IPOS AS LOTTERIES: SKEWNESS PREFERENCE AND FIRST-DAY RETURNS

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We find that IPOs with high expected skewness experience significantly greater first-day returns. The skewness effect is stronger during periods of high investor sentiment and is related to differences in skewness across industries as well as time-series variation in the level of skewness in the market. IPOs with high expected skewness earn more negative abnormal returns in the following one to five years. High expected skewness is also associated with a higher fraction of small-sized trades on the first day of trading, which is consistent with a greater shift in holdings from institutions to individuals. The results suggest that first-day IPO returns are related to a preference for skewness.

JEL Classification: G11, G12, G14

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1 Introduction

The expected utility theory of von Neumann and Morgenstern (1944) has shaped our understanding of financial markets for decades. In recent years, however, a growing body of literature reveals patterns in how people evaluate risks that are difficult to understand within this framework. One type of behavior not well explained is individuals' affinity for lotteries. People tend to place high subjective valuations on large but low probability gains, which leads to a preference for gambles with highly right-skewed payoffs (e.g., Kahneman, Daniel and Tversky (1979)).

Recent theoretical work has begun to explore the asset pricing implications of replacing traditional expected utility theory with non-standard preferences that better reflect the experimental evidence regarding investors' attitudes toward risk. For example, Barberis and Huang (2008) show that in an economy with cumulative prospect theory agents (Kahneman, Daniel and Tversky (1992)), the overweighting of low probability gains can cause securities with highly right-skewed return distributions to become "overpriced" relative to values obtained in an economy with standard expected utility agents. A similar asset pricing prediction emerges from the endogenous probabilities models of Brunnermeier and Parker (2005) and Brunnermeier et al. (2007), and the heterogeneous agent model of Mitton and Vorkink (2007). Recent empirical evidence provides support for this prediction: Zhang (2006) and Boyer et al. (2010) show that stocks with high idiosyncratic skewness subsequently earn low average returns.[1]

In this paper, we explore the idea that a preference for skewness plays a role in the pricing of initial public offerings (IPOs). IPO prices in the U.S. are usually determined by the bookbuilding method, in which investment banks consult with institutional investors to gauge demand and determine the value of new equity offerings. The new stocks later become available to retail investors on the first day of trading in the secondary market. Institutional investors tend to hold large, well-diversified portfolios and

[1] Bali et al. (2011) also find return evidence that is consistent with a preference for lottery-like stocks, documenting that stocks with a high maximum daily return over the previous month significantly underperform the benchmark. In other related work, Kapadia (2006) creates a cross-sectional skewness factor and finds that loadings on this factor are negatively related to returns.

are generally regarded as more sophisticated and less susceptible to cognitive biases than individual investors (e.g., Battalio and Mendenhall (2005); Grinblatt, Mark and Keloharju (2001)). Moreover, Kumar (2009) provides evidence that individual investors prefer stocks with lottery-like features, whereas Kumar (2005) indicates that institutional investors are averse to idiosyncratic skewness.[2]

If individuals trading in the secondary market exhibit more skewness preference than institutions participating in the primary market, then first-day IPO returns will be positively related to expected skewness. It has been well established that prices jump substantially on the first day of trading. Traditional explanations for IPO underpricing focus on information asymmetries (e.g., Beatty and Ritter (1986); Rock (1986)), and recent work considers the effects of investor over-optimism (Cornelli et al. (2006); Ljungqvist, Alexander et al. (2006); Derrien (2005)). Our goal in this paper is not to cast doubt on existing explanations but rather to introduce a new, additional source of initial IPO returns related to a preference for skewness. Our findings suggest that differences in skewness preference between institutions and individual investors are an important incremental source of first-day IPO returns.

Our argument rests on the idea that primary market participants do not fully recognize the higher valuations that retail investors attach to highly skewed securities. Simplistically, it is possible that institutional investors and underwriters do not fully realize the added value that retail investors place on highly skewed securities. Alternatively, primary market participants may recognize the impact of skewness in the secondary market but choose not to fully incorporate this information into the IPO price due to risk considerations. Previous work outlines conditions under which secondary market values are only partially incorporated into the offer price that may be relevant for skewness preference. For example, Ljungqvist et al. (2006), and Derrien (2005) develop models in which primary market participants actively exploit sentiment investors by selling overpriced IPOs. However, initial investors must be

[2] Kumar (2005) presents evidence that the smallest and least diversified 10% of institutions exhibit a preference for skewness more similar to individual investors, yet these institutions are unlikely to have a strong influence in the IPO bookbuilding process due to their small size and limited holdings. Kumar reports an average portfolio size of $64 million and 22 stocks held for the smallest and least diversifed funds.

compensated for the risk that high sentiment may end prematurely, which prevents the IPO price from fully incorporating the views of retail investors (see also Cornelli et al. (2006)). In other work, underwriters choose not to fully incorporate information about the secondary market price into the IPO price due to concerns about litigation or reputational risk involved with potentially overpricing the issue (Tinic (1988); Lowry and Shu (2002)). Empirically, Derrien (2005) provides evidence that high individual investor optimism leads IPOs to be overpriced and still exhibit positive first-day returns, which supports the view that secondary market conditions are only partially incorporated into the offer price (see also Purnanandam and Swaminathan (2004); Dorn (2009)).

In our analysis, we estimate IPOs' expected skewness using recent returns from their industry peers and computing the intra-industry skewness. Companies in the same industry have similar firm characteristics and are subject to the same technological and regulatory shocks. Thus, newly-listed firms from industries with highly right-skewed returns are more likely to have high expected skewness. Boyer et al. (2010) find industry skewness is useful in predicting future return skewness at the stock level. In our setting, we show that industry skewness is useful at predicting future idiosyncratic skewness for IPOs.

We find a strong relation between our measure of expected skewness and first-day returns. IPOs with higher expected skewness experience significantly greater returns on the first day of secondary trading. For example, IPOs ranked in the bottom third of expected skewness earn first-day returns of 11.44% vs. 25.78% for IPOs in the top third. The results are robust to alternative methodologies and controls for valuation uncertainty, deal characteristics, and industry and market conditions. First-day returns for IPOs are related to both cross-sectional variation in expected skewness across industries as well as time-series variation in the level of skewness in the market. Moreover, we find greater differences in first-day returns between high- and low-skewness groups during periods of high consumer confidence.

Transaction data from the first day of trading provides additional supporting evidence. We use the fraction of small-sized trades as a measure of retail trading intensity (Ofek and Richardson (2003)), and look for evidence of skewness-based clientele effects. We find significantly larger fractions of small trades for IPOs with high expected skewness, which is consistent with a greater shift from institutional investors to individuals on the first day of trading for high expected skewness stocks. The evidence supports the view that first-day returns are related to individual investors' preference for stocks with lottery-like features.

Our final analysis examines longer-horizon returns.[3] We find that IPOs with high expected skewness subsequently earn substantially lower abnormal returns over the next one to five years. For example, IPOs in the bottom third of expected skewness do not significantly underperform their sample of matching firms in the three years following the issuance, whereas IPOs in the top third underperform by a statistically significant 17.54%. Higher first-day returns combined with lower longer-term performance is consistent with skewness preferring investors causing IPOs to become overpriced (relative to the value implied by more traditional preferences) and subsequently earn low excess returns.

