Information Precision and Long-Run Performance of Initial Public Offerings

Frank Ecker*
(Duke University)

IPO firms' information precision is not only generally low, but also likely to be initially estimated with considerable error due to a lack of an information history. I find that the deviation between expected and realized information precision is predictably associated with the magnitude and the persistence of long-run abnormal returns after an IPO. An initial underestimation (overestimation) of information precision results in positive (negative) abnormal returns over the period investors update their beliefs. The positive abnormal returns of firms with unexpectedly high information precision are less persistent than the negative abnormal returns of firms with unexpectedly low information precision.

* Fuqua School of Business, Duke University, Durham, NC 27708. Email: frank.ecker@duke.edu. I thank Liesbeth Bruynseels, Jennifer Francis, Holger Haaf, Hellmuth Milde, Per Olsson, Katherine Schipper, Hartmut Wächter and seminar participants at Duke University, the Swedish Institute for Financial Research (SIFR), the Tilburg University Spring Camp, and the University of Trier for their helpful comments and suggestions.

Information Precision and Long-Run Performance of Initial Public Offerings

1. Introduction and Motivation

This study proposes and tests an information-precision-based explanation for both the existence and the persistence of long-term positive and negative abnormal returns following initial public offerings (IPOs). Starting with Ritter (1991), who reported average negative abnormal returns over the three years following an IPO, previous research has focused on documenting explaining the existence (or non-existence) of long-term underperformance in broad samples. However, even if the average IPO firm underperforms, individual IPO firms exhibit both negative and positive long-term abnormal returns. I propose that cross-sectional differences in the abnormal performance of IPO firms can be explained by deviations between ex-ante expected and ex-post realized information precision parameters. I focus on information precision for two reasons. First, prior analytical and empirical research provides evidence of information precision being a determinant of stock prices in equilibrium. Second, and more importantly for this study, I expect investors to estimate this pricing parameter with considerable error at the time of the IPO, due to the arguably little or no public information history about fundamentals (Epstein and Schneider (2008)). In the time after the IPO, investors gradually adjust their prior beliefs towards the firm's realized information precision, leading to abnormal returns during the adjustment period.

IPO firms with initially overestimated information precision (and thus underestimated cost of equity capital) earn significant negative post-IPO abnormal returns, while the opposite is true for firms whose information precision has been underestimated at the time of the offering. They earn significantly positive abnormal returns. In addition, I find that positive post-IPO abnormal returns are significantly less persistent than negative abnormal returns, consistent with investors updating their beliefs faster when realized information signals are of higher precision.

I hypothesize that, at the time of the offering, investors assess the information precision of IPO firms in an unbiased fashion, but with considerable error, because of the lack of firm-specific information preceding the offering. To draw general inferences about the credibility of information both from and about a given firm, it is essential to calibrate estimates of future performance against subsequent realizations. Although firms provide one to three years of financial statements in the offering prospectus (Regulation S-X), the usefulness of these statements for the assessment of information precision is limited for at least two reasons. First, firms may restate their financial statements for the offering prospectus (APB Opinion No. 20, SFAS No. 154, Teoh, Welch and Wong (1998)). Second, and more importantly, there are generally few or no public announcements and/or records of public announcements for the period preceding the public offering. Thus, realized values as documented in the financial statements at the time of the offering cannot be used to confirm earlier announcements.

As a result, while information precision has been shown to have significant pricing implications for broad samples of firms in equilibrium (e.g., Francis, LaFond, Olsson and Schipper (2004, 2005), Lambert, Leuz and Verrecchia (2007, 2008), Epstein and Schneider (2008)), information precision for an IPO firm is largely unknown at the date of the offering and needs to be assessed by investors before a pricing equilibrium can be reached. In contrast to standard Bayesian updating of prior beliefs using signals of limited, but known precision, Epstein and Schneider (2008) model investors as also being uncertain ("ambiguous") about the information precision. I identify initial public offerings as a setting in which investor ambiguity about the information precision is arguably large and hard to resolve at the time of the IPO. Therefore, I hypothesize that investors have to condition IPO prices not only on an expected value for future information *per se*, but also on an expected value for future information *precision*. The dissemination of information about realized outcomes in the post-IPO period enables investors to update their initial estimates of information precision and to decrease their uncertainty about information precision. Each new piece of post-IPO information will be judged, partially, as either confirmation or revision of earlier announcements and will be used to update the perceived precision of previous, current and future information. During this learning process, investors replace their expected values with realized information precision parameters.

My main hypothesis is that the deviation between expected and realized information precision is associated with differences in abnormal long-run performance of IPO firms. If the realized information precision is lower (higher) than the expected information precision, the stock price will decline (increase) as more information becomes available. This updating process leads to a negative (positive) abnormal return over a potentially lengthy period after the offering.

My analysis is based on a sample of 6,766 initial public offerings from 1980 to 2006. The empirical distribution of the 6,766 firm-specific deviations of the realized information precision parameter from the expected information precision parameter (hereafter, *Deviation*) shows only a negligible systematic error. The median *Deviation* is indistinguishable from zero, suggesting that investors rationally assess the information precision parameter for the typical IPO firm. Consistent with this finding, the average IPO firm in my sample does not exhibit any abnormal performance over my sample period. There is, however, considerable cross-sectional variation in *Deviation*. This finding provides evidence that there is considerable error in the estimate of information precision for some IPO firms. Similarly, there is substantial cross-sectional variation in abnormal returns that is systematically associated with the deviation variable. For example, value-weighted calendar-time portfolios containing the quartile of IPO firms with the most overestimated information precision earn an abnormal return of -0.90% per month (t = -2.50) over and above the Fama and French (1993) 3-factor model during the year after the IPO. In contrast, the firms with the most underestimated information precision show a significant positive return of 1.20% per month (t = 4.28). These abnormal returns decline over the two to three years following the IPO, consistent with investors gradually correcting their prior beliefs about information precision as more information arrives. With the updating becoming more complete, the magnitude of abnormal returns diminishes.

Higher-quality realized information should cause faster updating of information precision. Consequently, the positive abnormal returns of firms with unexpectedly high information precision should be less persistent than the negative abnormal returns of firms with unexpectedly low information precision. Consistent with this prediction, I find that the positive abnormal returns for firms with initially underestimated information precision are limited to the first ten months after the IPO, whereas negative abnormal returns are significant for up to 18 months.

In summary, this study proposes an explanation for why some IPO firms outperform while others underperform. Overall, the results are consistent with an efficient market under information precision, where rational investors place a low weight on highly imprecise information and increasingly more weight on increasingly more precise information. They are also consistent with Epstein and Schneider's (2008) model in that investors impute expected future information precision in today's prices. In fact, the empirical evidence in this paper suggests investors who gradually learn about the precision of information itself. The apparent abnormal stock market performance is therefore a reflection of rational investor caution in the pricing of a newly public firm with little or no information history.

The rest of the paper is arranged as follows. In Section 2, I derive the hypotheses on the cross-sectional differences in abnormal returns and connect my paper to prior research on methodological issues in the estimation of long-term abnormal returns. In Section 3, I describe the selection of IPO firms and the construction and empirical validation of the main variables, and provide descriptive statistics on the calendar-time portfolios for the main tests. The main results on the portfolio level and important extensions are discussed in Section 4, followed by robustness checks in Section 5. Section 6 concludes.

2. Hypotheses Development and Prior Research

2.1 Hypotheses Development

My framework for investor pricing of IPO firms assumes that a firm's value is based on the information that is available about that firm. If the information set is complete and each piece of information is precise, rational investors will correctly value the firm. New value-relevant information, by definition, changes investors' estimates of discounted future cash flows, whereas the cost of capital only changes if new information induces a change in the perceived riskiness of future cash flows.

Using this traditional framework as a starting point, information "risk" could be defined in two ways. First, the information set about the firm could simply be incomplete.[1] In other words, there might be information asymmetry either between management and market participants or between different groups of market participants. Second, the information about a specific firm might be imprecise. In an equilibrium model of a perfectly competitive market, Lambert, Leuz and Verrecchia (2008) explore the respective effects of information asymmetry and information precision on the cost of capital. They conclude that, while both definitions of information risk are not necessarily mutually exclusive, it is the average information precision that has direct pricing consequences. A change in information asymmetry will only affect the cost of capital to the extent that the average information precision changes simultaneously.

However, while standard Bayesian theory (and Lambert et al.'s equilibrium analysis) assumes that the precision of new information is known, Epstein and Schneider (2008) formalize the idea of a second dimension of potential uncertainty, which they label investor ambiguity. In their model, investors not only face potentially imprecise information, but are also uncertain about the signal's precision itself. Depending on the information content, good or bad, investors will revise their expectation about the precision of future information, and immediately impute this revision into current prices. In other words, a change in expected information precision will have immediate expected returns consequences.

---

[1] This is different from Merton (1987), who assumes some investors are unaware of certain stocks. In contrast, this approach assumes that all investment opportunities are known, but some investors might lack pieces of information about specific firms.

Based on Epstein and Schneider's (2008) argument, I assume that new information is not only used to update expectations about the future, but also to confirm or correct previously released information, thereby helping investors to make ex-post assessments of the (perceived) information precision. I hypothesize that this updated perceived information precision is the new expected future information precision with immediate pricing consequences. While confirming signals do not induce investors to revise their estimates of future cash flows, they potentially increase the perceived information precision, thereby leading to lower expected returns. In turn, correcting signals might cause investors to revise their beliefs about fundamentals and also change the perceived information precision, and therefore the perceived riskiness of cash flows.[2]

Building on this recent theoretical research, I offer and test an explanation for IPO abnormal returns that builds on rational investors who not only face imprecise information, but are also uncertain about the information precision per se. Investors are assumed to form an expected value of information precision based on available information. I argue that, due to the lack of information history of IPO firms, investors knowingly *estimate* this pricing parameter at the time of the IPO with potentially considerable error. After the IPO, the firm publicly disseminates information, both directly to the market (e.g., quarterly financial results, ad-hoc announcements, etc.) and indirectly through analysts. As investors receive this new information, they gradually revise their prior beliefs, converging toward the firm's realized information precision parameter. Assuming rational expectations, the expected value for information precision should, on average, equal the realized information precision, although individual firms would be expected to have positive or negative deviations between the realizations and the expectations. If investors' prior belief is an overestimation of the information precision and the initial expected return is consequently too low, the stock price should decline; i.e., there will be negative abnormal returns in the

---

[2] During this process of assessing the correct information precision parameter for IPO pricing, realized returns and expected returns will be affected in opposite directions. A decrease in information precision will lead to higher expected returns and lower realized returns over individual IPO firms' holding periods. Hence, in this non-equilibrium setting, realized returns cannot be used as proxies for expected returns.

post-IPO period as investors revise downward their information precision assessment. If, on the other hand, investors underestimate information precision and assume too high an expected return, there will be positive post-IPO abnormal performance. This explanation can thus predict both negative and positive abnormal returns following IPOs.

My second hypothesis – on the persistence of the abnormal returns – builds on the first. In general, more precise post-IPO information should allow for a faster assessment of the true information precision of an IPO firm, while less precise information requires waiting for further confirmative signals to be imputed into price. Building on the result in Ecker et al. (2006) that the average IPO firm has low information precision relative to more seasoned firms, I hypothesize that abnormal returns of IPO firms can persist for an extended time period. I further predict that the abnormal return persistence is linked to the direction and magnitude of the “surprise” in the information precision parameter in the following way. If investors’ expectation for the information precision parameter is too high and requires a downward adjustment, investors will be negatively surprised by the low information precision and therefore more cautious in relying on new pieces of information. In other words, while a Bayesian investor would only impute a portion of the entire value implications into current price when information is imprecise, this portion will be even lower when the new information is even less precise than initially expected. If, on the other hand, the information precision was initially underestimated, the value implications of previous and current information were not adequately incorporated into price. Greater-than-expected precision of new information creates a quicker resolution of the uncertainty about the true information precision, shortening the period of (positive) abnormal returns. In summary, if the sign of the surprise in the information precision parameter determines the sign of the long-run abnormal performance, negative abnormal returns should be more persistent than positive abnormal returns.

