Prospect theory and IPO returns in China

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Abstract

This paper investigates whether prospect theory (PT) or a preference for lottery-like gains on stocks can explain the peculiarities of IPO returns in China. Chinese IPOs offer investors two potential lottery-like gains. One is potentially huge first day returns as Chinese issuers leave more money on the table and the other is that a particular IPO may in the long run become the next Alibaba. Consistent with the skewness preference hypothesis, we find that expected skewness is associated with high first-day returns and low long-term performance for a sample of 748 book-built Chinese IPOs issued over the 2005-2012 period. A one-standard-deviation increase in the expected skewness of an IPO stock can not only lead to an increase of 6.67 percentage points in the first-day return but also predict a decrease of 10.80-12.23 percentage points in the post-IPO abnormal return. Further analysis suggests that retail demand around the IPO event tends to increase with expected skewness, indicating that PT investors indeed overweight those extremely low probability events, leading to high first-day returns and low long-term abnormal returns.

JEL Classification: G32

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1. Introduction

Barberis and Huang (2008) theoretically analyze the asset pricing implications of transformed probability weightings for security price tail events using an equilibrium model. Investors in the model exhibit a preference for positive skewness or a tendency to overpay for securities with right-skewed payoffs, a common psychological trait highlighted in both the prospect theories of Kahnman and Tversky (1979) and Tversky and Kahnman (1992).[1] The Barberis and Huang model generates a new prediction that a positively skewed security will be overpriced relative to the valuation it would command in an economy with standard expected utility investors and will earn a negative average return.

Over the past few years, several studies provide empirical evidence consistent with this prediction, including Kumar (2009), Boyer, Mitton and Vorkink (2010), Bali, Cakini and Whitelaw (2011), Conrad, Dittmar and Ghysels (2013), Conrad Kapadia and Xing (2014), Eraker and Ready (2015), and Barberis Mukherjee and Wang (2016). However, there is relatively few evidence in support of Barberis and Huang (2008) in the IPO context. Green and Hwang (2012) document supportive evidence that first-day returns are positively related to expected skewness for 7,975 US IPO stocks over the 1975-2008 period, but they only offer limited support for the prediction that IPO stocks with greater expected skewness tend to have lower long-run abnormal returns.

Why does Barberis and Huang (2008) receive so few empirical success in the IPO context? One potential reason for the gap between the theoretical analysis and its empirical support is the institutional arrangements associated with the US book-building practice. It is well documented that the book-building practice in the US and other developed markets allows their underwriters to extract private information from institutional investors to price IPO stocks. To the extent that private information gathered from those asymmetrically informed investors in the book building can be incorporated into the offer price, the optimal choice for underwriters, as shown in Benveniste and Spindt (1989), is to underprice new issues using part of private information. To the extent that public information can be incorporated into the offer price, the

[1] The cumulative prospect theory in the latter generalizes the prospect theory (PT) concept of the earlier book. Researchers in finance now employ PT to encompass both.

best choice for a wealth-maximizing underwriter who considers the trade-off between the potential increase in underwriting revenues and the expected cost of price support in the aftermarket as demonstrated in Derrien (2005), is also to underprice new issues using part of public information. Using part of information to price an IPO stock can create problems for empirical tests of behavioral explanations for IPO anomalies, including skewness preferences. Specifically, given that both the offer price and the first-day closing price are affected by the presence of sentiment investors due to their preference for the future skewness of an IPO stock's return, the same information content contained in the numerator and the denominator of the first-day return will cancel out each other by and large thus it is less likely to observe a positive relationship between expected skewness and first-day returns. For this particular reason, the empirical relationship between expected skewness and first-day returns will be underestimated in the US context.

In this article, we attempt to address the empirical problem common to IPOs in the US context and elsewhere using a sample of Chinese book-built IPOs. The Chinese context can be the most suitable test setting to examine the empirical predictions of Barberis and Huang (2008) because its institutional arrangements ensure that no information regarding the presence of investor sentiment will enter into the offer price. Pricing IPOs in China has started to follow a new double-tranche book-building approach since the year of 2005. Similar to the US practice, this new book-building approach allows the lead underwriter to solicit the buying interest of institutional investors through the first offline tranche. The offer price of a new issue decided by the first tranche will be the fixed price at which retail investors subscribe for new shares through the second online tranche. However, in sharp contrast to the US practice that share allocation is usually done at the discretion of the underwriter, it has to be done pro rata in China. In other words, underwriters have no discretion over share allocation and all subscription orders submitted from institutional investors will receive the same rate of allocation in proportion to their subscription size. The implication of this incentive-incompatible arrangement is that the efficient price discovery mechanism associated with the traditional book-building process, an important feature recognized by Benveniste and Spindt (1989), Sherman and Titman (2002), Ljungqvist and Wilhelm (2002) to shed lights on the underpricing of new issues, no longer works in China – few private information can be effectively collected in this setting, including information on the presence of investor sentiment.

We hypothesize that skewness preference can explain post-IPO prices through the presence of investor sentiment. Previous studies such as Derrien (2005), and Ljungqvist, Nanda and Singh (2006) show that the presence of investor sentiment can be important for pricing IPOs. They both demonstrate that investor sentiment is positively related to IPO first-day returns while negatively related to post-IPO stock performance in the long run. Different from these two studies which assume the presence of retail investors is random or unpredictable, we argue that their presence can be predicted using information on the skewness of an IPO stock's return. Barberis and Huang (2008) show that a positively skewed stock can be overpriced relative to the price that it would command in an economy with expected utility investors, due to the presence of PT investors. Holding constant the number of new shares issued for an IPO stock, the first-day closing price is largely decided by the demand created by PT investors. The higher the expected skewness, the greater the retail demand, and the greater the first-day return. Therefore, there should be a positive relationship between the expected skewness of an IPO stock and its first-day return. To the extent that PT investors realize their valuation mistakes over longer horizons, there should be a negative relationship between expected skewness and the long-run performance of an IPO stock.

To examine this skewness preference hypothesis, we use the approach proposed by Zhang (2006b) and also employed by Green and Hwang (2012) more recently to measure how lottery-like an IPO stock's return distribution is. Specifically, we use all stocks that belong to the same industry defined by 2-digit SIC codes and their monthly returns over the three-month period before the offering date to generate the return distribution for a certain industry. We estimate the expected skewness of an IPO stock's return using the tail of this probability distribution. A positive value, known as right skewness, indicates that the right tail of industry returns is further away from the median than its left tail.