Our findings are distinct from the literature on return coskewness. Kraus and Litzenberger (1976) and Harvey and Siddique (2000) examine coskewness and find a negative relation with stock returns. Our emphasis is on idiosyncratic skewness which is relevant when investors hold portfolios that are not well diversified. An asset's coskewness with the market is potentially value relevant for both institutional investors in the primary market and individual investors in the secondary market, and as such we would not expect to see a positive relation between first-day IPO returns and coskewness. Empirically, we find no relation between first-day IPO returns and coskewness, which suggests the difference in skewness preference between institutions and individuals is related to idiosyncratic skewness. Taken together, our findings highlight the importance of return skewness in asset pricing and support the implications of recent theoretical models that incorporate a preference for skewness.

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[3] Ritter (1991) finds evidence of longer-term underperformance for IPOs, and Ritter and Welch (2002) suggest that over-optimism among retail investors may explain high first-day returns and low long-run returns.

2 Data and Methodology

2.1 Data Sources

The data for equity IPOs is from the Thomson Financial Securities Data new issues database. We exclude firms not covered by CRSP within one day of the IPO (4% of the sample). We further require firms to be covered by the Field-Ritter dataset of IPO founding dates.[4] We eliminate IPOs belonging to FF30-industry 30 (consisting of firms unassigned to other industries). We obtain financial-statement, financial-market, and trade data from the Compustat, CRSP, and TAQ databases, respectively. Data on the University of Michigan consumer confidence index comes from the Federal Reserve Bank of St. Louis. Overall, our sample consists of 7,975 IPOs over the 1975-2008 period.

2.2 Expected Skewness Measure

Our measure of expected skewness of IPO *i* at time *t* is similar to Zhang (2006):

$$Skew_{i,t} = \frac{(P_{99}-P_{50})-(P_{50}-P_{1})}{(P_{99}-P_{1})} \qquad (1)$$

where P_j is the *j*th percentile of the log monthly return distribution pooled across all stocks within the FF30-industry of IPO *i* over three months preceding the month of the offering.[5] If the right tail is further away from the median than the left tail, realizations of $Skew_{i,t}$ are positive, indicating that the distribution is right skewed. The denominator controls for the dispersion of the distribution.[6] Unlike the traditional third central moment measure of skewness, our estimator is based only on the tail of a distribution and better captures the idea that skewness preferring investors care primarily about the tail events when

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[4] More details about the data can be found in Field and Karpoff (2002) and in Appendix A of Loughran and Ritter (2004).

[5] For example, if there are *N* stocks in the IPO's FF30-industry at the time of the offering, then $Skew_{i,t}$ is computed from the distribution formed from the *N**3 monthly returns. The results are robust to computing industry skewness using cumulative three-month returns. The results also hold when measuring industry skewness over one, two, or six months preceding the month of the offering. A longer time-series increases the likelihood of capturing small probability events. On the other hand, recent returns likely convey more information about ex-ante expectations.

[6] The dispersion of the distribution may be linked to valuation uncertainty which has been argued to affect first-day returns (e.g., Lowry et al. (2010)).

judging how lottery-like a stock's return distribution is (e.g., Barberis and Huang (2008); Bali et al. (2011); Zhang (2006)).[7]

The rationale behind assigning industry-level estimates to the IPO in question is that companies within an industry share similar firm characteristics and are subject to the same technological and regulatory shocks. As a result, newly-listed firms from industries with high expected skewness are more likely to have highly positively skewed returns.

We classify firms into 30 industries. A finer industry partition increases the similarity between stocks within an industry and potentially improves the precision of the expected skewness estimator. On the other hand, it also reduces the number of observations used to estimate expected skewness and reduces the likelihood of capturing small probability events. We choose the FF30 industry classification as a middle ground. In practice, the results are robust to alternative Fama-French industry categorizations (17, 38, 48, and 49 industries).

We first assess the validity of our expected skewness estimator by examining its usefulness at predicting (future) idiosyncratic skewness for IPOs. We follow Boyer et al. (2010) and compute firm *i*'s "idiosyncratic skewness" at time *t*, $is_{i,t}$, as:

$$is_{i,t} = \frac{1}{N(t)} \frac{\sum_{d \in S(t)} \varepsilon_{i,d}^3}{iv_{i,t}^3} \quad (2)$$

$$iv_{i,t} = \left(\frac{1}{N(t)} \sum_{d \in S(t)} \varepsilon_{i,d}^2\right)^{1/2} \quad (3)$$

where *S(t)* denotes the set of trading days from the first day of aftermarket trading through the end of month 1, 3, 6, or 12; *N(t)* denotes the number of days in this set; $\varepsilon_{i,d}$ denotes the residual of firm *i* on day *d* from regressing daily excess returns on the daily Fama and French (1993) three factors over *S(t).* This measure from Boyer et al. (2010) is more accurately described as skewness of idiosyncratic returns rather

[7] The results are very similar when measuring skewness using the 5th and 95th percentiles rather than the 1st and 99th percentiles; the results also hold when calculating expected skewness using the third central moment rather than percentiles. Moreover, the results are not sensitive to excluding stocks with prices below $5 or using mid-quotes instead of closing transaction prices.

than idiosyncratic skewness. To ensure that we adequately control for return coskewness, we also examine the skewness of residuals from a market model where we also include the square of the market return.

Each month, we rank IPOs in ascending order on the basis of *skew* and form three portfolios. We exclude IPOs postdating the respective IPOs in order to avoid use of forward-looking information. For example, we assign IPOs conducted in January 2000 into portfolios by first ranking all IPOs in our sample, excluding those with offering dates after January 31, 2000.[8] If a January 2000 IPO's *skew* is below the 33rd percentile, it is assigned to the low-skewness portfolio; if its *skew* is between the 33rd and 66th percentile, it is assigned to the medium-skewness portfolio; and if its *skew* is above the 66th percentile, it is assigned to the high-skewness portfolio. We follow this approach for all months in which there is at least one IPO. Portfolios are held for one, three, six, or twelve months.

Table 1 reports the average post-ranking idiosyncratic skewness across the low, medium, and high expected skewness portfolios. The results show that our estimator of expected skewness is useful at predicting future return skewness, and the relation is robust when using alternative measures of idiosyncratic skewness. For example, when portfolios are evaluated one month after the ranking period, the average post-ranking idiosyncratic skewness is 0.253 for the low expected skewness portfolio vs. 0.347 for the high expected skewness (Panel A). The difference in the average idiosyncratic skewness between the low- and high-skewness portfolios is statistically significant at the 1% level, where standard errors are Newey and West (1987) adjusted with 24 lags. We make similar observations when portfolios are held for three, six, or twelve months.

