Rent Seeking, Brokerage Commissions, and the Pricing and Allocation of Shares in Initial Public Offerings

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Abstract

Using investor bidding data from 175 Chinese IPOs, we examine the effects of underwriters' rent-seeking incentives. We find that Chinese IPO underwriters, with no discretion to allocate more shares to favored investors, instead favor mutual funds paying them greater brokerage commissions by discounting offer prices to make more orders from them eligible for IPO share allocations, which results in greater IPO underpricing. Further, underwriters choose price levels at which there are more bids from commission-paying mutual funds as offer prices. Rent seeking is more pronounced for underwriters who are top brokers and therefore place more weight on bidding investors' interests.

Key words: IPO Pricing; Rent Seeking; Mutual Funds; Underwriters; Brokerage Commissions

JEL number: G24; G28; G32

1. INTRODUCTION

The interactions between institutional investors and underwriters in the initial public offering (IPO) process have interested financial economists for a long time, and different theories on these interactions have been developed to explain IPO underpricing and share allocations in the literature. For example, the information extraction theory posits that underwriters could use their discretion in IPO pricing and share allocation to induce regular investors who possess private information about IPOs to reveal this information in the book-building process (see Benveniste and Spindt (1989) for the relevant theory and Cornelli and Goldreich (2001, 2003), Chemmanur, Hu, and Huang (2010), and Hanley and Hoberg (2010) for supporting evidence).[1] The IPO price stabilization theory argues that underwriters may allocate underpriced shares to investors who agree to hold the shares for longer periods, or buy additional shares in the immediate aftermarket (e.g., Aggarwal (2000), Fishe (2002), Jenkinson and Jones (2004), and Hao (2007)). The rent-seeking theory argues that hot IPOs are allocated to investors to generate future brokerage commissions or investment banking business for the underwriters (e.g., Loughran and Ritter (2002, 2004)).[2] Earlier studies have found evidence consistent with the information extraction theory on IPO pricing and with all three of the above theories on IPO share allocation. However, possibly due to data limitations, the existing literature has not fully examined the implications of the rent-seeking theory on IPO pricing. In this paper, we use detailed institutional IPO bidding data from the Chinese IPO market to fill this gap by providing the first study that directly explores how underwriters set IPO offer prices, taking business relationship with their brokerage clients into account.

In a typical book-building process, an underwriter announces a price range and collects bids with quantity-price information from institutional investors to construct a demand schedule. After consulting with the issuer, the underwriter chooses the offer price and distributes shares to investors with bidding prices above the offer price. The rent-seeking theory predicts that, in this book-building process,

[1] See also Chemmanur (1993), who suggests that IPO underpricing is a means of inducing information production by outsiders about the firm.

[2] See Ritter and Welch (2002) and Ritter (2011) for excellent surveys of the theoretical and empirical IPO underpricing literature and the literature on IPO share allocation.

underwriters have incentives to maximize their own revenues when setting IPO offer prices and determining IPO share allocation. For example, in the IPO share allocation process, they distribute underpriced shares to investors paying brokerage commissions to them with an implicit profit-sharing mechanism (e.g., Reuter (2006), Nimalendran, Ritter, and Zhang (2007), Jenkinson and Jones (2009), Goldstein, Irvine, and Puckett (2011)). The underwriter's rent-seeking incentive should have similar effects on the IPO offer price-setting process. As noted in Ritter (2011), if the underwriter is able to capture part of the money left on the table, it creates an incentive for the underwriter to recommend a lower offer price than would be optimal for the issuer, resulting in greater underpricing. Since brokerage commissions are one of the most convenient ways for the underwriter to share the money left on the table with IPO investors, we posit that underwriters are likely to favor investors paying brokerage commissions to them when setting IPO prices. The implications of this rent seeking by underwriters are likely to be two-fold: first, underwriters deliberately underprice IPOs to make more soft-dollar paying investors eligible for IPO share allocation, thus compensating them for their brokerage business; second, underwriters set a lower IPO offer price to leave a larger amount of money on the table which these investors are able to profit from.[3]

A theoretical paper that models the incentives of underwriters to engage in rent seeking by allocating underpriced IPO shares to clients of their non-IPO businesses is Fulghieri and Spiegel (1993). By modeling investment banks as multiproduct firms, they develop a theory of how IPO underwriters allocate IPO shares among their clients. They show that, all else equal, larger clients receive a greater dollar value of underpriced shares from investment banks.[4] Intuitively, these effects arise from the desire of the investment bank underwriting the IPO to promote future sales of their other (non-IPO underwriting) services (such as their brokerage business) by giving underpriced IPO firm shares to their best customers

[3] As we discuss later, Chinese underwriters do not have the discretion to allocate shares to whichever institutions they please, unlike in the US. This means that they need to lower the offer price in order to ensure that the institutions they wish to allocate shares to bid above the eventual offer price to allow underwriters to allocate shares to them.

