Internet Appendix for

"Corporate Fraud and Business Conditions: Evidence from IPOs" [*]

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This supplement document contains a detailed description of various robustness tests and extensions of the paper.

I. Robustness

A. Alternative Sample Specifications

A.1. Internet IPO Firms As a Separate Industry

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

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

A.2. False Detection

Many papers have used lawsuits to proxy for the presence of corporate financial fraud (e.g., Beasley (1996), Beasley, Carcello, and Hermanson (1999), and Li (2008) use AAERs; Helland (2004), Srinivasan (2005), Fich and Shivdasani (2007), and Peng and Röell (2008) use class action lawsuits). A disadvantage of using lawsuits as a 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 subsample thus contains 30 IPO frauds and 3,005 non-fraudulent IPOs. We observe the same concave relationship between investor beliefs and the propensity of fraud. The coefficient on *Ind. EPS Growth* in Model 1 of Table III is 3.775 (p = 0.06), and that on the squared term is -10.804 (p = 0.02).

Finally, frivolous lawsuits, by definition, are lawsuits associated with low probabilities of fraud being actually committed. As another robustness test of our results, we first use Model 1 in Table III to predict the fraud propensity at the IPO stage for each sample firm. We then exclude firms in our IPO fraud sample (i.e., Z=1) that have low predicted fraud propensities (i.e., in the bottom 10% of the distribution), as they are most likely to be wrongly sued according to our

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

model. Next, we re-run the base models in Table III. Our results are robust to this sample restriction. For example, for Model 1 in Table III, the coefficient on *Ind. EPS Growth* is 3.695 (p = 0.00), and the coefficient on (*Ind. EPS Growth*)^2 is -5.10 (p = 0.00). Our results also remain unchanged when we use the alternative cutoff of the bottom 25%.

A.3. Accounting-related vs. Non-accounting-Related Frauds

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

A.4. Subsample Analysis

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

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

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

B. Fundamental Industry Differences and Time Effects

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

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

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

C. Monitoring by the SEC

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

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

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

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

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

D. Alternative Proxies for Investor Beliefs

To capture the varying level of institutional investors' optimism, in the main article we use 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 III and IV using several alternative proxies.

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

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

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

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

E. Other Robustness Tests

E.1. Additional Control Variables

Since we use class action lawsuits and SEC litigations instead of earnings irregularities as proxies for detected fraud, fraud detection in our study is closely related to triggers of securities litigation. In our detection equation of the bivariate probit model, we include firm-specific and industry-related time-varying factors that are known to affect a firm's litigation risk. The time-varying firm-specific and industry-specific variables in our detection equation should also be correlated with accounting measures identified in the accounting literature.

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

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

- Days Sales in Receivables Index: $DSRI = \frac{(receivables/sales)_t}{(receivables/sales)_{t-1}}$

- Gross Margin Index: $GMI = \frac{((sales - COGS)/sales)_{t-1}}{((sales - COGS)/sales)_t}$

- Asset Quality Index: $AQI = \frac{(1 - (CurrentAssets - NetPPE)/TotalAssets)_t}{(1 - (CurrentAssets - NetPPE)/TotalAssets)_{t-1}}$

- Sales Growth Index: $SGI = \frac{sales_t}{sales_{t-1}}$

- Accruals to Total Assets: $TATA = \frac{TotalAccruals_t}{TotalAssets_t}$, where Total Accruals is defined as Current Assets – Cash – Current Liabilities – Current Maturities of Long-term Debt – Income Taxes – Depreciation and Amortization.

As Table IA.III indicates, our main results are robust to the inclusion of these accounting measures.

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

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

E.2. Alternative Regression Specification

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

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

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

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

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

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

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

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

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

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

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

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

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

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

We find from Table IA.V that neither the fraction of IPOs backed by a venture capitalist or *VC Specialty Score* change monotonically as investor beliefs rise. In addition, the distribution of VC-backed IPOs across investor belief quintiles indicates that our regression results are not driven by a few observations with unique characteristics or extreme values.

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

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

E.5. Underwriter's Monitoring Incentives

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

Underwriters themselves can be subject to lawsuits alleging fraud in the IPO process. Can our results for *IB Specialty Score* be caused by private securities lawyers' incentive to chase the "deep pockets" of large underwriters? We explore this possible alternative interpretation in three ways.