Our expected skewness measure is analogous to using the fitted values from the predictive regression: $is_{i,t} = \alpha + \beta Skew_{i,t-1} + \varepsilon_{i,t}$. Although we implicitly assume α is equal to zero and β is equal to one, estimating these parameters does not change the inferences since we examine relative levels of expected skewness. We also consider additional explanatory variables in the predictive regression such as

[8] We exclude future IPOs when estimating the skewness breakpoints to make the procedure implementable. We find very similar results when forming breakpoints using the full sample.

industry return, firm age, firm size (ln proceeds), and dummy variables for internet, Nasdaq, and NYSE firms. We find modest improvements in R-squared for the skewness predictive regression, and anticipating our findings in the next section, we find a marginally stronger relation between expected skewness and first day returns. We choose our simple *Skew* measure as a conservative benchmark (e.g. firm age and size are already known to be related to first-day IPO returns). In additional analysis, we also examine the relation between first-day returns and ex post firm-level idiosyncratic skewness during the year following issuance.

Table 2 reports the distribution of IPOs by estimated expected skewness and FF30-industries. Despite differences in an industry's IPO distribution across low, medium, and high-skewness portfolios, most industries have at least 20% of their IPOs falling into the low-skewness portfolio and at least 20% of their IPOs falling into the high-skewness portfolio. The exceptions are the Tobacco Products, Retail, and Beer & Liquor industries, where the fraction of IPOs falling into the high-skewness portfolio is 0%, 12%, and 15%, respectively.

3 Average Initial Returns and Expected Skewness

3.1 Portfolio Approach

We begin our main analysis by examining differences in average initial returns across IPOs with low, medium, and high expected skewness. For each IPO, we calculate the initial return as the return from offer price to closing market price on the first day of trading. We rank IPOs in ascending order on the basis of *Skew* as described above and form three equally-weighted portfolios.

Table 3, Panel A reports the average initial returns across IPOs with low, medium, and high estimated expected skewness. High-skewness IPOs, on average, experience an initial return of 25.78%. In contrast, low-skewness IPOs experience an average initial return of only 11.44%. The difference in average initial return is 14.34%. The *t*-statistic of the difference is 11.15 where standard errors are calculated using White (1980)'s heteroskedasticity-consistent method. We make a similar observation when comparing the median initial returns across IPOs with low, medium, and high estimated expected skewness. The median initial return of high-skewness IPOs is 9.09%. In contrast, the median initial return of low-skewness IPOs is only 4.17%. The difference in median initial returns is 4.92% and statistically significant at all conventional levels. We obtain standard errors using the heteroskedasticity-consistent Markov-chain marginal bootstrap method of He and Hu (2002).

We also report results when following a calendar-time type approach. We first calculate the average (median) initial return of IPOs with low, medium, and high expected skewness *separately for each year*. We then report the time-series average of the annual means (medians) for each of the three portfolios. To illustrate by example, the average initial return of 25.78% for high-skewness IPOs reported in Panel A is computed as the average initial return across all 1,987 high-skewness IPOs in our sample. In Panel B, we first sort high-skewness IPOs by the year of the public offering and compute the average initial return of high-skewness IPOs separately for each year. The average initial return of 16.88% for high-skewness IPOs reported in Panel B is the time-series average of the annual means. We employ this approach since IPOs cluster in time and we are concerned that the differences reported in Panel A are driven by a few sample years. However, Table 3, Panel B reports that both mean and median initial returns increase monotonically in estimates of expected skewness, and the difference in initial returns between high- and low-skewness IPOs continues to be both economically and statistically significant.

Figure 1 shows the results for different subperiods. Consistent with the results reported in Table 3, Panel B, high-skewness IPOs experience higher initial returns than low-skewness IPOs in each of the 6 subperiods, and the relation is monotonic in 5 of the 6 periods. There is considerable variation over time, however, with the 1995-2000 period experiencing the largest difference in initial returns. This time period is often considered to be a period of high investor sentiment (e.g., Baker and Wurgler (2007)). In Section 3.3.2, we examine the interaction between investor sentiment and skewness-preference more directly. Overall, results from univariate sorts are consistent with part of the IPO's initial return being related to the IPO's expected skewness.

3.2 Expected Skewness: Time-Series vs. Cross-Section

Variation in *Skew* reflects both changes across industries and over time. In this section, we explore the marginal effects. We calculate estimates for expected market skewness as:

$$MarketSkew_{i,t} = \frac{(P_{99}-P_{50})-(P_{50}-P_1)}{(P_{99}-P_1)} \qquad (4)$$

where P_j is the *j*th percentile of the log monthly return distribution across all stocks over three months preceding the month of the offering. By construction, variation in *Market-Skew*, only reflects time series variation in the lottery-like aspects of a typical stock in the market.

To gauge the effect of time series variation in an IPO's expected skewness on first-day returns, we rank IPOs in ascending order on the basis of *Market-Skew* at the time of the IPO and form three equally-weighted portfolios. Table 4 reports the average initial returns across IPOs with low, medium, and high *Market-Skew*. High market skewness IPOs, on average, experience initial returns of 28.21%. In contrast, low market skewness IPOs experience average initial returns of 13.81%. The difference in average first-day return is 14.40%. The *t*-statistic of the difference is 10.56, where standard errors are calculated using White (1980)'s heteroskedasticity-consistent method.

To explore marginal effects, we rank IPOs sequentially in ascending order on the basis of *Market-Skew* and *Skew*. As reported in Table 4, both cross-sectional and time-series variation in an IPO's expected skewness seem to be important in explaining first-day returns. Within each *Market-Skew* category, initial returns increase from low *Skew* to high *Skew*. The difference in average initial returns between high- and low-skewness IPOs ranges from 7.00% to 18.44%. Vice versa, within each *Skew* category, first-day returns increase from low *Market-Skew* to high *Market-Skew*. The difference in average initial returns between high and low market-skewness IPOs ranges from 9.48% for low skewness IPOs to 18.44% for high-skewness IPOs. The results suggest first-day returns for IPOs are related to both cross-sectional variation in expected skewness across industries as well as time-series variation in the overall level of skewness in the market.

3.3 Regression Approach

One concern with the univariate results is that our measure of expected skewness may be related to firm or market characteristics previously shown to determine initial returns. We address this issue in a regression context. The dependent variable is the initial return, calculated as the return from offer price to closing price on the first day of trading. Our main independent variable of interest, *Skew*, is defined as above and measures the IPO's lottery-like features. To distinguish between idiosyncratic skewness and coskewness, we include a measure of *Coskewness* which is calculated as the average firm-level coskewness (over the previous three months) within the IPO's industry using the approach in Kraus and Litzenberger (1976).[9] Motivated by existing research, we include along with the skewness measure a variety of controls based on market conditions, industry conditions, firm characteristics, and deal characteristics.

3.3.1 Control Variables

Following the prior literature, we include *Age*, which is the age of the firm in years at the time of the IPO. Young firms' returns tend to be more positively skewed than older firms' returns, yet firm age may also be related to valuation uncertainty which has been argued to influence first-day returns (e.g., Baron (1982); Rock (1986); Beatty and Ritter (1986)). Other explanatory variables include: *Internet*, defined to be an indicator for whether the IPO is categorized as an internet company;[10] *Nasdaq* and *NYSE*, defined to be indicator variables for whether the IPO is listed on NASDAQ or NYSE (e.g., Lowry et al. (2010)); *Ln(Proceeds),* which is the natural logarithm of total proceeds (in million$1975); *Price Adjustment*, which is the absolute value of the percentage change between the offer price and the average of the high and low initial filing prices; *Top-Tier Underwriter*, defined to be an indicator for whether the lead

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[9] Using the methodology of Harvey and Siddique (2000) produces similar results.