We find evidence consistent with Barberis and Huang (2008) for a sample of 748 China's book-built IPOs issued over the 2005-2012 period. First, we find that there is a positive relationship between first-day returns and expected skewness, even after controlling for other known firm and deal characteristics. A one-standard-deviation increase in the expected skewness leads to an increase of 6.67 percentage points in the first-day return, which is not only significant in statistical terms but also economically meaningful relative to the average first-day return of 66.79%. Our finding is also in line with Green and Hwang (2012), since they document that a one-standard-deviation increase in the expected skewness can lead to an increase of 0.86 - 4.45 percentage points in the first-day return for 7,975 US IPOs over the 1975-2008 period. Second, we find robust evidence that there is indeed a negative relationship between post-IPO abnormal returns and expected skewness as predicted by Barberis and Huang (2008). This negative relationship is statistically significant both when we use Jensen's alpha estimated from the Fama-French three-factor calendar-time regressions over the 36 post-IPO months as our measure for long-run abnormal returns, and when we use the buy-and-hold returns over the 36 post-IPO event months adjusted by the returns over the same period for size- and B/M-matched non-IPO comparables. A one-standard-deviation increase in the expected skewness can predict a decrease of up to 12.23 percentage points in post-IPO abnormal returns.

To complement our argument that skewness preference drives retail demands leading to high initial overvaluation on the first-trading day and low long-run abnormal returns, we examine whether expected skewness can predict retail demands. Without any detailed information on the identity of investors, previous studies usually measure retail demands 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. Since grey market investors include not only retail investors but also smaller institutions[2], there clearly is a gap between grey market investors and retail investors in the pre-IPO market. Green and Hwang (2012) use retail trading to proxy for small investors' trading, assuming that retail investors tend to trade in smaller dollar amounts. This assumption can be difficult to maintain since not all wealthy individuals in China and elsewhere trade in small amounts. Thus using a threshold adopted by previous studies such as "below USD10,000" (Lee, 1992; Bessenbinder and Kaufman, 1997) or an algorithm-generated threshold such as the Lee and Radhakrishna (2000) algorithm cannot classify retail trades accurately.

In this article, we take advantage of the institutional arrangement in China to overcome

[2] See Footnote 4 in Cornelli et al. (2006) for more information.

this measurement problem since information on retail demands for shares of IPO stocks should be released to the general public. This unique arrangement allows us to measure retail demands directly and thus facilitates a sharper and more powerful identification strategy on the relationship between the presence of retail investors and expected skewness. Specifically, we use the number of valid subscription orders received from retail accounts to measure the number of retail investors in the IPO market, given that only one subscription order is allowed for each retail account. We also use the aggregate RMB amount of subscription funds transferred from retail investors to the lead underwriter to measure the monetary size of the retail demand for an IPO stock. Our third measure is the allocation rate among retail investors for oversubscribed IPOs, defined as the number of shares offered divided by the number of shares subscribed. Using these three direct measures, we find consistent evidence that there is a positive relationship between expected skewness and retail demands, even after controlling for a battery of control variables. A one-standard-deviation increase in expected skewness can lead to an increase in the number of retail investors by 38,403, an increase in the size of subscription funds by RMB 18,266.27 million, and a decrease in the probability of obtaining an allocation by 0.28%.

Our study contributes to the literature in two important ways. First, it has been empirically difficult to investigate whether investor sentiment affects first-day returns, mainly because the impact of investor sentiment on the first-day closing price and the offer price will be cancelled out each other at the first-day return. Using a sample of IPOs where their offer prices are all determined by a given formula thus have nothing to do with investor sentiment, Shen, Coakley and Instefjord (2013) address this empirical problem in the Chinese context. Our study differs from Shen et al. (2013) not only because we use a more contemporary setting and a much larger sample but also because we further attribute the presence of investor sentiment to skewness preference, a potential force that drives retail investors to overpay new issues in the short run.

Second, there has been a surge of interest in the impact of investor sentiment on post-IPO prices. Motivated by Miller (1977), Derrien (2005) and Ljungqvist et al. (2006) among others theoretically analyze the implications for pricing IPOs in the presence of sentiment investors. Their seminal works have received a great deal of empirical support in the IPO context, including Derrien (2005), Cornelli et al. (2006), Jiang and Li (2013), Shen, Coakley and Instefjord (2013), and Clarke, Khurshed, Pande and Singh (2016). Different from previous studies which use pre-IPO trading in European grey markets (Derrien, 2005; Cornelli et al., 2006), in Hong Kong (Jiang and Li, 2013), and in Indian (Clarke et al. 2016) to measure retail demands indirectly, we use a set of direct measure for retail demand to show that retail demands tend to increase with expected skewness, leading to high first-day returns and low post-IPO abnormal returns in the long run.

The rest of this article is organized as follows. Section 2 provides a brief description of institutional background and hypothesis development. Section 3 explains data, sample and variables of interest used in this study before Section 4 presents results for our main analysis and some additional tests. Section 5 provides a concluding remark.

2. Institutional background and hypothesis development

Prior to 2005, *The Securities Law of the People's Republic of China* stipulates 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 stock market regulator that is similar in nature to the SEC in the USA. The CSRC introduced a book-building approach in 2005 to bring the IPO pricing mechanism more in line with international practice. What follows is a brief description of two salient features of the institutional arrangements for Chinese IPOs. One relates to how the IPO offer price is determined in the book-building process involving institutional investors only and the other is how oversubscribed shares are allocated among retail investors.

Under the new book-building approach, two separate tranches determine the pricing of an IPO and the allocation of shares, respectively. In the first tranche, participation in book building is limited to institutional investors and the IPO offer price is assessed on the basis of those bids obtained for a fixed quantity of the IPO stock offered for sale. This process is very similar to the one in the USA: i) institutional investors can bid for new issues at various prices; ii) the underwriter collects these bids and builds up the order book which records the demand for an

IPO stock; iii) the final offer price is not determined until the end of the process.

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 first tranche. In the USA, the issuer and the underwriter determine the allocation of shares between bidders at their discretion. The latter can ensure that aggressive bidders will be rewarded with large share allocations for revealing value-relevant information truthfully. However, there is no discretion in the Chinese context – share allocation must be implemented pro rata between institutional investors. Every participating institutional investor ends up with the same allocation rate. Thus institutional investors are not encourages to reveal their private information and so value-relevant information collected through the Chinese book building process is insufficient to ensure effective price discovery.

In the second tranche, retail investors submit their orders for the shares of an IPO stock at the fixed price determined in the first tranche. In cases of oversubscription – and the vast majority of Chinese IPOs are oversubscribed – share allocation between retail investors must be 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 shares subscribed will be assigned one lottery ticket which carries a unique lottery number. This lottery mechanism for share allocation[3] is one of two key aspects of the lottery-like nature of Chinese IPOs during the course of our sample period. It seems likely to induce retail investors to regard making an IPO subscription order as akin to buying a lottery ticket. The potential reward for those lucky investors receiving an allocation is the possibility of a stake in China's next Alibaba.

