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PII: S0929-1199(17)30202-X
DOI: https://doi.org/10.1016/j.jcorpfin.2017.12.027
Reference: CORFIN 1335

To appear in: *Journal of Corporate Finance*

Received date: 2 April 2017
Revised date: 13 December 2017
Accepted date: 19 December 2017

Please cite this article as: Zhiqiang Wang, Bingbai Su, Jerry Coakley, Zhe Shen , Prospect theory and IPO returns in China. The address for the corresponding author was captured as affiliation for all authors. Please check if appropriate. Corfin(2017), https://doi.org/10.1016/j.jcorpfin.2017.12.027

Prospect theory and IPO returns in China[1]

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December 13, 2017

Abstract

This paper provides a new cumulative prospect theory (PT) perspective on IPOs by proposing a median-based expected skewness measure as the reference point for potential investors. Since our sample of 837 book-built Chinese IPOs over the 2006-2012 period comprises of 30% negative and 70% positive skewness issues, this paper reveals novel findings on the left-skewed IPOs that enjoy a mean first-day return of 65.61% compared with 56.55% for the right-skewed subsample. A one standard-deviation increase in skewness lead to an increase of 10.41 percentage points in the first-day return which is virtually 50% larger than that on right-skewed IPOs. While left-skewed IPOs exhibit a significantly positive relationship between offer price discounting and (absolute) skewness, the relationship for right-skewed IPOs is insignificant. A one-standard-deviation shock to skewness deepens discounting by left-skewed IPOs by 21.21 percentage points, making such IPOs susceptible to nominal price illusion. A skewness shock attracts more than double the mean value of retail orders to the left- than to the right-skewed subsample although the latter attracts 26% more investors. Prospect theory suggests that investors in left-skewed IPOs tend to flip to exploit the deep discounting (relative to their underlying value) on the first trading day rather than gamble on possible long run gains. Relatedly, their long run return measures are independent of absolute skewness but we find significantly inverse relationships between these variables for right-skewed IPOs. Overall, our PT framework provides the basis for a more nuanced picture of the motives for IPO investment and their contrasting implications for initial and long run returns.

JEL Classification: G32
Keywords: Skewness, IPO, Retail Demand, First-day Return, Long-term Performance

[1] We thank Jeff Netter (the Editor) and an anonymous reviewer for their valuable guidance and insightful comments which substantially improved the exposition of this paper. We also thank Ana Maria Fuertes, Qinghao Mao, Zheng Qiao, Qian Sun, seminar participants at Xiamen University, and the 2017 EFMA Conference (Athens) for their helpful comments on early versions of this paper. We acknowledge financial support from the National Natural Science Foundation of China (71572159, 71472160, 71232005, 71472161, 71790601). All remaining omissions and errors are ours.

Prospect theory and IPO returns in China

1. Introduction

China is now one of the world's largest IPO markets and boasts some unique features relative to established markets. The average first day returns on 2,512 Chinese initial public offerings (IPOs) over the 1990-2013 period was 118.4%. From an international perspective, this return was over 7 times the corresponding returns of 16.9 and 16.0% for both the USA and UK, respectively.[2] Besides potentially huge first day returns, Chinese IPOs offer a lottery-like gain to investors: the potential that any particular IPO may become the next Tencent (owner of the WeChat social messaging app) or Alibaba, making them extremely attractive to prospective investors.[3] Moreover, allocation of new IPO shares among retail investors is by means of an actual lottery mechanism. The short and long run upside potential of Chinese IPOs implies that there is huge excess demand for new issue shares. This is illustrated by an average allocation rate of just 1.5% in our sample which implies that new issues are oversubscribed 66 times on average. Given these features and that many studies mention IPOs as an example of lottery-like investments, Chinese IPOs would seem a natural candidate for study.

Quite a few studies of lottery-like investments have recently appeared in the literature that highlight features of the tail(s) of return distributions and depart from the standard expected utility theory framework. The Mitton and Vorkink (2007) heterogeneous agent model links expected skewness and the idiosyncratic skewness of underdiversified investors. This model's new results derive from having standard expected utility investors and nonstandard or lotto investors. Using this framework, Boyer, Mitton and Vorkink (2010) find a negative relationship between idiosyncratic skewness and expected returns.[4] Likewise, Green and Hwang (2012) apply this framework in a pathbreaking study of IPOs. They establish that first-day returns are positively related to expected skewness for a sample of 7,975 US IPO stocks over the 1975-2008 period. IPO stocks with high expected skewness have low

[2] See the 2015 update of Table 1 from Loughran, Ritter and Rydqvist (1994) for IPOs in 25 countries: https://site.warrington.ufl.edu/ritter/files/2015/05/Initial-Public-Offerings-International-Insights-2015-05-21.pdf

[3] While the Chinese Alibaba Group went public in New York as the largest US-listed IPO only in 2014, Chinese investors had been aware of other IPO stars such as Apple and Amazon.

[4] See also Kumar (2009), Bali, Cakini and Whitelaw (2011), Conrad, Dittmar and Ghysels (2013), Conrad, Kapadia and Xing (2014), and Eraker and Ready (2015).

cumulative long-run percentage returns but not low average returns in calendar time, both relative to style matched non-issuing stocks. The skewness effect is associated with a higher proportion of small trades on the first trading day, consistent with a transfer from institutions to individuals, and is stronger during high investor sentiment years.

Other studies appeal more directly to the prospect theory of Kahneman and Tversky (1979) and Tversky and Kahneman (1992).[5] The main contribution of prospect theory is that investors' objective probability preferences are transformed by a subjective weighting function. The implication is that all objective probabilities are transformed but, in an obvious link to skewness, the biggest changes apply in the tails. Low probability events are assigned bigger weights so that investors are induced to gamble on low probability upside events and to prefer insurance for low probability downside events. Barberis and Huang (2008) develop a theoretical PT model where investors exhibit a preference for positive skewness or a tendency to overpay for securities with right-skewed payoffs. Their model generates the prediction that a positively skewed security will be overpriced relative to its expected utility valuation and thus it will earn negative average returns. Barberis, Mukherjee and Wang (2016) develop an empirical framework for applying PT to individual stock returns. They envisage the PT investor as involved in a two-step procedure: representation and valuation. The mental representation of risk step is the most challenging and they assume the investor employs (60 months of) past returns for this purpose. PT valuation is straightforward and just involves the application of the Tversky and Kahneman (1992) formulae.

The first contribution of this paper is that it employs expected skewness as a reference point for IPO investors within a PT framework. This is an adaptation of the Barberis et al. (2016) concept of the mental representation of risk applied to IPOs.[6] While Barberis et al. (2016) are able to use five years of monthly returns as their reference point, such data are not available for firms embarking on an IPO. Intuitively we conjecture that investors form a picture of IPO risk by examining most recent three-month returns on the traded stocks in the industry (sector) to which the IPO belongs. The Zhang (2006b) expected skewness concept is chosen as the

[5] The cumulative prospect theory (CPT) in the latter generalizes the prospect theory (PT) concept of the earlier book. We follow researchers in finance who employ PT to encompass both.

[6] While the seminal Green and Hwang (2012) US IPO study also uses expected skewness, they do not conceptualise it as a reference point and so ignore negative expected skewness.

reference point because it provides a median-based measure of tail risk in contrast to the standard third-moment mean-based measure.

One crucial implication of employing expected skewness as a reference point is that our sample data do not accord with the popular focus on lottery-like right-tailed risk. Instead they point to a more nuanced picture of IPO skewness. The overall mean (median) expected skewness of our sample of 837 Chinese IPOs is 0.0722 (0.0790) which could lead one to conclude that the standard skewness preference framework would be the appropriate one to apply for analysis. Closer inspection reveals that the negative expected skewness or left-skewed subsample of 251 IPOs (30% of the total) has a mean (median) of –0.1097 (-0.0823) while the corresponding figures for the 586 (30% of the total) right-skewed IPO subsample are 0.1501 (0.1435). These differences are statistically and economically significant at better than the 1% levels. The strong implication of left-and right-skewed IPOs yields very different reference points for potential investors but this has been ignored thus far in the literature.

The presence of both negative and positive IPO skewness raises the question of how they can both be analysed in a PT framework as care has to be exercised in dealing with negative expected skewness values. While large negative expected skewness values are mathematically less than small values, the use of absolute (negative) values renders the economic interpretation the same as for the corresponding positive values. Thus, as a first approximation, the concept of absolute skewness enables one to analyse the full sample in a unified fashion and this overturn results that employ raw skewness data.[7] The problem is that it assumes that investors treat negative and positive values symmetrically while PT suggests that investor are loss averse. Thus, we propose the use of a simple but efficient regression model with an indicator function for separating negatively- from positively-skewed IPOs where both are conditioned on a common set of control variables.[8] This allows us to test for the potential asymmetric effects of negative and positive expected skewness in an IPO context.

The paper's second contribution is that our empirical analysis of IPOs with negative expected skewness results in a set of nuanced and novel findings, some of which seem puzzling

[7] While our full sample of 837 Chinese IPOs shows no significant relationship between initial returns and expected skewness, the use of absolute skewness leads to a significantly positive relationship.
[8] From an estimation viewpoint, separate analysis of the left- and right-skewed subsamples involves a loss of power as large amounts of data are discarded in both cases.

at first glance. For instance, the left-skewed subsample unexpectedly yields a mean initial return of 65.61% while that of the right-skewed subsample is just 56.55%. PT can help shed light on the distinct behavior in both tails of the expected skewness distribution. We conjecture that left-skewed IPOs will exhibit a low to moderate chance of bankruptcy thus will have to be fairly deeply discounted relative to their intrinsic value to compensate investors for this very high left tail risk. This has two short run effects. On one hand, low priced IPOs are subject to the Birru and Wang (2016) price illusion effect which leads to increased demand. This nudges the price back towards fair value. On the other hand, many investors in left-skewed IPOs flip during the first day's trading and take (almost) certain profits rather than gamble on the very low probability prospect of the IPO becoming the next Alibaba or Tencent (or even a growth stock). Our conjecture thus is that deep discounting reflected in the offer price and the related excess retail demand is the basis for the extremely high mean initial returns earned by left-skewed IPOs.[9]

This conjecture is validated by regression results indicating a significantly positive relationship between offer price discounting and absolute (expected) skewness for the left-skewed subsample only and by a significantly positive relationship between two direct measures of retail demand and absolute skewness. Moreover, our results show that long run return measures for left-skewed issues are independent of absolute skewness since the impact of first day trading is that their market prices revert upwards towards to levels around their underlying value. By contrast, our conjecture is that the offer price of right-skewed IPOs will be close to (sometimes above) intrinsic value due to excess demand for such issues generated by the prospect of lottery-like returns. This implies no relationship between discounting and expected skewness and this is borne out in our empirical results. Thus, their high mean initial returns of 56.55% is likely due to continued excess demand for these issues on (and after) the first trading day as indicated by a positive relationship between initial returns and two direct retail demand measures. The implication of this excess demand is that prices rise well above intrinsic value. Our regression results indicating a negative relationship between long performance measures and right-tailed skewness - as predicted by Barberis and Huang (2008) - offer support for these

[9] Based on the Tversky and Kahneman (1992) weighting function parameterisation, only objective probabilities up to 0.35 get scaled up. We take the latter as the upper bound of moderate risk.

conjectures.

Our study links to the wider IPO literature. First, it has been empirically difficult to investigate whether investor sentiment affects IPO first-day returns, mainly because the impact of investor sentiment on the first-day closing price and the offer price cancel out in the first-day return definition. The studies by Derrien (2005) and Ljungqvist, Nanda and Singh (2006) show that investor sentiment generated by retail investor demand is crucial to the pricing of IPOs. They both demonstrate that investor sentiment is positively related to IPO first-day returns but negatively related to long run post-IPO stock performance. These two studies assume the participation of retail investors in IPOs is random or unpredictable.

Previous studies are only able to measure retail demand or the presence of investor sentiment indirectly. For example, Cornelli, Goldreich and Ljungqvist (2006) and Dorn (2009) use prices from pre-IPO trading in the European grey markets to proxy for small investor valuations, assuming that the typical grey market investor is a small investor. Green and Hwang (2012) use retail trading to proxy for small investors' trading on the assumption that retail investors trade in smaller dollar amounts. This assumption may not always hold since not all wealthy individuals in China and elsewhere trade in small amounts. Thus, the threshold adopted by previous studies such as "below USD10,000" (Lee, 1992; Bessembinder and Kaufman, 1997) or an algorithm-generated threshold such as that in Lee and Radhakrishna (2000) may not result in a meaningful classification of small trades. Moreover, to the extent that institutional investors in practice often split their large orders, the misclassification problem can be even more serious.

By contrast, our study complements previous empirical studies by employing two direct measures of retail demand.[10] The findings indicate that the latter tends to increase with expected skewness, leading to high first-day returns, and, for the right-skewed sample only, low post-IPO abnormal returns in the long run.

The rest of the paper is thus organized as follows: Section 2 outlines the institutional background and hypothesis development. Section 3 details the IPO sample. Section 4 describes the data and variables and analyses the empirical results. Section 5 presents the results of

[10] To the best of our knowledge, institutional arrangements in Hong Kong and India also allow one to obtain direct measures of retail demand. See Jiang and Li (2013) and Clarke, Khurshed, Pande and Singh (2016) for more details.

additional analysis. Section 6 concludes.

2. Institutional Background and Hypothesis Development

2.1 IPO Prices and Allocation in China

Prior to 2005, *The Securities Law of the People's Republic of China* stipulated that the offer price of an IPO stock should be determined jointly by the lead underwriters and the IPO firm, and that the IPO firm should seek approval from the China Securities Regulatory Committee (CRSC) before it proceeds with its A-share issue. The CRSC is the Chinese equivalent to the SEC in the USA. It introduced a book-building approach in 2005 to bring the IPO pricing mechanism more in line with international practice. The *Administration Measures of Stock Issuance and Underwriting* (the AMSIU, thereafter) which regulates IPO activities in China is characterized by the following features:

1) There are two separate tranches under this new book-building approach. Basically, the IPO offer price is determined in the first offline tranche where underwriters solicit indications of buying interests from institutional investors, build up the order book and determine the final offer price for an IPO stock. In contrast to the first tranche where participation is virtually limited to institutional investors, participation in the follow-up second tranche is by retail investors, who subscribe for new shares online at the fixed price determined in the first tranche.

2) There are two different stages of book building even within the first offline tranche. According to the AMSIU, IPO firms and underwriters should use the first stage, also known as "preliminary book-building" (*chubu xunjia* in Chinese), to decide the offer price range based on indications of interests received and then proceed to the second stage, also known as "book-building" (*leiji toubiao xunjia* in Chinese), to determine the IPO offer price. The only exception is that for IPOs to be listed in the Medium-and-Small or ChiNext Board, IPO firms and underwriters can choose to determine the offer price using indications of interests received in the first stage, without proceeding to the second stage. What happens in the second stage is very similar to the US practice in that: i) institutional investors can bid for new issues at various prices within the range; ii) the underwriter collects this bid information and

builds up the order book for a particular IPO stock; iii) the IPO offer price is assessed on the basis of those bids obtained in the second stage for the fixed quantity of the IPO stock offered for sale.

3) According to the AMSIU, institutional investors can decide whether they want to participate in the first stage of book building. However, those who do not participate in the first stage or those who fail to provide valid bids in the first stage will be excluded from share allocation in the second stage. Bids are invalid if i) institutional investors do not pay in full for their share subscriptions before the deadline; ii) the bid price is outside the offer price range chosen by the underwriter; or iii) other circumstances specified in the AMSIU.

4) One aspect that separates the expected outcome of the book-building approach in China from that in the USA is the incentive mechanism for share allocation among institutional investors. In the USA, the issuer and the underwriter can use their discretion to determine the allocation of new shares between institutional investors, which can ensure that investors who bid for more new shares at higher prices will be rewarded with disproportionately larger share allocations for truthfully revealing value-relevant information. However, there is no similar incentive mechanism in place in this context because Chinese underwriters enjoy absolutely no discretion at all. Share allocation must follow a pre-determined pro rata rule under which institutional orders with bid prices greater than the offer price will receive shares in proportion to the size of their bids. This proportion or allocation rate is decided as the number of new shares sold over the number of new shares subscribed. For this reason, institutional investors are not encouraged to reveal their private information in the first- or second-stage of book-building and so value-relevant information revealed through the Chinese book building approach is rather limited or insufficient to ensure effective price discovery.