[10] We follow the internet categorization in Loughran and Ritter (2004) made available on Jay Ritter's website: http://bear.warrington.ufl.edu/ritter/ipodata.htm. Information on the Carter and Manaster (1990) reputation rank is also obtained from Jay Ritter's website.

underwriter's Carter and Manaster (1990) rank is greater than or equal to eight; *Venture-Backed Deal* (from SDC), defined to be an indicator for whether the issuing firm has venture capital banking; *Share Overhang*, calculated as the natural logarithm of (1 + ratio of retained shares to shares offered), and *Pure Primary*, defined to be an indicator for whether the offering consists of primary shares only.

We also include a number of controls for market conditions. *Retail Investor Optimism* is the University of Michigan Consumer Confidence Index and proxies for over-optimism, which has been argued to positively relate to initial returns (e.g., Cornelli et al. (2006); Derrien (2005)). *Market Return* is the compounded daily return on an equally weighted index over 15 trading days, ending on the day prior to the offer, and measures the extent to which public information on the true value of the firm obtained during the registration period is incorporated in the offer price (e.g., Lowry and Schwert (2004)). *IPO Volatility* is the volatility of initial returns of IPOs over three months prior to the IPO in question. To the extent that the offer price is a forecast of the secondary market price, high valuation uncertainty likely results in large positive and negative pricing errors (e.g., Lowry et al. (2010)). We also include a number of time period indicators (1990-1998, 1999-2000, and 2001-2008) to capture known variation in initial returns (e.g., Loughran and Ritter (2004)).

Finally, to address the concern that our results are an artifact of an omitted industry characteristic, we include FF30-industry fixed effects, *Industry Volatility*, *Industry Return*, *Industry Momentum*, and *Industry Turnover*. *Industry Volatility* is measured as the average idiosyncratic volatility of stocks in the IPO's FF30-industry the month prior to the IPO. Motivated by Boyer et al. (2010), *Industry Return* is the IPO's FF30-industry return over month *t-1*, *Industry Momentum* is the cumulative industry return over months *t-13* through *t-2*, and *Industry Turnover* is the average industry turnover (of NYSE stocks) over month *t-1*.

3.3.2 Regression results

The coefficient estimates from various regression specifications are reported in Table 5. When regressing initial returns on *Skew* by itself, we obtain a coefficient estimate of 0.327 (*t*-statistic of 10.22). The coefficient estimate on *Skew* suggests that a one-standard deviation increase in *Skew* leads to a 4.45% increase in first-day returns. The coefficient estimate on *Skew* is consistent with the hypothesis that part of the IPO's initial return can be explained by investors' preferences for securities with lottery-like return distributions.

When controlling for market conditions, and firm- and deal characteristics, the coefficient estimate on *Skew* becomes 0.110 with a *t*-statistic of 4.44. The estimate suggests that a one-standard deviation increase in *Skew* leads to a 1.50% increase in initial returns, which is economically meaningful relative to the average initial return of 17.6%. The coefficient on *Coskewness* is insignificant. The positive and significant relation between measures of expected skewness and first-day returns, on one hand, and the insignificant relation between initial returns and measures of coskewness, on the other, suggests that the difference in skewness-preference between institutions and individuals is related to idiosyncratic skewness.[11]

To further address concerns that our expected skewness estimator is proxying for valuation uncertainty, we partition *Skew* into positive and negative realizations. Past extreme returns within an industry may coincide with greater valuation uncertainty, but we would expect the relation to be roughly symmetric. In other words, valuation uncertainty, and therefore initial return, is likely to increase with both large positive and negative returns. On the other hand, the lottery perspective predicts the relation to be asymmetric, with large negative returns being associated with lower expected skewness and therefore lower initial returns.[12]

Table 5 reports estimates from a regression of initial returns on *Right Skew* and *Left Skew* separately, where *Right Skew* is measured similar to *Skew* as the difference between the 99th and 50th

[11] The skewness effects implied by the regression coefficients are smaller than those implied by the results reported in Table 3. Part of the difference is the assumed linear specification. If we use a 3-group indicator variable for skewness more similar to the approach in Table 3, the difference in initial returns between the high- and low-skewness groups with all the controls is over 4% and statistically significant.

[12] IPOs from industries with negative realizations of *Skew* still have positively skewed future returns (i.e. they are still lotteries), but their returns are less positively skewed than other IPOs.

percentile of the log monthly return distribution of stocks in the IPO's FF30-industry over the preceding three months, and *Left Skew* is difference between the 50th and the 1st percentile. The resulting coefficient estimates are 0.153 (*t*-statistic 4.05) for *Right Skew* and, more importantly, -0.120 (*t*-statistic -3.35) for *Left Skew*. Together, the results imply that our skewness measure is proxying for lottery-like return distributions rather than valuation uncertainty.

The last column in Table 5 presents results when including controls for industry characteristics. The coefficient estimate on *Skew* becomes smaller in magnitude but with an estimate of 0.063 and a *t*-statistic of 2.51 remains economically meaningful and statistically significant. In untabulated results, we also examine the relative effects of industry and market skewness (as in Table 4) in a regression context. When we include *Skew* and *Market-Skew* by themselves in the regression, the coefficients are 0.155 (*t*-stat 4.31) and 0.295 (*t*-stat 4.76), which suggests that first-day IPO returns are related to both cross-sectional and time series variation in the level of expected skewness. Including the full set of control variables results in coefficients of 0.120 (*t*-statistic = 3.92) on *Skew* and -0.114 (*t*-statistic = -2.05) on *Market-Skew*. Although the negative coefficient estimate on *Market-Skew* is surprising, the industry and market return controls which are responsible for the negative coefficient may themselves be related to expected skewness.

In Table 2 we provide evidence that our expected skewness measure correlates with subsequent realized idiosyncratic skewness. In untabulated results, we also directly examine the relation between initial returns and future ex post idiosyncratic skewness measured during the year following issuance (excluding the first-day return). The results are consistent with our hypothesis and the coefficients are similar in magnitude and statistically stronger. For example, a one standard deviation increase in ex ante *Skew* results in a (4.45%, 1.5%, 0.9%) higher first-day return (corresponding to columns 1, 3, and 7 in Table 5). The corresponding numbers when using ex post idiosyncratic skewness are 3.9%, 1.5%, and 1.1%.

In our last set of regressions, we examine the interaction effects of expected skewness with firm age and investor sentiment.[13] Firms that have been operating for many years are less likely to have a lottery-like return distribution; a breakthrough by one firm within an industry may thus have a smaller effect on an older firm's perceived upside potential. If industry skewness predominantly affects the perceived upside of young firms, then sorting IPOs on expected skewness should produce larger spreads in first-day returns for young firms. Investor optimism may also strengthen the effects of skewness preference on prices by decreasing investors' sensitivity to losses and increasing their willingness to hold undiversified positions in highly skewed securities (Barberis and Huang (2008)). In addition, optimism may lead investors to overestimate the dollar payoff of the low probability gain, thus amplifying the influence of skewness preference on prices.