First, we include in regressions in Table VI only IPO firms with lead underwriters whose market share ranks greater than the sample mean of 7.5 (i.e., large underwriters with potentially deep pockets). *IB Specialty Score* is still negatively (-0.466) and significantly (p = 0.01) related to the fraud propensity. Second, as noted in Section I.A.2 of this Internet Appendix, we focus on SEC AAER lawsuits, which are less likely to be subject to the deep pockets concern. We find that the impact of investment bank specialty on fraud is again significant: more skilled investment banks reduce the probability of fraud (coefficient is 1.952 and p = 0.00). Finally, in the subsample analysis (the 1995 to 2002 IPOs), 31 out of 78 IPO fraud cases named the lead underwriters as codefendants. We find that *IB Specialty Score* is not significantly different between these 31 cases and the rest of the IPO fraud cases, implying that *IB Specialty Score* is not strongly correlated with the probability of underwriters being sued. These results confirm our view that greater investment bank specialization leads to lower fraud.

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

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

To check the robustness of the hump-shaped relationship between fraud propensity and investor beliefs as predicted in PSW, we report the characteristics of IPOs and fraud within each quintile of investor belief variables in the raw data set. To ensure that this hump-shaped relationship is not driven by a few observations with extreme values within a particular quintile, Table IA.VII reports the number of IPOs, number of unique industries, and number of unique years in addition to the fraction of IPOs associated with fraud for each quintile.

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

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

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

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

II. Extensions

A. Uncertainty of Investor Beliefs and Propensity for Fraud

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

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

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

In Models 2 and 3 we classify industries into low and high uncertainty groups, respectively, based on the sample median of the industry cash flow volatility. We then re-run our bivariate probit regression for each subsample. 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 and high uncertainty industries.

Cash flow volatility may not be as good a measure of investor uncertainty about business conditions as the dispersion in EPS growth forecasts, so in Panel B we capture industry uncertainty using the latter measure. Our findings are similar to those in Panel A: controlling for uncertainty does not change the concave relationship between investor beliefs and the 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 subsamples.

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

B. Consequences of IPO Frauds

B.1. Failure Rates of IPO Frauds

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

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

B.2. Post-IPO Frauds

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

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

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

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

III we include *Firm EPS Growth*, the consensus EPS growth forecast at the firm level, as a measure of firm-specific investor beliefs.

Results are reported in Table IA.X. We observe that the coefficient on the hot IPO industry dummy is positive and significant. This indicates that firms going public during periods of high investor beliefs have a higher likelihood of committing fraud post-IPO. Our result thus provides evidence consistent with PSW: a higher portion of bad firms raised capital through their IPO without committing fraud during the period of high investor beliefs than during the period of low investor beliefs.[7]

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

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

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Table IA.I
Abnormal Investor Beliefs

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

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

Table IA.II
Controlling for the SEC's Capacity

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

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

Table IA.III
More Controls in Fraud Detection Equation

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

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

Table IA.IV
Probit Specification

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

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

Table IA.V
Summary Statistics of VC Backing by Investor Beliefs Quintiles

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

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

Table IA.VI
Controlling for VC Firm's Age at IPO

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

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

Observations	2,778	1,299
Log pseudo-likelihood	-407	-192

Table IA.VII
Investor Beliefs and Incidence of IPO Fraud

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

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

Table IA.VIII
Investor Beliefs, Uncertainty and Fraud

The dependent variable is the dummy variable Z, where Z=1 if a firm committed fraud at the IPO stage and then got caught later, and Z=0 otherwise. The 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 Huber-White-Sandwich robust standard errors clustered by industry (in square brackets) are reported. **, *, and + indicate significance at the 1%, 5%, and 10% levels, respectively. In Panel A, 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 and high uncertainty groups based on the overall sample median industry cash flow uncertainty. In Panel B, for each year and each industry, *Ind. Belief Dispersion* is the industry median of analysts' EPS growth forecast dispersion. We group industries into low and high uncertainty groups based on the overall sample median industry EPS growth forecast dispersion.

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

difference between (2) and (3)

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

Table IA.IX
Status of Alleged Fraudulent Firms

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

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

Table IA.X
Investor Beliefs and Firms' Propensity to Commit Fraud Post-IPO

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

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