2.2 Related literature and the skewness hypothesis

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. The most notable example is that people usually prefer a gain of \$5,000 with a small chance of 0.1% to a certain gain of \$5, while they also demonstrate a strong preference for a certain loss of \$5 over a loss of \$5,000 with a small probability of

[3] See Appendix for a more detailed description on how lucky numbers are selected for share allocation among retail investors.

0.1%. Under the Tversky and Kahneman (1992) cumulative prospect theory framework, the preferences revealed in the example implies:

$$v(5)\cdot\pi(1) < v(5000)\cdot\pi(0.001) \quad (1)$$

$$v(-5)\cdot\pi(1) > v(-5000)\cdot\pi(0.001) \quad (2)$$

where, $v(\cdot)$ is the value function and $\pi(\cdot)$ is the weighting function. Given that the value function is concave in gains and $\pi(1)=1$, substituting $v(5000) < 1000\cdot v(5)$ into Eq. (1) gives $\pi(0.001) > 0.001$. Note also that the value function is convex in losses and $v(-5) < 0$, substituting $v(-5000) > 1000\cdot v(-5)$ into Eq. (2) yields the same result.

Building upon this psychological evidence, Barberis and Huang (2008) theoretically analyze the impact of investor preference over the lottery-like features of asset prices. They show that, in an economy where investors evaluate risk according to cumulative prospect theory, securities with high skewness value can become overpriced and exhibit negative returns in the future. Several studies provide empirical evidence consistent with this novel prediction, including Kumar (2009), Boyer et al. (2010), Bali et al. (2011), Conrad et al. (2013), Conrad et al. (2014), Eraker and Ready (2015), and Barberis et al. (2016).

What is the evidence on the relationship between expected skewness and first-day returns? Previous studies report evidence that retail demand drives post-IPO prices, including Cornelli et al. (2006) and Dorn (2009). In the presence of investor sentiment around the IPO event, both Derrien (2005) and Ljungqvist et al. (2006) have shown that underwriters can take advantage of overvaluation due to optimistic retail investors by setting an offer price above a firm's intrinsic value. Thus there should be a positive relationship between retail demand and first-day returns. Building upon previous theoretical analysis and empirical findings, we posit that retail demand for an IPO stock is driven by the skewness of its return distribution. Barberis and Huang (2008) show that securities can be overpriced due to the fact that some investors exhibit a preference those with high skewness. If investors demonstrate a skewness preference for IPOs and overpay for high skewness IPO shares on the first day of trading, this implies a positive relationship between first-day returns and expected skewness.

Hypothesis 1: First-day returns are positively related to expected skewness.

The logical next question is whether the initial overvaluation due to skewness preference tends to reverse in the long run. At the heart of Barberis and Huang (2008) view is the novel prediction that securities with high skewness will generate low average returns in the future. In the IPO context, if initial overvaluation is really driven by skewness preference, then expected skewness can predict long-run reversal in IPO stock prices. Note that this return reversal has nothing to do with fundamentals or other behavioral explanations.

Hypothesis 2: Long-run abnormal returns are negatively related to expected skewness.

Finally, can skewness preference impact on the presence of investor sentiment? The skewness preference hypothesis rests on an implicit assumption that retail investors' buying decision is closely related to the skewness of an IPO stock's return. Assuming that the population of retail investors is fixed and their skewness preference is constant over time, the number of retail investors attracted to the IPO market will depend on how lottery-like an IPO stock is. The higher the expected skewness, the greater the retail demand is likely to be for an IPO stock. This forms the basis of our third hypothesis:

Hypothesis 3: Retail demand is positively related to expected skewness.

3. Data, sample and variables

3.1 Data and sample

Our sample includes 748 Chinese A-share book-built IPOs over the period January 2005 to December 2012. It starts from 2005 because Chinese issuers started using the book-building IPOs approach in that year. Our sample ends in December 2012 because a three-year post-IPO period is required to estimate the long-run abnormal return and several new regulations were introduced by the CSRC in 2013. For example, both the Shanghai and Shenzhen Stock Exchanges issued a notice in 2013 that a number of new monitoring measures over trading in the initial post-IPO period would be introduced.[4] One stipulates that the first-day IPO closing price would not be permitted to exceed its offer price by more than 144%. Given this, the first-day closing price might not fully reflect the impact of retail demand after 2013. The CSRC also

[4] 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".

made another reform announcement in 2013.[5] Under this proposal, underwriters would be given full discretion on share allocation among institutional investors. This reform would provide an incentive for institutional investors to reveal private information in the book-building process, leading to offer prices potentially containing private information on the presence of investor sentiment due to skewness preference. Excluding IPOs issued after 2013 preserve the unique feature of our sample of Chinese IPOs that include virtually no price relevant private information from the book-building process.

Following the literature, IPOs for financial firms or utilities firms are excluded. We retrieve a wide range of offer and firm characteristics for these sample IPOs from CSMAR, WIND and CVSource. Daily price data are downloaded from the CSMAR and WIND to estimate first-day returns and long-term performance for these sample IPOs

3.2 Main variables

3.2.1 Expected skewness

All stocks belonging to the same industry defined by 2-digit SIC codes are used to measure how lottery-like an IPO's stock return distribution is. This is because all stocks in an industry are subject to similar regulatory, technological and industry shocks. Specifically, all monthly returns of the same-industry stocks are pooled over the three-month period before the offer date to generate the return distribution. Following Zhang (2006b) and Green and Hwang (2012), we define the expected skewness of an IPO stock as follows:

$$Skewness_j = \frac{\left(Percentile_{99} - Percentile_{50}\right) - \left(Percentile_{50} - Percentile_1\right)}{\left(Percentile_{99} - Percentile_1\right)} \qquad (1)$$

where $Percentile_k$ is the k^{th} percentile of the log monthly return distribution across all stocks that fall within the same 2-digit SIC industry as an IPO stock j. The numerator measures the distance of each tail from the median and is positive for right-skewed distributions. The denominator gives the dispersion of the distribution. The expected skewness measure is based on the tails of the return distribution and so departs from the traditional third central moment

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

measure of skewness.

3.2.2 First-day return

We follow the literature and define the first-day return as the percentage difference between the offer price and the first-day closing price:

$$IR_j = \left[\frac{P_{j,1} - P_{j,0}}{P_{j,0}}\right] \times 100\% \tag{2}$$

where $P_{j,1}$ is the first-day closing price and $P_{j,0}$ is the offer price.