To summarize, I identify the IPO market as a *non*-equilibrium setting[3] in which I expect both pronounced deviations between expected and realized information precision *and* a low level of information precision for individual firms. While these deviations are hypothesized to explain pronounced deviations between expected and realized returns, the generally low information precision for these young firms is assumed to prevent a quick adjustment process, making it possible for abnormal returns to persist over a lengthy period after the IPO. As investors learn to reliably assess information precision over time, both deviations are hypothesized to decline.

2.2 Literature on Long-term Abnormal (IPO) Performance

Beginning with Ritter (1991), researchers have found that the average buy-and-hold return of IPO stocks is significantly lower than the average return of non-IPO firms of similar size. One stream of research takes the underperformance as given and develops explanations for it. Eckbo and Norli (2005), and Benninga, Helmantel and Sarig (2005) offer risk-based explanations for IPO firms' underperformance and argue that IPOs have lower risk than implied by an asset pricing model that is valid for seasoned firms only. Eckbo and Norli link the underperformance to the higher trading liquidity of IPO shares. Benninga, Helmantel and Sarig (2005) hypothesize that IPO firms have lower risk because the option to re-privatize is a larger portion of their value than is the case for seasoned firms. As the value of this

---

[3] It is important to note that, while I rely on Lambert et al.'s and Epstein and Schneider's evidence that information precision is (negatively) associated with expected returns, I neither probe this association on *equilibrium* (expected) returns, nor do I have to assume a specific functional form of this association. For example, the literature has proposed both a linear, additive association using asset pricing models (see, e.g., Francis, LaFond, Olsson and Schipper (2004, 2005), Core, Guay and Verdi (2008), Kim and Qi (2008), Ogneva (2008)) as well as a multiplicative association, where information (im)precision acts as a magnifier of fundamental risk (e.g., Yee (2006); Chen, Dhaliwal and Trombley (2007); Epstein and Schneider (2008)). On a second dimension, both theoretical and empirical research has also explored a direct association between information precision and expected returns as well as an indirect association through traditional risk factors (Lambert, Leuz and Verrecchia (2007); Bhattacharya, Ecker, Olsson and Schipper (2008)). As an indication for the insignificance of this question in my non-equilibrium setting, the abnormal return results on the portfolio level show little sensitivity to the inclusion an information precision factor in the asset pricing model (see Table 7).

option has a negative correlation to overall economic growth, IPO firms are considered less risky than seasoned firms.

Behavioral theories for post-IPO underperformance focus on overoptimism and undetected earnings management. Ritter (1991) explains the post-IPO underperformance with investor overoptimism. Teoh, Welch and Wong (1998) start with the premise of high information asymmetry between investors and issuers at the time of the offering. Their analysis of earnings components shows positive abnormal current accruals, which they interpret as managers intentionally overstating current accruals to boost the offer price. They argue that, as post-IPO accruals revert and thereby reveal their earnings management, investors bid down IPO firms' share prices. It should be noted that these explanations focus on IPO underperformance only, while my analyses focus on the cross-sectional variation of abnormal returns, independent of the center of this distribution. In particular, these four explanations are unable to accommodate systematic reasons for positive abnormal returns.

Another research stream questions, mostly on methodological grounds, the very existence of average IPO underperformance. Research on abnormal return measurement, including post-IPO returns, has not produced a consensus on a single methodology.[4] Fama (1998) argues, and Mitchell and Stafford (2000) provide corroborative evidence, that calendar-time portfolio regressions and/or average monthly abnormal returns as developed in Jaffe (1974) and Mandelker (1974) are preferred, as these methodologies neither overstate the magnitude of abnormal returns (independent of the sign), nor understate the associated standard errors (e.g., due to the lack of independence in the observations).

---

[4] A considerable body of research has considered the general question of what abnormal returns metric to use, for example, buy-and-hold abnormal returns, cumulative abnormal returns, or average abnormal returns (e.g., Fama (1998), Mitchell and Stafford (2000), Brav (2000), Barber and Lyon (1997), and Lyon, Barber and Tsai (1999). While model misspecification errors in abnormal returns will be compounded in buy-and-hold abnormal returns, the problem is less serious when abnormal returns are calculated monthly to arrive at cumulative or average abnormal returns. Conrad and Kaul (1993) add to this discussion by showing that long-term cumulative abnormal returns are susceptible to bid-ask-spread bounces in returns. Both average abnormal returns and intercepts of a calendar-time approach are robust against these two criticisms as they both average across potential misspecification errors in monthly observations (rather than cumulating or compounding them).

Loughran and Ritter (2000), however, argue that these methods can be of low power, making it more difficult to detect patterns in abnormal returns.

Based on this prior research, I use calendar-time portfolio regressions in my main tests, recognizing the conservative nature of this methodology. Briefly, a calendar-time portfolio mimics an investment strategy with periodic portfolio rebalancing, where an asset pricing model is used to control for risk. The result is a time-series of monthly portfolio returns that accounts for cross-correlation in the returns of IPO stocks because no inference is based on cross-sectional standard errors. This is of particular importance for my analysis as the IPO market expands and contracts over time ('hot' and 'cold' IPO markets).

3. Sample Construction and Test Design

3.1 Calendar-time Portfolio Construction and Average Abnormal Returns

I obtain a sample of initial public offerings from 1980 to 2006 from the Securities Data Company (SDC) database. Similar to Chemmanur and Paeglis (2005) and Lowry and Schwert (2004), I omit real estate investment trusts (REITs) (SIC 6798) and closed-end funds (SIC 6726); following Ritter (1991) and Teoh, Welch and Wong (1998), I exclude penny stocks with an offer price of one dollar or less and unit offerings. Monthly prices and returns as well as the number of shares outstanding from January 1980 to December 2007 are obtained from CRSP. I require sample firms to have data on CRSP within two calendar months after the offering month. Similar to Ritter (1991), I exclude the stock return from the IPO day to the end of the initial listing month; the returns series for the tests start in (calendar) Month 1 after the listing. I also exclude the months of and after any seasoned equity offering (SEO).[5] Delisting

[5] As prior literature has documented an abnormal performance following SEOs (see, e.g., Mitchell and Stafford (2000)), the inclusion of these events could potentially overstate the magnitude and especially the persistence of any post-IPO abnormal returns.

returns of firms that delist during the test periods are included if available on CRSP. Finally, I require at least 100 trading days with returns data on CRSP between Months 1 and 12 after the offering to calculate the event-time information precision proxies as described in Section 3.2.

The selection procedure yields a sample of 6,766 IPO firms. The year distribution in Table 1, Panel A, shows an increase in offerings until the mid-90s with a maximum of 643 firms in 1996. There are fewer issues in the early years of the sample period as well as in the early 2000s. Panel B is consistent with prior evidence in that IPOs cluster by industry. About 17% of the IPO are from the computer industry, followed by electronic equipment and restaurants with 445 and 422 issues, respectively.

This sample of firms is used to form monthly calendar-time portfolios for the test of long-term abnormal returns. For the full-sample descriptive results in this section, I require 12 firms to form an IPO portfolio. There is a sufficient number of firms to estimate abnormal returns from July 1980 to December 2007 (330 months). For the main tests, I form three different portfolios containing firms in Months 1 to 12 (1 to 24, 1 to 36) after their IPO, labeled '1 Year' ('2 Years', '3 Years') in the tables. For example, a firm with an IPO in June 1980 is included in the '1 Year' ('2 Years', '3 Years') calendar-time portfolios from July 1980 to June 1981 (1982, 1983).

Table 2 provides descriptive statistics on equal-weighted and value-weighted portfolios' excess returns over the risk-free rate and the number of firms included. The last row of each panel contains descriptive statistics on the average market capitalization of the firms in the portfolios. Panel A describes the time series when only one-year-old firms are included into the portfolios, and Panels B and C provide the same information for portfolios that also include two- and three-year-old firms.

Across all panels, excess returns to value-weighted portfolios exceed those of equal-weighted portfolios. Whereas the median (mean) excess return for value-weighted portfolios ranges from 1.32% to 1.44% (0.71% to 0.93%), the median (mean) equal-weighted excess return is 0.70% to 0.89% (0.22% to 0.43%). Firms of age 1 – 12 months are a subset of the firms of 1 – 24 months and those, in turn, are a subset of firms that are at most three years old. By definition, the number of firms in the portfolio is increasing over the panels, from 234 firms in the average '1 Year' portfolio to 559 in the average '3 Years' portfolio. The standard deviation of the returns series is therefore higher in Panel A, although the difference across panels is relatively small.

The monthly excess portfolio returns are the dependent variables in the asset pricing regressions.

$$R^{\#}_{p,m} - R_{F,m} = \alpha^{\#}_{p} + \beta^{\#}_{p}(R_{M,m} - R_{F,m}) + s^{\#}_{p}\, SMB_m + h^{\#}_{p}\, HML_m + \varepsilon^{\#}_{p,m} \tag{1}$$

The superscript # stands for either equal- or value-weighted. $R_{M,m}$ is the value-weighted CRSP market index, $R_{F,m}$ is the risk-free rate in month m. SMB_m is the monthly return on the zero-investment portfolio which is long in small firms and short in big firms; HML_m is the monthly return on the zero-investment portfolio which is long in high-BM firms and short in low-BM firms. In both specifications, the regression intercept $\alpha^{\#}_{p}$ is interpreted as the monthly abnormal return.

Table 3 presents the intercepts for value-weighted and equal-weighted calendar-time portfolios. Because research has used post-IPO investment horizons longer than three years, I show the abnormal returns on holding IPO stocks for up to five years after the initial offering. The 3-factor abnormal return estimates for value-weighted portfolios range from 0.02% to 0.39% per month, generally not significant. In contrast, all the alpha estimates for equal-weighted portfolios show negative signs, with the estimate on portfolio with firms no older than two years being significant (t = -2.71).

Although the center of the cross-sectional distribution of post-IPO abnormal returns does not have implications for my proposed explanation for post-IPO performance, I have reported both equal- and value-weighted results for the full sample for comparison with prior research. Overall, these differences in results between equal- and value-weighted portfolios are consistent with prior literature (e.g., Loughran and Ritter (1995), Brav and Gompers (1997), Mitchell and Stafford (2000), and Ritter and Welch (2002)). For my main tests, however, I concentrate on the value-weighted results for two reasons: First, Fama (1998) states that underperformance is restricted to very small firms. He argues that, as all asset pricing models including the 3-factor model have problems in explaining the returns of the smallest firms, the likelihood of an apparent underperformance induced by equal-weighting is higher. Value-weighting thus partially mitigates this “bad-model problem.” His second argument for value-weighting, also discussed by Brav, Geczy and Gompers (2000), is that this approach captures the total wealth effect for investors in the appropriate way. For these reasons, my main results are based on value-weighted portfolios. To further investigate the role of firm size in my results, I provide several robustness tests on both the portfolio and the firm-specific level (Subsections 5.1 and 5.4).

3.2 Empirical Proxies for Information Precision

My tests require an empirical proxy for both investors’ expectations of information precision at the time of an IPO and the realized information precision. Several empirical studies operationalize information precision using earnings quality metrics. For example, Francis, LaFond, Olsson and Schipper (2004) compare the pricing effects of various earnings quality metrics using the implied cost of capital metric by Brav, Lehavy and Michaely (2005).

My proxy for information precision is an event-time version of the returns-based earnings quality metric, e-loading, as developed in Ecker, Francis, Kim, Olsson and Schipper (2006). The e-loading is the firm-specific slope coefficient on an information-precision mimicking factor (*IPfactor*) from an asset pricing regression, and thus a returns-based representation of information precision. Ecker et al. consider several earnings quality metrics as underlying constructs for an *IPfactor*, and perform validity (association) tests of the respective loadings in various settings with arguably low information precision such as accounting restatements or accounting violation lawsuits.

