long-term forecasts are likely to be noisier than short-term ones.

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 "(*Ind. Book-Building*)$^{-1}$" with *OAL* and re-estimate our results. Our findings remain unchanged.

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.

8.5 Other Robustness Tests

As described in detail in the internet appendix of this paper, our results are also robust to alternative definitions of the presence of venture capitalists in IPO firms, additional control variables such as sales growth and accounting accruals (Beneish 1999), and to alternative specification of the timing of the IPO fraud. In addition, our findings are not driven by alternative hypotheses such as variation in underwriters' exposure to litigation.[17]

9. CONCLUSIONS

In this paper we use a sample of firms that went public between 1995 and 2002 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 models 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 consistent with 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 high level of industry expertise. Also, short-term compensation generally has a positive and significant impact on a firm's fraud propensity, as predicted by Hertzberg. Nevertheless, the level of investor beliefs on fraud continues to have an independent, hump-shaped impact on the incidence of fraud even after controlling for executive compensation.

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, thoug 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).

Finally, we evaluate the role of the uncertainty of investor beliefs. We find evidence partially consistent with Kumar and Langberg (2008) that high uncertainty increases the *average* incidence of fraud, although the marginal effect is not significant after controlling for the level of

[17] Additional discussions, extensions, and robustness results are available at the internet version of the paper: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1024229.

investor beliefs. This suggests that uncertainty may play a secondary role in affecting the incidence of fraud.

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.

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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 Fama-French 49 industry classification.	IBES database	Industry median forecasted sales growth 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 1 if the year is in and after 2002, and 0 otherwise		
Ind. Litigation	Log of total market value of all litigated firms in an industry in a year (from our litigation 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	This variable is measured at the average of the information in the IPO year and in the two years after IPO.
Return Volatility	Standard deviation of daily stock returns	CRSP	This variable is measured at the average of the information in the IPO year and in the two years after IPO.
Stock Turnover	Number of shares traded in a year divided by the number of shares outstanding.	CRSP	This variable is measured at the average of the information in the IPO year and in the two years after IPO.
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	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. CF Uncertainty	Industry median standard deviation of operating cash flow (scaled by total book assets) in the previous 10 years.	COMPUSTAT	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. Belief Dispersion	Industry median of firms' EPS growth forecast dispersion.	IBES	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.
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 offices of the Wharton School and Columbia University	
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 1: 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	3297	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.

Beginning Year	**Ending 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 2: 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)	3005	0.153 (0.176)	2.652**
(Ind. Book-Building)$^{-1}$	110	1.408 (1.445)	3005	1.399 (1.402)	1.179
Ind. Q	110	2.074 (2.357)	3005	2.041 (2.264)	0.689
Assets (Millions)	110	103.9 (5436)	2766	89.06 (711.4)	1.263
Ind. Litigation	110	66.20 (132.13)	3005	49.72 (108.8)	2.418*
Stock Return	110	-0.234 (-0.151)	3005	0.046 (0.006)	-5.604**
Return Volatility	110	0.049 (0.055)	3005	0.046 (0.051)	1.769^{+}
Stock Turnover	110	1.464 (1.817)	3005	1.194 (3.014)	2.962**
Ind. ST Incentive	110	0.610 (0.607)	3005	0.621 (0.615)	-0.981
Ind. LT Incentive	110	0.332 (0.325)	3005	0.315 (0.321)	1.326
Ind. CF Uncertainty	110	0.146 (0.155)	3005	0.133 (0.153)	0.510
Ind. Belief Dispersion	110	2.595 (2.787)	3005	2.117 (2.640)	1.352
VC Backed	110	1.000 (0.528)	3005	0.000 (0.452)	1.548
VC Specialty Score	107	0.029 (0.206)	2930	0.000 (0.198)	0.974
IB Specialty Score	110	0.083 (0.137)	3005	0.111 (0.196)	-3.384**
IB Hiring	110	0.554 (0.933)	3005	0.554 (0.788)	1.414
IB Employment	110	3.454 (6.483)	3005	3.454 (5.430)	1.279
IB Ranking	110	8.501 (7.989)	3000	8.100 (7.512)	1.993*

Table 3: Investor Belief and Firms' Propensity to Commit Fraud at IPO

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. Model 4 is a spline regression with cutoff points being the quintile break points for Ind. EPS Growth. **, * and + indicate significance at 1%, 5% and 10% levels respectively.

P(F=1)	(1)	(2)	(3)	(4)
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]	
EPS Spline 1 (lowest belief)				3.048*
				[1.428]
EPS Spline 2				7.602
				[6.739]
EPS Spline 3				21.380*
				[8.647]
EPS Spline 4				-2.022
				[2.133]
EPS Spline 5 (highest belief)				-1.418$^+$
				[0.808]
Log(Assets)	0.133**	0.087**	0.109**	0.128**
	[0.051]	[0.028]	[0.030]	[0.046]
After SOX	1.397	0.254	0.154	1.085
	[0.816]	[0.135]	[0.119]	[0.821]
Constant	-4.113**	-3.891**	-4.213**	-3.883**
	[1.020]	[0.559]	[0.608]	[0.904]
P(D=1|F=1)				
Ind. Litigation	0.002**	0.001**	0.001**	0.002**
	[0.001]	[0.0003]	[0.0004]	[0.001]
Stock Return	-0.861*	-0.739**	-0.708**	-0.848*
	[0.352]	[0.199]	[0.178]	[0.352]
Return Volatility	16.257	3.575**	4.092**	16.158
	[13.717]	[1.205]	[0.979]	[11.428]
Stock Turnover	0.070	0.252**	0.208**	0.086
	[0.064]	[0.070]	[0.048]	[0.084]
Log(Assets)	0.109	0.134**	0.129**	0.078
	[0.063]	[0.034]	[0.033]	[0.073]
After SOX	-0.470	0.269*	0.277*	-0.673
	[0.517]	[0.118]	[0.124]	[0.475]
Constant	-3.694*	-4.902**	-4.804**	-2.480
	[1.711]	[0.742]	[0.714]	[1.978]
Observations	2876	2876	2876	2876
Pseudo-likelihood	-433	-430	-431	-428