3.2.3 Long-term performance

Following Lyon, Barber and Tsai (1999), we consider 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. First, we estimate the event-time BHAR 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:

$$BHAR_j = \prod_{t=1}^{36}\left(1 + r_{j,t}^{IPO}\right) - \prod_{t=1}^{36}\left(1 + r_{j,t}^{non-IPO}\right) \tag{3}$$

where $r_{j,t}^{IPO}$ and $r_{j,t}^{non-IPO}$ are the returns for IPO firm j and for its matching non-IPO firm over the event month t, respectively. Following Chan, Wang and Wei (2004) and Shen et al. (2013), we select non-IPO matching firms based on size and B/M characteristics. We use tradable shares to calculate both market capitalization and B/M ratio.[6] These matching non-IPO firms are required to have a trading record of at least 3 years in the stock market.

Second, we use Jensen's alpha estimated from the Fama-French three-factor model over the 36 post-IPO calendar months as an alternative measure of long-run stock performance. Specifically, we regress the monthly returns in excess of the risk-free rate for IPO firms on three monthly risk factors. We define the post-IPO abnormal monthly return as the intercept estimated from time-series regressions after adjusting for risk compensation:

$$r_{j,\tau} - r_{f,\tau} = \alpha + b \cdot \left(r_{m,\tau} - r_{f,\tau}\right) + s \cdot SMB_\tau + h \cdot HML_\tau + \varepsilon \tag{4}$$

where $r_{j,\tau}$, $r_{m,\tau}$ and $r_{f,\tau}$ are the returns to the IPO firm j, to the market portfolio m, and to

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

the risk-free assets f, respectively, over the calendar month τ ; $\left(r_{m,\tau} - r_{f,\tau}\right)$, *SMB* and *HML* are the monthly excess return on the market, the average return on three small portfolios minus the average return on three big portfolios, and the average return on two value portfolios minus the average return on two growth portfolios, respectively, with six size-value portfolios constructed in a manner similar to Fama and French (1993).

3.3 Control variables

Previous studies document that a number of variables can be relevant for first-day returns or long-term performance. To examine the relationship between expected skewness and post-IPO prices, we have to include control variables. 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 VC reputation (Nahata, 2008; Krishnan, Masulis, Ivanov and Singh, 2010). 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). Previous studies, including Chan, Wang and Wei (2004), Fan, Wong and Zhang (2007), Kao, Wu and Yang (2009), Gao (2010), Tian (2011), Shen et al. (2013), Chen, Wei, Li, Sun and Tong (2015), also document evidence that profitability, the leverage ratio, the fraction of state ownership, the proportion of tradable shares, the number of days elapsed between offering and listing, and the deliberate extent of IPO underpricing are important determinants of post-IPO prices in the Chinese context. Finally, we include the number of IPOs in the same calendar month (*MktSent1*), and the market return in the same calendar month (*MktSent3*) to control for market-level sentiment. We include year dummies in all regression specifications to control for year fixed effects.

4. Main Results

4.1 Descriptive statistics

Table 1 provides descriptive statistics for the main variables in our sample IPO firms and several interesting observations emerge. First, while the mean (median) expected skewness is as small as -0.0213 (0.0146), its standard deviation 0.2689 is relatively large, indicating that expected skewness varies a lot across IPO firms. Second, the first-day closing price is higher than the offer price on average. This yields a mean first-day return of 0.6679, consistent with previous studies. Third, these sample IPOs tend to underperform relative to their non-IPO comparables, since the BHAR in the three-year post-IPO period for a median IPO is -0.2709 while the monthly abnormal return for the median IPO over the period of three years is -0.2681. These findings are also consistent with prior research. Fourth, the sample IPO firms usually go public in their 7th year. Fifth, they are generally profitable as the median *ROA* is 0.1187, and their offer prices are set well below their industry peers because the median *Profitability* is -0.1133. Finally, the mean number of retail investors participating in the IPO market is 449, 287. These investors create a sizeable demand of RMB185 billion, leading to a very low mean allocation rate among retail investors.

[Table 1 around here]

4.2 *Expected skewness and first-day returns*

We estimate the following regression to examine whether there is a positive relationship between expected skewness and first-day returns:

$$IR_j = \alpha_1 + \alpha_2 * Skewness_j + \sum_{i=3}^{n}\left(\alpha_i * X_j\right) + \varepsilon \tag{5}$$

where *IR* is the first-day return of an IPO stock; *Skewness* is the expected skewness; *X* is a vector of control variables.

Table 2 summarizes the regression results.

[Insert Table 2 around here]

Column (1) give the results for a regression that includes all variables (including three proxies for investor sentiment) except *Skewness* as independent variables to explain first-day returns. It reveals that first-day returns are significantly positively related to leverage (*Leverage*), the fraction of state ownership (*State*), and the divergence of analyst forecasts (*Analysts_std*) and significantly negatively related to issue size (*IssueSize*) and firm age (*Age*). When *Skewness* is included in the regression, the results in Column (2) indicates that a significantly positive relationship between expected skewness and first-day returns after controlling for other firm characteristics. Given the coefficient estimate of *Skewness* is 0.248, significant at the 5% level, and the standard deviation of *Skewness* is 0.2689 as reported in Table 1, a one-standard deviation increase in expected skewness would lead to an increase of some 6.67 percentage points (=0.248*0.2689) in first-day returns on average.

This finding is consistent 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 right skewness is a significant 0.153 but that on expected skewness falls to 0.063.

The key to the above finding is whether the explanatory power of skewness preference might be subsumed by proxies for other behavioral explanations since skewness preference may not be the only reason for the impact of investor sentiment. To shed lights on this issue, we control for the potential impacts of other behavioral explanations by including measures of investor sentiment in the regressions specified in Columns (3) - (6). Three different measures included in our analysis are: 1) *Orders*, defined as the number of valid subscription orders received for the second offline tranche, 2) *RMB*, the value of demand defined as the number of new shares subscribed multiplied by the offer price, and 3) *Allocation*, defined as the allocation rate among retail investors using the lottery approach. A larger value of *Orders* and *RMB* indicate a stronger retail demand while a larger value of *Allocation* suggests that retail demand is not excessive. For the regression in Column (3) which includes *Orders* as well as *Skewness*, the coefficient on *Skewness* is 0.225 (*t*-statistics = 2.48). For the regression in Column (4), which includes both *Skewness* and *RBM*, the coefficient on *Skewness* is 0.227 (*t*-statistics = 2.52). In Column (5) where we include *Skewness* as well as *Allocation*, the coefficient on *Skewness* is 0.233 (*t*-statistics = 2.59). In the results in Column (6) which include *Skewness* and three measures for investor sentiment, the coefficient on *Skewness* is 0.209 (t-statistics = 2.30). These findings suggest that the positive relationship between expected skewness and first-day returns is robust not only to a set of control variables but also to alternative behavioral explanations.