[4] Formally, in the Fulghieri and Spiegel (1993) model, the objective of the investment banks underwriting the IPO in allocating underpriced IPO shares to their institutional clients is to signal their true quality. However, in practice, IPO underwriters may also have other objectives, such as developing and maintaining long-term relationships with these institutions, thereby generating higher brokerage commissions in the future from them. We will focus on this latter objective in our empirical analysis.

of these services. In equilibrium, the allocation of underpriced IPO firm shares to a client will be greater the more the bank expects to gain from that client in future transactions. While Fulghieri and Spiegel (1993) develop their model with a focus on book-building IPOs in the US (where IPO underwriters have complete discretion in both IPO pricing and share allocation), in the Chinese context, IPO underwriters have discretion only in fixing the IPO offer price and have to allocate shares to all bidders who bid above the eventual IPO offer price. This means that the Fulghieri and Spiegel (1993) model generates very sharp predictions for the pricing of IPO firm shares in the Chinese context (since the IPO share allocation channel has been mostly shut off in that context), which we are able to test using the very detailed data available to us on institutional bidding in Chinese IPOs.

The unique institutional setting in the Chinese A-share market allows us to test the predictions of the rent-seeking theory of IPO pricing against those of the information extraction and stabilization theories directly.[5] First, the China Security Regulation Commission (the counterpart of SEC in China, CSRC henceforth) requires underwriters to disclose order books with information on investor identities, bidding prices, quantities, and allocations to the public since 2010. Thus, we are able to observe the bidding and allocation information that is unavailable in other markets (e.g., the US market) but critical to our understanding of the IPO price-setting process. Second, brokerage commissions paid to investment banks vary much across different types of investors due to CSRC regulations, creating a significant exogenous variation in brokerage relationships among investors. For example, mutual fund trades are required to be executed via special brokerage service provided by investment banks, which charges a higher commission rate (around 0.08%) than the ordinary service to trades from other investors (around 0.03%). Third, brokerage commissions that a mutual fund pays to every broker it uses, along with information on other fund characteristics, are also reported in detail in compliance with the CSRC's regulations. This allows us to calculate the brokerage commissions for each underwriter-mutual fund pair precisely. Last, the effects of rent-seeking incentives on IPO pricing should be more pronounced for

[5] Meanwhile, China now has the second largest IPO market around the world by dollar raised, according to Doidge, Karolyi, and Stulz (2013), and is of great interest by itself.

Chinese underwriters (relative to the US, for example), because IPO underwriters in China lack the discretion in share allocation that US underwriters have (to engage in allocating shares to whichever institutions or other investors that they wish to give shares to): in China, IPO share allocations are done on a *pro rata* basis (i.e., any rationing will be done as a function of the shares bid for), so that a lower offer price is the primary channel that Chinese underwriters are able to use to distribute the money left on the table to commission-paying investors.

We analyze the order books of 175 IPOs that are not likely to be affected by the CRSC's interference on pricing in the Chinese A-share market to investigate the effects of underwriters' favoritism towards commission-paying investors on IPO price-setting. In practice, when an underwriter has compiled the IPO demand schedule based on the order information in the IPO book, it starts from the market clearing price and searches for the optimal offer price from high to low price levels along the demand schedule. Our empirical tests focus on how the choice of the offer price is determined in this searching process.

First, we explore the effects of underwriters' favoritism towards commission-paying investors on deliberate underpricing, that is, the discount from the market clearing price to the offer price. This measure captures underwriters' efforts to lower the offer price directly, which is not observable without the data on order books. We find that the offer prices are discounted to a greater extent if the distributions of orders from commission-paying mutual funds are skewed towards lower price levels in the demand schedules. This observation suggests that underwriters deliberately lower the offer prices to allow more orders from mutual funds, who pay more brokerage commissions to them, to be eligible for IPO share allocations. There is no such a pattern for other types of investors that pay fewer commissions on average, including investment banks, insurance companies, trust firms, and financial companies. Results on orders from commission-paying mutual funds are robust after controlling for the information extraction effect documented in Cornelli and Goldreich (2003) for offer price-setting, the long-term investor effect documented by Jenkinson and Jones (2004) for IPO share allocations, and other mutual fund

characteristics. Taken together, we find strong and robust evidence on deliberate underpricing by underwriters that is consistent with the predictions of the rent-seeking theory.

Next, we examine the effects of underwriter favoritism among bidders for IPO shares on IPO underpricing. Intuitively, this favoritism should be positively correlated with initial returns because the offer prices are set at lower levels. We find consistent evidence: initial returns are larger when orders from mutual funds paying commissions to the underwriter are distributed around lower price levels in the demand schedule. Orders from other types of investors have no such effect. The effects of this favoritism are robust to controlling for the information extraction and long-term investor effects. Evidence on initial returns supports the rent-seeking theory, suggesting that underwriters favor mutual fund investors paying commissions to them by deliberately lowering offer prices so that such investors are able to participate in IPO share allocation, resulting in greater IPO underpricing.

We then test the predictions of the rent-seeking theory in a marginal scenario. Since we argue that underwriters search for the potential offer price from high to low price levels in the demand schedule to include more orders from commission-paying mutual funds so as to later allocate more shares to them, they would stop searching at price levels at which orders from commission-paying mutual funds are concentrated. Put differently, the probability that a price level is chosen as the offer price should be positively correlated with the size of orders from commission-paying mutual funds at that price level. We run price-level conditional logit regressions to test this conjecture and find supporting evidence. Specifically, a price level is more likely to be chosen as the IPO offer price if there are more orders from commission-paying mutual funds at that level; there is no such effect in the case of other types of investors. This effect is robust to controlling for orders from mutual funds that are more informed and that are more likely to hold their allocations for a longer period.