5) Retail investors submit their subscription orders for the shares of an IPO stock at the fixed price in the second tranche. In cases of oversubscription – and the vast majority of Chinese IPOs are hugely oversubscribed – share allocation between retail investors is implemented through a pure lottery mechanism. The latter is the second distinctive

feature of the Chinese IPO process. Under the lottery mechanism, every 1,000-share order is assigned one lottery ticket with a unique lottery number.[11] This lottery mechanism for share allocation is a key aspect of the lottery-like nature of Chinese IPOs over the course of our sample period. Its likely impact is to induce retail investors into thinking that making an IPO subscription order is akin to buying a lottery ticket. The long run potential reward for those lucky investors receiving an allocation is the possibility of a stake in China's next Tencent or Alibaba.

2.2 Related Literature and Expected Skewness Hypotheses

Psychologists have provided convincing evidence that individuals tend to overweight low-probability outcomes in their decision making relative to the weight that the outcome would receive under expected utility theory. Building upon this psychological evidence, Barberis and Huang (2008) theoretically analyse the impact of investor preferences over the lottery-like features on asset prices. They show that, in an economy where investors evaluate risk according to cumulative prospect theory, securities with high skewness can become overpriced and exhibit negative returns in the future. This prediction is vindicated in the empirical PT study of Barberis et al. (2016). Several other studies using a skewness preference approach provide empirical evidence consistent with this novel prediction as well, including Kumar (2009), Boyer et al. (2010), Bali et al. (2011), Conrad et al. (2013), and Eraker and Ready (2015).

Chinese IPOs make an interesting case study in the context of prospect theory for several reasons. First and foremost, Chinese IPOs offer investors two potential lottery-like gains. One is potentially huge first day returns as Chinese issuers leave record amounts of money on the table. The other is that any particular Chinese IPO is seen as having the potential of becoming the next Tencent or Alibaba. The second reason is that Chinese IPOs are subject to huge levels of retail demand and are oversubscribed by up to 70 times on average. It is possible that expected skewness can help explain huge waves of investor sentiment for Chinese IPOs. However, in sharp contrast, there is little or no excess demand for new issues in advanced

[11] Every 1000-share will be given a lottery number if it is an IPO for Shenzhen Stock Exchange while every 500-share will be given a lottery number if it is an IPO for Shanghai Stock Exchange.

economies, such as the USA, where underwriters can adjust the offer price to accommodate excess demand.

The final reason is that data on direct measures of retail demand for Chinese IPOs are available and their links with expected skewness can be developed and tested. Green and Hwang (2012) show that individual investors exhibit a greater degree of skewness preference than do institutions and that this drives first-day IPO returns. This is in line with previous studies - including Cornelli et al. (2006) and Dorn (2009) – that report evidence that retail demand drives post-IPO prices. In the presence of investor sentiment around the IPO event, both Derrien (2005) and Ljungqvist et al. (2006) show that underwriters can take advantage of overvaluation due to optimistic retail investors by setting the offer price above a firm's intrinsic value.

Accordingly, this paper uses the Barberis and Huang (2008) and Barberis et al. (2016) PT framework to analyse both left-skewed and right-skewed (lottery-like) IPO stocks. In both cases, investors will overweight the probability of losses and gains, respectively, and this logically leads to distinct but related hypotheses for both. Our framework nests the skewness preference hypothesis that implies a positive relationship between first-day returns and expected skewness.

Hypothesis 1A: First-day returns for all (positively-skewed) IPOs are directly related to expected skewness.

The skewness preference hypothesis rests on the implicit assumption that retail investor buying decisions are linked to the expected skewness of lottery-like IPO stocks. This hypothesis is likely to receive strongest support for our subsample of right-skewed IPOs that make up 70% of our sample of Chinese IPOs and that are likely to attract the highest excess demand for their shares.

Hypothesis 1A overlooks the left-skewed IPOs that that make up 30% of our sample. As a first approximation, assume that investors treat positive and negative values of skewness symmetrically. This can be captured by employing the absolute values (modulus) of negative skewness. The intuition is that high absolute (negative) expected skewness IPOs also have to offer high compensation to attract loss averse investors (the details are discussed below). The fact that the modulus leaves unaffected the expected skewness of right-skewed IPOs suggests a direct relationship between first day returns and absolute skewness for the full sample as well as for left-skewed IPOs. This suggests the following more intuitively plausible hypothesis 1B:

Hypothesis 1B: First-day returns for all (negatively skewed) IPOs are positively related to absolute expected skewness.

Some 30% of our sample IPOs exhibit left-skewed expected returns (i.e. losses) and so exhibit a low to moderate chance of bankruptcy. These have been ignored in the emergent IPO skewness literature. It raises the obvious question of why investors would be attracted to negative expected skewness IPOs. Under PT, loss averse investors will demand high compensation for such IPOs. Issuers respond by discounting the issue (the median discount is -22.70% in our left-skewed subsample) relative to its intrinsic value to attract investors and this is the major attraction of left-skewed IPOs. The more left-skewed the stock, the deeper the discount leading to an inverse relationship between skewness and discounting. If a left-skewed IPO were to flop and the first-day price fall below the offer price, then investors would face a certain loss. The larger the discount, the greater the probability of a price rise towards its intrinsic value region and thus of profiting from flipping. Hence, they can gamble on the prospect that the price will rise and so the investor horizon for left-skewed IPOs is very short term. This leads to the following novel hypothesis for left-skewed IPOs:

Hypothesis 2A: There is a negative relationship between absolute expected skewness of left-skewed IPOs and discounting.

Flipping considerations do not arise with right-skewed IPOs as the prospect of lottery-like gains ensures excess demand for such issues and that would discourage discounting. Nonetheless, issuers may still be tempted to discount their offer prices to compete with left-skewed IPOs and to attract investors with long term horizons. Not that the median discount is -16.08% in our right-skewed subsample which makes the sign unpredictable. This leads to the following hypothesis:

Hypothesis 2B: There is a positive (negative) relationship between expected skewness of right-skewed IPOs and discounting.

The issuers of left-skewed IPOs have to attract demand from loss-averse investors and so will be forced to discount and leave generous amounts of money on the table as an inducement. This increases the possibilities for flipping such IPOs and earning short run profits.

Thus, the most left-skewed IPOs are likely to be deeply underpriced. For such IPOs, the more negatively skewed they are, the higher the amount of money left on the table, and so the higher retail demand is likely to be. This leads to the following hypothesis:

Hypothesis 3A: Retail demand for left-skewed IPOs will be higher the higher the absolute expected skewness.

Previous studies - including Cornelli et al. (2006) and Dorn (2009) - report evidence that retail demand drives post-IPO prices. In the presence of investor sentiment around the IPO event, both Derrien (2005) and Ljungqvist et al. (2006) show that underwriters can take advantage of overvaluation due to optimistic retail investors by setting the offer price above a firm's intrinsic value. The latter is not germane to the expected skewness hypothesis since its implicit assumption is that retail investor buying decisions are largely linked to the IPO's lottery features. Although right-skewed IPO issuers do not need to leave much money on the table to attract investors, they are also likely to discount their offer prices to compete with deeply-discounted (left-skewed) IPOs. The latter may mitigate the prediction that the higher the expected skewness, the greater the retail demand is likely to be for an IPO stock. This leads to the following hypothesis:

Hypothesis 3B: Retail demand for right-skewed IPOs will be higher the higher the expected skewness.

The next logical question is whether the initial overvaluation relative to intrinsic value due to skewness preference tends to reverse in the long run. At the heart of the Barberis and Huang (2008) and Barberis et al. (2016) view is the novel prediction that securities with high expected skewness will generate low average returns in the future. This issue is nuanced in the IPO context. If initial overvaluation is driven by deep discounting rather than by lottery-like features as in the case of left-skewed IPOs, then prices will tend to return to intrinsic value in the short and not the long run. This leads to the following novel hypothesis:

Hypothesis 4A: Long-run abnormal returns are independent of expected skewness for left-skewed IPOs.

By contrast, if initial overvaluation is driven by positive expected skewness, discounting and related excess retail demand, then the first day closing price is likely to be driven well above intrinsic value. In such cases, expected skewness hypothesis predicts long-run reversal in such

IPO stock prices towards their underlying value.

Hypothesis 4B: Long-run abnormal returns are negatively related to expected skewness for right-skewed IPOs.

3. Our IPO Sample

We start with 1,169 Chinese A-share book-built IPOs over the period from January 2005 to December 2013. The sample period starts from 2005 because Chinese issuers started using the book-building approach to IPOs in that year. It ends in December 2013 because a three-year post-IPO period is required to estimate the long-run abnormal return and also because several new regulations introduced by the CSRC (China Securities Regulatory Commission) in 2013 imply that the first-day closing price might not fully reflect the impact of retail demand after 2013. For example, both the Shanghai and Shenzhen Stock Exchanges issued a notice in 2013 that several new monitoring measures over trading in the initial post-IPO period would be introduced.[12] One stipulates that the first-day IPO closing price would not be permitted to exceed its offer price by more than 144%. The CSRC also made another reform announcement in 2013[13] under which underwriters would be given full discretion on share allocation among institutional investors. This reform provides an incentive for institutional investors to reveal private information in the book-building process, leading to the IPO offer price potentially containing more private information, including that on the presence of investor sentiment due to skewness preference. Excluding IPOs issued after 2014 preserves the unique feature of our sample of Chinese IPOs that include virtually no price relevant private information from the book-building process.

We exclude 26 financial IPOs and 15 utilities IPOs. We retrieve from CSMAR, WIND and CVSource a wide range of offer and firm characteristics for the remaining IPOs. Daily price data from CSMAR and WIND are employed to estimate expected skewness,

[12] See more details for the Shanghai Stock Exchange Announcement 2013 No.20 "A Notice by the Shanghai Stock Exchange Regarding Strengthening Monitoring Over the Trading in the Initial Post-IPO Period" and the Shenzhen Stock Exchange Announcement 2013 No.142 "A Notice by the Shenzhen Stock Exchange Regarding Strengthening Monitoring Over the Trading in the Initial Post-IPO Period".

[13] See more details for the CSRC Announcement 2013 No.42 "An Opinion by the CSRC Regarding Further Reform of the IPO Process", available at the following address: http://www.csrc.gov.cn/pub/zjhpublic/G00306201/ndbg/201311/P020131130527675150742.doc

first-day returns and long-term performance for these IPOs. We further exclude 275 IPOs since the number of log monthly returns available to estimate the skewness measure in these cases is less than 100. We also drop 16 IPOs where there is insufficient information on retail demand or other variables. This screening procedure yields a final sample of 837 IPOs over the 2006-2012 period.[14]

Table 1 depicts the yearly and industry distribution of the final sample.

[Table 1 around here]

Panel A presents the yearly distribution of the 837 IPOs. The sample is not distributed equally across years and part of the reason for the variation is the suspension of new listings imposed by the government. For example, due to the split share structure reform[15] which started in early 2005 and ended in mid-2006, the CSRC halted IPOs for that period to reduce the supply of shares to the market. Thus, only 15 IPOs were completed in 2005 before the suspension and 66 IPOs after the suspension. Due to the 2008-2009 financial crisis, the CSRC also suspended the IPO process from September 16, 2008 until July 10, 2009 and so the IPO numbers in 2008 and 2009 are smaller. The third suspension period spans the period from November 16, 2012 to December 31, 2013, in part due to the preceding dramatic market decline, and so there were only 2 listings in 2013. Our final sample appears to be representative of the initial sample since they follow similar trends across the years.

Panel B presents the industry distribution of our sample IPOs. These 837 IPOs are quite widely distributed across industries. Manufacturing clearly accounts for the largest number of sample IPOs (594) that make up some 70.97% of the total. Two sectors, C38 (Electronic Machinery & Apparatus) and C39 (Computers, Communications & Other Electronic Devices), together account for 227 IPOs or over a third of the manufacturing industry. The second largest sector is I63-I65 (Information Technology & Software), but that accounts for only 14.10% of the final sample. Even within manufacturing, there is a lot of variation across sectors. One can see that many manufacturing sectors do not have a single IPO over our sample period. Since our selection procedure is not biased against any particular

[14] The implication is the small numbers of IPOs in 2005 and 2013 are excluded.

[15] The reform aimed to remove the most salient market friction, making non-tradable shares tradable. Several studies examine the implication of this important event, including Firth, Lin, and Zou (2010), Li, Wang, Cheung and Jiang (2011), Chen, Chen, Schipper, Xu and Xue (2012), Liao, Liu and Wang (2014)

industry (except for finance and utilities), the final sample is broadly representative of the initial sample in terms of industry distribution.

4. Data and Empirical Results

4.1 Variables and Descriptive Statistics

Expected Skewness

Following the standard industry classification defined by the CSRC, we classify all IPO and non-IPO firms into industry groups, including Agriculture, Forestry, Fishing & Farming (A01-A05), Mining (B06-B12), Manufacturing (C13-C43), Construction (E47-E50), Wholesale & Retail Trade (F51-F52), Transportation, Warehousing & Postal Service (G53-G60), Hotels & Restaurants (H61-H62), and IT & Software (I63-I65). All non-IPO stocks belonging to the same industry are used to measure how lottery-like an IPO's stock return distribution is as these are subject to similar regulatory, technological, and industry shocks. The only exceptions are manufacturing stocks. Manufacturing is the largest industry group containing a wide range of 25 different sectors such as Food (C14), Chemicals (C28), Pharmaceuticals (C29), and Computers, Communications & Other Electronic Devices (C39). Since non-IPO stocks which fall into the same manufacturing industry may not be very relevant to a particular manufacturing IPO stock, relying on industry returns to measure expected skewness could lead to large measurement errors. To minimize this problem, we use all non-IPO stocks belonging to the same sector within the manufacturing industry instead to measure the expected skewness for manufacturing IPOs.

We follow Zhang (2006b) and Green and Hwang (2012) in defining the expected skewness of returns. For the latter, all log monthly returns of the same-industry or -sector stocks over the three-month period before the offer date are pooled to generate the return distribution. The expected skewness of an IPO stock *j* is given as follows:

$$Skewness_j = \frac{\left(Percentile_{99} - Percentile_{50}\right) - \left(Percentile_{50} - Percentile_{1}\right)}{\left(Percentile_{99} - Percentile_{1}\right)} \tag{1}$$

where $Percentile_k$ is the k^{th} percentile of the log monthly return distribution across all stocks that fall within the same industry as IPO stock *j*. The numerator gives the difference in distance of each tail from the median and so is positive for right- and negative for left-skewed distributions. The denominator gives the dispersion of the distribution. Note that this is a median-based skewness measure in contrast to the mean-based traditional third central moment measure of skewness. It will be apparent from the descriptive statistics of our sample IPOs below that there are notable differences between the mean and median of many variables both within and across subsamples. This is why expected skewness can be regarded as a neat formalization of retail investor's representation of the risk of an IPO based on its returns over the three months prior to the IPO.

First-day Returns and Long-term Performance

We follow the literature in defining the first-day return as the percentage difference between the offer price and the first-day closing price. Following Lyon, Barber and Tsai (1999), we start from the 2^{nd} trading date and use both the event-time BHAR (buy and hold abnormal return) and the calendar-time abnormal return estimated using factor regressions to measure post-IPO abnormal returns. BHAR are estimated as the difference between the buy-and-hold return for IPO firms over the 36 post-IPO event months and the buy-and-hold return for comparable non-IPO firms over the same period. Following Chan, Wang and Wei (2004), non-IPO matching firms are selected based on size and book-to-market (B/M) characteristics. We use tradable shares to calculate both market capitalization and B/M ratio.[16] These matching non-IPO firms are required to have a trading record of at least 3 years in the stock market.

Jensen's alpha estimated from the Fama-French three-factor model (Fama and French, 1993) over the 36 post-IPO calendar months is used as an alternative measure of long-run stock performance. Specifically, the monthly returns in excess of the risk-free rate for IPO firms are regressed on three monthly risk factors: market risk premium, *SMB* and *HML*. The post-IPO abnormal monthly return is defined as the intercept estimated from time-series monthly regressions after adjusting for risk compensation.

Control Variables

[16] Unreported regression results are very similar when we include non-tradable shares to calculate size and B/M.

Previous studies document a number of variables that are potentially relevant for first-day returns or long-term performance. For example, Ritter (1984) and Beatty and Ritter (1986) among others argue that ex-ante uncertainty regarding the new issue should predict the extent of underpricing. Typical measures for ex-ante uncertainty at the firm level include IPO proceeds (Amihud, Hauser and Kirsh 2003), firm age at the time of offering (Megginson and Weiss, 1991), underwriter reputation (Carter and Manaster, 1990; Carter, Dark and Singh 1998; Loughran and Ritter, 2004), auditor reputation (Beatty 1989), and venture capital reputation (Nahata, 2008; Krishnan, Ivanov, Masulis, and Singh, 2011). Typical measures for information uncertainty at the market level include the accuracy of analyst forecasts and the dispersion of analyst forecasts (Barron, Kim, Lim, and Stevens, 1998; Zhang, 2006).