4.3 Expected skewness and long-term performance

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

$$BHAR_j = \alpha_1 + \alpha_2 * Skewness_j + \sum_{i=3}^{n}\left(\alpha_i * X_j\right) + \varepsilon \tag{6}$$

$$Jensen's\_Alpha_j = \alpha_1 + \alpha_2 * Skewness_j + \sum_{i=3}^{n}\left(\alpha_i * X_j\right) + \varepsilon \tag{7}$$

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 expected skewness of an IPO stock; *X* is a vector of control variables.

The regression results are presented in Table 3.

[Table 3 around here]

The table reveals robust evidence of a negative relationship between long-term performance and expected skewness as predicted by Barberis and Huang (2008). Panel A gives the results when the dependent variable is the long-term stock performance measured as *BHAR*, while Panel B provides them for *Jensen's_Alpha* as the dependent variable. Regression results in both panels suggest that the coefficient on *Skewness* is negative and statistically significant after controlling for other known firm characteristics. Given that the coefficient on *Skewness* is – 0.455 (t-statistics = 1.89) in Column (2) of Panel A and its standard deviation is 0.2689 from Table 1, a one-standard-deviation increase in expected skewness could lead to a decrease in *BHAR* of approximately 12.23 percentage points (= – 0.455*0.2689) on average. Similarly, a one-standard-deviation increase in expected skewness could imply a fall in *Jensen's_Alpha* of approximately 0.30 percentage points (= – 0.011* 0.2689) on average. Note that a monthly decrease in *Jensen's_Alpha* of 0.30 percentage points is equivalent to a decrease in 10.80 percentage points (= – 0.30*36) over a 36-calendar-month period. Even after controlling for retail demand in the pre-IPO period, measured as *Orders*, *RMB* and *Allocation*, results reported in Columns (2) – (6) of both Panels A and B reveal that the coefficient on *Skewness* remains significantly negative, indicating the explanatory power of *Skewness* is unlikely to be subsumed by other behavioral factors.

Our findings are consistent with Barberis and Huang (2008) who predict low long-run abnormal returns when positively skewed securities are overvalued by PT investors. Green and Hwang (2012) also find some evidence in support of the central prediction of Barberis and Huang (2008) using an event-time matching firm approach over a five-year horizon. Their results indicate that there is a significant difference in Cumulative Abnormal Returns (*CAR*) over three and five years following the issuance between the top and bottom third skewness portfolios. However, while they find that high-skewness IPO firms significantly underperform their matching firms at the three- and five-year horizons, 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.

Our approach differs from that in Green and Hwang (2012) at least in three different respects. First, we use the BHAR in the event-time approach and the Jensen's alpha in the calendar-time approach to measuring long-term performance, both of which are reported more reliable as documented in Lyon et al. (1999). Second, the finding of a negative relationship between expected skewness and long-term performance is robust to alternative measures of long-term abnormal returns. Finally, our finding is consistent with previous studies which document a negative relationship between first-day returns and long-run stock performance, including Ritter (1991) and Shen et al. (2013).

4.4 Expected skewness and retail demand

Our analysis has produced a positive relationship between expected skewness and first-day returns and a negative relationship between expected skewness and long-term stock performance. We have shown that the positive relationship between expected skewness and first-day return is robust to controlling for retail demand and that the negative relationship between expected skewness and long-run abnormal returns is also robust to controlling for retail demand, However, it is possible that these results may be driven by retail demand. To strengthen the belief that retail demand affects first-day returns through the skewness channel, we thus investigate the relationship between retail demand and expected skewness by estimating the following three regressions.

$$Orders_j = \alpha_1 + \alpha_2 * Skewness_j + \sum_{i=3}^{n}\left(\alpha_i * X_j\right) + \varepsilon \tag{8}$$

$$RMB_j = \beta_1 + \beta_2 * Skewness_j + \sum_{i=3}^{n}\left(\beta_i * X_j\right) + u \tag{9}$$

$$Allocation_j = \gamma_1 + \gamma_2 * Skewness_j + \sum_{i=3}^{n}\left(\gamma_i * X_j\right) + \upsilon \tag{10}$$

where *Orders* is the number of retail investors defined as the number of valid subscription orders received from retail investors in the second tranche; *RMB* is a measure of retail demand defined as the number of new shares subscribed multiplied by the offer price; *Allocation* is the rate of allocation between retail investors using the lottery approach; *Skewness* is the expected skewness of an IPO stock; *X* is a vector of control variables.

Table 4 presents the regression results.

[Table 4 around here]

Using three different measures for retail demand, we find robust evidence of a positive relationship between expected skewness and retail demand. In Panel A where the dependent variable is *Orders*, the coefficient on *Skewness* is a significant 142,341.1 (*t*-statistics = 2.81). High *Skewness* IPO stocks are associated with a greater number of retail orders placed by PT investors. The results in Panel B (where the dependent variable is *RMB*) and in Panel C (where the dependent variable is *Allocation*) are weaker and significant only at the 10% significance level. These findings suggests that the skewness of an IPO stock can predict the presence of retail investors in the IPO market, thus consistent with our argument that skewness preference affects post-IPO prices through retail demand in the pre-IPO period.

5. Conclusions

This paper takes advantage of two unique institutional arrangements in the Chinese IPO market to examine whether skewness preference can influence post-IPO prices through the presence of investor sentiment. First, share allocation among institutional investors participating in the book-building process is not at the discretion of IPO underwriters in China and this is likely to hamper effective price discovery. The implication is that the IPO offer price contains much less private information elicited from institutional investors than it does in advanced markets like that in the USA. The concern that the empirical relationship between first-day returns and expected skewness will be underestimated can be alleviated using Chinese book-built IPOs. Second, retail demand for IPO stocks should be released to the general public so we can use its direct measure to complement the literature which relies largely on indirect measures.

Consistent with our hypothesis, our regression analysis reveals a significantly positive relationship between expected skewness and first-day returns for a sample of 784 Chinese book-built IPOs over the 2005-2012 period. A one-standard-deviation increase in expected skewness of an IPO stock leads to a 6.67 percentage point increase in the first-day return. The results also indicate a significantly negative relationship between expected skewness and long-term performance in both event and calendar time. A one-standard-deviation increase in expected skewness can predict a decrease of 10.80-12.23 percentage points in the post-IPO abnormal return. Taken together, these findings suggest that the presence of investor sentiment due to skewness preference around the IPO event can account for both high first-day returns and low long run post-IPO abnormal returns. Our findings suggest that prospect theory can shed light on IPO anomalies and, through the key role of expected skewness, on the Alibaba effect in China.