The economic magnitudes of the underwriter rent-seeking effect are sizable. A one standard deviation increase in commission-paying mutual funds' demand results in a 1.9% decrease in price discounts, a 4.1% increase in initial returns that translates into 27.5 million RMB in the money left on the table, and a 49.6% increase in the odds ratio that a price level is chosen as the offer price.

We next do additional tests to explore how underwriters' dependence on brokerage revenues alters our main results. If an underwriter is also a major brokerage house and relies heavily on brokerage revenues, it will care more about the interests of commission-paying investors than the issuing firm. It is also more convenient for such underwriters to establish an implicit profit-sharing agreement with mutual funds that are their important brokerage clients. Thus we expect to observe a more pronounced effect of favoritism towards commission-paying investors from underwriters that are top brokers. Consistent with our conjecture, we find that our main results are more significant for underwriters with commission revenues ranking in the top tercile among all investment banks.

In the final part of the paper, we attempt to rule out an alternative tipping mechanism that may explain our main findings. This mechanism suggests underwriters may give advice or leak information to commission-paying institutions to bid a somewhat higher price to get more IPO allocations. We argue that, in practice, it is not rational for either investors or underwriters to use such an illegal mechanism frequently due to the resulting higher offer prices and greater legal risks. Empirically, we do not find evidence that the effect of brokerage commissions is less pronounced for more compliant underwriters, as predicted by the tipping mechanism. We therefore believe that a tipping mechanism is unlikely to be at work in generating our results.

The rest of the paper is organized as follows. Section 2 discusses the relation of our paper to the existing literature. Section 3 describes the institutional background of Chinese IPO markets. Section 4 reports our sample selection procedures and presents summary statistics. Section 5 presents our results on deliberate underpricing and initial returns. Section 6 presents our results on offer price determination. Section 7 reports results on underwriter characteristics and IPO offer price determination. Section 8 discusses alternative mechanisms. Section 9 concludes. Appendix A provides a figure giving the distances of IPO prices from regulatory price caps. Appendix B lists the definitions of various variables. Appendix C provides additional tests ruling out a tipping mechanism as an alternative explanation for our results.

2. RELATION TO THE EXISTING LITERATURE

Our paper makes contributions to two strands in the IPO literature. First, we contribute to the IPO underpricing literature on how underwriters' rent-seeking incentives affect offer price-setting, which allows us to develop a better understanding of agency problems in IPOs. Since the money left on the table (received by investors and underwriters with an implicit profit-sharing mechanism such as brokerage commissions) is determined not only by allocations (the quantity effect) but also by IPO underpricing (the price effect), the rent-seeking theory predicts lower IPO offer prices besides favorable IPO share allocations to commission-paying investors (Ritter, 2011). Consistent with this conjecture, we find evidence that the brokerage commissions paid by investors to underwriters make the latter lower the offer prices directly, resulting in underpricing to a greater extent. This result is also consistent with Goldstein et al. (2009), which suggests that investors concentrate their trading with particular brokerage firms for preferential treatment. Previous studies on underwriters' rent-seeking behaviors mainly focus on IPO share allocations because of the lack of data on the IPO price-setting process and brokerage commissions.[6] To the best of our knowledge, this paper is the first study that directly tests the predictions of the rent-seeking theory of IPO pricing.

Second, our research complements the existing literature by providing details and direct evidence on IPO pricing and allocation dynamics. Despite the large body of literature on IPO pricing and share allocation, there remains little evidence on how the actual IPO process works in practice, since underwriters' books are proprietary information (in the US, for example). An important paper that studies how IPO price setting works in practice is Cornelli and Goldreich (2003). They show that European investment banks use information in IPO order books to set the IPO offer price, by documenting that informative limit prices have a strong influence on the IPO offer prices. Using similar Chinese bidding data, Cao et al. (2016) find IPOs with higher levels of bid dispersion experience greater first-day returns

[6] For example, Reuter (2006) uses data on the top 10 investment banks to which mutual funds paid the largest amount of commissions and documents a positive relation between commissions that mutual funds paid to lead underwriters and their reported holdings of IPO shares. Nimalendran, Ritter, and Zhang (2007) find that investors trade liquid stocks to affect their IPO allocations by generating more commissions. Goldstein et al. (2011) further find that investors, especially transient investors, pay a larger amount of soft dollars by increasing round-trip stock trades, increasing average commissions per share, and paying unusually high commissions on some trades.

than other IPOs. These findings are consistent with Benveniste and Spindt (1989)'s information extraction hypothesis. Regarding how IPO share allocations work in practice, Cornelli and Goldreich (2001) show that investment banks allocate more shares to bidders who provide information in their bids, which is also consistent with the information extraction hypothesis. Jenkinson and Jones (2004) show that bidding investors who are perceived to be long-term holders of the IPO stock are favored in share allocations, supporting the market stabilization hypothesis as in Aggarwal (2000). The findings of our empirical study suggest that underwriters search for the optimal offer price to set from high to low price levels along the demand schedule, choosing their final IPO offer price based on their own rent-seeking objectives as well as other motivations important to the IPO issuers. Thus, while we test the rent-seeking theory against the information extraction and the price stabilization theories, we find that the rent-seeking theory dominates.