Prior research has not only confirmed the validity of those measures for uncertainty in the Chinese context, but also managed to identify a number of important variables for post-IPO returns, such as the lag number of days elapsed between offering and listing (Chan et al., 2004; Fan, Wong and Zhang, 2007; Tian 2011; Shen et al., 2013), leverage (Fan et al., 2007; Chen, Wei, Li, Sun and Tong, 2015), the percentage of state ownership retained in the IPO firm (Kao, Wu and Yang, 2009; Tian, 2011; Liu, Uchida and Gao, 2014), the legal environment[17] (Liu et al., 2014; Chen et al., 2015). All these are included in our regression analysis as control variables. We also include the number of IPOs in the same calendar month to control for market-level sentiment, and a set of year dummies to further control for unobservable year fixed effects.

Table 2 presents descriptive statistics for the main variables used for analysing our sample of 837 IPO firms. We split the full sample into the left-skewed subsample where the expected skewness of an IPO stock is negative and the right-skewed subsample where the it is positive. Several interesting observations emerge when we compare descriptive statistics for two subsamples and the full sample.

[17] The NERI (National Economic Research Institute) index was originally prepared by Fan and Wong in 2001, and updated later regularly. It has five sub-indices for 1) government decentralization, 2) development of non-state sectors, 3) development of product markets, 4) production factors markets, and 5) market intermediaries and the legal environment. Several studies use the NERI index to measure the development of institutions in different provincial areas, including Wang, Wong and Xia (2008), Firth, Lin and Wong (2008), Wu, Wu and Rui (2012), Xu, Xu and Yuan (2013) and Dong, Liu, Shen and Sun (2016). Following Liu et al. (2014) and Chen et al. (2015), we use the fifth sub-index to measure the legal environment.

[Table 2 around here]

Panel A provides descriptive statistics for the full sample. It is interesting to compare and contrast the mean and median of relevant variables. On one hand, both are very similar for a range of variables including expected skewness. First, the mean and median expected skewness are reactively similar at 0.0722 and 0.0790, respectively. Second, the sample IPO firms usually go public in their 8th year since the mean value of Log (1+Age) is 2.0560 and its median is 2.1972. Third, they are generally profitable as the mean (median) *ROA* is 0.1375 (0.1239). Finally, the mean (median) number of retail investors participating in the IPO market is 0.43 million (0.30 million) and they create a sizeable mean (median) demand of around RMB167 billion (around RMB167 billion).

On the other hand, the mean and median diverge sharply for several key variables. First, there is a huge divergence between the mean and median first-day returns. The mean first-day return of 59.27% is 1.66 times the median of 35.69%. Second, these sample IPOs tend to underperform relative to their non-IPO comparators. The mean monthly BHAR in the three-year post-IPO period is -0.6051 which is more than three times the corresponding median BHAR of -0.1837. Finally, the median sample IPO is discounted by 16.91% relative to its intrinsic value. In sharp contrast, the mean *Discounting* implies the IPOs are overpriced by 39.78% on average.

Panel B presents descriptive statistics for the left- and right-skewed subsamples and here we focus on the differences within and between the two subsamples. First, the absolute mean and median expected skewness are considerably higher for the 586 right-skewed IPOs than for the 251 left-skewed IPOs and the differences are statistically significant in both cases. The difference is considerably more in the case of the two medians: the right-skewed median of 0.1435 is some 1.74 times the left-skewed median of (-)0.0823. Second, equality of mean and median tests on *IR* and *BHAR* suggest no significant differences between these variables for two subsamples even if their actual values do diverge. However, their within subsample values diverge sharply. Thus, the median values of *IR* and *BHAR* are considerably smaller (in absolute terms) than their corresponding means in both subsamples. Finally, the *Discounting* differences are interesting. The mean right-skewed subsample offer price is overpriced by 48.27% relative to intrinsic value and this is more than double the corresponding mean left-skewed subsample overpricing of 20.19%. By contrast, the median right-skewed subsample discount is -16.08% lower in absolute than the corresponding mean left-skewed subsample discount of -22.70%.

Table 3 presents correlation matrices both for the full sample and for two subsamples.

[Table 3 around here]

First, the unconditional correlation between first-day return and raw expected skewness is -0.25 for the negatively-skewed subsample, while the unconditional correlation between first-day return and raw expected skewness is 0.10 for the positively-skewed subsample. Second, the unconditional correlation between raw expected skewness and discounting for the left-skewed subsample is -0.00, which appears to suggest that there is no relationship between these two variables. Third, there is no evidence of a positive relationship between retail demand and the absolute value of expected skewness for both negatively- and positively skewed IPOs. For the subsample of negatively-skewed IPOs, the correlation between expected skewness and Log(*Orders*) is 0.36 while the correlation between expected skewness and Log(*RMB*) is 0.28. For the subsample of positively-skewed IPOs, the correlation between expected skewness and Log(*Orders*) is 0.43 while that between expected skewness and Log(*RMB*) is 0.38. Fourth, for the left-skewed subsample, the unconditional correlation between expected skewness and BHAR is -0.17 but the corresponding correlation between expected skewness and Jensen's alpha is 0.07. For the right-skewed subsample, the unconditional correlation between expected skewness and BHAR is -0.24 but the corresponding correlation between expected skewness and Jensen's alpha is 0.04. Finally, we note that correlations between other firm characteristics are generally low, implying that we do not have to worry too much about the multicollinearity issue in our multivariate analysis.

4.2 Expected Skewness and First-day Returns

We estimate Equation (2) to examine whether there is a positive relationship between expected skewness and first-day returns. We also estimate Equation (3) to examine whether there is a positive relationship between absolute expected skewness and first-day returns. Equation (4) gives the same relationship as Equation (3) but employs an indicator function for the impact of expected skewness of left- from right-skewed IPOs on first day returns. Thus, the Equation (4) regression will yield separate slope coefficients for the left- and right-skewed subsamples but common coefficients for the control variables and the slope.

$$IR_j = \alpha_1 + \alpha_2 * Skewness_j + \sum_{i=3}^{n} \left(\alpha_i * X_j \right) + \varepsilon \tag{2}$$

$$IR_j = \alpha_1 + \alpha_2 * \left| Skewness_j \right| + \sum_{i=3}^{n} \left(\alpha_i * X_j \right) + \varepsilon \tag{3}$$

$$IR_j = \alpha_1 + \alpha_2 * \left| Skewness_j \right| * I_L + \alpha_3 * Skewness_j * \left(1\text{-}I_L \right) + \sum_{i=4}^{n} \left(\alpha_i * X_j \right) + \varepsilon \tag{4}$$

where *IR* is the first-day return of an IPO stock; *Skewness* is the expected skewness; I_L is an indicator function equal to 1 when *Skewness* < 0 and 0 otherwise; |*Skewness*| is the absolute value of *Skewness*; *X* is a vector of control variables. Note that (1-I_L) captures the subsample with nonnegative expected skewness.

Table 4 presents regression results for Equation (2) in Panel A. Panel B gives the results using absolute expected skewness, and Panel C presents the results for Equation (4).

[Insert Table 4 around here]

Panel A reveals no statistically evidence of a positive relationship between first-day return and expected skewness for the full sample and so rejects Hypothesis 1A. Column (1) presents the results for a regression that includes *Skewness* as the only independent variable, Colum (2) further includes a set of year dummies to control for unobserved year fixed effects while Columns (3) and (4) also include control variables. For instance, the coefficient on *Skewness* is -0.007 (*t*-statistics = -0.04) in Column (4). However, when we replace *Skewness* by |*Skewness*| in the Panel B regressions, the results change significantly. Note that this implicitly assumes that investors react symmetrically to the same absolute values of both negative and positive expected skewness. Now the coefficients on |*Skewness*| for all regressions are significantly positive, even though they decline somewhat when including year dummies and the control variables. The results now support Hypothesis 1A.

Panel C presents the results from separating negatively- from positively-skewed IPOs by means of an indicator function but conditioning on a common set of control variables in Equation (4). This allows for asymmetric effects of negative and positive expected skewness. They indicate a significantly positive relation between first-day returns and expected skewness across four regression specifications. The coefficient on |*Skewness*| for the left-skewed subsample in Column (4) is 1.202 (*t*-statistics = 2.59) after controlling for firm characteristics. This implies that a one-standard-deviation increase in expected skewness would lead to an increase of 10.41 percentage points (1.202*0.0866) in the first-day return for left-skewed IPOs. Interestingly, this economic impact is virtually 50% larger than that on right-skewed IPOs (see below). This is a novel finding in the expected skewness literature and supports Hypothesis 1B for left-skewed IPOs.

The coefficient on *Skewness* for the right-skewed subsample in Column (4) is 0.758 (*t*-statistics = 3.17) which, interestingly is smaller than the corresponding figure of 1.202 for the left-skewed subsample. This implies that one a one standard-deviation increase in expected skewness would lead to an increase of 7.09 percentage points (0.758*0.0936) in the first-day return for right-skewed IPOs. This finding is consistent not only with our Hypothesis 1B, but also with Barberis and Huang (2008) who posit that high first-day returns are driven by high first-day closing prices due to PT investors demonstrating a strong skewness preference rather than by low offer prices. It complements Green and Hwang (2012) who find evidence of a significant positive relationship between first-day returns and expected skewness for a sample of 7,975 US IPOs issued during the 1975-2008 period. They find a significant coefficient estimate of 0.327 on expected skewness without any control variables, indicating a one-standard-deviation increase in the expected skewness leads to a 4.45% increase in first-day returns. Including control variables, the coefficient on expected skewness falls to 0.063 but it must be noted that they employ a much larger US sample that spans a longer sample period.

The Table 4 results provide new and surprising insights on the relationship between first day returns and expected skewness. Although the results show no significant relationship for the full sample using raw expected skewness in Panel A, they become significantly positive when we employ absolute skewness in Panel B by assuming that investors react symmetrically to similar values of both negative and positive expected skewness. When we relax the latter assumption by separating left- from right-skewed IPOs using an indicator function in Panel C, not only are the impacts in the separate subsamples statistically significant but the economic impact of expected skewness is economically much stronger for the left-skewed subsample. They underline the importance of separating left- from right-skewed IPOs in investigating the impact of expected skewness on first day returns. Furthermore, the larger economic impact on left-skewed IPOs suggests that distinct mechanisms are at play for these IPOs that have been ignored in the literature so far. These are investigated in the following subsections.

4.3 *Why Do Retail Investors Buy Negatively-skewed IPOs?*

While the previous empirical analysis shows a positive relationship between first-day return and absolute expected skewness, it also hinted at a tendency of retail investors to be more averse to the more negatively-skewed IPOs. One possible explanation is that, IPO firms knowing retail investors are highly loss averse towards more negatively-skewed IPOs, discount their new shares relative to their intrinsic value. The low prices resulting from discounting implies that such IPOs are subject to the Birru and Wang (2016) price illusion effect. This leads to increased demand and the tendency for prices to revert towards their intrinsic value region. The related prospect of subsequent price rises on the first day's trading – that can be captured by flipping – has the potential to make left-skewed IPOs attractive to retail investors.

To explore this possibility, we follow Purnanandam and Swaminathan (2004) and measure the ex-ante discounting of an IPO price using the P/E ratio at the offer price and the median P/E ratio of all firms belonging to the same industry. Discounting is defined as the percentage difference between the offer price and the median market price:

$$\left(\frac{P}{E}\right)_{IPO} = \frac{P_{IPO} \times Shares\ Outstanding}{Prior\ Fiscal\ Year\ Earnings} = \frac{P_{IPO}}{EPS} \tag{5}$$

$$\left(\frac{P}{E}\right)_{Match}^{Median} = \frac{P_{Market} \times Shares\ Outstanding}{Prior\ Fiscal\ Year\ Earnings} = \frac{P_{Market}}{EPS} \tag{6}$$

$$Discounting = \frac{P_{IPO} - P_{Market}}{P_{Market}} = \frac{P_{IPO}}{P_{Market}} - 1 = \frac{(P/E)_{IPO}}{(P/E)_{Market}} - 1 \tag{7}$$

Table 2 shows that the median discounting for the full sample is -0.1691, indicating that well over half (57.95%) of IPOs are priced below their fair value. This finding is consistent with Gao (2010), who uses the same methodology to separate the discounting component, or deliberate underpricing, from first-day returns for a sample of 217 Chinese IPOs from July 2006 to April 2008. The fact that median discounting is -0.2270 for the left-skewed subsample and -0.1608 for the right-skewed subsample seems to suggest that left-skewed IPOs are more deeply discounted than are right-skewed IPOs.

We estimate the following two regressions to examine the impact of skewness on discounting for the full sample in Equation (8) and for our two subsamples in Equation (9):

$$Discounting_j = \alpha_1 + \alpha_2 * \left|Skewness_j\right| + \sum_{i=3}^{n}\left(\alpha_i * X_j\right) + \varepsilon$$

(8)

$$Discounting_j = \alpha_1 + \alpha_2 * \left|Skewness_j\right| * I_L + \alpha_3 * Skewness_j * \left(1\text{-}I_L\right)$$

$$+\sum_{i=4}^{n}\left(\alpha_i * X_j\right) + \varepsilon \qquad (9)$$

where *Skewness* is the expected skewness; |*Skewness*| is the absolute value of *Skewness*; I_L is an indicator function equal to 1 when *Skewness* < 0 and 0 otherwise; *X* is a vector of control variables.

Table 5 presents regression results for Equation (8) in Panel A and for Equation (9) in Panel B.

[Table 5 around here]

Panel A reveals no evidence of a positive relationship between discounting and absolute skewness for the full sample on average. However, regression results change substantially in Panel B where we an indicator function separately to examine the impact of (absolute) expected skewness on discounting for two subsamples. Consistent with our Hypothesis 2A, the coefficient on |*Skewness*| is -2.449 (*t*-statistics = -2.18) in Column (4) after controlling for other firm characteristics, which implies that a one-standard-deviation increase in the absolute value of expected skewness can explain a deeper discount of almost 21.21% (=-2.449*0.0866) relative to the value defined by the median industry P/E. We do not find any evidence of such a negative relationship between discounting and expected skewness for the right-skewed IPO subsample as the coefficient on *Skewness* is insignificant across all regression specifications in Panel B. All these specifications reject Hypothesis 2B.

The implication is that deep discounting is unique to negatively-skewed IPOs and that its impact is substantial. A one-standard-deviation shock to absolute skewness deepens discounting by some 21 percentage points. Recall that low priced IPOs resulting from discounting are subject to the Birru and Wang (2016) price illusion effect which leads to increased retail demand. The related prospect of subsequent price rises on the first day's trading encourages flipping. This underlines the centrality of discounting in making left-skewed IPOs an attractive investment. By contrast, the discounting of right-skewed IPOs is independent of expected skewness.

4.4 Expected Skewness and Retail Demand

Using direct measures for the presence of investor sentiment, we empirically examine the relationship between retail demand and expected skewness. Two direct measures are employed: Log(*Orders*), defined as the logarithm of the number of valid orders received from retail investors in the second tranche, and Log(*RMB*) defined as the logarithm of the monetary value of retail demand (number of new shares subscribed multiplied by the offer price). We estimate the following two regressions:

$$Log(Orders_j) = \alpha_1 + \alpha_2 * \left|Skewness_j\right| + \sum_{i=3}^{n}\left(\alpha_i * X_j\right) + \varepsilon \tag{10}$$

$$Log(RMB_j) = \beta_1 + \beta_2 * \left|Skewness_j\right| + \sum_{i=3}^{n}\left(\beta_i * X_j\right) + u$$

(11)

where the modulus on the *Skewness* variable ensures positive values only for the expected skewness of an IPO stock; *X* is a vector of control variables. We expect the coefficient estimate on |*Skewness*| to be positive.

We also estimate the following two specifications to examine whether investors have different preference for positively and negatively skewed IPOs.

$$Log(Orders_j) = \alpha_1 + \alpha_2 * \left|Skewness_j\right| * I_L + \alpha_3 * Skewness_j * \left(1\text{-}I_L\right) + \sum_{i=4}^{n}\left(\alpha_i * X_j\right) + \varepsilon \tag{12}$$

$$\mathrm{Log}\left(RMB_j\right) = \beta_1 + \beta_2 * \left|Skewness_j\right| * I_L + \beta_3 * Skewness_j * \left(1\text{-}I_L\right) + \sum_{i=4}^{n}\left(\beta_i * X_j\right) + u \tag{13}$$

where *Skewness* is the expected skewness; |*Skewness*| is the absolute value of *Skewness* for the left-skewed subsample; I_L is a dummy, equal to 1 when *Skewness* < 0 and 0 otherwise.