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Table 1: Descriptive statistics

This table provides descriptive statistics for variables used in this study. *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; *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 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 incomes over total assets in the pre-IPO year; *Leverage* is the leverage ratio, estimated as total liabilities over total assets prior to listing; *Profitability* is the percentage difference between the offering P/E and the industry P/E; *IssueSize* is 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 two times over the past three years, and 0 otherwise; *Big4* 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 proportional of state holdings in the firm; *Tradable* is the proportion of tradable shares; *Age* is the firm age since establishment; *TimeLag* is the number of days elapsed between offering and listing; *Analysts_std* is the standard deviation of one-year forward looking EPS by analysts; *Analysts_bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *MktSent1* is the number of IPOs in the same calendar month; *MktSent3* is the market return in the same calendar month; *Orders* is the number of valid subscription orders received using the online fixed-price approach; *RMB* is the number of new shares offered multiplied by the offer price; *Allocation* is the rate of allocation between retail investors using the lottery approach.

Variables	Min	Max	Mean	Median	Standard Deviation
Skewness	-0.06167	0.7114	-0.0213	0.0146	0.2689
IR	-0.2316	5.3812	0.6679	0.3899	0.8443
BHAR	-24.1089	4.8533	-0.8160	-0.2709	1.7511
Jensen's Alpha	-0.3709	-0.0171	-0.2649	-0.2681	0.0356
ROA	0.0063	0.5877	0.1320	0.1187	0.0769
Leverage	0.0512	0.9784	0.4874	0.4871	0.1666
Profitability	-8.8048	60.4259	0.7565	-0.1133	3.6557
IssueSize	9.3181	15.7114	11.1298	11.0394	0.8499
Underwriter	0.0000	1.0000	0.3837	0.0000	0.4866
Big4	0.0000	1.0000	0.0388	0.0000	0.1932
VC-backed	0.0000	1.0000	0.4572	0.0000	0.4985
State	0.0000	1.0000	0.1036	0.0000	0.2529
Trablable	0.4000	1.0000	0.7971	0.8000	0.0335
Age	0.0000	26.0000	7.5414	7.0000	4.6025
Timelag	6.0000	217.0000	12.7166	12.0000	8.5735
Analysts_std	0.0351	2.9414	0.4252	0.3667	0.2675
Analysts_bias	-1.4400	1.9300	0.0502	0.0594	0.2453
MktSent1	1. 0000	37.0000	24.0869	26.0000	8.6460
MktSent3	-0.2284	0.2983	0.0042	0.0032	0.0924
Orders	8,482	4,077,219	449,287	330,886	446,926
RMB (*100m)	35.09	27,384.05	1,852.15	971.11	2,894.21
Allocation (%)	0.0129	65.5208	1.1114	0.6005	3.0110

Table 2: Expected Skewness and First-day Returns

This table reports regression results for the relationship between expected skewness and first-day returns. The dependent variable is *IR*, the first-day return of an IPO stock defined as the percentage difference between its first-day closing price and its offer price. We use three measures to control for the presence of investor sentiment: *Orders* 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, and *Allocation* defined as the rate of allocation between retail investors using the lottery approach. *Skewness* is the expected skewness of an IPO stock's return defined as the tail of the probability distribution generated by monthly returns of all stocks in the same industry over the three-month period before the offer date; *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; *Profitability* is the percentage difference between the offering P/E and the industry P/E; *IssueSize* is 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 two times over the past three years, and 0 otherwise; *Big4* 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 proportional of state holdings in the firm; *Tradable* is the proportion of tradable shares; *Age* is the firm age since establishment; *TimeLag* is the number of days elapsed between offering and listing; *Analysts_std* is the standard deviation of one-year forward looking EPS by analysts; *Analysts_bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *MktSent1* is the number of IPOs in the same calendar month; *MktSent3* is the market return in the same calendar month. Year dummies are included in all regressions. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
Skewness		0.248***	0.225**	0.227**	0.233***	0.209**
		(2.77)	(2.48)	(2.52)	(2.59)	(2.30)
Orders			0.000***			0.000
			(2.41)			(1.32)
RMB				0.000***		0.000*
				(2.63)		(1.77)
Allocation					-0.014***	-0.009**
					(-2.41)	(-1.99)
ROA	0.469	0.795	0.786	0.685	0.746	0.681
	(1.03)	(1.64)	(1.63)	(1.41)	(1.54)	(1.41)
Leverage	0.451**	0.518**	0.497**	0.428*	0.519**	0.443*
	(1.98)	(2.24)	(2.16)	(1.82)	(2.23)	(1.88)
Profitability	-0.004	-0.007	-0.007	-0.006	-0.007	-0.007
	(-0.89)	(-1.40)	(-1.51)	(-1.34)	(-1.47)	(-1.48)
Log (*IssueSize*)	-0.452***	-0.458***	-0.463***	-0.456***	-0.454***	-0.457***
	(-9.15)	(-9.26)	(-9.25)	(-9.06)	(-9.16)	(-9.01)
Underwriter	0.015	0.010	0.020	0.003	0.015	0.005

	(0.30)	(0.20)	(0.38)	(0.05)	(0.30)	(0.10)
Big4	0.120	0.127	0.068	-0.028	0.134	-0.025
	(1.05)	(1.11)	(0.56)	(-0.21)	(1.15)	(-0.18)
VC-backed	0.020	0.033	0.036	0.031	0.037	0.036
	(0.39)	(0.65)	(0.72)	(0.62)	(0.73)	(0.73)
State	0.498***	0.480***	0.463***	0.446***	0.481***	0.445***
	(3.69)	(3.56)	(3.40)	(3.26)	(3.56)	(3.23)
Tradable	-1.366	-1.425	-1.577*	-1.451	-1.449	-1.552
	(-1.55)	(-1.63)	(-1.70)	(-1.61)	(-1.60)	(-1.63)
Log (1+*Age*)	-0.066*	-0.064*	-0.062*	-0.058	-0.061*	-0.058
	(-1.80)	(-1.73)	(-1.71)	(-1.61)	(-1.67)	(-1.60)
Timelag	0.018***	0.017***	0.017***	0.017***	0.017***	0.017***
	(7.25)	(7.36)	(7.31)	(7.59)	(7.51)	(7.65)
Analysts_std	0.052	0.047	0.047	0.045	0.045	0.044
	(0.566)	(0.50)	(0.50)	(0.49)	(0.48)	(0.47)
Analysts_bias	0.293***	0.245**	0.208*	0.228**	0.236**	0.206*
	(2.78)	(2.33)	(1.94)	(2.15)	(2.25)	(1.92)
MktSent1	-0.019***	-0.020***	-0.018***	-0.017***	-0.020***	-0.016***
	(-5.54)	(-5.67)	(-4.74)	(-4.59)	(-5.52)	(-4.22)
MktSent3	1.572***	1.517***	1.555***	1.605***	1.523***	1.606***
	(4.54)	(4.35)	(4.41)	(4.58)	(4.35)	(4.55)
Number of Obs.	748	748	748	748	748	748
Adjusted R^2	0.393	0.397	0.402	0.404	0.399	0.405