Table 4: Investor Belief, Incentive of Venture Capitalist and Fraud at IPO

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 the "VC Backed" dummy variable and "VC Specialty Score" with each quintile of the investor belief proxy, "Q#_EPS" corresponds to the quintiles 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]
(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	2801	2801	2876	2876
Log pseudo-likelihood	-421	-413	-433	-430

Table 5: Investor Belief, Incentive of Underwriters and Fraud at IPO

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 the "IB Specialty Score" with each quintile of the investor belief proxy, "Q#_EPS" corresponds to the quintiles 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]
(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	2872	2872	2876	2872
Log pseudo-likelihood	-437	-435	-401	-401

Table 6: Investor Beliefs, CEO Compensation, and 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.

Panel A

This table reports firm fixed effect regressions of executive compensation on contemporaneous investor beliefs about business conditions (the industry median EPS growth forecast). All firm characteristics are lagged. The Huber-White-Sandwich robust clustered standard errors are reported.

	(1) ST Incentive	(2) LT Incentive
Ind. EPS Growth	0.090**	-0.088**
	[0.017]	[0.016]
(Ind. EPS Growth)^2	-0.070**	0.070**
	[0.014]	[0.013]
Sales Growth	-0.010	0.007
	[0.011]	[0.011]
ROA	-0.120**	0.106**
	[0.042]	[0.041]
Stock Return	-0.008	0.006
	[0.004]	[0.005]
Tobin's Q	-0.011**	0.014**
	[0.003]	[0.004]
Log(Assets)	-0.075**	0.091**
	[0.005]	[0.005]
Constant	2.150**	-1.564**
	[0.114]	[0.113]
Observations	18531	18531
Number of Firms	2727	2727
R-squared	0.033	0.043

Table 6 continued.

Panel B

P(F=1)	(1)	(2)	(3)	(4)	(5)	(6)
Ind. ST Incentive	1.368**		1.998**		2.832**	
	[0.366]		[0.563]		[0.688]	
Ind. LT Incentive		-1.373**		-1.850**		-1.637*
		[0.340]		[0.584]		[0.759]
Ind. EPS Growth	1.913**	2.324**				
	[0.457]	[0.521]				
(Ind. EPS Growth)^2	-2.771**	-3.290**				
	[0.665]	[0.722]				
(Ind. Book-Building)$^{-1}$			1.508**	1.281**		
			[0.546]	[0.300]		
((Ind. Book-Building)$^{-1}$)^2			-0.277**	-0.234**		
			[0.099]	[0.055]		
Ind. Q					1.311**	1.538**
					[0.276]	[0.262]
(Ind. Q)^2					-0.228**	-0.270**
					[0.048]	[0.046]
Log(Assets)	0.090**	0.090**	0.129**	0.100**	0.112**	0.088**
	[0.035]	[0.031]	[0.032]	[0.031]	[0.031]	[0.033]
After SOX	0.353**	0.342**	0.590**	0.443**	0.171	0.284**
	[0.119]	[0.117]	[0.204]	[0.136]	[0.138]	[0.108]
Constant	-4.087**	-2.829**	-6.448**	-3.865**	-6.574**	-4.231**
	[0.743]	[0.498]	[1.155]	[0.632]	[1.108]	[0.664]
P(D=1|F=1)						
Ind. Litigation	0.002**	0.002**	0.002**	0.002**	0.001**	0.001**
	[0.0004]	[0.0004]	[0.0004]	[0.005]	[0.0003]	[0.0002]
Stock Return	-0.694**	-0.705**	-0.727**	-0.737**	-0.735**	-0.660**
	[0.180]	[0.176]	[0.188]	[0.186]	[0.226]	[0.164]
Return Volatility	5.195**	5.843**	10.945**	6.986**	3.884**	2.414*
	[1.343]	[1.523]	[3.592]	[1.761]	[1.184]	[1.189]
Stock Turnover	0.142**	0.148**	0.114**	0.158**	0.200**	0.168**
	[0.037]	[0.042]	[0.038]	[0.039]	[0.044]	[0.042]
Log(Assets)	0.113**	0.116**	0.141**	0.132**	0.132**	0.070*
	[0.039]	[0.035]	[0.040]	[0.035]	[0.033]	[0.035]
After SOX	0.262*	0.269*	0.326**	0.292*	0.257*	0.265*
	[0.110]	[0.112]	[0.124]	[0.130]	[0.119]	[0.112]
Constant	-4.437**	-4.523**	-5.139**	-4.875**	-4.804**	-3.538**
	[0.815]	[0.754]	[0.932]	[0.761]	[0.703]	[0.707]
Observations	2866	2866	2866	2866	2866	2866
Log pseudo-likelihood	-433	-433	-429	-431	-429	-438

Table 7: 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	2876	1370	1506
Median Predicted P(F=1)		8.09%	8.40%
Wilcoxon Z-score for difference between (2) and (3)		-0.793	

Table 7 continued.

Panel B: Industry EPS Growth Forecast Dispersion

For each year and each industry, "Ind. Belief Dispersion" is the industry median of firms' 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	2876	1423	1453
Median Predicted P(F=1)		6.97%	8.31%
Wilcoxon Z-score for difference between (2) and (3)		-8.137**	

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. ESP Growth").