E-loadings offer two advantages, relative to other earnings quality metrics in an IPO setting. First, e-loadings estimations do not require a time series of accounting data (which is simply not attainable for IPO firms). Second, using a time-specific *IPfactor* assures that e-loadings can be calculated in event time and are therefore applicable to corporate events that are not aligned in calendar time.

My primary underlying earnings quality metric for the construction of *IPfactor* is accruals quality (*AQ*), as defined by Dechow and Dichev (2002) and modified by McNichols' (2002). There are two reasons for this design choice: First, the construct validity tests in Ecker et al. (2006) show the superiority of e-loadings based on *AQ* compared to loadings based on the nine other metrics they consider. Second, accruals quality is explicitly not designed to capture only "discretionary" earnings quality, but incorporates the earnings quality effects that are due to the firm's fundamentals as well. This is important as prior literature pointed out that [6]

I follow the cross-sectional approach of Francis, LaFond, Olsson and Schipper (2005) and Ecker et al. (2006) and estimate Equation (2) over a minimum of 20 firms in a given industry[7] for all Compustat firm-years with the necessary data in fiscal years 1975 to 2006 (all variables are scaled by average total assets in fiscal year *T*).

$$CurAcc_{j,T} = \varphi_{0,T} + \varphi_{1,T}\, CFO_{j,T-1} + \varphi_{2,T}\, CFO_{j,T} + \varphi_{3,T}\, CFO_{j,T+1} + \varphi_{4,T}\, \Delta \mathrm{Re}v_{j,T} + \varphi_{5,T}\, PPE_{j,T} + \upsilon_{j,T} \qquad (2)$$

where $CurAcc_{j,T} = \Delta CA_{j,T} - \Delta CL_{j,T} - \Delta Cash_{j,T} + \Delta STDEBT_{j,T}$ = current accruals in year *T*;
$CFO_{j,T} = NIBE_{j,T} - TA_{j,T}$ = firm *j*'s cash flow from operations in year *T*;
$NIBE_{j,T}$ = firm *j*'s net income before extraordinary items (Compustat #18) in year *T*;
$TA_{j,T} = (\Delta CA_{j,T} - \Delta CL_{j,T} - \Delta Cash_{j,T} + \Delta STDEBT_{j,T} - DEPN_{j,T})$ = firm *j*'s total accruals in year *T*;
$\Delta CA_{j,T}$ = firm *j*'s change in current assets (Compustat #4) between year *T-1* and year *T*;
$\Delta CL_{j,T}$ = firm *j*'s change in current liabilities (Compustat #5) between year *T-1* and year *T*;
$\Delta Cash_{j,T}$ = firm *j*'s change in cash (Compustat #1) between year *T-1* and year *T*;
$\Delta STDEBT_{j,T}$ = firm *j*'s change in debt in current liabilities (Compustat #34) between year *T-1* and year *T*;
$DEPN_{j,T}$ = firm *j*'s depreciation and amortization expense (Compustat #14) in year *T*, and

---

[6] As a second construct, I consider absolute discretionary accruals (|*DA*|) from a modified Jones (1991) model, as introduced by Dechow, Sloan and Sweeney (1995). The $|DA_{j,T}|$ measure are the absolute values of the residuals from the following industry-year-specific regression, similar to Kothari, Leone and Wasley (2005):

$$TA_{j,T} = \lambda_{0,T}\frac{1}{Assets_{j,T-1}} + \lambda_{1,T}\frac{\Delta \mathrm{Rev}_{j,T} - \Delta AR_{j,T}}{Assets_{j,T-1}} + \lambda_{2,T}\frac{PPE_{j,T}}{Assets_{j,T-1}} + DA_{j,T}$$

where $\Delta AR_{j,T}$ = firm *j*'s change in accounts receivable (Compustat #2) in year *T*; and $Assets_{j,T-1}$ = firm *j*'s total assets (Compustat #6) in year *T-1*. While absolute point estimates are generally slightly lower, the main results remain significant and qualitatively unaffected.

[7] I follow Fama and French's (1997) classification of 48 industries throughout.

$\Delta Rev_{j,T}$ = firm j's change in revenues (Compustat #12) between year T-1 and year T.

$AQ_{j,T}$ is the standard deviation of five residuals, $\upsilon_{j,T}$, from fiscal years T-5 to T-1,[8] intended to capture the imprecision of current accruals mapping into cash flows. Focusing on the levels of these residuals would only reveal a predictable accounting bias. Large (small) values of $AQ_{j,T}$ correspond to poor (good) information quality.

For the factor construction, each firm with an *AQ* estimate is assigned to an *AQ* decile using a dynamic portfolio technique that allows for differences in fiscal year ends as well as over-time changes in accruals quality. Specifically, deciles are formed on the first day of each month *m* based on a firm's most recent value of *AQ* prior to *m*; firms with the smallest (largest) *AQ* values are placed in the first (tenth) decile. The *AQ* metric is assumed to be known by the stock market three months after the firm's fiscal year end. Thus, firm *j*'s *AQ* signal for fiscal year *T*, where fiscal year *T* ends in month *n*, will determine firm *j*'s ranking for months $n+4$ through $n+15$. The *AQ*-factor-mimicking portfolio, *IPfactor*, is the difference between the daily returns of the two poorest-*AQ* quintiles and the two best-*AQ* quintiles. Note that *IPfactor* is estimated using all firms with *AQ* data available.

The *realized* information precision parameter is the loading on *IPfactor* obtained from an augmented 3-factor asset pricing regression on daily excess returns over the first (event-)year after the initial offering. This e-loading reflects the market evaluation of information precision as captured by *IPfactor* over and above the other three factors included in the model:

[8] Note that the calculation of the accruals quality metric over the years T-5 to T-1 accounts for the fact that Equation (2) contains the (lead) cash flow from year $T+1$.

$$R_{j,t} - R_{F,t} = \alpha_j + \beta_j (R_{M,t} - R_{F,t}) + s_j\ SMB_t + h_j\ HML_t + e_j\ IPfactor_t + \varepsilon_{j,t} \tag{3}$$

The subscript *t* denotes the trading days in the first year after the IPO; $R_{j,t}$ = firm *j*'s return on day *t*; $R_{F,t}$ = the risk free rate on day *t*; $R_{M,t}$ = the market return on day *t*; SMB_t = small-minus-big factor on day *t*; HML_t high-minus-low book-to-market factor on day *t*.[9]

These minimal data requirements mean that the e-loading, as an information precision proxy for an IPO firm, can be estimated much earlier relative to the IPO than alternative information quality measures. Importantly, because it can be estimated in event time, the e-loading is available over the period during which investors start observing the IPO firm's accounting and other information releases.

Although estimating e-loadings imposes relatively minor data requirements, the estimation does require a time-series of returns. By definition, neither returns nor information precision metrics are available for newly public firms. Relying on prior research, I use the industry average e-loading to proxy for an IPO firm's *expected* information precision parameter. Ritter (1998) emphasizes that the valuation of an IPO firm is, in general, not different from the valuation of any other stock. Because of the difficulties of predicting future cash flows for young growth companies, however, he argues that using price multiples from comparable firms with similar characteristics is preferred to a discounted cash flow model. For the general firm, Alford (1992) provides evidence that the industry peers are the best source of comparable firms. Specifically, he shows that forecasting errors are minimized when the forecast is based on an industry average price multiples. Kim and Ritter (1999) confirm the validity of valuing IPO stocks using industry price multiples and firm-specific earnings forecasts. I focus on the industry information precision as expected value in an attempt to control for the part of information precision that is inherent in the business model and competitive environment.

---

9 Data for the market factor, *SMB* and *HML* are from Ken French.

To calculate the *expected* information precision parameter, I start by estimating firm-and-year specific e-loadings analogous to (3) for all firms with a minimum of 100 trading days in a given year from 1979 to 2005. Based on the Fama-French (1997) industry classification scheme, I form 48 industries. The lagged industry average e-loading is my first proxy for the expected value of information precision for all IPO firms of the same industry in a given year. By construction, the e-loadings of IPO firms in the respective offering years are excluded from this calculation.

Higher e-loadings indicate lower information precision. The firm-specific deviation variable ($Deviation_j$) is the industry e-loading less the IPO-firm-specific e-loading, such that a positive (negative) deviation indicates an upward (downward) revision in the IPO firm's information precision parameter.

$$Deviation_j = \overline{e_{IND_j}} - e_j \tag{4}$$

I will use this deviation variable in its simple form in the following tests, thereby maximizing the sample of IPO firms. At the end of the main analysis (Section 4.3.1), I probe the potential crudeness of the *Deviation* variable using two modifications, which impose further data restrictions. Briefly, I use both a fitted value from the validation regressions below and a matching technique similar to Kim and Ritter (1999) to yield an alternative proxy for the expected value of information precision.

Descriptive data on the distributions of e-loadings, industry averages and *Deviation* for the full IPO sample are reported in Table 4. *Deviation* has a negative mean of -0.0232 and a positive median of 0.0058. While the mean is statistically significant (at the 0.01 level), the median is not (p-value 0.2310), and both mean and median are economically very small. I interpret these results as suggesting that investors make no or small systematic errors in the initial estimation of information precision for the full sample of IPO firms. This result is consistent with rational expectations regarding information precision, where the average expectation is close to the average realization. However, the large standard deviation suggests substantial error for individual IPO firms.

3.3 Validation of the Deviation Variable

In this subsection, I probe the construct validity of the *Deviation* variable in its simple form by relating it to intuitive potential determinants of (expected) information precision. At the same time, the results help identify variables that can potentially be used to refine the metric, as attempted in Section 4.3.1.

Although pre-offering news about IPO firms is generally sparse, making it difficult to estimate pre-IPO information precision, firm-specific characteristics are likely to be associated with the difficulty of this estimation. I consider several firm characteristics explored by prior literature in different contexts: firm age, offer volume, the existence of public debt at the time of the IPO, underwriter reputation, venture-capital backing and membership in a high-tech industry.

With respect to firm age, I hypothesize older firms to be well established and more stable than younger firms and thus show higher congruence between information in the offering prospectus and post-IPO financial reports. The absolute value of the deviation variable is therefore presumably smaller (*Deviation* is closer to zero) for older firms. However, I still expect the lack of information on which to base an estimate of information precision to dominate the effects of firm age. (Regardless of firm age, there is relatively little information available for an IPO firm.)

Firm age is defined as the year of the IPO less the founding year.[10] The sample for this test contains the 5,474 IPO firms of my full sample for which founding years are available on Jay Ritter's website. The mean (median) age in this sample is 15 (8) years with a standard deviation of 20.84 years. This considerable cross-sectional variation in my sample firms' ages at the time of the IPO suggests the possibility of considerable variation in the reliability of the pre-IPO estimates of information precision.

---

[10] Data on founding years and underwriter reputation are described in Loughran and Ritter (2004) and are available on Jay Ritter's website, http://bear.cba.ufl.edu/ritter/ipodata.htm.

The second firm-specific variable I consider as a possible determinant of cross-sectional differences in the deviation variable is the dollar volume of the IPO.[11] I conjecture that the firm's disclosures are more comprehensive, the larger the dollar volume of the offering. At the same time, larger offerings are likely to be covered by mass media, given the relatively higher need for broad information dissemination to the market. More disclosure should reduce investor concerns about the value of the IPO firm and in turn provide more information to assess information precision. Thus, I hypothesize that the absolute deviation is smaller for larger offerings and expect a negative coefficient on the natural log of offer volume. In addition, 130 firms of the reduced sample had public debt outstanding in the year of the IPO and had therefore been providing information on Form 10-K prior to the first equity offering. I therefore expect the absolute value of the deviation for these firms to be lower.

Information precision could also be affected by characteristics of underwriters and firm owners. Brav and Gompers (1997) examine the role of venture capitalists in IPO firms and their influence on post-issue performance. Among other functions, venture capitalists provide management expertise and put management structures in place. Similar to the underwriting investment bank, they repeatedly bring new firms to the market and should thus be cautious not to have underperformers on their record. Both functions could, ceteris paribus, lead to higher information reliability for venture-capital-backed IPOs and IPOs with a high-reputation underwriter.[12] In contrast, I hypothesize that the information precision is likely to be lower for a firm in a high-tech industry due to the comparatively higher outcome uncertainty and the heterogeneity of the businesses.