Table 6 presents regression results for Equations (10) and (11) in Panel A and for Equations (12) and (13) in Panel B.

[Table 6 around here]

By employing the |*Skewness*| variable, the Panel A regressions assume that investors do not differentiate between right- and left-skewed IPOs. In Column (1) where the dependent variable is Log(*Orders*), the coefficient on |*Skewness*| is 0.427 (*t*-statistic = 3.23), which indicates that high |*Skewness*| IPO stocks are associated with a larger number of retail orders by PT investors on average. This positive relationship remains strong even after controlling for other firm characteristics in Column (2) since the coefficient is 0.335 (*t*-statistic = 2.71). The regression results in Columns (3) and (4) with Log(*RMB*) as the dependent variable show a similar picture. The coefficient on |*Skewness*| is also significantly positive at 0.773 (*t*-statistic = 5.03) when we exclude other firm characteristics in Column (3). It is 0.601 (*t*-statistic = 4.06) in Column (4) where we control for the impacts of other firm-level variables.

Panel B examines the relationship between retail demand and expected skewness by separating left- from right-skewed IPOs. To the extent that investors may be attracted to discounted left-skewed IPOs, one would expect the coefficient on |*Skewness*|*I_L to be positive. To the extent that investors prefer IPO stocks offering lottery-like returns, one would expect the coefficient on *Skewness**(1-I_L) to be positive also. The Log(*Orders*) regression results show that the coefficient on |*Skewness*|*I_L is 0.388 (*t*-statistics= 2.01) and that on *Skewness**(1-I_L) is 0.324 (*t*-statistics= 2.58) in Column (2), after controlling for other firm characteristics. The Log(*RMB*) regression results reveal that the coefficient on |*Skewness*|*I_L is 0.617 (*t*-statistics= 2.37) and that on *Skewness**(1-I_L) is 0.598 (*t*-statistics= 4.05) in Column (4), after controlling for the other firm characteristics.

These findings reveal significant evidence of a positive relationship between both retail demand measures and (absolute) expected skewness. The finding of significantly positive relationships between Log(*Orders*) and Log(*RMB*) and |*Skewness*| for left-skewed IPOs is consistent with Hypothesis 3A. On average, a one-standard-deviation increase in |*Skewness*| for left-skewed IPOs implies an increase of 0.0336 (0.388*0.0866) in Log(*Orders*) and 0.0534 (0.617*0.0866) in Log(*RMB*). These translate into increase of 30.0k retail investors and of RMB415.2 million relative to their mean levels, respectively. These economic impacts are quite substantial, suggesting that deep discounting makes these IPOs very attractive flipping prospects for loss averse investors. The finding of significantly positive relationships between Log(*Orders*) and Log(*RMB*) and *Skewness* for right-skewed IPOs is less surprising and is consistent with both skewness preference and our Hypothesis 3B. A one-standard-deviation increase in *Skewness* for right-skewed IPOs leads to an increase of 0.0303 (0.324*0.0936) in Log(*Orders*) and 0.0560 (0.598*0.0936) in Log(*RMB*). These represent increases of 37.9k retail investors and an increase of about RMB206.7 million in the average value of retail orders.

It is interesting to compare the economic impacts on the left and right-skewed subsample as their mean *Orders* and their *RMB* values are quite similar in dimension. A skewness shock attracts 26% more retail orders to the right- than to the left-skewed subsample, consistent with the notion that lottery IPOs generate more investor sentiment. By contrast, a skewness shock attracts more than double the value of retail orders to the left- than to the right-skewed subsample. This is consistent with our view that left-skewed IPOs also offer short run lottery-like investment opportunities.

In sum, the evidence of a positive relationship between skewness and retail demand both for the left-skewed subsample and for the right-skewed subsample is both statistically and economically significant. Surprisingly, following skewness shocks, the left-skewed subsample attracts much larger investment in monetary terms but the right-skewed subsample attracts relatively more investors spending smaller amounts on their orders.

4.5 Expected Skewness and Long-term Performance

We finally examine the relationship between long-term performance and expected skewness by estimating the following two regressions:

$$BHAR_j = \alpha_1 + \alpha_2 * \left|Skewness_j\right| + \sum_{i=3}^{n}\left(\alpha_i * X_j\right) + \varepsilon \tag{14}$$

$$Jensen's\_Alpha_j = \beta_1 + \beta_2 * \left|Skewness_j\right| + \sum_{i=3}^{n}\left(\beta_i * X_j\right) + u \tag{15}$$

where *BHAR* is the buy-and-hold return of an IPO stock in the 36 post-IPO event months relative to the buy-and-hold return of a size and B/M comparable non-IPO stock over the same period; *Jensen's_Alpha* is the abnormal monthly return estimated from the Fama-French three-factor model over the 36 post-IPO calendar months; |*Skewness*| is the absolute expected skewness of an IPO stock; *X* is a vector of control variables.

Similarly, we estimate the following two regression specifications where an indicator function allows for the relationship between long-term stock performance and (absolute) expected skewness to differ in our two subsamples:

$$BHAR_j = \alpha_1 + \alpha_2 * \left|Skewness_j\right| * I_L + \alpha_3 * Skewness_j * \left(1\text{-}I_L\right) + \sum_{i=4}^{n}\left(\alpha_i * X_j\right) + \varepsilon \tag{16}$$

$$Jensen's\_Alpha_j = \beta_1 + \beta_2 * \left|Skewness_j\right| * I_L + \beta_3 * Skewness_j * \left(1\text{-}I_L\right) + \sum_{i=4}^{n}\left(\beta_i * X_j\right) + u \tag{17}$$

Table 7 presents regression results for Equations (14) and (15) in Panel A, and for Equations (16) and (17) in Panel B.

[Table 7 around here]

Panel A reveals mixed support for a negative relationship between absolute expected skewness and long-term stock performance as predicted by Barberis and Huang (2008). *BHAR* is the dependent variable for the regressions in Columns (1) – (4) and the coefficients on |*Skewness*| are not significant at conventional levels after controlling for a wide range of firm characteristics in regressions (3) and (4). By contrast, with *Jensen's_Alpha* as the dependent variable, the coefficients on |*Skewness*| in Columns (5) – (8) regressions are all negative and statistically significant. A one-standard-deviation increase in absolute skewness implies from Column (8) a fall in *Jensen's_Alpha* of approximately 0.39 percentage points (– 0.042*0.0934) on average. This is equivalent to a decrease of 15.04 percentage points (=1.0039^{36}-1) over a 36-calendar-month period.

Panel B permits us to examine the relationship between long-term stock performance and (absolute) expected skewness in our two subsamples. A novel finding is that the results show no statistically significant relationship between |*Skewness*| and long-term stock performance for left-skewed IPOs either with *BHAR* or *Jensen's_Alpha* as the dependent variables. The coefficients on |*Skewness*|*I_L are insignificantly different from zero across all eight regressions and supports Hypothesis 4A. One way of interpreting these results is that the flipping on the first day and subsequent early post-IPO day trading activities serves to maintain the IPO price in the region of its intrinsic value in contrast to right-skewed IPOs whereas lottery trading demand will tend to inflate IPOs prices above intrinsic value.

By contrast, the coefficients on *Skewness**(1-I_L) for the right-skewed IPOs are significant at the 5% level or better for all but regression (3). The coefficient values are -1.560 (*t*-statistics = -2.02) in Column (4) and -0.046 (*t*-statistics = -4.64) in Column (8), both controlling for other firm characteristics. A one standard-deviation increase in expected skewness leads to a decrease in *BHAR* of approximately 14.60 percentage points (-1.560*0.0936) on average. Similarly, a one-standard-deviation increase in expected skewness implies from Column (8) a fall in *Jensen's_Alpha* of approximately 0.45 percentage points (–0.048*0.0936) on average. This is equivalent to a decrease of 17.54 percentage points

(1.0045^{36}-1) over a 36-calendar-month period. These findings are consistent with our Hypothesis 4B and Barberis and Huang (2008) who predict low long-run abnormal returns when positively-skewed securities are overvalued by PT investors. Our findings are robust not only to alternative reliable measures for detecting long-term abnormal return according to Lyon, Barber and Tsai (1999)[18], but also to the inclusion of a plethora of control variables.

Green and Hwang (2012) also find some evidence in support of the central prediction of Barberis and Huang (2008) using a matching firm approach over a five-year horizon. Their results using the event-time approach show a significant difference in Cumulative Abnormal Returns (*CAR*) over three and five years following the issuance between the top and bottom tercile skewness portfolios. However, their results using a calendar-time matching firm approach do not produce strong evidence of a significant difference in abnormal returns for monthly portfolios sorted by expected skewness, perhaps because they mix right- and left-skewed IPOs in their analysis.

To sum up, skewness shocks have large negative economic impacts on long term performance measure like *BHAR* and *Jensen's_Alpha*. By contrast, we find strong and robust evidence of a negative relationship between skewness and long-term performance for our positively-skewed IPO subsample, the most appropriate subsample for testing skewness preference. However, our left-skewed subsample exhibits no significant relationship between skewness and long run performance. The latter is perhaps not surprising given the very short-term investor horizon for such stocks.

5. Additional Analysis

5.1 Does state ownership matter?

Our baseline analysis relies on all non-IPO stocks belonging to the same industry to estimate the expected skewness of an IPO stock. Given that China has two very different types of firms, state-owned enterprises (SOEs) and non-SOEs, using log monthly returns of all non-IPO stocks to estimate expected skewness may not be representative of the skewness of a

[18] Unfortunately, we are unable to assert that our results are consistent with previous studies documenting a negative relationship between first-day returns and long-run stock performance, including Ritter (1991) and Shen et al. (2013), because we exclude first day returns.

particular IPO firm, SOE or non-SOE, thus our regression results might be biased. Using an improved measure of expected skewness which takes account of some potential difference between SOEs and non SOEs, we repeat our empirical analysis and examine whether our main findings continue to hold.

We first separate SOEs from non-SOEs for our IPO sample and for the non-IPO sample. Following previous studies such as Sun and Tong (2003), we define a listed firm as an SOE if the percentage of state ownership is greater than 50%, or the ultimate owner is the state. In a similar fashion, we define an IPO as a share issue privatization (also known as SIP, where privatized SOEs issue new shares to the general public) if the percentage of state ownership in the pre-IPO year is greater than 50%, or the ultimate owner is the state. Log monthly returns of all listed SOEs (non-SOEs) over the most recent three months are used to estimate the expected skewness of an SOE (non-SOE) firm going public. Separating non-IPO sample into SOE and non-SOE subsamples has led to a substantial drop in the sample size of monthly returns so we require now a minimum number of 50 log monthly returns in previous three months instead to maintain accuracy and consistency.

Table 8 presents regression results using this *Skewness_SOE3m*, defined as the expected skewness of an IPO stock's return using the tails of the probability distribution generated by monthly returns of all SOE or non-SOE stocks in the same industry over the most recent three-month period before the offer date.

[Table 8 around here]

The regression results are very similar to our previous analysis. More specifically, Panel A does not reveal evidence of a positive relationship between first-day return and expected skewness, a positive (negative) relationship between discounting and (absolute) expected skewness, or a positive relationship between retail demand and expected skewness. However, after separating left- from right-skewed IPOs in Panel B, we find that the coefficients on both $|Skewness\_SOE3m|*I\_SOE3m_L$ and $|Skewness\_SOE3m|*(1-I\_SOE3m_L)$ are significant in Column (1) where the dependent variable is *IR*, indicating that there is a positive relationship between first-day return and absolute expected skewness for two subsamples. We also find that the coefficient on $|Skewness\_SOE3m|*I\_SOE3m_L$ is significantly negative while the coefficient on $|Skewness\_SOE3m|*(1-I\_SOE3m_L)$ is not in Column (2) where the dependent variable is

Discounting, consistent with our main findings in Section 4.3. Also, consistent with our previous analysis, we find that the coefficients on both |*Skewness_SOE3m*|**I_SOE3m*$_L$ and |*Skewness_SOE3m*|*(1-*I_SOE3m*$_L$) are significant in Column (3) where the dependent variable is Log(*Orders*)and in Column (4) where the dependent variable is Log(*RMB*). Finally, Panel B does reveal robust evidence of a negative relationship between long-term performance and expected skewness for positively-skewed IPOs again. In Column (5) where the dependent variable is *BHAR*, the coefficient on |*Skewness_SOE3m*|*(1-*I_SOE3m*$_L$) is -2.039 (*t*-statistics = -2.10) while the coefficient on |*Skewness_SOE3m*|**I_SOE3m*$_L$ is not statistically significant. In Column (6) where the dependent variable is *Jensen's Alpha*, the coefficient on |*Skewness_SOE3m*|*(1-*I_SOE3m*$_L$) is -0.041 (*t*-statistics = -3.97) while the coefficient on |*Skewness_SOE3m*|**I_SOE3m*$_L$ is not statistically significant.

These findings suggest that our main findings, especially those looking at two skewness-based subsamples, are not sensitive to the use of an alternative measure of expected skewness. These findings also imply that, while there can be some systematic difference between SOEs and non-SOEs, the difference between them in the calculation of expected skewness is not huge.

5.2 Does allocation discretion matter?

At the heart of the information-revelation model due to Benveniste and Spindt (1989) is the discretion enjoyed by IPO underwriters over share allocation among asymmetrically informed investors. By giving priority in the allocation to regular investors, underwriters can induce them to reveal their private information truthfully by bidding for more new shares at higher prices. With virtually no variation in this institutional arrangement of the US context, one cannot examine whether allocation discretion plays such an important role as assumed in previous studies in collecting useful information from informed investors. However, such an opportunity presents itself in the Chinese context, due to a recent reform to the AMSIU introduced by the CSRC in December 2013 which aims to bring pricing IPOs more in line with international practices by giving underwriters some discretion over share allocation among institutional investors. Before the 2013 AMSIU reform, IPO shares oversubscribed by institutional investors can only be allocated using the pro rata rule, which implies that the same allocation rate will apply to all institutional orders regardless of order size. After the reform became effective on December 13, 2013, underwriters could decide on the proportion that applies to the number of new shares subscribed by a certain type of institutional investors, such as public funds, social insurance funds, pension funds and insurance funds, which creates new incentive for these investors to reveal useful information in their bids.

Does allocation discretion improve information production in the book-building process? We examine whether the 2013 AMSIU reform can influence the bidding behavior of institutional investors in two steps. First, we examine whether more information is revealed in the first stage of book building by comparing the offer price range and the midpoint of the filing range for IPOs issued before and after the revision. Both the offer price range and the midpoint can capture valuation uncertainty associated with the new issue revealed to the underwriter after the first-stage of book building. To the extent that the 2013 AMSIU reform can induce institutional investors to reveal more information, we expect that the offer price range should become smaller and that the midpoint should increase. Second, we examine whether more information is revealed in the second stage of book building by comparing the upward revision from the midpoint of the filing range, a typical measure used in the literature such as Loughran and McDonald (2013), for IPOs issued before and after the reform. If the reform is effective in improving information production, we should observe a greater upward revision for IPOs issued after the reform.

To facilitate our empirical analysis, we construct a matched sample of IPOs which are fundamentally similar except that some treatment IPOs occur after the reform while the other control IPOs happen before the reform. For this purpose, we start with 580 IPOs issued between December 14, 2013 and December 31, 2016. After excluding those IPOs that do not even proceed to the second stage of book-building, and those that do not have sufficient information for the variables of our interest, 431 IPOs remain. Each of these 431 IPOs is then matched to the most similar IPO prior to December 13, 2013. We require that the control firms (IPOs prior to the reform) must operate in the same industry as the treatment firms (IPOs after the reform), and they are most similar in market capitalization and book-to-market ratio because these capture systematic differences in risk components. We end up with a well-matched sample of 862 IPOs to estimate the following three regressions for our empirical analysis:

$$Range_j = \alpha_1 + \alpha_2 * Reform_j + \sum_{i=3}^{n} \left(\alpha_i * X_j \right) + \varepsilon \tag{18}$$

$$MidPoint_j = \alpha_1 + \alpha_2 * Reform_j + \sum_{i=3}^{n} \left(\alpha_i * X_j \right) + \varepsilon \tag{19}$$

$$UP\_Revision_j = \alpha_1 + \alpha_2 * Reform_j + \sum_{i=3}^{n} \left(\alpha_i * X_j \right) + \varepsilon$$

(20)

where *Range* is the offer price range of an IPO j, defined as the difference between the highest price and the lowest; *MidPoint* is the midpoint of the offer price range of IPO_j; *UP_Revision* is the upward revision from the midpoint of the filling range of IPO_j, defined as the difference between the offer price and the midpoint of the proposed price range standardized by the midpoint if the difference is greater than the midpoint, and 0 otherwise; *Reform* is a dummy variable, which is equal to 1 for IPOs after December 13, 2013 and 0 otherwise; *X* is a set of control variables all defined in the previous regressions. Note that we include all firm characteristics variables used in our previous analysis, except for *Time Lag* and year dummies. We drop the variable *Time Lag* because this information is not available at the time of book-building. Unreported analysis shows that it makes little difference to the regression results whether or not we include *Time Lag* in the regressions. We drop year dummies in all regressions because this analysis is focused on whether they are issued before or after the 2013 AMSIU reform thus the year of public listing is less important.