We investigate the interaction effects by forming rank variables for expected skewness, age, and investor sentiment, based on the 33rd and 66th percentiles (i.e. each variable is a one, two, or three). In untabulated results, we find support for both conjectures. After including the controls as in Table 5, we find the difference in initial returns between high- and low-skewness IPOs is 2.4% higher for young firms than for old firms (*t*-stat 2.2). Similarly, the difference in initial returns between high- and low-skewness IPOs is 4.0% larger during periods of high consumer confidence than in periods of low consumer confidence (*t*-statistic = 3.27).[14]

[13] We obtain data on firms' founding dates from Jay Ritter's website: http://bear.warrington.ufl.edu/ritter/ipodata.htm.

[14] In additional analysis, we explore whether first-day IPO returns can be linked to regional differences in gambling propensity. We draw from Kumar et al. (2010) that Catholics appear more prone to gambling than Protestants, and examine whether the skewness effect is stronger among IPOs with headquarters in counties with relatively high ratios of Catholics to Protestants (CP ratios). The results provide some support for this conjecture. We observe that the difference in average initial returns between high and low-skewness IPOs is 2% larger for IPOs with headquarters in counties with relatively high CP ratios (*t*-statistic = 1.70). Information on religious congregations by county and group was graciously provided by Oliver Spalt.

4 Additional Analysis

4.1 Retail Investor Trading

If individual investors exhibit a preference for securities with lottery-like features, the same measures of expected skewness that predict first-day IPO returns should also predict a larger fraction of trades initiated by individuals on the first day of trading. Following Ofek and Richardson (2003) among others, we assume that retail investors tend to trade in smaller dollar amounts and examine the relation between small buyer-initiated trades and expected skewness for IPOs.

Specifically, we estimate pooled regressions on the subsample of all IPOs between January of 1993 and August of 2000 that are covered by the TAQ database. The sample period is determined by the availability of the TAQ database and the difficulty of assigning trades after the New York Stock Exchange's conversion to decimals beginning in August of 2000. The dependent variable is the dollar value of trades that are small and buyer-initiated over the total dollar value of all trades, *Small-buys*. Trades are classified as small if their value is below $10,000 (e.g., Lee (1992); Bessembinder and Kaufman (1997)). Trades are classified as buyer-initiated using the Lee and Ready (1991) algorithm. Our independent variables are: *Skew*, *Age*, *Coskewness*, *Internet*, *Nasdaq*, *NYSE*, *Ln(Proceeds), Retail Investor Optimism*, and *Market Return*. *T*-statistics are calculated using White (1980)'s heteroskedasticity-consistent method and are reported in parentheses.

The results are presented in Table 6. Consistent with our hypothesis, we observe a positive coefficient estimate on *Skew*. When regressing *Small-buys* on *Skew*, the coefficient estimate on *Skew* equals 0.056 (*t*-statistic of 5.29), suggesting that a one standard deviation increase in *Skew* leads to a 0.76% increase in *Small-buys* (which translates to a 0.82 standard deviation increase in *Small-buys*). After controlling for firm and deal characteristics and market conditions, the coefficient estimate on *Skew* becomes 0.049 (*t*-statistic of 4.92), which suggests that a one standard deviation increase in *Skew* leads to a 0.67% increase in *Small-buys*.

On average, 5.7% of the trades on the first day of trading are classified as small buyer-initiated trades. Aggarwal (2003) shows that institutions flip roughly 25% of their allocated shares in the first two days of trading, which indicates that *Small-buys* likely understates the exchange of shares between institutions and individuals. Taken together, our results suggest that high-skewness stocks experience an economically meaningful increase in flipping activity from institutions to individuals on the first day of trading.

4.2 Long-Run Performance

Our evidence suggests investors take positions in IPOs because they value the small chance of a very large positive return. Although our emphasis is on first-day returns, we examine longer-term performance to build support for our claim that large first-day returns for high-skewness firms are driven by high first day closing prices rather than low offer prices. If buying pressure by skewness-preferring investors causes IPOs to become overpriced, IPOs with higher expected skewness should not only experience larger first-day returns but also lower average subsequent returns. Ritter (1991) presents evidence that IPOs underperform over longer horizons, and more recently, Field and Lowry (2009) show underperforming firms tend to be more widely held by individuals. In this section, we investigate the relation between expected skewness at the time of the IPO and longer-term performance.[15]

We examine the long-run performance of high- and low-skewness IPOs relative to matching firms where returns are measured beginning with the closing price on the first-day of trading. Specifically, each IPO is matched with a non-issuing firm in the same size decile having the closest book-to-market ratio. Non-issuing firms are those that have been listed on NASDAQ/AMEX/NYSE for at least five years. We use NYSE firms only for determining the size decile breakpoints, and we use the closing market price on the first day of trading for the IPO and the market capitalization at the end of the previous month for the matching firm. Book-to-market ratios for IPOs are computed using the first recorded post-issue book value and the post-issue market capitalization is calculated using the closing market price on

[15] Kapadia (2006) finds related evidence that IPOs underperform during periods of high market skewness. Our emphasis here is on cross-sectional differences in performance rather than differences over time.

the first CRSP-listed day of trading.[16] For the matching firms, we use the Compustat-listed book value of equity for the most recent fiscal year ending at least four months prior to the IPO date, along with the market capitalization at the close of trading at month-end prior to the month of the IPO with which it is matched.

Table 7 presents long-run returns of IPOs and their matching firms, as well as differences in performance. Regardless of the holding-period, style-matched returns monotonically decrease from low to high expected skewness IPOs. For example, IPOs in the bottom third of expected skewness do not significantly underperform their sample of matching firms in the three years following the issuance, whereas IPOs in the top third underperform by a statistically significant 17.54%. In the five years after the offering, the difference in abnormal returns between low and high-skewness IPOs grows to 31% and remains statistically significant. Combined with the finding that first-day returns for IPOs monotonically *increase* from low- to high expected skewness (Table 3), our results provide evidence that investors with a preference for highly positively skewed securities have price impact causing these securities to become overpriced and subsequently earn low average style-adjusted returns.

Table 7 also reports results from a calendar-time approach. At the end of every month, we form equally-weighted portfolios using all firms that have had an IPO during the previous 12/36/60 months (and their corresponding matching firms) and we compute the time-series mean of those monthly portfolio returns. Consistent with other work on IPOs (e.g., Loughran and Ritter (2000)), the evidence of long-horizon underperformance is generally weaker using a calendar-time approach, which suggests new issues tend to perform worse during IPO waves. The difference in style-matched returns between low- and high-skewness IPOs is no longer statistically significant. However, the results provide some support

[16] We require IPOs to be covered by COMPUSTAT within twelve months of the offering. If a non-issuer gets delisted, the second-closest matching firm on the original IPO date is substituted, on a point-forward basis. If an issuing firm is delisted within a year, its return for that year is calculated by compounding the CRSP value-weighted market index for the rest of the year.

for our hypothesis in that long-run performance is reliably negative only among the high-skewness group (for the three and five year holding periods).[17]

5 Conclusion

An important prediction of theoretical models that incorporate investors' propensity to overweight low probability gains is that securities with lottery-like features can become overpriced relative to the values implied by standard investor preferences (e.g., Brunnermeier and Parker (2005); Brunnermeier et al. (2007); Mitton and Vorkink (2007); Barberis and Huang (2008)). We argue that while individual investors overweigh low probability gains, institutional investors' preference for skewness may be better described by traditional expected utility preferences. To the extent that primary market participants do not fully incorporate individual investors' skewness preference when setting the offer price, examining the effect of an IPO's expected skewness on first-day returns provides an interesting setting to test the hypothesis that securities with lottery-like return distributions can become overpriced.