In sum, I test the relation of the (absolute) deviation variable and the firm characteristics using the following regression:

---

[11] Data on offer volume, venture-capital backing and high-tech industry membership are obtained from the SDC database.

[12] Managerial expertise at IPO firms is also at the focus of Chemmanur and Paeglis (2005). In their view, better management is able to "convey the intrinsic value of their firm more credibly to outsiders".

$$Abs(Deviation_j) = \lambda_0 + \lambda_1\, Firm\ Age_j + \lambda_2 \log(Offer\, Volume_j) + \lambda_3\, PublicDebt_j$$
$$+ \lambda_4\, HighTech_j + \lambda_5\, UWRank_j + \lambda_6\, VCbacked_j + \varepsilon_j \qquad (5)$$

Table 5 summarizes the pooled regression results. As expected, the conditional mean λ_0 is positive and highly significant across all specifications. Firm age has a modest, but highly significant effect on *Deviation* of -0.0017 per year (t = -7.91). This finding is consistent with the hypothesis that the (unsigned) mis-estimation is smaller for older, more stable firms. The coefficients on offer volume are negative and reliably non-zero. I interpret this evidence as supporting the hypothesis that larger offers are associated with more disclosure to a broader set of investors and therefore allow for a more accurate pre-IPO assessment of the firm's information precision, over and above the impact of firm age. In addition, the dummy for the existence of public debt and underwriter reputation load negatively, indicating the richer information environment for these firms. I speculate that unexpectedly positive coefficient on venture-capital backing is due to the venture capitalists taking firms public in a relatively early stage in their lifecycle.

Overall, I view these results, generally aligned with intuition, as confirming the construct validity of the *Deviation* variable.

4. Tests on Abnormal Portfolio Returns

4.1 The magnitude of abnormal returns

For my main tests, I rank firms according to *Deviation* (the difference between the expected and realized information precision parameter) at the beginning of each sample month to form four monthly portfolios of the highest-, the two intermediate- and the lowest-deviation firms. To keep the sample of monthly observations constant and thus facilitate comparisons to the full sample tests, I require three firms per month (compared to the previous twelve firms).[13]

Table 6 provides statistics on *Deviation*, excess returns and average size for portfolios that include firms up to two years after the IPO (330 monthly observations). The average portfolio consists of 104 firms. For each deviation quartile, I report the value-weighted excess portfolio return and the mean market capitalization. As a monthly ranking procedure does not ensure that *Deviation* is always negative for the lowest-deviation portfolio and always positive for the highest-deviation portfolio, I include descriptive data for the mean deviation per portfolio as well. The summary statistics show that more than 90% of the Quartile 1 and 2 portfolios have a positive mean deviation and, equivalently, the vast majority of the other two portfolios has a mean negative deviation. This simplifies the interpretation of later results because the average information precision for the two high-quartile portfolios has been underestimated and the information precision of the other two portfolios has been overestimated.

The mean and median excess portfolio returns are positive for Quartiles 1 to 3 and negative for the quartile of the highest-deviation firms. Moreover, there is a clear trend across the *Deviation* quartiles in that the mean (median) value-weighted excess returns monotonically decrease from 1.29% to -0.15% (1.45% to 0.11%). Thus, separating the sample by *Deviation* reveals differences in the excess returns of the portfolios.

The average (median) market capitalization of the firms in the portfolios does not show a monotonic pattern across quartiles. The mean size is slightly increasing over Quartiles 1 to 3, but (significantly) smaller for the highest-deviation quartile. Small firms are overrepresented in the lowest-deviation quartile, reinforcing the need to explore the role of size.

---

[13] Results are virtually unaffected when at least 10 firms are required, as proposed by Mitchell and Stafford (2000).

Table 6 also provides descriptive data on the portfolios' average underwriter reputation rank, taken from Loughran and Ritter (2004), the average proportion of IPO firms in the portfolio with venture-capital backing, and the average proportion in a high-tech industry. Data on venture capital backing is from the SDC database. The high-tech indicator variable follows the very broad classification of high-tech industries on the SDC database, including pharmaceuticals, medical devices and telecom firms.

Ranking on the basis of *Deviation* does not control for risk factors, so the differences in excess returns in Table 6 could reflect different risk sensitivities and thus differences in expected returns. I estimate abnormal returns by including each portfolio's time series of excess returns as the dependent variable in the asset pricing regressions. In addition, I form a fifth time series as the returns difference between the highest- and the lowest-deviation quartiles to directly assess the statistical significance of abnormal returns differences. To control for risk, I use both the Fama-French (1993) 3-factor model of Equation (1) and a 4-factor model which adds a fourth factor, *IPfactor*, to explicitly capture any expected returns consequences of information precision.[14]

Table 7, Panel A, summarizes the abnormal returns for holding periods of one to three years, based on the 3-factor model. The monthly abnormal returns on a 1-year investment horizon are 1.20% (t = 4.28) for the highest-deviation quartile and -0.90% (t = -2.50) for the lowest-deviation quartile. The difference between highest- and lowest-deviation quartiles is 2.10% per month (t = 4.55). On an annualized basis, one-year-old IPO firms with initially underestimated information precision outperform the asset pricing model by 15.39% per year; firms with initially overestimated information precision parameters underperform by 10.28%.

[14] Note that this paper focuses on abnormal returns in a non-equilibrium setting, and not on expected return effects of certain factors in equilibrium. Hence, I add *IPfactor* in an attempt to ensure that the magnitude and significance levels of the abnormal returns estimates are not overstated due to an omitted information precision factor. As Table 7 shows, my abnormal results are not sensitive to the specification of the asset pricing model.

Generally, firms in the intermediate quartiles do not show an abnormal performance across the three investment horizons. The exception is the 1-year portfolio with the second-highest deviation firms (Quartile 2) with a significant positive abnormal return of 0.73% per month (t = 2.69). Increasing the holding period monotonically reduces the absolute magnitude of abnormal returns. Highest-deviation firms that are included for two and three years outperform the 3-factor model by 0.80% and 0.68% (with t-statistics of 3.71 and 3.61, respectively). Conversely, lowest-deviation firms underperform in their first two and three years by -0.76% and -0.36% (t-statistics are -2.32 and -1.23, respectively). The difference between lowest- and highest quartile-deviation remains economically and statistically significant, although it decreases from 2.10% (t = 4.55) to 1.56% (t = 4.00) and 1.04% (t = 2.98) per month as the investment horizon lengthens.

When the asset pricing model is augmented by *IPfactor* (Panel B), there is a monotonic decrease in abnormal returns across the deviation-quartiles; the difference between the extreme quartiles is consistently slightly larger than in the 3-factor model, ranging from 2.24% (t = 5.25) for the 1-year portfolio to 1.14% (t = 3.48) for the 3-years portfolio. Overall, however, the model of expected returns (3-factor or 4-factor) seems to have only a modest influence on the magnitude of abnormal returns. A comparison of adjusted R^2s shows that the 4-factor model is better specified for this sample of IPO portfolios. For brevity, I report only 4-factor results in the remaining tests; 3-factor results are very similar.

In summary, although the average firm shows little evidence of post-IPO abnormal performance, I find evidence of both an outperforming and an underperforming segment of the IPO population when the sample is partitioned on *Deviation*. The results in Table 7 thus support my first main hypothesis: An initial overestimation of an IPO firm's information precision leads to a gradual downward revision of the price in the aftermarket. Conversely, if market participants initially underestimate the firm's information precision, the price is revised upward.

4.2 The persistence of abnormal returns

Some studies seem to imply that abnormal returns last for the entire period over which researchers estimated buy-and-hold abnormal returns or cumulative abnormal returns. However, this ignores the shortcomings of both these metrics in estimating persistence as they mimic the researcher's choice of investment horizons. In fact, the results reported in Table 7 show that the intercepts of the extreme deviation quartiles decrease in absolute magnitude with increasing investment horizons. Consequently, the difference between the highest-deviation quartile and the lowest-deviation quartile monotonically decreases from 2.24% per month for a one-year holding period to 1.67% and 1.14% for the two-year and the three-year holding periods, respectively. As the firms in the 1-year portfolio are a subset of the longer-horizons portfolio firms, this decrease raises the question of the persistence of the abnormal returns of the highest- and the lowest-deviation firms. Prior research seems to imply that the investment horizon, though pre-determined by the researcher, can be used to assess the persistence of abnormal returns. The *actual* persistence of an abnormal return, however, cannot be inferred from the horizon over which the abnormal return is measured.

To obtain estimates for abnormal returns persistence, I modify the calendar-time portfolio methodology. First, I shorten the investment horizon for a specific firm to three calendar months. Second, I use rolling windows of three months length.[15] In essence, I start with a portfolio of IPO firms that are at most three months past their IPO date and continue estimating abnormal returns for the portfolio of firms in their post-IPO Months 2 to 4, 3 to 5, and so on, up to 22 to 24. Mechanically, the number of monthly observations decreases from 299 for the 1-to-3-Months portfolio to 265 for the 22-to-24-Months portfolio.

---

[15] Ideally, one would estimate the persistence of mispricing using monthly, not quarterly, rolling windows. However, the number of IPOs in each sample month must be large enough to form a portfolio. The loss of monthly observations for one-month portfolios is about 30% compared to the three-months specification leading to considerably higher standard errors.

Figure 1 depicts the 4-factor abnormal return estimates for the different rolling windows where the x-axis labels represent the last months of the estimation window. The top (bottom) line shows the abnormal returns for the highest- (lowest-) deviation firms. The filled dots mark statistically significant abnormal returns at the 10% level. For the overperforming (highest-deviation) firms, the abnormal return of the rolling-3-months portfolio decreases from 2.14% (t = 4.11) in the first 3 months after the IPO to 1.05% (t = 2.11) for firms that have been listed for 8 to 10 months. The results support the conclusion that firms listed for 11 months or longer do not exhibit significant overperformance.

In contrast, the lowest-deviation firms experience significant underperformance beginning in the fifth post-IPO month. For these firms, the abnormal performance is -1.28% (t = -2.50). With two exceptions for End-Months 13 and 15, the significantly negative abnormal returns persist up to Month 18 after the IPO.

These results are consistent with my second hypothesis. If information is of higher precision than initially expected, investors accelerate their assessments of the true information precision parameter and impute this information into prices more quickly. As a consequence, the positive abnormal returns of the highest-deviation firms do not persist beyond 10 months. In contrast, firms with surprisingly low information precision show negative abnormal returns over the first 18 months after the offering. Information about these firms is less precise, so investors will update their prior beliefs more slowly, and take more time to assess the true information precision of the IPO firms. In addition, the lowest-deviation firms take longer after the IPO before statistically significant negative abnormal returns materialize. That is, it appears that when the realized information precision is lower than expected, investors require more information (i.e., more time) to detect and price the deviation in the first place.

4.3 Extensions

4.3.1 Potential crudeness of Deviation *as partitioning variable*

In this section, I address the potential concern of using the lagged industry average e-loading as sole prior for the information precision parameter. I take two different approaches to refining the Deviation variable. The first approach is following Kim and Ritter (1999)'s matching technique based on industry, time and size. Specifically, for each sample firm, I select comparable firms from the same industry that went public within one year prior to the IPO, but also had at least 50 trading days on CRSP. This procedure yields 16.5 comparable firms for the average IPO firm. Further, I restrict the comparable firm set to the (at most) ten firms closest in size to the IPO firm. Like Kim and Ritter, I chose sales for the matching as sales are probably the commonly used size metric that is least affected by the offering proceeds. If available on Compustat, I take the last pre-IPO sales, if not, the first post-IPO figure. The expected information precision parameter is the average e-loading for these comparable firms, estimated over a period of at least 50 trading days that ends on the day before the IPO. *Deviation2* is the difference between this expected and the realized information precision parameter as estimated above.