Table 9 presents regression results in three panels.

[Table 9 around here]

First, Panel A reports regression results on the relationship between offer price range and the 2013 AMSIU reform dummy. The dependent variable for those regressions in Panel A is *Range*. For the 862 IPOs that have the second stage of book-building, the reform to the AMSIU in December 2013 reduces the offer price range because the coefficient on *Reform* is significantly negative. Although the coefficient on *Reform* in Column (1) is not significant, it becomes significant when we control for *Midpoint* in Column (2) and when we control for more firm characteristics in Column (3). These findings seem to indicate that the offer price range provided by underwriters becomes smaller.

Second, Panel B reports regression results for the relationship between the midpoint of offer price range and the 2013 AMSIU reform dummy. The dependent variable for those regressions in Panel B is *MidPoint*. For the 862 IPOs, the coefficient on *Reform* is significantly positive at the 1% level even after controlling for the offer price range in Column (2) and controlling for more firm characteristics in Column (3). This implies that not only does the filing range become smaller, but also the midpoint becomes larger. Taken together, he regression results reported in these two panels suggest that more information is revealed in the first stage of book building, leading to reduced valuation uncertainty.

Finally, Panel C reports regression results for the relationship between upward revision and the 2013 AMSIU reform dummy. The dependent variable for those regressions in Panel C is *Up_Revision*. We find that the coefficient on *Reform* is positive but not significantly different from zero, which appears to suggest that there is no more private information revealed in the second-stage of book-building for 431 IPOs issued after the reform.

Why is more information revealed in the first stage of book building but not in the second stage? This can be explained by the fact that the 2013 AMSIU reform not only gives underwriters allocation discretion to improve price discovery, but also introduces a new exclusion requirement for the second-stage book-building. The latter can prevent some useful information from being incorporated into the determination of the offer price. According to the new version of the AMSIU, underwriters and issuers should exclude no less than top 10% of share subscriptions ranked by bid price and determine the offer price based on the remaining share subscriptions. The new AMSIU further requires that those subscriptions excluded in the IPO price determination process will not receive any share allocation in the end. The purpose of these two new requirements is to encourage institutional investors to bid more cautiously and produce less upwardly biased bid prices in the book building process. It seems that the positive effect of improved allocation discretion on upward revision is offset by the negative effect of the newly introduced exclusion requirement in the second stage. The reason why the positive effect of improved allocation discretion on valuation uncertainty is not affected is because the newly introduced exclusion requirement is specifically made for the second stage. Thus, the decision on the offer price range based on all institutional bids in the first stage is not affected.

6. Conclusions

Cumulative prospect theory (PT) departs from expected utility in suggesting that investors exhibit distinct behavior in relation to gains and losses relative to a reference point, suggesting that both tails of the return distribution matter for prospective investors. However, the extant literature has tended to focus on lottery-like or right-tailed returns only. This paper provides a new PT perspective on IPOs by proposing the use of expected skewness as a reference point. Since our sample of 837 book-built Chinese IPOs 2006-2012 divides into 30% left-skewed and 70% right-skewed issues, the implication is that one has to separately investigate both subsamples. Our analysis from a simple regression model using an indicator to identify the separate subsamples produces a far more nuanced picture of IPO skewness than hitherto presented in the literature.

Our study produces novel results for our subsample of 251 negatively-skewed Chinese IPOs in contrast to those for the right-skewed subsample that tend to follow the extant skewness preference literature. It provides evidence that absolute[19] expected skewness is positively related to first-day returns. A one standard-deviation increase in skewness lead to an increase of 10.41 percentage points in the first-day return which is virtually 50% larger than that on right-skewed IPOs. While left-skewed IPOs exhibit a significantly positive relationship between offer price discounting and skewness, the relationship for right-skewed IPOs is insignificant. A one-standard-deviation shock to skewness deepens discounting by left-skewed IPOs by 21 percentage points which makes such IPOs susceptible to nominal price illusion. The latter provides an important reason for the tendency by investors to buy and flip deeply discounted left-skewed IPOs in the expectation that the price will mean revert upwards towards its intrinsic value region. A skewness shock attracts more than double the mean monetary value of retail orders to the left- than to the right-skewed subsample although the later attracts 26% more investors. Relatedly, their long run return measures are independent of absolute skewness but we find significantly inverse relationships between two measures of long run performance and skewness for the right-skewed subsample.

Our study confirms that Chinese IPOs demonstrate lottery-like features that impact on initial returns and long run performance for both left- and right-skewed IPOs. Overall, our PT framework provides the basis for a richer more nuanced picture of the motives for IPO investment and for the contrasting patterns in initial and long run returns.

[19] Recall that the use of absolute skewness permits a more intuitive interpretation of negative skewness values.

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Table 1: Sample distribution

Panel A presents the year distribution of 837 IPOs.

Year	The initial sample	The final sample	Percentage (%)
2005	15	0	0.00
2006	66	42	5.02
2007	125	72	8.60
2008	77	58	6.93
2009	99	70	8.36
2010	348	262	31.30
2011	282	214	25.57
2012	155	119	14.22
2013	2	0	0.00
Total	1,169	837	100.00

Panel B presents the industry distribution of 837 IPOs

Industry Classification	IPO Firms	%
Agriculture, Forestry, Fishing & Farming (A01-A05)	4	0.48
Mining (B06-B12)	23	2.75
Manufacturing – Major Grain & Sideline Food Processing (C13)	0	0.00
Manufacturing – Food Production (C14)	0	0.00
Manufacturing – Wine, Beverage & Tea (C15)	1	0.12
Manufacturing – Tobacco Products (C16)	0	0.00
Manufacturing – Textile (C17)	0	0.00
Manufacturing – Textile Garment & Clothing (C18)	0	0.00
Manufacturing – Leather, Fur & Feather (C19)	0	0.00
Manufacturing – Timber (C20)	0	0.00
Manufacturing – Furniture (C21)	0	0.00
Manufacturing – Papermaking & Paper Products (C22)	0	0.00
Manufacturing – Printing & Recording Media (C23)	0	0.00
Manufacturing – Education, Arts, Sports & Entertainment Products (C24)	0	0.00
Manufacturing – Petroleum Processing (C25)	0	0.00
Manufacturing – Chemical Products (C26)	80	9.56
Manufacturing – Pharmaceutical Products (C27)	63	7.53
Manufacturing – Chemical Fiber (C28)	0	0.00
Manufacturing – Rubber & Plastics Products (C29)	7	0.84
Manufacturing – Non-metals Products (C30)	30	3.58
Manufacturing – Ferrous Metal Smelting & Processing (C31)	0	0.00
Manufacturing – Non-ferrous Metal Smelting & Processing (C32)	19	2.27
Manufacturing – Metal Products (C33)	1	0.12
Manufacturing – General Equipment (C34)	48	5.73
Manufacturing – Specialized Equipment (C35)	82	9.80
Manufacturing – Automobile (C36)	35	4.18
Manufacturing – Railway, Shipping, Aviation & Other Transportation Equipment (C37)	1	0.12
Manufacturing – Electronic Machinery & Apparatus (C38)	100	11.95
Manufacturing – Computers, Communications & Other Electronic Devices (C39)	127	15.17
Manufacturing – Instruments & Meters (C40)	0	0.00
Manufacturing – Other Manufacturing (C41)	0	0.00
Manufacturing – Recycling & Repairing (C42)	0	0.00
Utilities (D43)	0	0.00
Construction (E44-E50)	36	4.30
Wholesale & Retail Trade (F51-F52)	29	3.46
Transportation, Warehousing & Postal Service (G53-G60)	23	2.75
Hotels & Restaurants (H61-H62)	0	0.00
Information Technology & Software (I63-I65)	118	14.10
Finance (J66-J69)	0	0.00
Real Estate (K70)	10	1.19

Leasing & Business Service (L71-L72)	0	0.00
Scientific Research & Technology Service (M73-M75)	0	00.00
Irrigation, Environment & Public Facilities Administration (N76-N78)	0	00.00
Residential Service, Repairs & Other Service (O79-O81)	0	00.00
Education (P82)	0	00.00
Health & Social Work (Q83-Q84)	0	00.00
Culture, Sports & Entertainment (R85-R89)	0	00.00
Miscellaneous (S90)	0	00.00
Total	837	100.00

Table 2: Descriptive statistics

This table provides descriptive statistics for the full sample of 837 IPOs. *Skewness* is the expected skewness of an IPO stock's return defined using the tails of the probability distribution generated by log monthly returns of all stocks in the same industry over the three-month period before the offer date; |*Skewness*| is the absolute value of *Skewness*; *IR* is the first-day return of an IPO stock defined as the percentage difference between its first-day closing price and its offer price; *BHAR* is defined as the buy-and-hold return of an IPO stock in the 36 post-IPO event months relative to the buy-and-hold return of a size and B/M comparable non-IPO stock over the same period of time; *Jensen's Alpha* is the abnormal monthly return estimated from the Fama-French three-factor model over the 36 post-IPO calendar months; *ROA* is net income over total assets in the pre-IPO year; *Leverage* is the leverage ratio, estimated as total liabilities over total assets prior to listing; Log(*Issue Size*) is the logarithm of the IPO proceeds measured as the offer price multiplied by the number of new shares offered; *Underwriter* is a dummy, equal to 1 if the lead underwriter has been recognized as one of top 10 underwriters at least twice over the past three years, and 0 otherwise; *Big 4* is a dummy, equal to 1 if financial reporting is audited by one of big 4 accounting firms; *VC-backed* is a dummy, equal to 1 if the firm has been supported by venture capital; *State* is the proportion of state holdings in the firm; Log (1+*Age*) is the logarithm of 1 plus firm age since establishment; *Time Lag* is the number of days elapsed between offering and listing; *Divergence of Opinion* is the standard deviation of one-year forward looking EPS by analysts; *Analyst Bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *Hi-Tech* is a dummy variable, which is equal to 1 if the IPO is operating in the hi-tech industry; *Legal* is the investor protection index prepared by Fan et al. (2011); *Market Sentiment* is the number of IPOs in the same calendar month; *Orders* is defined as the number of valid subscription orders received from the second offline tranche; *RMB* defined as the number of new shares subscribed multiplied by the offer price; *Discounting* is defined as the percentage difference between the offer price of an IPO stock and the median market price of the same-industry stocks. The *t*-statistics and adjusted *Chi*-square reported in parentheses in Panel B are for tests for equality of mean and median of each variable, respectively. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Descriptive statistics for the full sample

Variables	Min	Max	Mean	Median	Std. Dev
Skewness	-0.3423	0.4820	0.0722	0.0790	0.1502
|*Skewness*|	0.0000	0.4820	0.1380	0.1287	0.0934
IR	-0.2316	6.2674	0.5927	0.3569	0.7690
BHAR	-28.5670	6.4730	-0.6051	-0.1837	1.9176
Jensen's Alpha	-0.3314	-0.1064	-0.2460	-0.2498	0.0338
ROA	-0.0018	0.5877	0.1375	0.1239	0.0791
Leverage	0.0465	0.9682	0.4677	0.4666	0.1689
Log (*Issue Size*)	8.2610	15.7146	11.0625	10.9623	0.8668
Underwriter	0.0000	1.0000	0.4002	0.0000	0.4902
Big 4	0.0000	1.0000	0.0442	0.0000	0.2057
VC-backed	0.0000	1.0000	0.4767	0.0000	0.4998
State	0.0000	1.0000	0.1058	0.0000	0.2524
Log (1+*Age*)	0.0000	3.3673	2.0560	2.1972	0.5924
Time Lag (days)	7.0000	50.0000	12.2533	11.0000	4.2480
Divergence of Opinion	0.0269	2.1482	0.4097	0.3559	0.2463
Analyst Bias	-2.4100	1.9300	0.0306	0.0491	0.2735

Hi-Tech	0.0000	1.0000	0.0251	0.0000	0.1565
Legal	0.1800	19.8900	12.4464	13.9900	5.2031
Market Sentiment	1.0000	37.0000	22.5639	24.0000	8.6520
Log (*Orders*)	4.1647	6.6504	5.4701	5.4755	0.3679
Log (*RMB*)	9.6103	12.4675	10.9406	10.9276	0.4589
Discounting	-16.4285	31.8541	0.3978	-0.1691	2.6241

Panel B: Descriptive statistics for two subsamples

	251 IPOs (*Skewness*<0)			586 IPOs (*Skewness*>=0)			Difference = Negative - Positive	
	Mean	Median	Std. Dev	Mean	Median	Std. Dev	Mean Difference	Median Difference
Skewness	-0.1097	-0.0823	0.0866	0.1501	0.1435	0.0936	-0.2598^{***} (-37.61)	(354.81)
IR	0.6561	0.3565	0.8853	0.5655	0.3602	0.7126	0.0906 (1.61)	(0.00)
BHAR	-0.5258	-0.1779	1.7056	-0.6390	-0.1995	2.0020	0.1132 (0.48)	(0.23)
Jensen's Alpha	-0.2377	-0.2398	0.0374	-0.2495	-0.2533	0.0315	0.0118^{***} (5.65)	(25.01)
ROA	0.1515	0.1343	0.0898	0.1315	0.1198	0.0733	0.0200^{***} (3.71)	(6.69)
Leverage	0.4549	0.4595	0.1726	0.4732	0.4732	0.1671	-0.0183 (-0.92)	(0.78)
Log (*Issue Size*)	11.0655	10.9187	0.9326	11.0612	10.9734	0.8378	0.0043 (0.56)	(0.08)
Underwriter	0.4343	0.0000	0.4967	0.3857	0.0000	0.4872	0.0486 (1.62)	(2.39)
Big 4	0.0598	0.0000	0.2375	0.0375	0.0000	0.1903	0.0223 (0.70)	(0.27)
VC-backed	0.4900	0.0000	0.5009	0.4710	0.0000	0.4996	0.0190 (0.66)	(0.34)
State	0.1016	0.0000	0.2553	0.1075	0.0000	0.2513	-0.0059 (-0.24)	(1.50)
Log (1+*Age*)	2.0287	2.1972	0.6328	2.0677	2.1972	0.5743	-0.0390 (-0.53)	(0.00)
Time Lag (days)	12.6295	12.0000	4.8902	12.0922	11.0000	3.9347	0.5373^{**} (2.32)	(2.93)
Divergence of Opinion	0.4438	0.3649	0.3039	0.3950	0.3525	0.2156	0.0488^{**} (2.06)	(0.11)
Analyst Bias	0.0012	0.0400	0.2988	0.0433	0.0500	0.2612	-0.0421^{*} (-1.86)	(1.07)
Hi-Tech	0.0279	0.0000	0.1650	0.0239	0.0000	0.1528	0.0040 (-1.11)	(0.75)
Legal	12.0516	12.3900	5.2213	12.6155	13.9900	5.1905	-0.5594 (-1.49)	(0.15)
Market Sentiment	20.7012	21.0000	7.9911	23.3618	25.0000	8.8067	-2.6606^{***} (-5.69)	(14.86)
Log (*Orders*)	5.4539	5.4478	0.3511	5.4770	5.4869	0.3750	-0.0231 (-0.85)	(1.07)
Log (*RMB*)	10.9499	10.9313	0.4984	10.9366	10.9268	0.4412	0.0133 (0.39)	(0.03)
Discounting	0.2019	-0.2270	2.1993	0.4817	-0.1608	2.7838	-0.2798 (-1.38)	(0.78)

Table 3: Correlation analysis

Skewness (1) is the expected skewness of an IPO stock's return defined using the tails of the probability distribution generated by log monthly returns of all stocks in the same industry over the three-month period before the offer date; *IR* (2) is the first-day return of an IPO stock defined as the percentage difference between its first-day closing price and its offer price; *BHAR* (3) is defined as the buy-and-hold return of an IPO stock in the 36 post-IPO event months relative to the buy-and-hold return of a size and B/M comparable non-IPO stock over the same period of time; *Jensen's Alpha* (4) is the abnormal monthly return estimated from the Fama-French three-factor model over the 36 post-IPO calendar months; *ROA* (5) is net income over total assets in the pre-IPO year; *Leverage* (6) is the leverage ratio, estimated as total liabilities over total assets prior to listing; Log (*Issue Size*) (7) is the logarithm of IPO proceeds measured as the offer price multiplied by the number of new shares offered; *Underwriter* (8) is a dummy, equal to 1 if the lead underwriter has been recognized as one of top 10 underwriters at least twice over the past three years, and 0 otherwise; *Big 4* (9) is a dummy, equal to 1 if financial reporting is audited by one of big 4 accounting firms; *VC-backed* (10) is a dummy, equal to 1 if the firm has been supported by venture capital; *State* (11) is the proportion of state holdings in the firm; Log (1+*Age*) (12) is the logarithm of 1 plus the firm age since establishment; *Time Lag* (13) is the number of days elapsed between offering and listing; *Divergence of Opinion* (14) is the standard deviation of one-year forward looking EPS by analysts; *Analyst Bias* (15) is defined as the average difference between analyst's forecasting EPS and realized EPS; *Hi-Tech* (16) is a dummy variable, which is equal to 1 if the IPO is operating in the hi-tech industry; *Legal* (17) is the investor protection index prepared by Fan et al. (2011); *Market Sentiment* (18) is the number of IPOs in the same calendar month; Log(*Orders*) (19) is the logarithm of the number of valid subscription orders received from the second offline tranche; Log(*RMB*) (20) is the logarithm of the number of new shares subscribed multiplied by the offer price; *Discounting* (21) is defined as the percentage difference between the offer price of an IPO stock and the median market price of the same-industry stocks.