Finally, to the extent that the first stage of the IPO pricing process in China can be viewed as an auction open to institutions, our paper is also distantly related to the literature on auctioned IPOs: see, e.g., Kandel, Sarig, and Wohl (1999), Amihud, Hauser, and Kirsh (2003), Chiang, Qian, and Sherman (2011), Chiang et al. (2010), and Degeorge, Derrien, and Womack (2010). These studies, however, have focused on the implications of asymmetric information, with the exception of Chiang, Qian, and Sherman (2011), who focus on naïve learning by frequent IPO investors.

3. INSTITUTIONAL BACKGROUND

3.1 The IPO mechanism in China

The Chinese IPO market has been heavily regulated since its inception in early 1990s. Historically, Chinese regulators have tried several selling mechanisms for IPOs over time due to different market and political considerations, including fixed-price offerings based on price-earning ratios (1992-1994, 1995-1999, 2002-2004) and on-line auctions (1994-1995, 1999-2001). In 2005, the CSRC introduced a hybrid IPO mechanism and kept revising it in many aspects such as investor qualifications, allocation rules, and

information disclosure. This mixed mechanism is in use until now, and the basic design has stayed unchanged.

As shown in Figure 1, under the hybrid IPO mechanism a typical Chinese IPO consists of two tranches. The first tranche is a "crippled" book-building process, in which only institutional investors are allowed to participate, after which the IPO offer price is determined. We call this tranche "crippled book-building" since underwriters in this mechanism do not have any discretion in the allocation of shares, which are distributed to eligible investors on a *pro-rata* basis instead.[7] The second tranche is a fixed-price offering to retail investors, who accept the IPO offer price determined in the book-building tranche passively, and place orders only with the number of shares demanded at this fixed offer price. The pre-determined fraction of new shares sold in the first tranche varies from 20% to 50%, and is subject to adjustment to balance different demand levels from the two tranches.

3.2 The book-building tranche

The offering procedure in the crippled book-building tranche is somewhat similar to those of the traditional book-building procedure that is popular in the US. Figure 1 demonstrates the timeline of these steps with an illustrative example. Day *T* is the day when the new shares are sold to investors officially, i.e. the offering day. On day *T-7* (7 trading days before day *T*), the new offer is announced and a preliminary version of the prospectus is disclosed, which contains information on the offering firm and the offer but not on the offer price and allocations.

Roadshows are then organized to publicize the offer. This step usually takes 2-3 trading days, and only intuitional investors are allowed to participate in them. In roadshows, a valuation report prepared by the underwriter's analysts is disseminated among institutional investors. The report contains the suggested price range for the offer.

[7] This tranche may also be viewed as an IPO auction open only to institutional investors. Cao et al. (2006) call this tranche a "dirty multi-unit uniform price auction", and Ritter (2011) describes it as "procedures with some aspects of book-building". In this study we call it "a crippled book-building" because it inherits very similar procedures from the traditional book-building mechanism except allocation rules, which are discussed in detail in Section 3.2.

From the beginning of roadshows to 3 trading days before the offer (day *T-6* ~ day *T-3* in the example), institutional investors are invited to submit their indications of interest to the underwriter via an electronic system provided by the exchange. Unlike those in the US, these preliminary bids are all limit-price orders, in which the maximum price an investor is willing to pay for a given number of shares is specified. An investor is allowed to place three bids with different combinations of price and quantity, which is equivalent to the step bids in the traditional book-building process, as described in Cornelli and Goldreich (2001).

Once the order book is built, the underwriter is able to compile a demand schedule for the offer. The demand schedule shows, at each price level submitted by investors, how many shares are demanded and whom the demand is from. The price-setting process often starts in the evening of day *T-3*, and may last until the midnight if it is difficult to reach a consensus. In practice, the underwriter starts from the highest price level that clears the market and searches from high to low price levels along the demand schedule to determine the optimal offer price that balances the interests of the issuer, the market, and the underwriter itself.[8] The issuer is consulted for opinions during this process, but it is not permitted to sit in the price-setting meeting. The pricing decision and other supporting materials are filed with the CSRC on the next day (day *T-2*) and announced to the market on day *T-1*.

On day *T*, the formal offering day, institutional investors confirm their eligible orders, that is, preliminary orders with prices above or equal to the offer price, via the electronic system. The fixed-price offer to retail investors occurs on the same day, in which the fixed-price is the offer price determined on day *T-2* in the book-building tranche.

The most important difference between IPO book-buildings in China and those in the US is in IPO share allocations. The Chinese underwriters do not have any discretion in IPO share allocations, and shares are rationed on a *pro rata* basis to investors placing eligible orders.[9] Thus, if an underwriter wishes

[8] The CSRC used to give informal guidelines to underwriters on IPO pricing, which are typically price caps. These guidelines, however, are not binding, and are completely removed for some periods. We discuss the impact of these guidelines on our sample construction in detail in Section 4.1.

[9] In late 2010 the Shenzhen Stock Exchange introduced a lottery mechanism for IPO share allocation. The new allocation mechanism still allocates share on a *pro rata* basis but increases the number of shares per unit of allocation significantly. With

to favor an investor in the offering, the main strategy it can use is to lower the offer price so that the investor is eligible for share allocations even when it places a low price order. The IPO share allocation results are announced on day *T+1* and *T+2* for institutional investors and retail investors, respectively.

Finally, it takes 3-5 trading days for the underwriter to register the new shares with the central registry, and the trading of new shares starts on day *T+6* in our example.