The final subsample for tests with *Deviation2* consists of 5,561 IPO firms. The mean and median *Deviation2* are 0.0118 and 0.0142 (p-values of 0.1662 and 0.0374, respectively) with a cross-sectional standard deviation of 0.6364. *Deviation2* is designed to control for effects of a recent IPO as well as firm size effects. At the same time, the minimum estimation period for e-loadings is decreased to only 50 days, potentially increasing estimation error. Therefore, I expect the (absolute) abnormal returns estimates to be lower. In addition, significance levels are likely to be negatively affected by the smaller number of IPO firms in this subsample.

My second approach makes use of the validation regression in Section 3.3. Rather than restricting the set of comparable firms per se, the significant loadings in Table 5 suggest that the selected firm characteristics can also be used as instruments to refine the *Deviation* variable directly. For the 5,474 IPO firms with available firm age data, I split the sample by the sign of *Deviation* and re-estimate Regression (5) on the signed deviation variable, separately for both subsamples. I then modify the original deviation variable by adding the six products of *Deviation*-sign-specific coefficient estimates and the respective firm-specific variable values:

$$\begin{aligned} Deviation3_j = {} & Deviation_j + \lambda_1^{(+/-)}\, Firm\,Age_j + \lambda_2^{(+/-)}\, Offer\,Volume_j + \lambda_3^{(+/-)}\, PublicDebt_j \\ & + \lambda_4^{(+/-)}\, HighTech_j + \lambda_5^{(+/-)}\, UWRank_j + \lambda_6^{(+/-)}\, VCbacked_j + \varepsilon_j \end{aligned} \tag{6}$$

The average *Deviation3* is -0.0015 (p = 0.8156); the median *Deviation3* is 0.0251 (p = 0.0003). As expected from the mostly negative loadings in Table 5, this modified deviation variable has a standard deviation of 0.4639, or about 12% lower than the simple *Deviation* for this subsample. To the extent that *Deviation3* is designed as a refinement to *Deviation* and incorporates many firm-specific factors, albeit in a crude way, I expect portfolios based on *Deviation3* to show higher (absolute) abnormal returns and a higher spread in abnormal returns.

I repeat the main analysis using the four-factor asset-pricing model for the two subsamples introduced here, using *Deviation2* (Panel A) and *Deviation3* (Panel B). The results are tabulated in Table 8. For *Deviation2*, both the negative abnormal returns of the lowest-deviation portfolio and the positive abnormal returns of the highest-deviation portfolios have decreased slightly compared to Table 7, Panel B. For example, positive abnormal returns now range from 1.04% for the 1-year portfolio (t = 3.14) to an insignificant 0.29% for 3-years' portfolios (t = 1.35). The difference between the lowest- and highest-*Deviation* quartile for the 1-year (2-years, 3-years) portfolios decreases from 1.97% to 0.64% for the different horizons considered, but even the spread for the 3-years portfolios remains significant at the 10% level.

When the second modification, *Deviation3*, is used, the results are expectedly stronger than in the original specification, despite the decrease in sample IPO firms of 19%. The positive abnormal return estimates remain fairly unchanged, with the exception of the 2-years portfolio, which increases to 1.03% per month. The negative abnormal returns on the lowest-deviation portfolios, however, decreased. Overall, using the *Deviation3* leads to a 63 basis points increase in the abnormal returns spread compared to the original specification. That increase is monotonically declining over the investment horizons to 37 bp (17 bp) for the 3-years portfolio.

While I acknowledge that neither of these modifications in estimating a prior belief on the true information precision parameter is arguably complete (e.g., refer to the low adjusted R^2s in Table 5) and further refinements certainly possible, the results also support the main hypothesis of the paper and I view them as validating *Deviation* in its simple form as sole discriminating variable in my main tests.

4.3.2 Deviation and Seasoned Equity Offerings

As stated before, I expect investor's revision of information precision for IPO firms to be particularly great as their initial estimates at the time of the IPO cannot be based on a long history. In this extension, I corroborate the IPO results using a sample of firms with seasoned equity offerings during the same period. SEO firms are by definition more mature, have been listed longer and are therefore likely to have a richer information environment than IPO firms. At the same time, a seasoned equity offering might affect the information precision going forward due to changes in the business model and thereby introduces uncertainly about this parameter. Hence, I hypothesize that *Deviation* is also positively associated with abnormal returns after an SEO, but that the point estimates and the differences in abnormal returns between the highest- and lowest-deviation portfolios are smaller than for the IPO sample.

I repeat the main analysis on a sample of 5,084 first seasoned equity offerings during the same period 1980 to 2006, also obtained from the SDC database. The (simple) *Deviation*, calculated as for the IPO sample above, for this sample averages 0.0393 (t = 6.28), the median *Deviation* is 0.0629, also highly significant. The standard deviation across the sample SEO firms is about 16% smaller than for the IPO sample. Table 8, Panel C, summarizes the abnormal return results. Compared to the IPO results, the positive abnormal returns for the highest-deviation portfolio are cut in about half and turn insignificant for the 2-years portfolio already. The negative abnormal returns are generally lower,. Most importantly, the spread between abnormal returns estimates is, as hypothesized, much smaller than for the IPO sample, ranging from 1.88% for the 1-year portfolio to 0.45% for the 3-years portfolio, but remains significant.

5. Robustness tests

5.1 The role of size

There are several reasons why size could affect measures of abnormal post-IPO performance. First, small firms are overrepresented in the lowest-deviation portfolio. Second, as documented in prior literature (and also shown in Table 3), broad equal-weighted portfolios of IPO firms show a tendency to earn negative abnormal returns, whereas there is no such finding for value-weighted IPO portfolios. Third, asset pricing models are more likely to be mis-specified for (very) small firms. Fama and French (1993) report a monotonic trend in the intercepts of the 3-factor model for low-book-to-market (hereafter, BM) firms, with the smallest (largest) low-BM firms showing a significantly negative (positive) abnormal return. That is, the 3-factor model does not seem to capture differences in abnormal returns between small and big low-BM firms. As IPO firms are generally small with low-BM ratios, this issue is of particular importance here. To the extent that *Deviation* is positively correlated with size, abnormal returns and the associated significance levels are potentially overstated because of a misspecification of expected returns of low-BM firms.

To investigate whether size affects my results regarding the role of information precision in explaining post-IPO performance, I additionally split the deviation-quartile portfolios into size quartiles, requiring at least three firms per monthly portfolio, or equivalently, a total of 48 IPO firms in a given month. Size is the beginning-of-month market capitalization. The number of months in the returns series naturally declines, compared to the univariate sample split, in particular for the 1-year portfolio, which loses 11 monthly observations. I add returns series for the portfolio that is long in the smallest firms and short in the biggest firms, separately for each deviation quartile, to allow the assessment of the statistical significance of the difference in size-related abnormal returns.

Table 9 presents representative regression results for the 1-year portfolios, both value-weighted (Panel A) and equal-weighted (Panel B). Starting from the biggest size/lowest-deviation portfolio in Panel A, intercepts generally decline monotonically along both size and *Deviation*. Most importantly, the differences between the extreme categories are generally comparable, and the abnormal returns of the "High – Low" deviation portfolio is generally comparable to the overall-sample results in Table 7 across all size quartiles. The equal-weighted portfolio results in Panel B lead to the same conclusion.

Apparent underperformance for equal-weighted portfolios might also reflect an asset pricing model misspecification ("bad-model problem") for small firms in general. Fama (1998) suggests that all asset pricing models deliver a poor description of tiny firms' expected returns. Brav and Gompers' (1997) and Brav, Geczy and Gompers' (2000) empirical results support his hypothesis. I therefore address the potential concern that very small firms drive the underperformance results. Specifically, I use firm-month returns observations with a beginning-of-month market capitalization exceeding $50 million to form calendar-time portfolios. To control for the possibility that big firms drive the overperformance results, I exclude observations with a market capitalization of more than $1 billion in a separate test. The conclusions from the main test results about the monotonic patterns across quartiles and investment horizons remain the same (results not tabulated). In particular, both truncated samples still show significant differences between the extreme deviation quartiles.

Overall, I find evidence of under- and overperformance among the biggest IPO firms, depending on *Deviation*, and evidence of under- and overperformance among the lowest-deviation IPO firms, depending on size. This evidence indicates that *Deviation* and size are empirically different phenomena with respect to abnormal returns. Importantly, size effects on post-IPO abnormal returns do not subsume the effects of *Deviation*, which is intended to capture the influence of investors' revisions of their estimates of IPO firms' information uncertainty on share returns as new information arrives after the IPO.

5.2 Addressing potential methodological concerns

Calendar-time portfolios contain varying numbers of firms. As portfolio return variance is, all else equal, a decreasing function of the number of firms in the portfolio, it is likely that the variance of the regression residuals also changes through time. Consequently, the point estimates for abnormal returns would be unbiased, but no longer efficient. Mitchell and Stafford (2000) require at least 10 firms in any given monthly portfolio, and find that this requirement alone controls for most of the heteroscedasticity effects. My main tests require only three firm-month observations to avoid observation losses in the time series; results are virtually unaffected using the Mitchell and Stafford threshold.

To further address this potential problem of a time-varying variance of the regression residuals, Hou, Olsson and Robinson (2001) use a generalized, autoregressive, conditional heteroscedasticity model (GARCH 1,1). Specifically, their technique maximizes the joint likelihood of the following two equations:

$$R^{\#}_{p,m} - R_{F,m} = \alpha^{\#}_{p} + \beta^{\#}_{p}(R_{M,m} - R_{F,m}) + s^{\#}_{p}\, SMB_{m} + h^{\#}_{p}\, HML_{m} \left[+ e^{\#}_{p}\, IPfactor_{m} \right] + \varepsilon^{\#}_{p,m} \tag{7a}$$

$$\sigma^{2}(\varepsilon^{\#}_{p,m}) = \gamma_{0} + \gamma_{1}\, \sigma^{2}_{\varepsilon,m-1} + \gamma_{2}\, \varepsilon^{2}_{m-1} + \gamma_{3}\, n_{m} \tag{7b}$$

The residuals ε_t are normally distributed with zero mean and time-varying variance $\sigma^{2}(\varepsilon^{\#}_{p,m})$. Note that Hou et al.'s model deviates from a standard GARCH (1,1) model in that the residual variance is also a linear function of the number of firms in the portfolio (n_m). I find that using the GARCH specification for my tests generally leads to slightly more conservative abnormal returns estimates, but leaves significance levels and qualitative results unaffected.

A second method, proposed by Jaffe (1974) and Mandelker (1974) and advocated by Fama (1998), standardizes the monthly abnormal portfolio return by the standard deviation of individual abnormal returns (as a measure of precision).[16] While the calendar-time portfolio approach forms the portfolio first and then estimates abnormal returns, the Jaffe-Mandelker method first estimates the abnormal returns on a firm-specific basis and then forms a portfolio of monthly observations by averaging the firm-specific abnormal returns.

This method overcomes another potential criticism of the calendar-time portfolio approach. A single regression on the complete time-series of IPO portfolio returns assumes the factor loadings are constant over the sample period.[17] However, as Mitchell and Stafford (2000) point out, this may not be true as the portfolio composition changes through time. Specifically for my setting, IPOs cluster in time and by industry. At the same time, differences in risk sensitivities are more pronounced across industries than within a given industry. As firms drop out and other firms are included in the portfolio, the assumption of constant portfolio risk sensitivities might therefore be too stringent.

Building on the findings of prior literature, I implement the Jaffe-Mandelker approach in the following way. For each firm, I require 10 monthly return observations in the first three years after the issuance (after controlling for seasoned equity offerings and post-SEO months). This requirement decreases the IPO sample to 6,238 firms. Firm-specific abnormal returns are from 4-factor regressions. The abnormal IPO portfolio return in a given month is the (equal- or value-weighted) average firm-specific abnormal return of all firms with an IPO in the last one to three years (i.e. I use the same portfolio inclusion rules as before). I still require at least 3 firms per monthly portfolio; the result of this procedure is a time series of abnormal portfolio returns for the same months as in my main tests. The grand mean and the variance of this time series of monthly averages can be used to assess the magnitude and the

---

[16] Another potential control for heteroscedasticity, namely a weighted-least-squares estimation with weights proportional to the square root of the number of firms included, is rejected by Mitchell and Stafford (2000). They show that, in essence, the weighting scheme will weight each event equally and undo the main reason for forming calendar portfolios in the first place, namely the correction for cross-correlation.