Table 3: Expected Skewness and Long-term Stock Performance

This table reports regression results for the relationship between expected skewness and long-term stock performance. The dependent variable in Panel A is *BHAR*, 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. The dependent variable in Panel B is *Jensen's Alpha*, defined as the abnormal monthly return estimated from the Fama-French three-factor model over the 36 post-IPO calendar months. *Orders* is the number of valid subscription orders received from the second offline tranche; *RMB* is defined as the number of new shares subscribed multiplied by the offer price; *Allocation* is the rate of allocation between retail investors using the lottery approach; *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; *Skewness* is the expected skewness of an IPO stock's return defined as the tail of the probability distribution generated by monthly returns of all stocks in the same industry over the three-month period before the offer date; *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; *Profitability* is the percentage difference between the offering P/E and the industry P/E; *IssueSize* is the logarithm of 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 two times over the past three years, and 0 otherwise; *Big4* 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 proportional of state holdings in the firm; *Tradable* is the proportion of tradable shares; *Age* is the firm age since establishment; *TimeLag* is the number of days elapsed between offering and listing; *Analysts_std* is the standard deviation of one-year forward looking EPS by analysts; *Analysts_bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *MktSent1* is the number of IPOs in the same calendar month; *MktSent3* is the market return in the same calendar month. Year dummies are included in all regressions. 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: *BHAR* as the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
Skewness		-0.455*	-0.458*	-0.457*	-0.457*	-0.454*
		(-1.89)	(-1.91)	(-1.91)	(-1.90)	(-1.88)
Orders			0.000			-0.000
			(0.17)			(-0.98)
RMB				0.000		0.000*
				(1.55)		(1.77)
Allocation					-0.004	-0.002
					(-0.17)	(-0.09)
IR	-0.401***	-0.407***	-0.408***	-0.413***	-0.409***	-0.407***
	(-3.52)	(-3.58)	(-3.56)	(-3.66)	(-3.58)	(-3.60)
ROA	-1.431	-2.099	-2.062	-2.183	-2.110	-2.240
	(-1.14)	(-1.56)	(-1.53)	(-1.61)	(-1.56)	(-1.64)
Leverage	-0.044	-0.206	-0.194	-0.299	-0.204	-0.295
	(-0.08)	(-0.37)	(-0.35)	(-0.53)	(-0.37)	(-0.52)
Profitability	0.002	0.007	0.007	0.008	0.007	0.008
	(0.19)	(0.61)	(0.62)	(0.67)	(0.61)	(0.69)
Log (*IssueSize*)	-0.821***	-0.795***	-0.797***	-0.812***	-0.794***	-0.806***
	(-3.61)	(-3.53)	(-3.51)	(-3.56)	(-3.51)	(-3.52)
Underwriter	0.010	0.019	0.019	-0.007	0.017	-0.006
	(0.07)	(0.15)	(0.15)	(-0.05)	(0.12)	(-0.05)
Big4	0.243	0.228	0.185	-0.040	0.230	-0.110
	(0.54)	(0.52)	(0.42)	(-0.09)	(0.53)	(-0.26)
VC-backed	-0.058	-0.078	-0.077	-0.084	-0.077	-0.089
	(-0.42)	(-0.56)	(-0.55)	(-0.60)	(-0.55)	(-0.63)
State	0.522	0.514	0.511	0.496	0.516	0.488
	(1.16)	(1.15)	(1.14)	(1.12)	(1.15)	(1.11)
Tradable	-0.638	-0.427	-0.523	-0.494	-0.434	-0.347

	(-0.13)	(-0.09)	(-0.11)	(-0.10)	(-0.09)	(-0.07)
Log (1+*Age*)	-0.145	-0.144	-0.147	-0.151	-0.145	-0.150
	(-1.54)	(-1.54)	(-1.55)	(-1.59)	(-1.54)	(-1.57)
Timelag	0.001	0.001	0.001	0.002	0.001	0.002
	(0.13)	(0.20)	(0.19)	(0.31)	(0.20)	(0.24)
Analysts_std	-0.007	0.005	0.003	-0.006	0.004	-0.007
	(-0.02)	(0.01)	(0.01)	(-0.02)	(0.01)	(-0.02)
Analysts_bias	0.411	0.473	0.473	0.467	0.472	0.482
	(1.43)	(1.58)	(1.58)	(1.56)	(1.57)	(1.61)
MktSent1	0.009	0.014	0.015	0.015	0.015	0.014
	(0.74)	(1.11)	(1.10)	(1.17)	(1.11)	(1.01)
MktSent3	-1.296*	-1.307*	-1.273*	-1.231*	-1.303*	-1.390*
	(-1.74)	(-1.76)	(-1.68)	(-1.67)	(-1.75)	(-1.85)
Number of Obs.	748	748	748	748	748	748
Adjusted R^2	0.158	0.161	0.160	0.165	0.160	0.164

Panel B: *Jensen's Alpha* as the Dependent Variable

	(1)	(2)	(3)	(4)	(5)	(6)
Skewness		-0.011**	-0.011**	-0.011**	-0.012***	-0.012***
		(-2.56)	(-2.54)	(-2.55)	(-2.64)	(-2.64)
Orders			-0.000			-0.000
			(-1.11)			(-1.32)
RMB				0.000		0.000
				(0.00)		(0.48)
Allocation					-0.001	-0.001**
					(-2.12)**	(-2.20)
IR	-0.004	-0.003	-0.003	-0.003	-0.003	-0.003
	(-1.26)	(-1.37)	(-1.28)	(-1.36)	(-1.36)	(-1.28)
ROA	0.066***	0.050**	0.050**	0.050**	0.048**	0.047**
	(3.16)	(2.24)	(2.23)	(2.24)	(2.18)	(2.08)
Leverage	0.018**	0.014*	0.015*	0.014*	0.015*	0.015*
	(2.11)	(1.65)	(1.76)	(1.66)	(1.68)	(1.72)
Profitability	0.000	0.000	0.000	0.000	0.000	0.000
	(0.11)	(0.49)	(0.50)	(0.49)	(0.48)	(0.51)
Log (*IssueSize*)	-0.004*	-0.003	-0.003	-0.003	-0.003	-0.003
	(-1.91)	(-1.58)	(-1.48)	(-1.57)	(-1.52)	(-1.43)
Underwriter	-0.036	-0.002	-0.003	-0.003	-0.003	-0.003
	(-0.69)	(-1.17)	(-1.19)	(-1.30)	(-1.36)	(-1.35)
Big4	-0.003	0.000	0.000	0.000	0.001	-0.001
	(-1.27)	(0.07)	(0.03)	(0.06)	(0.09)	(-0.16)
VC-backed	0.000	-0.000	-0.001	-0.000	-0.000	-0.000
	(0.03)	(-0.21)	(-0.24)	(-0.21)	(-0.14)	(-0.20)
State	-0.010*	-0.011*	-0.011*	-0.011*	-0.010*	-0.010*
	(-1.70)	(-1.75)	(-1.77)	(-1.75)	(-1.71)	(-1.74)
Tradable	-0.067*	-0.062*	-0.059	-0.062*	-0.063*	-0.059*
	(-1.78)	(-1.66)	(-1.63)	(-1.65)	(-1.74)	(-1.76)
Log (1+*Age*)	0.003	0.003	0.003	0.003	0.003	0.003
	(1.54)	(1.56)	(1.55)	(1.54)	(1.50)	(1.51)
Timelag	0.000	0.000	0.000	0.000	0.000	0.000
	(1.14)	(1.30)	(1.05)	(1.30)	(1.40)	(1.13)
Analysts_std	-0.007*	-0.007	-0.007	-0.007	-0.007	-0.007
	(-1.66)	(-1.59)	(-1.57)	(-1.60)	(-1.63)	(-1.61)
Analysts_bias	-0.005	-0.004	-0.004	-0.004	-0.004	-0.004
	(-1.24)	(-0.89)	(-0.81)	(-0.89)	(-0.91)	(-0.80)