In our analysis, we use recent returns from industry peers to compute estimates of expected skewness for each IPO. We find that IPOs with high expected skewness experience significantly higher first-day returns than IPOs with low expected skewness. First-day returns for IPOs are related to both variation in expected skewness across industries as well as time-series variation in the level of skewness in the market. Moreover, the pricing effects are amplified during periods of high investor sentiment. High expected skewness is also associated with a greater shift in holdings from institutions to individuals. Finally, IPOs with high expected skewness on average earn more negative style-adjusted returns over the next one to five years. Taken together, the results suggest that skewness preference is an important incremental source of first-day IPO returns.

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[17] The results when measuring abnormal performance using the Fama-French three factors are similar in magnitude. For example, when forming portfolios based on firms with an IPOs in the previous three years, the monthly alpha for the low-skewness portfolio is -0.10% (*t*-statistic = -0.61); the monthly alpha for the high-skewness portfolio is -0.30% (*t*-statistic = -1.85).

References

Aggarwal, Rajesh. 2003. Allocation of Initial Public Ffferings and flipping activity. *Journal of Financial Economics* **68** 111–135.

Baker, Malcolm, JeffreyWurgler.2007. Investor sentiment in the stock market. *Journal of Economic Perspective* **21** 129–151.

Bali, Turan G., Nusret Cakici, Robert F. Whitelaw. 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics* **99** 427–446.

Barberis, Nicholas, Ming Huang. 2008. Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review* **98** 2066–2100.

Baron, David P. 1982. A model of the demand for investment banking advising and distribution services for new issues. *Journal of Finance* **37** 955–976.

Battalio, Robert H., Richard R. Mendenhall. 2005. Earnings expectations, investor trade size, and anomalous returns around earnings announcements. *Journal of Financial Economics* **77** 289–319.

Beatty, Randolph P., Jay Ritter. 1986. Investment banking, reputation and underpricing of Initial Public Offerings. *Journal of Financial Economics* **15** 213–232.

Bessembinder, Hendrik, Herbert M. Kaufman. 1997. A comparison of trade execution costs for NYSE and NASDAQ-listed stocks. *Journal of Financial and Quantitative Analysis* **32** 287–310.

Boyer, Brian H., Todd Mitton, Keith Vorkink. 2010. Expected idiosyncratic skewness. *Review of Financial Studies* **23** 169–202.

Brunnermeier, Markus K., Christian Gollier, Jonathan A. Parker. 2007. Optimal beliefs, asset prices, and the preference for skewed returns. *American Economic Review* **95** 159–165.

Brunnermeier, Markus K., Jonathan A. Parker. 2005. Optimal expectations. *American Economic Review* **95** 1092–1118.

Carter, Richard, Steven Manaster. 1990. Initial Public Offerings and underwriter reputation. *Journal of Finance* **45** 1045–1067.

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

Derrien, Francois. 2005. IPO pricing in "hot" market conditions: Who leaves money on the table? *Journal of Finance* **60**(1) 487–521.

Dorn, Daniel. 2009. Does sentiment drive the retail demand for IPOs? *Journal of Financial and Quantitative Analysis* **44** 85–108.

Fama, Eugene F., Kenneth R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* **33** 3–56.

Field, Laura C., Jonathan M. Karpoff. 2002. Takeover defenses of IPO firms. *Journal of Finance* **57** 1857–1889.

Field, Laura C., Michelle Lowry. 2009. Institutional versus individual investment in IPOs: The importance of firm fundamentals. *Journal of Financial and Quantitative Analysis* **44** 489–516.

Grinblatt, Mark, Matti Keloharju. 2001. What makes investors trade? *Journal of Finance* **56** 589–616.

Harvey, Campbell R., Akhtar Siddique. 2000. Conditional skewness in asset pricing tests. *Journal of Finance* **55** 1263–1295.

He, Xuming, Feifang Hu. 2002. Markov chain marginal bootstrap. *Journal of the American Statistical Association* **97** 783–795.

Kahneman, Daniel, Amos Tversky. 1979. Prospect theory: An analysis of decision under risk. *Econometrica* **47** 263–291.

Kahneman, Daniel, Amos Tversky. 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty* **5** 297–323.

Kapadia, Nishad. 2006. The next Microsoft? Skewness,idiosyncratic volatility, and expected returns.

Kraus, Alan, Robert H. Litzenberger. 1976. Skewness preference and the valuation of risk assets. *Journal of Finance* **31** 1085–1100.

Kumar, Alok. 2005. Institutional skewness preferences and the idiosyncratic skewness premium.

Kumar, Alok. 2009. Who gambles in the stock market? *Journal of Finance* **64** 1889–1933.

Kumar, Alok, Jeremy Page, Oliver Spalt. 2010. Religious beliefs, gambling attitudes, and financial market outcomes.

Lee, Charles M. C. 1992. Earnings news and small traders: An intraday analysis. *Journal of Accounting and Economics* **15** 265–302.

Lee, Charles M. C., Mark J. Ready. 1991. Inferring trade direction from intraday data. *Journal of Finance* **46** 733–746.

Ljungqvist, Alexander, Vikram Nanda, Rajdeep Singh. 2006. Hot markets, investor sentiment, and IPO pricing. *Journal of Business* **79** 1667–1702.

Loughran, Tim, Jay R. Ritter. 2000. Uniformly least powerful tests of market efficiency. *Journal of Financial Economics* **55** 361–389.

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

Lowry, Michelle, Micah S. Officer, G. William Schwert. 2010. The variability of IPO initial returns. *Journal of Finance* **65** 425–465.

Lowry, Michelle, G. William Schwert. 2004. Is the IPO pricing process efficient? *Journal of Financial Economics* **71** 3–26.

Lowry, Michelle, Susan Shu. 2002. Litigation risk and IPO underpricing. *Journal of Financial Economics* **65** 309–336.

Mitton, Todd, Keith Vorkink. 2007. Equilibrium underdiversification and the preference for *skew*¬ness. *Review of Financial Studies* **20** 1255–1288.

Neumann, John von, Oskar Morgenstern. 1944. Theory of Games and Economic Behavior. Princeton University Press, Princeton, NJ.

Newey, Whitney K., Kenneth D. West. 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* **55** 703–708.

Ofek, Eli, Matthew Richardson. 2003. Dotcom mania: The rise and fall of internet stock prices. *Journal of Finance* **58** 1113–1137.

Purnanandam, Amiyatosh K., Bhaskaran Swaminathan. 2004. Are IPOs really underpriced? *Review of Financial Studies* **17** 811–848.