4. DATA AND SAMPLE CONSTRUCTION

4.1 Data

Since 2010 Chinese underwriters are required to disclose IPO bidding information to the market. We hand collect the data from the disclosures from IPO firms, including bidders' names, institutions the bidders are affiliated with, prices, quantities, and number of shares allocated.[10] We then classify bidders into the following categories: mutual fund, insurance company, investment bank, trust firm, and financial firms. The mutual fund brokerage commission data are from the CSMAR database, which includes semiannual commission payments a mutual fund making to each brokerage service it has used in the past 6 months. The dollar amount of trades is also reported in the CSMAR database.

Our IPO information is from the Wind database. It provides information on important IPO dates, shares offered, proceeds, offer prices, underwriters, and industry classifications. We use stock price and firm fundamental data from the CSMAR database to calculate returns and other IPO firm-level controls. Other mutual fund information, including size, type, past investment returns, and end-of-period stock holdings, is also retrieved from the CSMAR database.

4.2 Sample construction

We have the bidding information for 850 IPOs. As mentioned in Section 3.2, the CSRC influences the pricing of IPOs with informal price caps in some periods. Though these guidelines are not compulsory

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the traditional method, the number of shares allocated to an investor is rounded down to whole shares; with the new method, the new shares are divided into a few lots, each of which may consist of several million shares. Then these lots are awarded to investors using a lottery mechanism.

[10] The Shenzhen Stock Exchange provides us bidding information on Shenzhen IPOs from June 2009 to November 2010.

and not followed in many IPOs, they may plague price-related research on Chinese IPOs. We follow the two steps to construct a sample that is subject to the CSRC's intervention to the least extent:

1) We restrict our sample IPOs between October, 2011 and October, 2012. During this period, the CSRC takes initiatives to make IPOs more market-based and stops giving guidelines on IPO pricing. There are 196 IPOs during this period, among which 6 are priced at the market clearing price. We exclude the 6 offers from our sample because the primary goal for their underwriters is to sell out the new shares rather than other information-based or agency-based considerations.[11]

2) It is reasonable to doubt that underwriters may still follow conventions and take price caps into consideration when pricing IPOs. To eliminate the potential influences of this consideration, we further exclude 15 IPOs priced within a 1% range of the price caps from our sample, leaving 175 IPOs in our final sample.[12] For those IPOs priced above the caps, apparently underwriters do not take the caps into consideration; for those priced below, the caps are not binding. Thus our sample is unlikely to be affected by the CSRC's intervention on pricing.

Figure A1 in Appendix A plots the distances from the offer prices to the price caps for IPOs in our sample period, which is defined as the difference between the offer price and the cap, divided by the cap. Only a very small fraction (8%) of the offers is susceptible to interventions. In the final sample of 175 IPOs, 90% are priced above the price caps, showing that the guidelines on pricing are removed during this period. So we believe that our results are not biased by the regulator's influences.

In untabulated analysis, we construct another sample consisting of all IPOs that are priced 5% higher or lower than the price caps during the whole period we have the bidding data. We obtain qualitatively similar results across all the main tests.

[11] The Chinese security law states that for a firm with a total equity of fewer than 400 million shares, at least 25% of total shares outstanding should be sold to the public during the offering to make the IPO successful; for larger firms with a total equity of more than 400 million shares, at least 10% should be sold to the public. It is common in China that the pre-determined number of shares offered is the minimum number satisfying this requirement, so the most important objective for the underwriters is to sell the new shares out.

[12] According to several major investment banks, the price cap is defined as the maximum of simple mean, share-weighed mean, and median of prices calculated with all bids, and simple mean, share-weighed mean, and median of prices calculated with mutual fund bids.

4.3 Summary statistics

Table 1 reports descriptive statistics of our sample. According to Panel A, 78 and 71 IPOs are from the CHINext and SME market in the Shenzhen Stock Exchange, respectively, and the remaining 26 are from the main board in the Shanghai Stock Exchange. An average IPO in our sample sells 4.6 million new shares to the public. A reasonable number of new shares (6.0% of the total shares) are sold to the institutional investors in the book-building tranche. The average IPO raises 670 million RMB, and IPOs in the main board are three times the size of those from the CHINext market in terms of IPO proceeds. 58.9% of our sample firms are backed by VC investors. On average the offer price is 8.3% higher than the hypothetical price cap, suggesting the pricing guidelines are not effective in our sample period. The average underpricing is 27.3%, which is smaller than that reported in Cao et al. (2016) for 2009 - 2012, suggesting the magnitude of underpricing decreases during that period.

Panel B reports statistics on the investors' bidding patterns in the book-building tranche. For an average IPO, there are 86.6 bidders that are affiliated with 47.6 institutions who place 98.9 bids. Our sample IPOs are heavily oversubscribed with an average overall subscription ratio of 43.7. In the book-building tranche, the subscription ratio is 21.6. IPOs are priced 10% lower than the share-weighted average bidding price. The standard deviation of the bidding prices is 15.3%, and the concentration ratio of demand, measured by the Herfindal index of top 5 largest orders in terms of shares, is 3.8. Consistent with Degorge, Derrien, and Womack (2010), underwriters choose the price level with a high demand elasticity of 62.2 (calculated as - percentage change in demand/percentage change in price from the offer price to the price immediate above) as the offer price.