Panel A: Correlation matrix for the full sample.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15	(16)	(17)	(18)	(19)	(20)	(21)
(1)	1.00																				
(2)	-0.05	1.00																			
(3)	-0.06	-0.19	1.00																		
(4)	-0.19	0.07	0.21	1.00																	
(5)	-0.15	-0.11	0.05	0.03	1.00																
(6)	0.07	0.08	-0.14	-0.05	-0.64	1.00															
(7)	0.02	-0.36	-0.22	-0.26	0.04	0.13	1.00														
(8)	-0.01	0.00	-0.01	0.03	0.00	-0.04	0.17	1.00													
(9)	-0.03	0.08	-0.12	0.03	-0.13	0.09	0.35	0.05	1.00												
(10)	-0.05	-0.08	0.03	-0.05	0.07	-0.13	-0.01	0.07	-0.09	1.00											
(11)	0.05	0.17	-0.09	0.07	-0.20	0.18	0.25	0.11	0.23	-0.13	1.00										
(12)	0.00	-0.14	0.14	0.12	-0.01	-0.08	-0.10	-0.06	-0.03	0.04	-0.12	1.00									
(13)	0.01	0.28	-0.12	-0.04	-0.05	0.09	-0.08	0.04	0.04	-0.04	0.17	-0.19	1.00								
(14)	-0.12	-0.13	-0.07	-0.06	0.36	-0.08	0.23	0.05	-0.07	0.11	-0.15	-0.06	-0.04	1.00							
(15)	0.09	0.10	-0.05	-0.04	-0.05	0.00	0.04	0.01	-0.01	-0.05	0.04	-0.05	0.05	-0.00	1.00						
(16)	0.01	-0.01	-0.05	0.04	-0.08	-0.01	0.13	-0.01	0.15	-0.08	0.24	0.00	0.02	-0.14	0.01	1.00					
(17)	0.04	-0.18	0.12	-0.03	0.08	-0.07	0.03	0.05	-0.02	0.04	-0.22	0.11	-0.13	0.05	-0.00	-0.02	1.00				

(18)	0.09	-0.36	0.03	-0.50	0.08	-0.15	0.23	-0.03	-0.15	0.13	-0.26	0.10	-0.14	0.12	0.03	-0.06	0.19	1.00			
(19)	0.04	0.38	-0.15	-0.06	-0.21	0.11	-0.05	-0.01	0.02	-0.10	0.22	-0.12	0.12	-0.27	0.11	0.05	-0.07	-0.12	1.00		
(20)	-0.00	0.32	-0.24	-0.02	-0.12	0.18	0.16	0.09	0.04	-0.11	0.27	-0.23	0.15	-0.07	0.12	0.04	-0.13	-0.18	0.78	1.00	
(21)	0.03	-0.03	-0.05	-0.03	0.04	-0.09	-0.03	-0.06	-0.04	0.03	-0.07	-0.09	-0.01	0.09	-0.08	-0.03	0.01	0.14	-0.01	-0.02	1.00

Panel B: Correlation matrix for the left-skewed subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15	(16)	(17)	(18)	(19)	(20)	(21)
(1)	1.00																				
(2)	-0.25	1.00																			
(3)	0.02	-0.24	1.00																		
(4)	-0.06	0.04	0.22	1.00																	
(5)	-0.03	-0.20	-0.02	-0.01	1.00																
(6)	-0.06	0.15	-0.13	-0.08	-0.60	1.00															
(7)	0.03	-0.33	-0.24	-0.39	0.13	0.05	1.00														
(8)	-0.14	-0.01	-0.01	0.10	0.05	-0.08	0.14	1.00													
(9)	0.05	0.02	-0.08	-0.10	-0.16	0.12	0.49	0.08	1.00												
(10)	-0.02	-0.08	0.01	-0.07	0.08	-0.15	-0.03	0.20	-0.11	1.00											
(11)	-0.08	0.20	-0.21	-0.03	-0.22	0.11	0.27	0.03	0.32	-0.14	1.00										
(12)	0.00	-0.17	0.27	0.25	0.02	-0.15	-0.15	0.02	-0.05	0.06	-0.04	1.00									
(13)	0.01	0.19	-0.22	-0.21	0.05	0.03	0.02	-0.02	-0.01	0.07	0.02	-0.17	1.00								
(14)	-0.07	-0.12	-0.13	-0.10	0.39	-0.09	0.29	0.09	-0.00	0.15	-0.19	-0.06	0.05	1.00							
(15)	0.01	0.17	-0.09	-0.01	-0.03	0.03	-0.06	-0.01	-0.02	-0.02	0.03	-0.11	0.13	-0.07	1.00						
(16)	0.05	0.00	-0.11	-0.02	-0.12	-0.03	0.10	-0.05	0.26	-0.12	0.22	0.05	0.05	-0.19	0.01	1.00					
(17)	0.04	-0.23	0.13	-0.06	-0.01	-0.06	0.00	0.05	-0.10	0.13	-0.16	0.11	-0.03	0.05	-0.02	0.08	1.00				
(18)	0.06	-0.25	-0.06	-0.55	0.15	-0.17	0.28	0.02	-0.06	0.15	-0.17	-0.04	0.13	0.16	-0.09	-0.02	0.13	1.00			
(19)	-0.21	0.43	-0.11	-0.18	-0.24	0.17	-0.08	0.01	0.06	-0.06	0.25	-0.19	0.13	-0.22	0.07	-0.04	-0.13	-0.02	1.00		
(20)	-0.26	0.38	-0.23	-0.08	-0.08	0.21	0.11	0.08	0.06	-0.10	0.24	-0.32	0.17	-0.00	0.06	-0.09	-0.20	-0.13	0.75	1.00	
(21)	0.10	-0.00	-0.07	-0.13	-0.04	0.01	-0.09	0.01	0.01	0.04	-0.02	-0.01	-0.01	0.13	-0.11	-0.03	-0.04	0.15	0.06	-0.00	1.00

Panel C: Correlation matrix for the right-skewed subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15	(16)	(17)	(18)	(19)	(20)	(21)
(1)	1.00																				
(2)	0.10	1.00																			
(3)	-0.09	-0.17	1.00																		
(4)	-0.13	0.07	0.20	1.00																	

(5)	-0.14	-0.07	0.08	0.02	1.00																
(6)	0.09	0.04	-0.14	-0.03	-0.66	1.00															
(7)	0.04	-0.38	-0.21	-0.20	-0.01	0.18	1.00														
(8)	0.11	-0.00	-0.02	-0.01	-0.03	-0.02	0.19	1.00													
(9)	-0.00	0.11	-0.14	0.11	-0.12	0.07	0.27	0.03	1.00												
(10)	-0.07	-0.08	0.04	-0.05	0.06	-0.12	-0.01	0.02	-0.08	1.00											
(11)	0.13	0.16	-0.05	0.13	-0.20	0.21	0.24	0.14	0.20	-0.13	1.00										
(12)	-0.06	-0.12	0.08	0.06	-0.03	-0.05	-0.07	-0.11	-0.02	0.03	-0.16	1.00									
(13)	0.13	0.33	-0.09	0.05	-0.13	0.13	-0.14	0.07	0.07	-0.10	0.26	-0.20	1.00								
(14)	-0.08	-0.15	-0.04	-0.05	0.32	-0.06	0.19	0.01	-0.13	0.09	-0.14	-0.06	-0.11	1.00							
(15)	0.07	0.06	-0.04	-0.03	-0.04	-0.01	0.10	0.03	0.00	-0.07	0.05	-0.02	0.02	0.06	1.00						
(16)	0.03	-0.01	-0.03	0.07	-0.07	-0.00	0.15	0.01	0.09	-0.06	0.25	-0.02	0.00	-0.11	0.02	1.00					
(17)	-0.02	-0.15	0.11	-0.00	0.13	-0.09	0.05	0.05	0.02	0.01	-0.25	0.11	-0.18	0.07	0.00	-0.07	1.00				
(18)	-0.07	-0.41	0.07	-0.46	0.08	-0.16	0.21	-0.03	-0.19	0.13	-0.29	0.16	-0.25	0.13	0.06	-0.07	0.21	1.00			
(19)	0.12	0.36	-0.16	-0.00	-0.20	0.19	-0.04	-0.01	-0.00	-0.11	0.20	-0.10	0.13	-0.30	0.13	0.09	-0.05	-0.16	1.00		
(20)	0.14	0.28	-0.25	0.01	-0.16	0.17	0.19	0.19	0.03	-0.12	0.28	-0.19	0.13	-0.11	0.16	0.10	-0.10	-0.20	0.80	1.00	
(21)	-0.04	-0.04	-0.05	0.01	0.08	-0.13	-0.00	-0.08	-0.05	0.03	-0.09	-0.12	-0.00	0.09	-0.07	-0.03	0.02	0.13	-0.03	-0.03	1.00

Table 4: Expected skewness and first-day returns

This table reports regression results before and after separating left- from right-skewed IPOs. The dependent variable is *IR*, defined as the percentage difference between its first-day closing price and its offer price. *Skewness* is the expected skewness of an IPO stock's return defined using the tails of the probability distribution generated by log monthly returns of all stocks in the same industry over the three-month period before the offer date; |*Skewness*| is the absolute value of *Skewness*; I_L is a dummy which takes the value of 1 if *Skewness*<0; *ROA* is net incomes over total assets in the pre-IPO year; *Leverage* is the leverage ratio, estimated as total liabilities over total assets prior to listing; Log(*Issue Size*) is the logarithm of the IPO proceeds measured as the offer price multiplied by the number of new shares offered; *Underwriter* is a dummy, equal to 1 if the lead underwriter has been recognized as one of top 10 underwriters at least twice over the past three years, and 0 otherwise; *Big 4* is a dummy, equal to 1 if financial reporting is audited by one of big 4 accounting firms; *VC-backed* is a dummy, equal to 1 if the firm has been supported by venture capital; *State* is the proportion of state holdings in the firm; Log (1+*Age*) is the logarithm of 1 plus firm age since establishment; *Time Lag* is the number of days elapsed between offering and listing; *Divergence of Opinion* is the standard deviation of one-year forward looking EPS by analysts; *Analyst Bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *Hi-Tech* is a dummy variable, which is equal to 1 if the IPO is operating in the hi-tech industry; *Legal* is the investor protection index prepared by Fan et al. (2011); *Market Sentiment* is the number of IPOs in the same calendar month. The *t*-values in parentheses use White's (1980) robust standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Regression results before separating left- from right-skewed IPOs

	Dependent Variable: *IR*			
	(1)	(2)	(3)	(4)
Skewness	-0.267 (-1.26)	0.235 (1.20)	-0.208 (-1.10)	-0.007 (-0.04)
ROA			0.014 (0.04)	-0.099 (-0.27)
Leverage			0.230 (1.26)	0.211 (1.16)
Log (*Issue Size*)			-0.383*** (-7.83)	-0.359*** (-6.99)
Underwriter			0.063 (1.38)	0.040 (0.89)
Big 4			0.594*** (2.93)	0.569*** (2.74)
VC-backed			-0.022 (-0.48)	-0.010 (-0.23)
State			0.424*** (3.56)	0.337*** (2.83)
Log (1+*Age*)			-0.122*** (-3.43)	-0.092** (-2.50)
Time Lag			0.028*** (416)	0.021*** (3.15)
Divergence of Opinion			0.058 (0.68)	0.079 (0.95)
Analyst Bias			0.287*** (3.68)	0.282*** (3.55)
Hi-Tech			-0.091 (-0.64)	-0.115 (-0.80)
Legal			-0.010** (-2.34)	-0.010** (-2.41)
Market Sentiment			-0.013*** (-4.22)	-0.008* (-1.74)
Year Dummies	No	Yes	No	Yes

Adjusted R^2	0.002	0.185	0.315	0.338

Panel B: Regression results using absolute skewness

	Dependent Variable: *IR*			
	(1)	(2)	(3)	(4)
|*Skewness*|	1.131*** (3.88)	0.884*** (3.43)	0.852*** (3.40)	0.832*** (3.45)
ROA			0.151 (0.42)	-0.009 (-0.02)
Leverage			0.224 (1.23)	0.200 (1.10)
Log (*Issue Size*)			-0.385*** (-7.78)	-0.361*** (-6.98)
Underwriter			0.052 (1.13)	0.029 (0.65)
Big 4			0.604*** (2.98)	0.574*** (2.76)
VC-backed			-0.014 (-0.31)	-0.004 (-0.09)
State			0.405*** (3.51)	0.330*** (2.86)
Log (1+*Age*)			-0.119*** (-3.37)	-0.086** (-2.38)
Time Lag			0.027*** (4.18)	0.020*** (3.16)
Divergence of Opinion			0.063 (0.75)	0.074 (0.90)
Analyst Bias			0.262*** (3.36)	0.265*** (3.34)
Hi-Tech			-0.103 (-0.75)	-0.128 (-0.92)
Legal			-0.010** (-2.38)	-0.010*** (-2.37)
Market Sentiment			-0.014*** (-4.44)	-0.008* (-1.88)
Year Dummies	No	Yes	No	Yes
Adjusted R^2	0.018	0.194	0.324	0.348

Panel C: Regression results after separating left- from right-skewed IPOs

	Dependent Variable: *IR*			
	(1)	(2)	(3)	(4)
constant	0.426*** (9.47)	0.809*** (10.44)	4.822*** (13.48)	4.639*** (8.09)
|*Skewness*|*I_L	2.023*** (3.68)	0.712 (1.29)	1.572*** (4.43)	1.202*** (2.59)
*Skewness**(1-I_L)	0.944*** (3.34)	0.917*** (3.74)	0.697*** (2.86)	0.758*** (3.17)
ROA			0.049 (0.12)	-0.045 (-0.12)

Leverage			0.202 (1.10)	0.192 (1.05)
Log (*Issue Size*)			-0.384*** (-11.82)	-0.364*** (-7.01)
Underwriter			0.045 (0.96)	0.028 (0.61)
Big 4			0.589*** (4.90)	0.570*** (2.75)
VC-backed			-0.018 (-0.40)	-0.006 (-0.15)
State			0.409*** (3.99)	0.339*** (2.89)
Log (1+*Age*)			-0.118*** (-3.08)	-0.086** (-2.37)
Time Lag			0.028*** (5.11)	0.021*** (3.20)
Divergence of Opinion			0.047 (0.47)	0.066 (0.79)
Analyst Bias			0.274*** (3.40)	0.269*** (3.43)
Hi-Tech			-0.108 (-0.73)	-0.129 (-0.93)
Legal			-0.009** (-2.14)	-0.009** (-2.33)
Market Sentiment			-0.013*** (-4.37)	-0.009** (-1.99)
Year Dummies	No	Yes	No	Yes
Adjusted R^2	0.026	0.193	0.329	0.348