Ritter, Jay R. 1991. The long-run performance of Initial Public Offerings. *Journal of Finance* **46** 3–27.

Ritter, Jay R., Ivo Welch. 2002. A review of IPO activity, pricing, and allocations. *Journal of Finance* **57** 1795–1828.

Rock, Kevin. 1986. Why new issues are underpriced. *Journal of Financial Economics* **15** 187–212.

Tinic, Seha M. 1988. Anatomy of the IPOs of common stock. *Journal of Finance* **43** 789–822.

White, Halbert. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* **48** 817–838.

Zhang, Yijie. 2006. Individual skewness and the cross-section of average stock returns.

Table 1
Predictive power of estimator for expected skewness

This table reports average (ex post) idiosyncratic skewness of IPOs sorted on estimates of expected skewness. The sample includes all IPOs between 1975 and 2008 that are traded on NASDAQ/AMEX/NYSE. In Panel A, (ex post) idiosyncratic skewness is calculated using daily excess stock returns relative to the Fama-French three-factor model (1993). In Panel B, (ex post) idiosyncratic skewness is calculated using residuals from a regression of daily excess stock returns on daily excess market returns and daily excess market returns squared. Estimates of expected skewness are calculated as $Skew = \frac{(P_{99}-P_{50})-(P_{50}-P_1)}{(P_{99}-P_1)}$, where P_j is the j^{th} percentile of the log monthly return distribution across all stocks within the IPO's FF30-industry over three months preceding the month of the offering. Each month, we rank IPOs in ascending order on the basis of estimated expected skewness (excluding IPOs postdating the respective IPOs) and form three equally-weighted portfolios. Portfolios are held for one, three, six, or twelve months. We report equally-weighted average idiosyncratic skewnesses (post-ranking-skewness) for each portfolio, as well as differences across portfolios. *T*-statistics are reported in parentheses where standard errors are Newey-West adjusted with 24 lags.

	Post-Ranking-Skewness			
	1-month	3-months	6-months	12-months
Panel A: Three-Factor-Model				
Low	0.253	0.329	0.342	0.373
	(15.14)	(16.44)	(15.70)	(15.73)
Medium	0.311	0.398	0.435	0.433
	(16.35)	(17.10)	(16.67)	(17.01)
High	0.347	0.432	0.451	0.502
	(14.97)	(16.17)	(14.68)	(13.85)
Δ(High-Low)	0.094	0.102	0.109	0.129
	(3.30)	(3.08)	(2.88)	(3.04)
Panel B: Market-Model				
Low	0.258	0.324	0.335	0.365
	(14.27)	(15.56)	(15.01)	(15.17)
Medium	0.323	0.388	0.417	0.410
	(15.44)	(16.09)	(15.88)	(16.21)
High	0.375	0.434	0.434	0.486
	(15.33)	(15.94)	(14.13)	(13.38)
Δ(High-Low)	0.116	0.110	0.099	0.121
	(3.82)	(3.21)	(2.60)	(2.84)

Table 2
Industry distribution of IPOs from 1975 to 2008

This table reports the number of IPOs by FF30-industry and the fraction of those falling into the low, medium, and high expected skewness portfolios. We assign IPOs to the skewness portfolios as described in Table 1.

			Expected Skewness		
		N	Low	Mediu m	High
1	Food Products	101	45%	27%	29%
2	Beer and Liquor	20	65	20	15
3	Tobacco Products	2	100	-	-
4	Recreation	200	44	28	29
5	Printing and Publishing	74	41	34	26
6	Consumer Goods	93	40	22	39
7	Apparel	56	55	20	25
8	Healthcare, Medical Equipment, Pharmaceuticals	957	31	38	31
9	Chemicals	79	28	35	37
10	Textiles	39	44	31	26
11	Construction and Construction Materials	168	47	29	24
12	Steel Works	72	39	35	26
13	Fabricated Products and Machinery	199	30	43	28
14	Electrical Equipment	249	27	34	40
15	Automobiles and Trucks	55	45	18	36
16	Aircraft, Ships, and Railroad Equipment	36	42	14	44
17	Precious Metals, Non-Metallic, and Metal Mining	19	42	37	21
18	Coal	8	25	38	38
19	Petroleum and Natural Gas	197	37	29	34
20	Utilities	49	45	27	29
21	Communication	316	42	31	27
22	Personal and Business Services	1,762	33	45	22
23	Business Equipment	913	32	42	25
24	Business Supplies and Shipping Containers	58	45	19	36
25	Transportation	207	51	27	22
26	Wholesale	386	47	31	22
27	Retail	460	52	37	12
28	Restaurants, Hotels, Motels	209	53	27	21
29	Banking, Insurance, Real Estate, Trading	991	49	30	21
	Observations	7,975	39	36	25

Table 3
First-day returns on IPOs and expected skewness

This table reports average (median) first-day returns of IPOs sorted on estimates of expected skewness. The first-day return is calculated as the return from offer price to closing market price on the first day of trading. We calculate estimates of expected skewness and assign IPOs to low, medium, and high expected skewness portfolios as described in Table 1. Panel A reports the pooled average (median) initial return of IPOs falling into the low, medium, and high expected skewness portfolios. In Panel B, we compute the average (median) initial return of low, medium, and high skewness IPOs separately for each year, and we report the time-series average of the annual means (medians). *T*-statistics are calculated using White's (1980) heteroskedasticity-consistent method and are reported in parentheses; in Panel A, the *t*-statistic for the median initial return is calculated using the heteroskedasticity-consistent Markov-chain marginal bootstrap method of He and Hu (2002).

	Mean Initial Return	Median Initial Return	Observations
Panel A: Pooled			
Low	11.44%	4.17%	3,120
Medium	18.55	7.50	2,868
High	25.78	9.09	1,987
Δ(High-Low)	14.34	4.92	
	(11.15)	(8.98)	
Panel B: Calendar Time			
Low	10.86	5.15	32
Medium	15.49	9.01	30
High	16.88	9.81	30
Δ(High-Low)	6.00	4.49	
	(2.84)	(3.03)	

Table 4
First-day returns on IPOs and expected skewness – Market vs. Industry

This table reports average first-day returns for IPOs sorted on estimates of market and industry skewness. The initial return is calculated as the return from offer price to closing market price on the first day of trading. We calculate estimates of expected (industry) skewness as described in Table 1. We calculate estimates of expected market skewness as $Market - Skew = \frac{(P_{99}-P_{50})-(P_{50}-P_1)}{(P_{99}-P_1)}$, where P_j is the j^{th} percentile of the log return distribution across all stocks over three months preceding the IPO. Each month, we rank IPOs sequentially in ascending order on the basis of estimated expected market skewness and estimated expected industry skewness (excluding IPOs postdating the respective IPOs) and form nine equally-weighted portfolios. For each portfolio, we report the average initial returns. *T*-statistics are calculated using White's (1980) heteroskedasticity-consistent method and are reported in parentheses.