Panel C reports the statistics on investor participation in our sample IPOs. In total, 1,123 bidders from 348 institutions place 17,311 bids in the sample IPOs. Mutual funds, investment banks, and insurance companies are the three largest IPO investors in terms of the number of investors, demand in shares and dollars, and shares allocated. For example, there are 484 mutual fund bidders who bid for 42.4% of the shares offered, and 42.8% of shares are distributed to them. Insurance companies have the largest average order size of 8.0 million shares or 82.9 million RMB. They, however, are relatively conservative

in the bidding process, since the fraction of their eligible demand, that is, demand with price above or equal to the offer price, is 9.4%, which is smaller than their fraction in demand for shares (12.9%).

5. RENT SEEKING AND DELIBERATE UNDERPRICING

We define deliberate underpricing as the discount from the market clearing price to the offer price. This discount is observable in the demand schedule, and captures an underwriter's effort to set the offer price below the level at which new shares could be sold out completely. In this section, we test whether underwriters favor commission-paying investors by deliberately underpricing IPOs in exchange for soft dollars, as predicted by the rent-seeking theory. We also examine the effects of this favoritism on IPO initial returns.

5.1 Testable Hypotheses

Since underwriters aren't able to allocate more shares to reward commission-paying investors due to the rationing system in China, they can establish a profit-sharing mechanism by lowering the offer price to 1) include more orders from commission-paying investors so as to eventually allocate them more IPO firm shares; and 2) to increase the magnitude of their initial returns. The rent-seeking theory predicts that underwriters' favoritism towards commission-paying investors will result in a larger discount in the offer price, besides more IPO share allocations to these investors as suggested by Reuter (2006) and Nimalendran, Ritter, and Zhang (2007).

Specifically, when an underwriter observes a demand schedule in which the bids from commission-paying investors are at higher prices, they are able to choose a higher offer price, because the investors from whom they receive brokerage commissions are eligible for allocations at this offer price. On the other hand, if bids from commission-paying investors are at relatively lower prices, the underwriters will have to choose a lower IPO offer price, in order to make more of the bids from such investors eligible for IPO share allocations. It is worth noting that mutual funds pay significantly higher brokerage commissions to underwriters than other types of investors (0.08% versus 0.03% on average).

They also have long-term business relationships with underwriters, which is helpful for establishing an implicit profit-sharing mechanism. Thus, in general, it is reasonable to expect that there exists favoritism towards mutual funds, which, in turn, affects IPO pricing. Based on these arguments, we develop the following testable hypotheses:

H1: *If the distribution of mutual fund orders is skewed towards higher bid prices, underwriters discount the IPO offer price less.*

H2: *Underwriters' favoritism towards various mutual funds can be explained by the brokerage commissions they have previously received from these mutual funds.*

5.2 Empirical framework

Our basic methodology to test for favoritism towards a group of investors is to examine whether underwriters take the distribution of the investor group's orders into consideration when they price equity in IPOs. The logic here is that, if the underwriters favor a group of investors, they are likely to set the offer price at a level that makes as many orders from that group as possible eligible for IPO share allocations. For example, if most of the orders from the favored group are with low prices, the underwriters are likely to choose a lower IPO offer price to accommodate the favored group. Because we can classify the bidding investors into different groups by a variety of characteristics, such as investor type, commissions paid, and industry expertise, we are able to pin down the source of this favoritism by relating IPO pricing outcomes to the distribution of orders from the group of investors with specific characteristics.

5.2.1 Main variables

We measure deliberate underpricing *Discount*, the discount from market clearing price to the offer price, as the difference between the market clearing price and the offer price, divided by the market clearing price. This measure could be calculated with information in underwriters' books, and better captures the underwriters' efforts to lower the offer prices than the traditional initial return measure.

To describe the distribution of investor orders across different price levels in a demand schedule, we first define *SkewDemand*, a skewness measure for the overall demand schedule

$$SkewDemand = \frac{Demand\ with\ top\ 1/3\ prices}{All\ demand} \tag{1}$$

which is the fraction of orders with high bidding prices in the demand schedule. Here we classify prices in the top tercile of the range from the market clearing price to the lowest bidding price as "high price". Intuitively, if a large fraction of the orders is with a relatively high price, the underwriters are able to set the offer price at high levels.

Besides the overall demand schedule, we compile the demand schedules for different types of bidding investors, including mutual funds (*Fund*), investment banks (*Inv. Bank*), insurance companies (*Insurance*), trust firms (*Trust*), and financial firms (*Financial*). Then we define *SkewInvs*, a similar skewness measure for each investor type's demand schedule

$$SkewInvs = \frac{Invs\ demand\ with\ top\ 1/3\ prices}{All\ Invs\ demand} / SkewDemand \tag{2}$$

where *Invs* could be replaced with *Fund*, *Inv. Bank*, *Insurance*, *Trust* and *Financial* to calculate the skewness of demand from different types of investors. The investor skewness measures are adjusted for the skewness of the overall demand schedule.

We further distinguish the mutual funds that pay large commissions from those that pay smaller or zero commissions and define the following two skewness measures

$$SkewPayComm = \frac{Comm\ paying\ fund\ demand\ with\ top\ 1/3\ prices}{All\ comm\ paying\ fund\ demand} / SkewDemand$$
$$SkewHighComm = \frac{High\ Comm\ fund\ demand\ with\ top\ 1/3\ prices}{All\ high\ comm\ fund\ demand} / SkewDemand \tag{3}$$

where *SkewPayComm* captures the skewness of the demand schedule of mutual funds whose families pay commissions (commission>0) to the underwriter in the year prior to the IPO, and *SkewHighComm* captures the skewness of the demand schedule of mutual funds whose families' commission payments in

the most recent year rank in the top half among all mutual funds bidding for the issue. These two measures are adjusted for the skewness of the overall demand schedule.