[17] This second concern is – in a cruder way – also addressed by the analysis of subperiods, described in the following subsection.

significance of these abnormal returns. Note that the abnormal returns measurement per se does not control for overlaps in the estimation period; the cross-correlation problem is overcome only by using monthly portfolios.

To control for heteroscedasticity following Jaffe (1974), Mandelker (1974) and Mitchell and Stafford (2000), I weight the monthly portfolio averages by the standard deviation of the firm-specific abnormal returns. This leads to a time series of standardized means which is used to estimate the significance level, labeled 't-stat (std.)'. Because the means presented in Table 10 are from the unweighted time series of abnormal portfolio returns, the signs of the abnormal returns and the standardized test statistics might differ. Therefore, I also report the t-statistics from the unweighted series (which might be affected by heteroscedasticity).

Table 10 presents the grand mean abnormal returns for equal- and value-weighted portfolios per deviation quartile. Independent of holding period and weighting scheme, the abnormal returns differences between lowest and highest deviation quartile exceed 0.75% (0.95%) per month for the 3-factor (4-factor) asset pricing model. Significance levels increase compared to my main tests, so I conclude that the previous findings are robust to this change in the methodology.

5.3 Analysis of subperiods

Splitting the time series of returns into subperiods is a cruder alternative to the Jaffe-Mandelker approach to allow the loadings in the asset pricing regression to change over time. A subperiod analysis may be particularly appropriate for an IPO setting because of the calendar-time clustering of IPOs, displayed in Table 1. Thus, the subperiod analysis addresses the concern of Loughran and Ritter (1995, 2000) that underperformance is concentrated in markets with many IPOs ("hot market phenomenon"). I hypothesize that the association between *Deviation* and abnormal returns is not time-period-specific.

Table 11 summarizes representative results for a holding period of two years; each subperiod consists of 106 months of portfolio returns for which I run separate regressions. The statistical power of the test decreases compared to the full sample period tests considerably. In each subperiod, the difference between the lowest and the highest deviation quartiles remains economically and statistically significant; in fact, it is highest in the last subperiod. I conclude that the association of *Deviation* and abnormal returns is not a time-specific phenomenon.

5.4 Firm-level tests

The Jaffe-Mandelker-type tests in Section 5.3 establish that *Deviation* can also be used to test for differences in firm-specific abnormal returns. In a regression analysis on the firm level (instead of the portfolio level), I explore whether the association of *Deviation* and firm-specific abnormal returns is affected by other firm characteristics such as size or operating performance.

So far, I have only been examining denominator (i.e., discount rate) effects in the valuation model. However, my explanation does not rule out that changes in operating performance (earnings growth) determine post-IPO abnormal returns. This possibility is related to the argument in Teoh, Welch and Wong (1998). As they focus on accruals reversals, they are restricted to predicting post-issue underperformance, whereas I allow for a positive surprise in earnings and therefore positive abnormal returns.

I use firm-specific 4-factor abnormal returns (as specified in the Jaffe-Mandelker approach) as the dependent variable. The measure of size, *MktCap*, is the natural log of the market capitalization as of the first month with returns data available on CRSP. I split my sample into two halves by transforming the deviation variable into a dummy, *DevDummy*, equal to 0 for positive deviations and 1 otherwise. As a negative deviation signals an initial overestimation of the firm's information precision, I expect a significantly negative incremental abnormal return. I stepwise combine *DevDummy*, size and operating performance in a regression in an attempt to disentangle numerator and denominator effects:

$$\alpha_j^{4f} = \lambda_0 + \lambda_1 \, DevDummy_j + \lambda_2 \, OpPerf_j + \lambda_3 \log(MktCap_j) + \varepsilon_j \qquad (8)$$

where $OpPerf_j$ is the average change in net income before extraordinary items over the same three years as used to estimate the abnormal return, scaled by market capitalization. If earnings data was not available for some years, the average consists of less than three change figures. The sample used for these tests consists of 5,496 IPO firms.

Table 12 summarizes the results. As expected, the deviation dummy loads negatively. The coefficients also confirm that abnormal returns and operating performance are positively related: the higher the change in earnings, the higher is the abnormal return. Note that my measure for operating performance (the realized average change in earnings) can be assessed only ex-post, so it is not surprising that, with hindsight, operating performance is positively associated with abnormal returns. The important result is that the loading on the deviation dummy does not meaningfully change after the inclusion of operating performance and remains highly significant.

6. Concluding Remarks

Previous research on initial public offerings (IPOs) has focused on the existence of and explanations for underperformance for the average IPO firm. In this study, I present and test an information-precision-based explanation for the cross-sectional variation in post-IPO abnormal returns. While prior theoretical and empirical research that has shown that information precision is priced by investors, I argue that this priced parameter cannot be assessed ex-ante for an IPO firm. Therefore, investors in IPO firms use an expected value for information precision in their pricing decisions. Depending on whether information precision has been initially underestimated (overestimated), the post-IPO stock price will be revised upward (downward) as firm-specific information becomes available. In this setting of a generally low level of information precision, this gradual revision process leads to the appearance of abnormal returns (i.e., returns not explained by equilibrium asset pricing models). As hypothesized, I find a significant relation between post-IPO abnormal returns and the deviation between expected and realized information precision. Consistent with the information precision of the *average* IPO firm being correctly estimated by rational investors, I find negligible *average* abnormal returns in my IPO sample.

Building on arguments by Epstein and Schneider (2008), the updating process is unlikely to occur quickly after the IPO. First, newly listed firms have low information precision compared to more seasoned firms. Second, updating the prior requires a sufficient amount of new information, implying dissemination over a potentially lengthy period. The speed of this updating process depends on the precision of new information; the more precise, the faster investors update their prior belief about the information precision parameter and the shorter is the post-IPO period over which abnormal returns persist. Thus, the second question I explore is the persistence of these apparent abnormal returns.

Using a rolling calendar-time portfolio approach, I find that positive abnormal returns disappear after the first nine post-IPO months, consistent with precise information allowing for a relatively fast assessment of the true information precision parameter. In contrast, negative abnormal returns persist for 18 months. Rational investors will not put much weight on less precise information; they will wait for confirming signals. The lower the precision of new information, the longer the updating of the parameter takes. The results are robust to a battery of sensitivity analyses using different asset pricing models, firm-specific designs and various estimation techniques.

References

Alford, A. 1992. The effect of the set of comparable firms on the accuracy of the price-earnings valuation method. *Journal of Accounting Research* 30: 94-108.

Barber, B. and J. Lyon. 1997. Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of Financial Economics* 43: 341-372.

Benninga, S., M. Helmantel and O. Sarig. 2005. The timing of initial public offerings. *Journal of Financial Economics* 75: 115-132.

Bhattacharya, N., F. Ecker, P. Olsson and K. Schipper. 2008. Direct and mediated associations among earnings quality, information asymmetry and the cost of equity. Working paper.

Brav, A. 2000. Inference in Long-Horizon Event Studies: A Bayesian approach with application to initial public offerings. *Journal of Finance* 55: 1979-2016.

Brav, A., C. Geczy and P. Gompers. 2000. Is the abnormal return following equity issuances anomalous? *Journal of Financial Economics* 56: 209-249.

Brav, A. and P. Gompers. 1997. Myth or reality? The long-run underperformance of initial public offerings: evidence from venture and non-venture-capital-backed companies. *Journal of Finance* 52: 1791-1821.

Brav, A., R. Lehavy and R. Michaely. 2005. Expected returns and asset pricing. *Financial Management* 34: 31-64.

Chemmanur, T. and I. Paeglis. 2005. Management quality, certification, and initial public offerings. *Journal of Financial Economics* 76: 331–368.

Chen, L., D. Dhaliwal and M. Trombley. 2007. The effect of fundamental risk on the market pricing of accruals quality. Working paper.

Core, J., W. Guay and R. Verdi. 2008. Is accruals quality a priced risk factor? *Journal of Accounting and Economics* 46: 2-22.

Dechow, P. and I. Dichev. 2002. The quality of accruals and earnings: The role of accrual estimation errors. *The Accounting Review* 77 (Supplement): 35-59.

Dechow, P., R. Sloan and A. Sweeney. 1995. Detecting Earnings Management. *Accounting Review* 70: 193-225.

Eckbo, B. and Ø. Norli. 2005. Liquidity risk, leverage and long-run IPO returns. *Journal of Corporate Finance* 11: 1-35.

Ecker, F., J. Francis, I. Kim, P. Olsson and K. Schipper. 2006. A returns-based representation of earnings quality. *Accounting Review* 81: 749-780.

Epstein L. and and M. Schneider. 2008. Ambiguity, information quality, and asset pricing. *Journal of Finance* 63: 197-228.

Fama, E. 1998. Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics* 49: 283-306.

Fama, E. and K. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33: 3-56.

Fama, E. and K. French. 1997. Industry costs of equity. *Journal of Financial Economics* 43: 153-193.

Francis, J., R. LaFond, P. Olsson and K. Schipper. 2004. Costs of equity and earnings attributes. *The Accounting Review* 79: 967-1010.

Francis, J., R. LaFond, P. Olsson and K. Schipper. 2005. The market pricing of accruals quality. *Journal of Accounting and Economics* 39: 295-327.

Hou, K., P. Olsson and D. Robinson. 2001. Does Takeover Increase Stockholder Value? Duke University working paper.

Jaffe, J. 1974. Special information and insider trading. *Journal of Business* 47: 410–428.

Jones, J. 1991. Earnings management during import relief investigations. *Journal of Accounting Research 2*9: 193-228.

Kim, Dongcheol and Y. Qi. 2008. Accounting Information Quality, Stock Returns, and Macroeconomic Conditions. Working paper.

Kim, M. and J. Ritter. 1999. Valuing IPOs. *Journal of Financial Economics* 53: 409-437.

Kothari, S.P., A. Leone and C. Wasley. 2005. Performance-matched discretionary accrual measures. *Journal of Accounting and Economics* 39: 163-197.

Lambert, R., C. Leuz and R. Verrecchia. 2007. Accounting information, disclosure, and the cost of capital. *Journal of Accounting Research* 45: 385–420.

Lambert, R., C. Leuz and R. Verrecchia. 2008. Information Asymmetry, Information Precision, and the Cost of Capital. Working paper.

Liu, J., D. Nissim and J. Thomas. 2002. Equity valuation using multiples. *Journal of Accounting Research* 40: 135–172.

Loughran, T. and J. Ritter. 1995. The new issues puzzle. *Journal of Finance* 50: 23-51.

Loughran, T. and J. Ritter. 2000. Uniformly least powerful tests of market efficiency. *Journal of Financial Economics* 55: 361-389.

Loughran, T. and J. Ritter. 2004. Why has IPO underpricing changed over time? *Financial Management* 33: 5-37.

Lowry, M. and G. Schwert. 2004. Is the IPO pricing process efficient? *Journal of Financial Economics* 71: 3-26.

Lyon, J., B. Barber and C. Tsai. 1999. Improved methods for tests of long-run abnormal stock returns. *Journal of Finance* 54: 165-201.

Mandelker, G. 1974. Risk and return: The case of merging firms. *Journal of Financial Economics* 1: 303–335.

McNichols, M. 2002. Discussion of 'The quality of accruals and earnings: the role of accrual estimation errors.' *The Accounting Review* 77 (Supplement): 61-69.

Merton, R. 1987. A simple model of capital market equilibrium with incomplete information. *Journal of Finance* 42: 483-510.

Mitchell, M. and E. Stafford. 2000. Managerial decisions and long-term stock price performance. *Journal of Business* 73: 287-329.

Ogneva, M. 2008. Accrual quality and expected returns: the importance of controlling for cash-flow shocks. Working paper.

Ritter, J. 1991. The long-term performance of initial public offerings. *Journal of Finance* 46: 3-27.