Table 5: Regression results for the relationship between discounting and skewness

This table reports regression results for the relationship between discounting and skewness. The dependent variable is *Discounting* defined as the percentage difference between the offer price of an IPO stock and the median market price of the same-industry stocks. *Skewness* is the expected skewness of an IPO stock's return defined using the tails of the probability distribution generated by monthly returns of all stocks in the same industry over the three-month period before the offer date; |*Skewness*| is the absolute value of *Skewness*; I_L is a dummy which takes the value of 1 if *Skewness*<0; *ROA* is net incomes over total assets in the pre-IPO year; *Leverage* is the leverage ratio, estimated as total liabilities over total assets prior to listing; Log(*Issue Size*) is the logarithm of the IPO proceeds measured as the offer price multiplied by the number of new shares offered; *Underwriter* is a dummy, equal to 1 if the lead underwriter has been recognized as one of top 10 underwriters at least twice over the past three years, and 0 otherwise; *Big 4* is a dummy, equal to 1 if financial reporting is audited by one of big 4 accounting firms; *VC-backed* is a dummy, equal to 1 if the firm has been supported by venture capital; *State* is the proportion of state holdings in the firm; Log (1+*Age*) is the logarithm of 1 plus firm age since establishment; *Time Lag* is the number of days elapsed between offering and listing; *Divergence of Opinion* is the standard deviation of one-year forward looking EPS by analysts; *Analyst Bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *Hi-Tech* is a dummy variable, which is equal to 1 if the IPO is operating in the hi-tech industry; *Legal* is the investor protection index prepared by Fan et al. (2011); *Market Sentiment* is the number of IPOs in the same calendar month. The *t*-values in parentheses are calculated using White's (1980) robust standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Regression results using absolute skewness

	(1)	(2)	(3)	(4)
|*Skewness*|	-1.198 (-1.18)	-0.912 (-0.96)	-0.733 (-0.76)	-0.555 (-0.60)
ROA			-3.267* (-1.86)	-2.954* (-1.68)
Leverage			-1.969** (-2.17)	-1.745* (-1.93)
Log (*Issue Size*)			-0.175 (-1.40)	-0.266** (-2.01)
Underwriter			-0.312 (-1.62)	-0.253 (-1.30)
Big 4			0.166 (0.47)	0.316 (0.87)
VC-backed			-0.047 (-0.25)	-0.030 (-0.17)
State			-0.137 (-0.38)	-0.063 (-0.17)
Log (1+*Age*)			-0.543*** (-2.80)	-0.400** (-2.09)
Time Lag			0.002 (0.08)	-0.016 (-0.65)
Divergence of Opinion			1.152*** (2.85)	1.187*** (3.05)
Analyst Bias			-0.810** (-2.22)	-0.947*** (-2.59)
Hi-Tech			-0.141 (-0.23)	-0.177 (-0.29)
Legal			-0.005 (-0.24)	-0.005 (-0.27)
Market Sentiment			0.042*** (3.71)	0.013 (1.16)
Year Dummies	No	Yes	No	Yes
Adjusted R^2	0.000	0.039	0.044	0.063

Panel B: Regression results after separating left- from right-skewed IPOs

	(1)	(2)	(3)	(4)
constant	0.585*** (3.28)	0.181 (1.13)	3.716** (2.51)	4.649*** (2.99)
$\|Skewness\|*I_L$	-3.000** (-2.42)	-2.437** (-2.13)	-2.368** (-2.04)	-2.449** (-2.18)
$Skewness*(1-I_L)$	-0.819 (-0.78)	-0.622 (-0.61)	-0.380 (-0.37)	-0.175 (-0.18)
ROA			-3.035* (-1.73)	-2.768 (-1.58)
Leverage			-1.918** (-2.13)	-1.704* (-1.89)
Log (*Issue Size*)			-0.176 (-1.40)	-0.253* (-1.94)
Underwriter			-0.294 (-1.53)	-0.244 (-1.26)
Big 4			0.199 (0.55)	0.334 (0.91)
VC-backed			-0.038 (-0.21)	-0.018 (-0.10)
State			-0.146 (-0.40)	-0.107 (-0.29)
Log (1+*Age*)			-0.546*** (-2.81)	-0.399** (-2.09)
Time Lag			0.002 (0.07)	-0.018 (-0.74)
Divergence of Opinion			1.188*** (2.88)	1.231*** (3.09)
Analyst Bias			-0.837** (-2.26)	-0.970*** (-2.62)
Hi-Tech			-0.130 (-0.21)	-0.175 (-0.29)
Legal			-0.006 (-0.31)	-0.007 (-0.35)
Market Sentiment			0.041*** (3.62)	0.014 (1.30)
Year Dummies	No	Yes	No	Yes
Adjusted R^2	0.003	0.040		0.065

Table 6: Expected skewness and retail demand in the IPO market

This table reports regression results for the relationship between expected skewness and retail demand. The dependent variables are Log(*Orders*) and Log(*RMB*). Log(*Orders*) is defined as the logarithm of the number of valid subscription orders received from the second offline tranche; Log(*RMB*) is defined as the logarithm of the number of new shares subscribed times the offer price; *Skewness* is the expected skewness of an IPO stock's return defined using the tails of the probability distribution generated by log monthly returns of all stocks in the same industry over the three-month period before the offer date; |*Skewness*| is the absolute value of *Skewness*; I_L is a dummy which takes the value of 1 if *Skewness*<0; *ROA* is net incomes over total assets in the pre-IPO year; *Leverage* is the leverage ratio, estimated as total liabilities over total assets prior to listing; Log(*Issue Size*) is the logarithm of the IPO proceeds measured as the offer price multiplied by the number of new shares offered; *Underwriter* is a dummy, equal to 1 if the lead underwriter has been recognized as one of top 10 underwriters at least twice over the past three years, and 0 otherwise; *Big 4* is a dummy, equal to 1 if financial reporting is audited by one of big 4 accounting firms; *VC-backed* is a dummy, equal to 1 if the firm has been supported by venture capital; *State* is the proportion of state holdings in the firm; Log (1+*Age*) is the logarithm of 1 plus firm age since establishment; *Time Lag* is the number of days elapsed between offering and listing; *Divergence of Opinion* is the standard deviation of one-year forward looking EPS by analysts; *Analyst Bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *Hi-Tech* is a dummy variable, which is equal to 1 if the IPO is operating in the hi-tech industry; *Legal* is the investor protection index prepared by Fan et al. (2011); *Market Sentiment* is the number of IPOs in the same calendar month. The *t*-values in parentheses are calculated using White's (1980) robust standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Regression results before separating left- from right-skewed IPOs

	Dependent Variable: Log(*Orders*)		Dependent Variable: Log(*RMB*)	
	(1)	(2)	(3)	(4)
|*Skewness*|	0.427*** (3.23)	0.335*** (2.71)	0.773*** (5.03)	0.601*** (4.06)
ROA		-0.593*** (-2.67)		-0.206 (-0.79)
Leverage		-0.010 (-0.10)		0.118 (0.95)
Log (*Issue Size*)		-0.029 (-1.26)		0.099*** (3.43)
Underwriter		0.007 (0.32)		0.025 (0.90)
Big 4		-0.027 (-0.29)		-0.193* (-1.85)
VC-backed		-0.032 (-1.50)		-0.025 (-0.97)
State		0.209*** (3.95)		0.238*** (3.20)
Log (1+*Age*)		-0.014 (-0.73)		-0.032 (-1.40)
Time Lag		-0.001 (-0.51)		0.003 (0.94)
Divergence of Opinion		-0.287*** (-4.51)		-0.120* (-1.81)
Analyst Bias		0.029 (0.69)		0.119*** (2.59)
Hi-Tech		-0.075 (-0.79)		-0.095 (-0.85)
Legal		-0.001 (-0.24)		-0.003 (-1.24)
Market Sentiment		-0.007*** (-3.54)		-0.006** (-2.34)

Year Dummies	Yes	Yes	Yes	Yes
Adjusted R^2	0.171	0.288	0.252	0.335

Panel B: Regression results after separating left- from right-skewed IPOs

	Dependent Variable: Log(*Orders*)		Dependent Variable: Log(*RMB*)	
	(1)	(2)	(3)	(4)
constant	5.388*** (164.28)	6.043*** (25.46)	10.750*** (243.09)	9.854*** (34.90)
$\|Skewness\|*I_L$	0.167 (0.83)	0.388** (2.01)	0.673*** (2.64)	0.617** (2.37)
$Skewness*(1-I_L)$	0.476*** (3.52)	0.324*** (2.58)	0.792*** (5.08)	0.598*** (4.05)
ROA		-0.598*** (-2.69)		-0.207 (-0.79)
Leverage		-0.011 (-0.11)		0.118 (0.95)
Log (*Issue Size*)		-0.030 (-1.27)		0.099*** (3.43)
Underwriter		0.007 (0.31)		0.025 (0.90)
Big 4		-0.028 (-0.30)		-0.193* (-1.85)
VC-backed		-0.032 (-1.51)		-0.025 (-0.98)
State		0.210*** (3.95)		0.239*** (3.20)
Log (1+*Age*)		-0.014 (-0.73)		-0.032 (-1.39)
Time Lag		-0.001 (-0.49)		0.003 (0.94)
Divergence of Opinion		-0.288*** (-4.55)		-0.121* (-1.82)
Analyst Bias		0.030 (0.71)		0.119*** (2.60)
Hi-Tech		-0.075 (-0.78)		-0.095 (-0.85)
Legal		-0.001 (-0.23)		-0.003 (-1.24)
Market Sentiment		-0.007*** (-3.55)		-0.006** (-2.34)
Year Dummies	Yes	Yes	Yes	Yes
Adjusted R^2	0.173	0.287	0.252	0.334

Table 7: Expected skewness and long-term stock performance

This table reports regression results for the relationship between expected skewness and long-term stock performance using the full sample in Panel A, and the subsamples in Panel B. *BHAR* is defined as the buy-and-hold return of an IPO stock in the 36 post-IPO event months relative to the buy-and-hold return of a size and B/M comparable non-IPO stock over the same period of time; *Jensen's Alpha* is defined as the abnormal monthly return estimated from the Fama-French three-factor model over the 36 post-IPO calendar months; *Skewness* is the expected skewness of an IPO stock's return defined using the tails of the probability distribution generated by log monthly returns of all stocks in the same industry over the three-month period before the offer date; |*Skewness*| is the absolute value of *Skewness*; I_L is a dummy which takes the value of 1 if *Skewness*<0; *ROA* is net incomes over total assets in the pre-IPO year; *Leverage* is the leverage ratio, estimated as total liabilities over total assets prior to listing; Log (*Issue Size*) is the logarithm of the IPO proceeds measured as the offer price multiplied by the number of new shares offered; *Underwriter* is a dummy, equal to 1 if the lead underwriter has been recognized as one of top 10 underwriters at least twice over the past three years, and 0 otherwise; *Big 4* is a dummy, equal to 1 if financial reporting is audited by one of big 4 accounting firms; *VC-backed* is a dummy, equal to 1 if the firm has been supported by venture capital; *State* is the proportion of state holdings in the firm; Log (1+*Age*) is the logarithm of 1 plus firm age since establishment; *Time Lag* is the number of days elapsed between offering and listing; *Divergence of Opinion* is the standard deviation of one-year forward looking EPS by analysts; *Analyst Bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *Hi-Tech* is a dummy variable, which is equal to 1 if the IPO is operating in the hi-tech industry; *Legal* is the investor protection index prepared by Fan et al. (2011); *Market Sentiment* is the number of IPOs in the same calendar month. The *t*-values in parentheses are calculated using White's (1980) robust standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Regression results for the full sample

	Dependent Variable: *BHAR*				Dependent Variable: *Jensen's Alpha*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
|*Skewness*|	-1.558** (-2.29)	-1.645** (-2.52)	-1.076 (-1.52)	-1.228* (-1.77)	-0.036*** (-3.00)	-0.050*** (-4.92)	-0.038*** (-3.51)	-0.042*** (-4.35)
ROA			0.027 (0.02)	-0.016 (-0.01)			0.007 (0.39)	-0.015 (-0.88)
Leverage			-0.914 (-1.51)	-1.008* (-1.66)			-0.013 (-1.59)	-0.023*** (-3.15)
Log (*Issue Size*)			-0.476*** (-3.30)	-0.418*** (-2.83)			-0.007*** (-4.83)	-0.002 (-1.49)
Underwriter			0.120 (0.84)	0.075 (0.51)			0.004** (2.02)	0.000 (0.09)
Big 4			-0.274 (-0.36)	-0.409 (-0.55)			0.005 (0.79)	-0.003 (-0.49)
VC-backed			-0.000 (-0.00)	-0.015 (-0.09)			-0.001 (-0.50)	-0.000 (-0.14)
State			0.347 (0.77)	0.315 (0.67)			0.006 (1.13)	-0.002 (-0.48)
Log (1+*Age*)			0.235** (2.49)	0.088 (0.93)			0.008*** (4.46)	0.007*** (4.28)
Time Lag			-0.047*** (-2.58)	-0.033* (-1.79)			-0.001*** (-3.12)	-0.001*** (-3.37)
Divergence of Opinion			-0.287 (-0.77)	-0.322 (-0.89)			0.007 (1.41)	0.006 (1.42)
Analyst Bias			-0.241 (-1.23)	-0.096 (-0.48)			-0.000 (-0.02)	0.005* (1.74)
Hi-Tech			-0.321 (-0.58)	-0.300 (-0.55)			0.007 (0.96)	0.007 (0.96)
Legal			0.036** (2.09)	0.036** (2.15)			0.000 (1.47)	0.000** (2.02)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market Sentiment			0.009 (0.80)	0.025** (2.02)			-0.002*** (-13.44)	-0.001*** (-3.48)
Year Dummies	No	Yes	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.005	0.043	0.086	0.110	0.009	0.412	0.320	0.457

Panel B: Regression results after separating left- from right-skewed IPOs

	Dependent Variable: *BHAR*				Dependent Variable: *Jensen's Alpha*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
constant	-0.400***	-0.196	4.741***	4.391***	-0.242***	-0.218***	-0.129***	-0.182***
	(-3.68)	(-1.02)	(3.23)	(3.00)	(-116.31)	(-83.37)	(-7.55)	(-10.68)
$\lvert Skewness \rvert * I_L$	-0.734	-0.280	0.178	0.428	0.029	-0.034*	0.008	-0.025
	(-0.87)	(-0.32)	(0.21)	(0.48)	(1.44)	(-1.97)	(0.45)	(-1.57)
$Skewness*(1-I_L)$	-1.731**	-1.905***	-1.347*	-1.560**	-0.049***	-0.052***	-0.048***	-0.046***
	(-2.40)	(-2.74)	(-1.72)	(-2.02)	(-4.23)	(-5.18)	(-4.56)	(-4.64)
ROA			-0.151	-0.179			0.001	-0.016
			(-0.10)	(-0.12)			(0.04)	(-0.98)
Leverage			-0.953	-1.043*			-0.014*	-0.023***
			(-1.55)	(-1.71)			(-1.79)	(-3.19)
Log (*Issue Size*)			-0.475***	-0.429***			-0.007***	-0.002
			(-3.29)	(-2.86)			(-4.73)	(-1.54)
Underwriter			0.106	0.068			0.004*	0.000
			(0.76)	(0.47)			(1.80)	(0.05)
Big 4			-0.300	-0.425			0.004	-0.003
			(-0.39)	(-0.57)			(0.61)	(-0.51)
VC-backed			-0.007	-0.026			-0.001	-0.000
			(-0.05)	(-0.16)			(-0.63)	(-0.21)
State			0.354	0.354			0.006	-0.002
			(0.78)	(0.74)			(1.18)	(-0.39)
Log (1+*Age*)			0.237**	0.087			0.008***	0.007***
			(2.53)	(0.93)			(4.58)	(4.28)
Time Lag			-0.047***	-0.031*			-0.001***	-0.001***
			(-2.57)	(-1.67)			(-3.09)	(-3.29)
Divergence of Opinion			-0.315	-0.361			0.006	0.006
			(-0.86)	(-1.02)			(1.22)	(1.35)