To check the robustness of the measures defined in above equations, we use an alternative price cutoff, that is, top quartile prices, to calculate these variables. Because underwriters are only able to choose the offer price among price levels below the market clearing price, we only use bids with prices below the market clearing price to construct the variables in equation (1)- (3).

In our sample, 41% (27%) of the mutual fund orders are within top tercial (quartile) price range; 41% (28%) of the commission-paying fund orders are within top tercile (quartile) price range. This observation suggests that there is a large fraction of orders (from commission-paying investors) with relatively low bidding prices, and it is reasonable to conjecture that underwriters have the incentive to lower offer prices to include some of those low-price orders from their friends for allocation.

5.2.2 Regression models

We test the H1 by estimating the following Tobit model:

$$Discount = a + bSkewFund + cControls + \varepsilon \quad (4)$$

where *SkewFund* is our main independent variable of interest as defined in equation (2). *Controls* contains a vector of variables that may affect *Discount*. First, we control for *SkewDemand*, which captures the impact of the skewness of the overall demand schedule on deliberate underpricing. A negative relation is expected since if most of the orders are with high prices, underwriters could price the issue higher. Following Cornelli and Goldreich (2003), we include *TDemand* and *NIns*, the total demand in times of shares offered and the number of institutions bidding for the offer, respectively, to control for overall demand for the offer. To absorb the impacts of the free-riding problem, that is, investors submit quasi-market orders by placing bids at very high price, we include in the regressions *HighBids*, calculated as the change in the clearing price if orders with the 5% highest prices are removed, divided by the current

market clearing price.[13] To control for the possibility that underwriters simply discount the offer price to include large bids or large investors, we include *LargeIns*, defined as the number of institutions in the largest bid size decile divided by the number of institutions with prices between the clearing price and the offer price (See Degorge, Derrien, and Womack (2010)).

We also follow the underpricing literature to include a few other controls, including *Assets*, the total assets of the offering firm; *IPOrtn*, time-weighted initial returns for IPOs in the most recent year; *MktRtn* and *MktVola*, secondary market return and volatility in the 3 months prior to the IPO, respectively. We also include exchange fixed effects, year fixed effects, underwriter fixed effects, and industry fixed effects in the analysis to absorb any influences varying only with exchange, year, underwriter, and industry. We provide detailed variable definitions in Appendix B.

To test the H2, we add the two variables measuring the skewness of the demand schedule of commission-paying mutual funds to equation (4):

$$Discount = a + bSkewComm + cSkewFund + dControls + \varepsilon \quad (5)$$

where *SkewComm* represents *SkewPayComm* and *SkewHighComm*, and other variables are defined in equation (4).

5.3 Baseline Results

5.3.1 Mutual fund bids and the discounts in offer prices

Table 2 reports the Tobit regression results testing H1 by estimating equation (4). Panel A and Panel B report the results with top tercile prices and top quartile prices as the cutoff for calculating skewness measures in equations (1) - (3), respectively. Our H1 argues that, underwriters discount the offer price less if the demand schedule of mutual funds is skewed towards high prices. We observe significant results that are consistent with this hypothesis. The coefficient estimates on *SkewFund* are significant and negative at the 1% level in columns (1) and (6), suggesting that the discount from the

[13] The free-riding problem has been formally shown in auction theory for Dutch auctions. Other studies, such as Biais and Faugeron-Crouzet (2002), show that in the French Mise en Vente mechanism, it is not advantages for bidders in an auction to bid artificially high prices.

market clearing price to the offer price is smaller if more mutual fund bids are at higher prices. The magnitude of this effect is also sizable. With a one standard deviation increase in *SkewFund*, the discount decreases by 1.1% and 1.0% according to column (1) and (6), respectively, which accounts for 9.3% and 8.8% of the average discount and could be translated to a 1.2% direct increase in the offer price.

In above regressions the coefficient estimates on the skewness of the overall demand schedule, *SkewDemand*, are significantly negative, suggesting that the higher the price that institutions bid, the higher is the offer price. We include *HighBids* to control for the effects of investors' free-riding behavior. We find that underwriters take the free-riding issue into consideration since the coefficient estimates are positive and significant, which is consistent with Degorge, Derrien, and Womack (2010). We don't observe significant coefficient estimates on *LargeIns*, suggesting that underwriters are unlikely to discount the offer price to favor large institutions. Regarding other control variables, we find that the discount is larger when the overall demand for IPOs is high, the IPO market is hot, and the secondary market is not performing well recently.

To check whether the above findings are driven by chance, we run placebo tests for the above findings on mutual funds by estimating equation (4) with the skewness of other major investor types' demand schedule as the key independent variable. Results for investment banks (*Inv. Bank*), insurance companies (*Insurance*), trust firms (*Trust*), and financial firms (*Financial*) are reported in columns (2) and (7), (3) and (8), (4) and (9), and (5) and (10), respectively. We don't find significant results for insurance companies, trust firms, and financial firms. Interestingly, the skewness of investment banks' demand schedule has a positive effect on *Discount*, which is opposite to the predications of the rent-seeking theory. This relation may be due to the competition among underwriters, but is beyond the scope of this study.