Ritter, J. 1998. Initial public offerings. In: Warren, Gorham, and Lamont: Handbook of modern finance, edited by D. Logue and J. Seward; reprinted (after modifications) in: *Contemporary Finance Digest* 2: 5-30.

Ritter, J. 2002. Investment banking and securities issuance. In: *Handbook of the economics of finance*, edited by G. Constantinides, M. Harris and R. Stulz: 253-304.

Ritter, J. and I. Welch. 2002. A review of IPO activity, pricing, and allocations. *Journal of Finance* 57: 1795-1828.

Teoh, S., I. Welch and T. Wong. 1998. Earnings management and the long-run market performance of initial public offerings. *Journal of Finance* 53: 1935-1974.

Yee, K. 2006. Earnings quality and the equity risk premium: a benchmark model. *Contemporary Accounting Research* 23: 833-877.

Table 1 - Distribution of IPO Sample by Year and Industry

The 48-industry classification in Panel B is taken from Fama and French (1997).

Panel A: Firm distribution by year

Year	# IPOs	Year	# IPOs
1980	58		
1981	179	1994	401
1982	71	1995	397
1983	380	1996	643
1984	174	1997	447
1985	178	1998	267
1986	371	1999	371
1987	290	2000	318
1988	122	2001	77
1989	124	2002	75
1990	102	2003	67
1991	248	2004	190
1992	359	2005	192
1993	486	2006	179
		Total	**6,766**

Panel B: Firm distribution by industry

Industry Name	Ind. Code	# IPOs	Industry Name	Ind. Code	# IPOs
Agriculture	1	25	Shipbuilding, Railroad Equipment	25	14
Food Products	2	75	Defense	26	12
Candy & Soda	3	9	Precious Metals	27	7
Beer & Liquor	4	20	Non-Metallic and Industrial Metal Mines	28	10
Tobacco Products	5	5	Coal	29	10
Recreation	6	76	Petroleum and Natural Gas	30	10
Entertainment	7	130	Utilities	31	160
Printing and Publishing	8	35	Communication	32	95
Consumer Goods	9	94	Personal Services	33	265
Apparel	10	81	Business Services	34	92
Healthcare	11	159	Computers	35	1,162
Medical Equipment	12	290	Electronic Equipment	36	445
Pharmaceutical Products	13	376	Measuring and Control Equipment	37	419
Chemicals	14	62	Business Supplies	38	149
Rubber and Plastic Products	15	48	Shipping Containers	39	41
Textiles	16	34	Transportation	40	21
Construction Materials	17	67	Wholesale	41	185
Construction	18	76	Retail	42	250
Steel Works	19	62	Restaurants, Hotels, Motels	43	422
Fabricated Products	20	15	Banking	44	157
Machinery	21	163	Insurance	45	338
Electrical Equipment	22	61	Real Estate	46	233
Automobiles and Trucks	23	60	Trading	47	36
Aircraft	24	65	Other	48	145
				Total	**6,766**

Table 2 - Descriptive Statistics on Full-Sample Portfolios of IPO Firms

The time series of monthly excess returns of value- and equal-weighted calendar-time portfolios over the period from July 1980 to December 2007 are labeled 'Exc. Return (VW)' and 'Exc. Return (EW)', respectively. Portfolios are composed of firms that completed IPOs during January 1980 to December 2006. '1 Year' ('2-Years', '3-Years') portfolios are portfolios containing firms with first returns data after issuance within the last (last two, last three) year(s). Statistics on the number of firms in the portfolios are given in the third line of each panel. The mean market capitalization, displayed in the last row, is the average market capitalization of the firms included in the portfolio.

Panel A: '1 Year' Portfolios (330 months)

	Mean	Std. Dev.	10%ile	25%ile	Median	75%ile	90%ile
Exc. Return (VW)	0.93%	7.86%	-7.89%	-3.47%	1.35%	5.47%	9.58%
Exc. Return (EW)	0.35%	7.97%	-8.75%	-4.02%	0.86%	5.22%	9.20%
# Firms	234	144	72	117	184	349	434
Mean Mkt. Cap.	355.29	355.41	57.53	112.37	183.05	567.76	841.56

Panel B: '2 Years' Portfolios (330 months)

	Mean	Std. Dev.	10%ile	25%ile	Median	75%ile	90%ile
Exc. Return (VW)	0.71%	7.50%	-8.12%	-3.58%	1.32%	5.10%	9.13%
Exc. Return (EW)	0.22%	7.86%	-8.66%	-4.29%	0.70%	4.55%	9.27%
# Firms	419	234	143	224	370	575	758
Mean Mkt. Cap.	335.57	318.88	60.21	101.99	185.95	535.82	762.37

Panel C: '3 Years' Portfolios (330 months)

	Mean	Std. Dev.	10%ile	25%ile	Median	75%ile	90%ile
Exc. Return (VW)	0.78%	7.21%	-7.58%	-3.55%	1.44%	5.23%	8.87%
Exc. Return (EW)	0.43%	7.72%	-8.18%	-4.21%	0.89%	4.63%	9.52%
# Firms	559	301	201	312	552	788	1,010
Mean Mkt. Cap.	309.50	268.04	59.13	98.68	192.66	523.66	672.68

Table 3 - Abnormal Returns on Full-Sample Portfolios of IPO Firms

The table displays the intercepts from 3-factor asset pricing regressions (OLS) on value-weighted and equal-weighted portfolio returns. For the value-weighted portfolios, the weights are adjusted at the beginning of each month according to the last closing price and the number of shares outstanding of the previous month. The first column contains the portfolio inclusion rule: Firms are included for the first post-IPO year, for the first two post-IPO years, etc. The sample consists of 330 monthly observations from July 1980 to December 2007.

	Value-weighted		**Equal-weighted**	
	Abnormal Return	t-stat	Abnormal Return	t-stat
1 Year	0.39%	1.98	-0.29%	-1.59
2 Years	0.12%	0.72	-0.50%	-2.71
3 Years	0.17%	1.20	-0.33%	-1.75
4 Years	0.12%	0.90	-0.23%	-1.26
5 Years	0.02%	0.17	-0.17%	-0.97
Mean	0.16%		-0.30%	
Median	0.12%		-0.29%	

Table 4 - Descriptive Statistics on E-Loadings, Industry Averages and Deviation

The summarizing data is for the sample of 6,766 IPO firms. 'E-loadings' are the coefficients on *IPfactor* in a daily 4-factor asset pricing regression over the first post-IPO year of returns data. 'Industry Average' is the lagged average of e-loadings from all firms in the same industry as each IPO firm. 'Deviation' is defined as the industry average less the IPO-firm's e-loading. The reported p-values for the mean (median) deviation are from a t-test (Wilcoxon signed rank test) against zero.

	Mean	Std. Dev.	10%ile	25%ile	Median	75%ile	90%ile
Industry Average	0.1577	0.1247	0.0078	0.0677	0.1614	0.2358	0.2901
E-loadings	0.1809	0.5330	-0.4419	-0.1414	0.1356	0.4746	0.8605
Deviation	-0.0232	0.5296	-0.6813	-0.3104	0.0058	0.2953	0.6079
p-values	*(0.0003)*				*(0.2310)*		

Table 5 – Firm-Age Regressions

This table presents regressions of the absolute value of the deviation variable on firm age, the natural log of offer volume, and dummy variables for the existence of public debt at the time of the IPO, membership of a high-tech industry and venture-capital backing. 'UWRank' is the underwriter reputation rank from Loughran and Ritter (2004). The sample consists of 5,474 firms from the original sample for which founding years are available on Jay Ritter's website.

	Intercept	Firm Age	Offer Volume	Public debt	High-Tech	UWRank	VCbacked	Adj. R2
Coeff.	0.4263	-0.0017	-	-	-	-	-	1.11%
t-stat	*74.29*	*-7.91*						
Coeff.	0.5144	-0.0013	-0.0294	-	-	-	-	2.17%
t-stat	*40.38*	*-5.80*	*-7.74*					
Coeff.	0.4271	-0.0017	-	-0.0860	-	-	-	1.24%
t-stat	*74.38*	*-7.49*		*-2.81*				
Coeff.	0.5071	-0.0007	-0.0240	-0.0390	0.0605	-0.0079	0.0185	3.17%
t-stat	*35.42*	*-3.14*	*-5.41*	*-1.27*	*5.82*	*-3.78*	*1.70*	

Table 6 - Description of the Deviation-Quartile Calendar-Time Portfolios

The table displays descriptive data on the deviation-quartile portfolios. 'Deviation' as the discriminating variable is defined as the the lagged industry average e-loading less IPO-firm's e-loading. Each month, firms that have completed an IPO in the last two years are ranked by their deviation variable and sorted into deviation-quartile portfolios. Separately for each of these four portfolios, I report descriptive statistics on the deviation variable, the value-weighted excess portfolio returns over the period from July 1980 to December 2007 (3308 months), and the market capitalization of firms in the portfolio.

	Mean	Std. Dev.	10%ile	25%ile	Median	75%ile	90%ile
Quartile 1 - Highest Deviation							
Deviation	0.5708	0.1066	0.4429	0.4852	0.5863	0.6492	0.7091
Exc. Return (VW)	1.29%	7.86%	-7.47%	-3.43%	1.45%	5.42%	9.91%
Size	342.2	393.9	55.1	91.1	191.2	455.1	868.2
UWRank	6.8355	0.9393	5.5488	6.0376	6.6942	7.7357	8.0505
VCbacked	0.3546	0.0835	0.2639	0.3023	0.3429	0.3953	0.4691
Hightech	0.5129	0.1220	0.3750	0.3968	0.5054	0.6000	0.6757
Quartile 2							
Deviation	0.1250	0.0739	0.0408	0.0848	0.1396	0.1819	0.2097
Exc. Return (VW)	0.89%	7.69%	-8.04%	-3.63%	1.38%	4.83%	9.51%
Size	376.0	352.9	62.3	103.8	209.0	581.0	933.5
UWRank	6.9376	0.8045	5.6382	6.6464	7.0010	7.3721	8.0170
VCbacked	0.3079	0.0923	0.1949	0.2414	0.2961	0.3509	0.4286
Hightech	0.4052	0.1030	0.2920	0.3363	0.3826	0.4556	0.5455
Quartile 3							
Deviation	-0.1618	0.0986	-0.3080	-0.2131	-0.1287	-0.0976	-0.0584
Exc. Return (VW)	0.32%	7.96%	-7.79%	-3.80%	0.63%	4.42%	9.82%
Size	387.6	422.4	68.6	126.7	245.6	461.8	813.8
UWRank	6.9067	0.7281	5.7705	6.6131	6.9048	7.3220	7.9330
VCbacked	0.3176	0.1076	0.1961	0.2586	0.2941	0.3453	0.4918
Hightech	0.3969	0.1526	0.2319	0.2934	0.3750	0.4464	0.6219
Quartile 4 - Lowest Deviation							
Deviation	-0.6907	0.1381	-0.9154	-0.7797	-0.6555	-0.6065	-0.5129
Exc. Return (VW)	-0.15%	10.48%	-11.58%	-5.73%	0.11%	6.03%	11.25%
Size	235.5	255.4	41.1	62.1	104.0	348.7	643.6
UWRank	6.3964	1.0499	4.8376	5.6788	6.4315	7.3239	7.9445
VCbacked	0.3393	0.1166	0.2167	0.2615	0.3067	0.3846	0.5430
Hightech	0.4473	0.1544	0.2823	0.3571	0.4157	0.5000	0.6535

Table 7 - Abnormal Return for Value-Weighted Deviation-Quartile Portfolios

Each month, firms that have completed an IPO in the last year are ranked by Deviation and sorted into value-weighted deviation-quartile portfolios. The highest-deviation (lowest-deviation) portfolio contains the firms with the most underestimated (overestimated) information precision parameter, relative to the industry average. Separately, I obtain a time series of returns for a zero-investment portfolio (labeled 'High – Low') that combines a long position in the highest-deviation portfolio and a short position in the lowest-deviation portfolio to assess the statistical significance of the abnormal returns difference. The value-weighted excess returns over the period from July 1980 to December 2007 (330 months) are evaluated against the 3-factor (Panel A) and 4-factor (Panel B) asset pricing model in an OLS regression. The last line displays the adjusted R^2s averaged over the four deviation-quartile-specific regressions. For Columns 3 and 4, I repeat these steps for firms with an IPO in the last two (three) years.