MktSent1	0.000	0.000	0.000	0.000	0.000	0.000
	(0.67)	(1.18)	(1.02)	(1.20)	(1.24)	(0.99)
MktSent3	-0.027*	-0.028*	-0.031*	-0.028*	-0.027*	-0.032**
	(-1.77)	(-1.80)	(-1.96)	(-1.79)	(-1.77)	(-2.02)
Number of Obs.	748	748	748	748	748	748
Adjusted R^2	0.362	0.366	0.368	0.366	0.368	0.370

Table 4: Expected Skewness and Retail Demand in the IPO market

This table reports regression results for the relationship between expected skewness and retail demands in the IPO market. We use three variables to measure retail demands: *Orders*, *RMB*, and *Allocation*. The dependent variable in Panel A is *Orders* defined as the number of valid subscription orders received from the second offline tranche. The dependent variable in Panel B is *RMB* defined as the number of new shares subscribed multiplied by the offer price. The dependent variable in Panel C is *Allocation* defined as the rate of allocation between retail investors using the lottery approach. *Skewness* is the expected skewness of an IPO stock's return defined as the tail of the probability distribution generated by monthly returns of all stocks in the same industry over the three-month period before the offer date; *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; *Profitability* is the percentage difference between the offering P/E and the industry P/E; *IssueSize* is 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 two times over the past three years, and 0 otherwise; *Big4* 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 proportional of state holdings in the firm; *Tradable* is the proportion of tradable shares; *Age* is the firm age since establishment; *TimeLag* is the number of days elapsed between offering and listing; *Analysts_std* is the standard deviation of one-year forward looking EPS by analysts; *Analysts_bias* is defined as the average difference between analyst's forecasting EPS and realized EPS; *MktSent1* is the number of IPOs in the same calendar month; *MktSent3* is the market return in the same calendar month. Year dummies are included in all regressions. 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: *Orders* as the Dependent Variable		Panel B: *RMB* as the Dependent Variable		Panel C: *Allocation* as the Dependent Variable	
	(1)	(2)	(3)	(4)	(5)	(6)
Skewness		142,341.1***		677.033*		-1.044*
		(2.81)		(1.82)		(-1.64)
ROA	-135,746.5	50955.55	2,853.385*	3,745.593**	-2.400**	-3.776***
	(-0.51)	(0.19)	(1.76)	(2.19)	(-1.98)	(-2.95)
Leverage	68,066.52	105,528.4	2,679.375***	2,859.445***	0.302	0.024
	(0.54)	(0.86)	(3.60)	(3.92)	(0.20)	(0.02)
Profitability	4,487.34*	2,987.34	-3.185	-10.315	-0.042**	-0.031**
	(1.68)	(1.08)	(-0.23)	(-0.67)	(-2.53)	(-2.39)
Log (*IssueSize*)	38,935.36	35,644.28	-44.726	-60.418	0.234	0.258
	(1.26)	(1.15)	(-0.23)	(-0.30)	(1.21)	(1.39)
Underwriter	-888.18	-3,674.61	552.977***	540.049***	-0.313	-0.293
	(-0.03)	(-0.12)	(2.81)	(2.76)	(-1.38)	(-1.35)
Big4	365,697.7***	370.366.3***	4,955.120***	4,973.193***	0.582	0.554
	(2.59)	(2.63)	(3.36)	(3.38)	(0.87)	(0.82)
VC-backed	-26,979.16	-19,509.35	14.230	49.938	0.365	0.310
	(-0.87)	(-0.63)	(0.08)	(0.29)	(1.34)	(1.27)

State	115,435.1	105,205.9	1,133.812*	1,084.652*	0.011	0.087
	(1.15)	(1.06)	(1.79)	(1.72)	(0.03)	(0.27)
Tradable	963,416.9	929,189.3	609.672	440.276	-1.490	-1.229
	(1.60)	(1.53)	(0.11)	(0.08)	(-0.25)	(-0.20)
Log (1+*Age*)	-1,862.18	-1,526.46	-14.213	-12.633	0.022	0.020
	(-0.53)	(-0.44)	(-0.61)	(-0.54)	(1.19)	(1.06)
Timelag	-1,099.48	-1,441.84*	-1.253	-2.901	-0.002	0.001
	(-1.27)	(-1.65)	(-0.20)	(-0.48)	(-0.21)	(0.06)
Analysts_std	4,445.29	1,295.30	62.280	47.112	-0.152	-0.128
	(0.06)	(0.02)	(0.14)	(0.11)	(-0.51)	(-0.42)
Analysts_bias	250,564.6***	222,705.5***	645.295*	512.994	-0.763***	-0.559*
	(4.14)	(3.57)	(1.88)	(1.37)	(-2.70)	(-1.64)
MktSent1	-13,437.84***	-13,935.70***	-90.714***	-93.056***	0.027*	0.031*
	(-4.94)	(-5.06)	(-6.50)	(-6.57)	(1.85)	(1.93)
MktSent3	-200,559.7	-231,339.1	-2,715.312**	-2,863.119**	0.251	0.479
	(-0.77)	(-0.89)	(-2.24)	(2.36)	(0.35)	(0.62)
Number of Obs.	748	748	748	748	748	748
Adjusted R^2	0.123	0.128	0.281	0.283	0.016	0.022

Appendix: China's Lottery Mechanism for Share Allocation among Retail Investors

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[7], 85824 (=35,824+50,000*1);

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

[7] 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.