	Skew				
	All	Low	Medium	High	Δ
Market-Skew					
Low	13.81%	11.69%	11.43%	18.69%	7.00%
					(4.85)
Medium	14.83	10.65	16.94	17.72	7.07
					(4.70)
High	28.21	21.18	29.15	37.13	15.94
					(5.03)
Δ(High-Low)	14.40	9.48	17.71	18.44	
	(10.56)	(6.18)	(6.95)	(5.89)	

Table 5

First-day returns on IPOs and expected skewness: Regression approach

This table reports coefficient estimates from pooled regressions of first-day returns on measures of expected skewness. The initial return is calculated as the return from offer price to closing market price on the first day of trading. *Skewness* is the estimate of expected skewness as described in Table 1. *Right Skewness* is the difference between the 99th and 50th percentile of the monthly return distribution of stocks in the IPO's FF30-industry over the preceding three months, and *Left Skewness* is the difference between the 50th and 1st percentile. The set of control variables are described in the text. *T*-statistics are calculated using White's (1980) heteroskedasticity-consistent method. We do not report the intercept.

	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
Firm Characteristics								
Skewness	0.327	(10.22)	0.110	(4.44)			0.063	(2.51)
Right Skewness					0.153	(4.05)		
Left Skewness					-0.120	(-3.35)		
Age			-0.001	(-5.84)	-0.001	(-5.84)	-0.001	(-5.08)
Coskewness			0.000	(0.36)	0.000	(0.38)	0.000	(0.26)
Internet			0.278	(6.96)	0.277	(6.94)	0.268	(6.82)
Nasdaq			0.073	(4.58)	0.072	(4.55)	0.068	(4.17)
NYSE			0.028	(1.56)	0.028	(1.59)	0.035	(1.97)
Deal Characteristics								
Ln(Proceeds)			0.015	(3.11)	0.015	(3.12)	0.013	(2.85)
Price Adjustment			0.375	(7.45)	0.375	(7.46)	0.369	(7.48)
Share Overhang			0.088	(10.66)	0.088	(10.44)	0.085	(10.42)
Pure Primary			0.004	(0.74)	0.004	(0.67)	0.016	(2.66)
Venture-Backed Deal			0.007	(0.86)	0.006	(0.69)	0.010	(1.16)
Top-Tier Underwriter			-0.008	(-0.95)	-0.008	(-1.00)	-0.005	(-0.55)
Market Characteristics								
Retail Inv. Optimism			0.002	(6.24)	0.002	(6.34)	0.001	(4.05)
Market Return			1.326	(9.85)	1.333	(9.96)	1.018	(7.55)
IPO Volatility			0.327	(5.09)	0.304	(4.84)	0.241	(3.98)
Y(1990-1998)			0.015	(2.19)	0.014	(1.91)	0.017	(2.09)
Y(1999-2000)			0.024	(0.49)	0.025	(0.51)	0.043	(0.86)
Y(2001-2008)			-0.023	(-1.94)	-0.021	(-1.74)	0.006	(0.31)
Industry Characteristics								
Industry Return							0.497	(5.06)
Industry Momentum							0.161	(6.62)
Industry Volatility							0.313	(1.38)
Industry Turnover							0.013	(0.81)
Industry Fixed Eff.	No		No		No		Yes	
Adj. R-squared	0.013		0.310		0.311		0.330	
Observations	7,975		7,603		7,603		7,603	

Table 6
Trades in IPOs and expected skewness

This table reports coefficient estimates from pooled regressions of small trades in IPOs on measures of expected skewness. The dependent variable is the dollar value of trades that are small and buyer-initiated over the total dollar value of trades. Trades are classified as small if their value is below $10,000. *Skewness* is the estimate of expected skewness as described in Table 1. The control variables are described in the text. *T*-statistics are calculated using White's (1980) heteroskedasticity-consistent method and are reported in parentheses. We do not report the intercept.

	Coef.	*t*-stat	Coef.	*t*-stat
Skewness	0.056	(5.29)	0.049	(4.92)
Age			-0.000	(-2.33)
Coskewness			-0.000	(-0.21)
Internet			0.067	(12.31)
Nasdaq			-0.005	(-0.39)
NYSE			-0.006	(-0.46)
Ln(Proceeds)			-0.026	(-10.72)
Retail Investor Optimism			0.002	(12.31)
Market Return			0.022	(0.51)
Adj. R-squared	0.006		0.161	
Observations	3,320		3,211	

Table 7
Expected skewness and long-run performance of IPOs

This table reports the performance of IPOs and style-matched stocks during the first five years after issuance. We calculate estimates of expected skewness and assign IPOs to low, medium, and high expected skewness portfolios as described in Table 1. Each IPO is matched with a non-issuing firm in the same size decile having the closest book-to-market ratio. Panel A reports equally-weighted average cumulative percentage returns on IPOs and style-matched stocks during the first five years after issuing. Panel B reports average monthly calendar returns of equally-weighted portfolios including IPOs (and style-matched stocks) that have gone public in the prior one year, three years or five years. *T*-statistics are calculated using White's (1980) heteroskedasticity-consistent method and are reported in parentheses.

Panel A: Cumulative Percentage Returns

Skew		1^{st} year	3^{rd} year	5^{th} year
Low	IPO firms	10.89%	36.16%	60.98%
	Matching firms	9.34	37.36	65.86
	Difference	1.55	-1.20	-4.88
		(0.85)	(-0.26)	(-0.41)
	Observations	2,792	2,692	2,101
Medium	IPO firms	6.95	24.88	54.95
	Matching firms	6.57	28.99	64.71
	Difference	0.39	-4.11	-9.76
		(0.20)	(-0.87)	(-1.09)
	Observations	2,686	2,608	2,027
High	IPO firms	-0.71	5.46	36.11
	Matching firms	9.31	23.00	72.14
	Difference	-10.02	-17.54	-36.03
		(-4.14)	(-4.20)	(-3.78)
	Observations	1,907	1,882	1,434
$\Delta(Difference_{High} - Difference_{Low})$		-11.57	-16.35	-31.15
		(-3.82)	(-2.64)	(-2.05)

Panel B: Calendar Time – Monthly Portfolio Returns

Skew		1^{st} year	3^{rd} year	5^{th} year
Low	IPO firms	0.78%	1.17%	1.19%
	Matching firms	1.25	1.30	1.26
	Difference	-0.47	-0.13	-0.07
		(-1.68)	(-0.71)	(-0.44)
Medium	IPO firms	1.14	0.87	0.87
	Matching firms	1.25	1.14	1.14
	Difference	-0.11	-0.27	-0.27
		(-0.33)	(-1.26)	(-1.42)
High	IPO firms	0.59	0.82	0.93
	Matching firms	1.30	1.28	1.27
	Difference	-0.71	-0.46	-0.34
		(-1.58)	(-2.31)	(-2.08)
$\Delta(Difference_{High} - Difference_{Low})$		-0.24%	-0.33%	-0.27
		(-0.48)	(-1.45)	(-1.31)

Figure 1. Expected skewness and average initial returns across subperiods.

This figure reports average initial returns on IPOs across subperiods. The initial return is calculated as the return from the offer price to closing market price on the first day of trading for the IPO. We calculate estimates of expected skewness and assign IPOs to the high-/medium/low-expected skewness portfolio as described in Table 1.