Table 8: Robustness checks using alternative variable specification

This table reports regression results using alternative expected skewness measure. Regressions in Panel A do not separate left- from right-skewed IPOs while regressions in Panels B do. The dependent variables in both panels are *IR*, *Discounting*, *Log*(*Orders*), *Log*(*RMB*), *BHAR*, and *Jensen's alpha*, respectively. *IR* is the first-day return of an IPO stock defined as the percentage difference between its first-day closing price and its offer price; *Discounting* is defined as the percentage difference between the offer price of an IPO stock and the median market price of the same-industry stocks; Log(*Orders*) is defined as the logarithm of the number of valid subscription orders received from the second offline tranche; Log(*RMB*) is defined as the logarithm of the number of new shares subscribed times the offer price; *BHAR* is defined as the buy-and-hold return of an IPO stock in the 36 post-IPO event months relative to the buy-and-hold return of a size and B/M comparable non-IPO stock over the same period of time; *Jensen's Alpha* is defined as the abnormal monthly return estimated from the Fama-French three-factor model over the 36 post-IPO calendar months; *Skewness_SOE3m* is the expected skewness of an IPO stock's return defined using the tails of the probability distribution generated by log monthly returns of all SOE or non-SOE stocks in the same industry over the most recent three-month period before the offer date; |*Skewness_SOE3m*| is the absolute value of *Skewness_SOE3m*; I_SOE3m_L is a dummy which takes the value of 1 if *Skewness_SOE3m* < 0; *ROA* is net incomes over total assets in the pre-IPO year; *Leverage* is the leverage ratio, estimated as total liabilities over total assets prior to listing; Log (*Issue Size*) is the logarithm of the IPO proceeds measured as the offer price multiplied by the number of new shares offered; *Underwriter* is a dummy, equal to 1 if the lead underwriter has been recognized as one of top 10 underwriters at least twice over the past three years, and 0 otherwise; *Big 4* is a dummy, equal to 1 if financial reporting is audited by one of big 4 accounting firms; *VC-backed* is a dummy, equal to 1 if the firm has been supported by venture capital; *State* is the proportion of state holdings in the firm; Log (1+*Age*) is the logarithm of 1 plus firm age since establishment; *Time Lag* is the number of days elapsed between offering and listing; *Divergence of Opinion* is the standard deviation of one-year forward looking EPS by analysts; *Analyst Bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *Hi-Tech* is a dummy variable, which is equal to 1 if the IPO is operating in the hi-tech industry; *Legal* is the investor protection index prepared by Fan et al. (2011); *Market Sentiment* is the number of IPOs in the same calendar month. The *t*-values in parentheses are calculated using White's (1980) robust standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Regression results before separating left- from right-skewed IPOs

	IR	*Discounting*	*Log(Orders)*	*Log(RMB)*	*BHAR*	*Alpha*
	(1)	(2)	(3)	(4)	(5)	(6)
Skewness_SOE3m	0.158 (0.80)	0.179 (0.31)	0.074 (0.98)	0.091 (1.01)	-1.129** (-2.15)	-0.024*** (-4.07)
ROA	-0.132 (-0.37)	-2.615 (-1.56)	-0.577*** (-2.71)	-0.228 (-0.90)	-0.097 (-0.06)	-0.020 (-1.23)
Leverage	0.143 (0.76)	-2.330*** (-3.20)	-0.055 (-0.57)	0.043 (0.38)	-0.970 (-1.55)	-0.025*** (-3.42)
Log (*Issue Size*)	-0.355*** (-6.58)	-0.308** (-2.46)	-0.026 (-1.50)	0.101*** (4.82)	-0.404*** (-2.65)	-0.002 (-1.60)
Underwriter	0.008 (0.17)	-0.317* (-1.72)	0.003 (0.13)	0.019 (0.65)	0.062 (0.39)	0.000 (0.20)
Big 4	0.624*** (2.75)	0.494 (1.27)	-0.010 (-0.15)	-0.181** (-2.35)	-0.555 (-0.66)	-0.007 (-1.49)
VC-backed	-0.031 (-0.67)	-0.053 (-0.29)	-0.035 (-1.45)	-0.029 (-1.03)	-0.056 (-0.33)	-0.001 (-0.28)
State	0.362*** (2.91)	-0.010 (-0.03)	0.231*** (4.22)	0.280*** (4.28)	0.311 (0.63)	-0.004 (-0.99)
Log (1+*Age*)	-0.098** (-2.53)	-0.429** (-2.24)	-0.015 (-0.72)	-0.036 (-1.41)	0.123 (1.28)	0.008*** (4.67)
Time Lag	0.022*** (3.08)	-0.016 (-0.65)	-0.000 (-0.07)	0.004 (0.99)	-0.032 (-1.58)	-0.001*** (-3.14)
Divergence of Opinion	0.115 (1.27)	0.695** (2.09)	-0.276*** (-5.07)	-0.111* (-1.70)	-0.355 (-0.91)	0.003 (0.75)
Analyst Bias	0.248*** (3.04)	-0.933 *** (-2.80)	0.021 (0.49)	0.111** (2.18)	-0.036 (-0.17)	0.007** (2.00)

Hi-Tech	-0.105 (-0.55)	-0.011 (-0.02)	-0.050 (-0.56)	-0.047 (-0.43)	-0.560 (-0.76)	0.005 (0.70)
Legal	-0.010** (-2.33)	-0.000 (-0.00)	-0.001 (-0.32)	-0.004 (-1.31)	0.034* (1.85)	0.000** (2.24)
Market Sentiment	-0.007 (-1.56)	0.008 (0.69)	-0.007*** (-3.33)	-0.005** (-2.09)	0.024* (1.84)	-0.001*** (-4.02)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.329	0.077	0.267	0.313	0.116	0.483

Panel B: Regression results after separating left- from right-skewed IPOs

	IR	*Discounting*	*Log*(*Orders*)	*Log*(*RMB*)	*BHAR*	*Alpha*
	(1)	(2)	(3)	(4)	(5)	(6)
constant	4.615*** (7.68)	5.651*** (3.51)	6.018*** (31.48)	9.879*** (43.50)	4.120*** (2.84)	-0.184*** (-10.73)
|*Skewness_SOE3m*|* I_SOE3m_L	1.095** (1.99)	-2.286* (-1.82)	0.385** (2.05)	0.722*** (3.24)	-0.002 (-0.00)	-0.013 (-0.76)
*Skewness_SOE3m** (1- I_SOE3m_L)	0.872*** (3.30)	-0.851 (-0.90)	0.309*** (2.60)	0.562*** (3.99)	-2.039** (-2.10)	-0.041*** (-3.97)
ROA	-0.060 (-0.17)	-2.734* (-1.65)	-0.556*** (-2.63)	-0.179 (-0.71)	-0.147 (-0.10)	-0.021 (-1.27)
Leverage	0.111 (0.59)	-2.297*** (-3.18)	-0.066 (-0.69)	0.023 (0.20)	-0.901 (-1.47)	-0.024*** (-3.23)
Log (*Issue Size*)	-0.364*** (-6.64)	-0.291** (-2.32)	-0.029* (-1.68)	0.096*** (4.58)	-0.400*** (-2.63)	-0.002 (-1.28)
Underwriter	-0.009 (-0.20)	-0.291 (-1.62)	-0.002 (-0.10)	0.008 (0.28)	0.082 (0.50)	0.001 (0.43)
Big 4	0.628*** (2.80)	0.469 (1.24)	-0.010 (-0.15)	-0.178** (-2.34)	-0.516 (-0.63)	-0.006 (-1.09)
VC-backed	-0.031 (-0.68)	-0.049 (-0.27)	-0.035 (-1.47)	-0.029 (-1.04)	-0.062 (-0.36)	-0.001 (-0.30)
State	0.363*** (2.94)	-0.018 (-0.05)	0.232*** (4.25)	0.280*** (4.33)	0.321 (0.64)	-0.004 (-0.82)
Log (1+*Age*)	-0.101*** (-2.62)	-0.426** (-2.23)	-0.016 (-0.76)	-0.038 (-1.50)	0.130 (1.35)	0.008*** (4.55)
Time Lag	0.023*** (3.18)	-0.017 (-0.71)	0.000 (0.01)	0.004 (1.10)	-0.032 (-1.56)	-0.001*** (-3.25)
Divergence of Opinion	0.124 (1.38)	0.690** (2.09)	-0.274*** (-5.04)	-0.105 (-1.62)	-0.380 (-1.00)	0.003 (0.62)
Analyst Bias	0.225*** (2.77)	-0.904*** (-2.71)	0.014 (0.32)	0.096* (1.90)	-0.000 (-0.00)	0.007** (2.46)
Hi-Tech	-0.110 (-0.59)	0.021 (0.03)	-0.052 (-0.58)	-0.050 (-0.47)	-0.607 (-0.83)	0.004 (0.50)
Legal	-0.009** (-2.16)	-0.002 (-0.09)	-0.000 (-0.17)	-0.003 (-1.11)	0.033* (1.84)	0.000** (2.23)
Market Sentiment	-0.007 (-1.52)	0.008 (0.67)	-0.007*** (-3.31)	-0.005** (-2.06)	0.024* (1.83)	-0.001*** (-3.77)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.342	0.079	0.272	0.328	0.120	0.486

Table 9: Robustness Checks Using a Revision to the Institutional Arrangements

This table reports regression results for the relationship between offer price range and a reform dummy in Panel A, the relationship between midpoint and a reform dummy in Panel B, and the relationship between upward revision and a reform dummy in Panel C, using a matched sample of 862 IPOs where 431 IPOs issued after the reform to the AMSIU in December 2013 are similar to another 431 IPOs issued before the reform. *Range* is the offer price range defined as the highest price minus the lowest price; *MidPoint* is the simple average between the highest price and the lowest price; *Up_Revision* is defined as the percentage upward revision from the mid-point of the filing range if the offer price is greater than the mid-point, and zero otherwise; *Reform* is a dummy which is equal to 1 for an IPO issued after December 13, 2013 where underwriters can allocate shares to institutional investors at their discretion, and 0 otherwise. *ROA* is net incomes over total assets in the pre-IPO year; *Leverage* is the leverage ratio, estimated as total liabilities over total assets prior to listing; Log (*Issue Size*) is the logarithm of the IPO proceeds measured as the offer price multiplied by the number of new shares offered; *Underwriter* is a dummy, equal to 1 if the lead underwriter has been recognized as one of top 10 underwriters at least twice over the past three years, and 0 otherwise; *Big 4* is a dummy, equal to 1 if financial reporting is audited by one of big 4 accounting firms; *VC-backed* is a dummy, equal to 1 if the firm has been supported by venture capital; *State* is the proportion of state holdings in the firm; Log (1+*Age*) is the logarithm of 1 plus firm age since establishment; *Divergence of Opinion* is the standard deviation of one-year forward looking EPS by analysts; *Analyst Bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *Hi-Tech* is a dummy variable, which is equal to 1 if the IPO is operating in the hi-tech industry; *Legal* is the investor protection index prepared by Fan et al. (2011); *Market Sentiment* is the number of IPOs in the same calendar month. The *t*-values in parentheses use White's (1980) robust standard errors. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: Impacts of the 2013 AMSIU reform on offer price range

	Dependent Variable: *Range*		
	(1)	(2)	(3)
Reform	-1.374 (-1.45)	-2.406*** (-4.46)	-1.878*** (-2.88)
MidPoint		0.989*** (18.61)	1.082*** (16.57)
ROA			-30.836*** (-5.05)
Leverage			-2.109 (-1.17)
Log (*Issue Size*)			-1.048*** (-3.26)
Underwriter			-0.052 (-0.09)
Big 4			1.956** (2.15)
VC-backed			3.792*** (6.52)
State			2.385*** (3.71)
Log (1+*Age*)			-0.355 (-0.56)
Divergence of Opinion			-2.222 (-1.56)
Analyst Bias			3.249** (2.41)
Hi-Tech			0.746 (0.97)
Legal			0.022 (0.38)
Adjusted R^2	0.001	0.677	0.713

Panel B: Impacts of the 2013 AMSIU reform on the midpoint of offer price range

	Dependent Variable: *Midpoint*		
	(1)	(2)	(3)
Reform	1.043 (1.32)	1.984*** (4.52)	1.721*** (3.50)
Range		0.684*** (22.55)	0.539*** (20.16)
ROA			36.308*** (6.56)
Leverage			0.607 (0.45)
Log (*Issue Size*)			1.675*** (6.55)
Underwriter			-0.514 (-1.32)
Big 4			-3.479*** (-4.34)
VC-backed			-0.766 (-1.59)
State			-3.739*** (-6.99)
Log (1+*Age*)			0.046 (0.11)
Divergence of Opinion			7.683*** (6.82)
Analyst Bias			0.239 (0.24)
Hi-Tech			0.695 (1.20)
Legal			0.004 (0.11)
Adjusted R^2	0.001	0.677	0.794

Panel C: Impacts of the 2013 AMSIU reform on offer price revision

	Dependent Variable: *Up_Revision*		
	(1)	(2)	(3)
Reform	0.007 (0.78)	0.017* (1.78)	-0.003 (-0.75)
Range		0.004*** (6.59)	0.005*** (7.64)
MidPoint		-0.004*** (-6.19)	-0.008*** (-7.73)
ROA			0.360*** (3.21)
Leverage			-0.072** (-2.24)
Log (*Issue Size*)			0.051*** (9.41)
Underwriter			-0.002 (-0.20)
Big 4			-0.059*** (-3.02)

VC-backed			-0.018** (-2.07)
State			-0.072*** (-5.68)
Log (1+*Age*)			0.017** (1.97)
Divergence of Opinion			0.014 (0.69)
Analyst Bias			0.030* (1.84)
Hi-Tech			-0.018 (-1.48)
Legal			0.000 (0.31)
Adjusted R^2	0.000	0.058	0.196

Appendix: China's lottery mechanism

All lottery tickets are numbered sequentially and enter for the lottery draw that follows for a particular IPO. The allocation rate for an IPO stock is defined as the number of shares offered divided by the number of shares subscribed. Assuming that the allocation rate is 0.05733852%, the detailed process for identifying winning lottery tickets is illustrated as follows:

a) The first step is to identify those winning tickets for the 0.05% allocation rate. The defined procedure is that five different tickets with ticket numbers ending with four particular numerals will be selected from every 10,000 consecutive numbers. For example, four numerals drawn from a random device in one particular order are 3473. Since five different combinations must be distributed uniformly over the neighborhood of 3473, some adjustments are needed to identify the other four combinations. If dividing the total number of lottery tickets by the number of winning tickets yields a whole number, adjustments are the whole number and its multiples. In this case, 10,000/5 produces the whole number 2,000, and thus using 2,000 and its multiples, the winning ticket numbers identified for the allocation rate of 0.05% are those ending up with 3437, 5437 (=3,437+2,000), 7437 (=3,437+2,000*2), 9437 (=3,437+2,000*3) and 1437 (=3,437-2,000).

b) The second step is to identify those winning tickets for the 0.007% allocation rate. Analogously, there will be a total of 7 tickets to be decided for each 100,000 tickets and they must be distributed evenly across its neighboring area. For illustration purpose, let us assume that a particular combination of numerals such as 10256 is randomly decided and we have to identify the other six combinations. Since dividing 100,000 by 7 does not give a whole number, the guideline suggests that we should take 0.007% as the sum of 0.005% and 0.002% and proceed to identify five combinations for each 100,000 and two combinations for each 100,000. In the latter two cases, we will obtain a whole number for adjustment for sure. In the former case where the allocation rate is 0.005%, adjustments are 20,000 (=100,000/5) and its multiples while in the latter case where the allocation rate is 0.002%, adjustments are 50,000 and its multiples. Following the same procedure, the winning numbers identified for the allocation rate of 0.007% are those ending up with 10256, 30256 (=10,256+20,000*1), 50256 (=10,256+20,000*2), 70256 (=10,256+20,000*3), 90256 (=10,256+20,000*4), 35824[20], 85824 (=35,824+50,000*1);

c) Those winning combinations for the 0.0003% allocation rate and beyond are identified in a similar fashion.

[20] In this case, we have to generate another combination of five numbers since 10256 is already identified as the winning combination following the procedure for 0.005% and cannot use again following the procedure for 0.002%. Let us assume that the newly-generated combination is 35824.

Highlights

- This paper provides a new cumulative prospect theory (PT) perspective on IPOs by proposing a median-based expected skewness measure as the reference point for potential investors.
- While left-skewed IPOs exhibit a significantly positive relationship between offer price discounting and (absolute) skewness, the relationship for right-skewed IPOs is insignificant.
- A skewness shock attracts more than double the mean value of retail orders to the left- than to the right-skewed subsample although the latter attracts 26% more investors.
- Prospect theory suggests that investors in left-skewed IPOs tend to flip to exploit the deep discounting (relative to their underlying value) on the first trading day rather than gamble on possible long run gains. Relatedly, their long run return measures are independent of absolute skewness but we find significantly inverse relationships between these variables for right-skewed IPOs.