Panel A: 3-Factor Abnormal Returns

	1 Year		2 Years		3 Years	
	Abnormal Return	t-stat	Abnormal Return	t-stat	Abnormal Return	t-stat
Highest	1.20%	4.28	0.80%	3.71	0.68%	3.61
Q2	0.73%	2.69	0.29%	1.30	0.21%	1.18
Q3	-0.02%	-0.07	-0.25%	-1.07	-0.05%	-0.20
Lowest	-0.90%	-2.50	-0.76%	-2.32	-0.36%	-1.23
High - Low	2.10%	4.55	1.56%	4.00	1.04%	2.98
Average Adj. R^2	66.70%		73.96%		77.82%	

Panel B: 4-Factor Abnormal Returns

	1 Year		2 Years		3 Years	
	Abnormal Return	t-stat	Abnormal Return	t-stat	Abnormal Return	t-stat
Highest	1.24%	4.50	0.82%	3.86	0.69%	3.69
Q2	0.74%	2.70	0.28%	1.28	0.21%	1.18
Q3	-0.07%	-0.22	-0.29%	-1.24	-0.08%	-0.36
Lowest	-1.00%	-2.95	-0.85%	-2.74	-0.45%	-1.62
High - Low	2.24%	5.25	1.67%	4.60	1.14%	3.48
Average Adj. R^2	65.82%		75.19%		78.92%	

Table 8 – Extensions of The Main Results

Each month, the sample of IPO firms is first split into deviation quartiles and then into size quartiles. For a specific month to be included in the sample, each of the resulting 16 portfolios must contain at least three firms. This requirement reduces the sample period to 307 months.

Panel A: Portfolios based on Deviation2 (# firms = 5,561)

	1 Year		2 Years		3 Years	
	Abnormal Return	t-stat	Abnormal Return	t-stat	Abnormal Return	t-stat
Highest	1.04%	3.14	0.62%	2.42	0.29%	1.35
Q2	0.64%	2.36	0.04%	0.18	0.30%	1.59
Q3	0.74%	2.45	0.51%	1.80	0.46%	1.86
Lowest	-0.93%	-2.73	-0.61%	-2.11	-0.35%	-1.28
High - Low	1.97%	4.15	1.23%	3.29	0.64%	1.85
Average Adj. R^2	67.62%		74.23%		77.92%	

Panel B: Portfolios based on Deviation3 (# firms = 5,474)

	1 Year		2 Years		3 Years	
	Abnormal Return	t-stat	Abnormal Return	t-stat	Abnormal Return	t-stat
Highest	1.18%	3.85	1.03%	4.36	0.78%	3.62
Q2	0.04%	0.18	-0.29%	-1.43	-0.12%	-0.66
Q3	-0.03%	-0.11	-0.39%	-1.64	-0.39%	-1.82
Lowest	-1.69%	-4.67	-1.01%	-3.05	-0.53%	-1.73
High - Low	2.87%	6.35	2.04%	5.10	1.31%	3.57
Average Adj. R^2	67.59%		74.84%		77.82%	

Panel C: (Simple) Deviation effect for SEO firms (# firms = 5,084)

	1 Year		2 Years		3 Years	
	Abnormal Return	t-stat	Abnormal Return	t-stat	Abnormal Return	t-stat
Highest	0.57%	2.38	0.10%	0.54	0.09%	0.52
Q2	0.13%	0.73	-0.08%	-0.57	-0.14%	-1.22
Q3	-0.13%	-0.62	-0.25%	-1.64	-0.25%	-1.76
Lowest	-1.31%	-4.19	-1.05%	-4.14	-0.37%	-1.93
High - Low	1.88%	4.88	1.16%	3.91	0.45%	1.88
Average Adj. R^2	66.87%		76.09%		79.97%	

Table 9 – Abnormal Portfolio Returns per Deviation and Size Quartiles

Each month, the sample of IPO firms is first split into deviation quartiles and then into size quartiles. For a specific month to be included in the sample, each of the resulting 16 portfolios must contain at least three firms. This requirement reduces the sample period to 307 months. Separately for the four size (deviation) quartiles, I form four zero-investment portfolios that combine a long position in the highest-deviation (biggest-firms) portfolios and a short position in the lowest-deviation (smallest-firms) portfolio to assess the statistical significance of the abnormal returns difference; these four portfolios are labeled 'High – Low' ('Big – Small'). Panel A (Panel B) displays value-weighted (equal-weighted) 4-factor abnormal returns and associated t-statistics on the resulting 24 time series.

Panel A: Value-weighted abnormal returns

'1 Year' portfolio time-series (317 months)

Size Quartile/ Deviation Quartile	Biggest		Q2		Q3		Smallest		Big - Small	
	Abnormal Return	t-stat	Abnormal Return	t-stat	Abnormal Return	t-stat	Abnormal Return	t-stat	Abnormal Return	t-stat
Highest	1.62%	4.48	0.33%	0.93	0.74%	1.77	-0.81%	-1.99	2.43%	4.42
Q2	1.01%	2.92	0.60%	1.81	0.37%	1.13	-0.82%	-2.03	1.83%	3.65
Q3	0.06%	0.16	-0.39%	-1.21	-0.46%	-1.32	-1.11%	-2.66	1.17%	2.29
Lowest	-0.88%	-2.14	-1.13%	-2.85	-1.13%	-2.73	-2.86%	-5.34	1.98%	3.14
High - Low	2.50%	4.63	1.46%	3.00	1.87%	3.40	2.05%	3.23		

Panel B: Equal-weighted abnormal returns

'1 Year' portfolio time-series (317 months)

Size Quartile/ Deviation Quartile	Biggest		Q2		Q3		Smallest		Big - Small	
	Abnormal Return	t-stat	Abnormal Return	t-stat	Abnormal Return	t-stat	Abnormal Return	t-stat	Abnormal Return	t-stat
Highest	1.43%	4.27	0.33%	0.93	0.68%	1.64	-0.90%	-2.21	2.33%	4.41
Q2	0.60%	2.07	0.49%	1.54	0.20%	0.63	-0.99%	-2.54	1.59%	3.46
Q3	-0.37%	-1.16	-0.42%	-1.34	-0.60%	-1.77	-1.28%	-3.21	0.91%	1.91
Lowest	-0.80%	-2.14	-1.09%	-2.80	-1.16%	-2.87	-2.63%	-4.86	1.83%	3.09
High - Low	2.22%	4.57	1.42%	2.92	1.85%	3.38	1.73%	2.70		

Table 10 - Abnormal Portfolio Returns per Deviation Quartile – Jaffe-Mandelker Method

This table displays the results for the Jaffe-Mandelker method to control for heteroscedasticity. First, firm-specific abnormal returns are estimated over the 36 months after the IPO (excluding the months of and after a subsequent seasoned equity offering) using the 4-factor model. Separately for firms within the first (first two, first three) year(s) after the IPO and for each deviation quartile, equal-weighted (value-weighted) abnormal portfolio returns are obtained by averaging the (weighted) abnormal return estimates of the firms selected. This table reports the grand time-series means of portfolio abnormal returns over the time from July 1980 to December 2007 and the associated t-statistics ('t-stat'). The standardized test statistic, labeled 't-stat (std.)', is from a time-series of monthly abnormal portfolio returns where each monthly abnormal portfolio return is divided by the standard deviation of firm-specific abnormal returns in this portfolio to control for heteroscedasticity.

Panel A: Average abnormal return on value-weighted portfolios for deviation quartiles

Deviation Quartile	1 Year			2 Years			3 Years		
	Abnormal Return	t-stat	t-stat (std.)	Abnormal Return	t-stat	t-stat (std.)	Abnormal Return	t-stat	t-stat (std.)
Highest	1.36%	17.47	11.45	1.48%	22.63	15.35	1.59%	25.92	17.48
Q2	0.58%	9.53	7.84	0.68%	14.61	13.79	0.76%	15.67	16.12
Q3	0.14%	1.67	3.17	0.18%	3.12	3.62	0.30%	5.47	4.66
Lowest	0.14%	1.05	-2.61	0.56%	4.59	1.79	0.84%	7.29	5.56
High - Low	1.22%	7.43	9.77	0.91%	6.31	9.69	0.75%	5.74	9.27

Panel B: Average abnormal return on equal-weighted portfolios for deviation quartiles

Deviation Quartile	1 Year			2 Years			3 Years		
	Abnormal Return	t-stat	t-stat (std.)	Abnormal Return	t-stat	t-stat (std.)	Abnormal Return	t-stat	t-stat (std.)
Highest	0.24%	4.30	5.54	0.13%	3.23	3.99	0.07%	1.92	2.98
Q2	-0.33%	-6.66	-5.23	-0.52%	-14.07	-13.64	-0.48%	-16.23	-16.83
Q3	-0.61%	-11.05	-10.23	-0.67%	-15.46	-15.46	-0.71%	-17.60	-18.41
Lowest	-0.97%	-11.91	-13.81	-0.99%	-15.56	-18.27	-0.88%	-17.34	-20.67
High - Low	1.21%	12.89	14.35	1.12%	14.82	15.36	0.95%	17.02	17.03

Table 11 - Abnormal Value-Weighted Portfolio Returns for Subperiods

The table summarizes 4-factor abnormal returns on the '2 Year' portfolios for different deviation quartiles and three subperiods of equal length (110 months each). For details on the portfolios, refer to Table 7.

Deviation Quartile	July 1980 : Aug 1989		Sept 1989 : Oct 1998		Nov 1998 : Dec 2007	
	Abnormal Return	t-stat	Abnormal Return	t-stat	Abnormal Return	t-stat
Highest	1.14%	3.07	0.64%	2.06	1.11%	2.57
Q2	0.02%	0.06	0.32%	1.37	0.60%	1.17
Q3	0.02%	0.06	-0.20%	-0.56	-0.73%	-1.43
Lowest	-0.25%	-0.58	-0.84%	-2.44	-1.06%	-1.43
High - Low	1.40%	2.55	1.48%	3.62	2.17%	2.48

Table 12 - Operating Performance Regressions

The table displays results from regressions of firm-specific 4-factor abnormal returns. *DevDummy* is the dummy variable which is zero for positive deviations and 1 for negative deviations, *OpPerf* is the average change in net income before extraordinary items in the first three years after the issuance, scaled by *MktCap*, which is the natural log of the market capitalization at the end of first month with returns data on CRSP. The sample consists of 5,496 firms for which firm-specific abnormal return estimates and operating performance data are attainable.

	Intercept	DevDummy	OpPerf	MktCap	Adj. R2
Coeff.	0.0012	-0.0068	-	-	0.49%
t-stat	*1.29*	*-5.31*			
Coeff.	0.0012	-0.0069	0.0029	-	0.63%
t-stat	*1.34*	*-5.35*	*2.93*		
Coeff.	-0.0048	-0.0069	0.0029	0.0014	0.78%
t-stat	*-2.22*	*-5.38*	*3.03*	*3.05*	

Figure 1 - Abnormal Portfolio Returns for Rolling 3-Months Investment Horizons

The graph shows 4-factor abnormal returns on value-weighted IPO portfolios of highest-deviation and lowest-deviation firms for rolling 3-months windows. I form two portfolios of lowest-deviation and, separately, highest-deviation firms with IPO in the last one to three months. I continue by using a rolling event-time window of three months length to form a second time-series of monthly returns for all the firms in Event-Months 2 to 5, Event-Months 3 to 6, etc. The labels on the x-axis are the respective end months of the time windows. The top line depicts abnormal returns (from the 4-factor model) for the highest-deviation quartile of IPO firms; the bottom line is for the lowest-deviation quartile. Filled dots mark abnormal returns that are significant at the 10% level.