5.3.2 Rent seeking and the discounts in offer prices

The above results have shown that underwriters favor mutual funds rather than other types of investors when pricing IPOs. We conjecture that the favoritism is caused by their rent-seeking incentives, that is, they in fact use their discretion on choosing IPO prices to include orders from mutual funds that

pay brokerage commissions to them for allocations. We test our hypothesis 2 by estimating equation (5), in which the key independent variable of interest is the skewness of the demand schedule of commission-paying mutual funds.

Our first measure for the skewness of the demand schedule of commission-paying mutual funds, *SkewPayComm*, depends on whether the mutual funds' families paid commissions to the underwriter in the year prior to the offer. Column (1) and (3) in Table 3 show that the coefficient estimates on the variable is significant and negative across regressions, no matter which cutoff we use to calculate the skewness measures. With a one standard deviation increase in *SkewPayComm*, *Discount* will decrease by 1.9% and 1.8% according to column (1) and (3), which could be translated to 2.2% and 2.0% increases in the offer price. Our second measure, *SkewHighcomm*, depends on the ranking of the mutual fund among all mutual funds bidding for the IPOs by the amount of commissions their families paid to the underwriter. We find weaker but consistent results in column (2) and (4). Across regressions in column (1) to (4), the coefficient estimates on *SkewFund* is insignificant after the commission-related skewness measures are included, suggesting the effects of brokerage commissions fully dominate those of mutual funds. Thus we find evidence that is consistent with our second hypothesis, that is, underwriters favor mutual funds by deliberately discounting the offer prices for the brokerage commissions they received.

5.4 Controlling for alternative mechanisms

So far our findings are consistent with the predictions of the rent-seeking theory. In this subsection, we run additional robustness tests to rule out the possibility that our results are driven by other major mechanisms documented in the literature.

5.4.1 The information production effect

In the first set of tests, we compare the effects of the rent-seeking variables against those of the information production proxies involved in various regressions. Benveniste and Spindt (1989) suggest that underwriters use underpricing to compensate bidders for the private information useful in pricing the

IPO that they provide. This point of view is supported widely in empirical studies on both book-building and auctioned IPOs. We construct 3 measures to capture the private information possessed by mutual funds. The first, an industry expertise measure of private information, denoted by *SkewIndExp*, is based on Reuter (2006), defined as the skewness of the demand schedule of mutual funds whose holdings in the same industry as the IPO firm rank in the top half among all mutual funds bidding for the offer, and calculated with equation (3). The second measure, *SkewInvRtn*, is a skewness measure based on the ranking of mutual funds' investment performance in the secondary market, assuming investors with superior past investment returns have better private information. The third measure, *SkewIPORtn*, is defined similarly but with mutual funds' past investment performance in the IPO market. Details on the construction of these measures are provided in Appendix B.

Columns (1) to (3) in Table 4 report regression results with the information proxies controlled and a price cutoff of the top 1/3 prices. We find that the coefficient estimates on the rent-seeking proxy, *SkewPayComm*, is still significant and negative, and the magnitudes are of similar size to that in column (1) in Table 3. These information proxies don't have significant effects as shown in column (1) to (3). These findings suggest that our results on the rent-seeking mechanism are robust after considering the effects of the information production mechanism.

5.4.2 The stabilization effect

The IPO book-building literature suggests that underwriters are likely to reward long-term investors who chose to implement a buy-and-hold strategy, so as to stabilize the aftermarket for the new shares (Aggarwal (2000), Fishe (2002), Jenkinson and Jones (2004)). In the second set of robustness tests, we attempt to control for this stabilization effect by including two flipping measures when estimating equation (5). The first measure, *SkewHold*, is defined as the skewness of the demand schedule of mutual funds ranking in the top half by the duration they hold their allocations, as inferred from their most recent two semi-annual reports. The second measure, *SkewNoFlip*, is based on the fraction of IPOs of which

mutual fund did not sell their allocations within 1 month according to the most recent two semiannual reports.

Column (4) and (5) in Table 4 report the regression results after controlling for the two stabilization measures. The coefficient estimates on *SkewPayComm*, are still negative and without significant changes in magnitudes. They are also significant at the 1% and 5% level, respectively. The coefficient estimates on *SkewHold* and *SkewNoFlip* are not significant statistically, suggesting that stabilization incentive does not play a significant role in determining the offer price. Overall, our results on the rent-seeking mechanism are robust to controlling for the stabilization effect.

5.4.3 Other effects

In column (6), we include *SkewNIPO*, based on the number of underwriters' IPOs in which the mutual fund participated in the most recent year, in our regression to control for a possible clientele effect. As noted by Binay, Gatchev, and Pirinsky (2007), underwriters favor institutions they have previously worked with, since the long-term relationship is useful to underwriters when the cost of placing issues is high. The coefficient estimate on *SkewNIPO* is insignificant, while the coefficient estimate on *SkewPayComm* is still negative and significant at the 5% level, suggesting that our main results are robust to controlling for the clientele effect.

In column (7) to (9), we further control for skewness measures of mutual fund demand schedules based on their size, history, and management fee when estimating equation (5). The evidence shows that our main results are robust to controlling for these variables.

In untabulated analysis, we also try the price cutoff of top quartile prices and *SkewHighComm* to construct the rent-seeking measure, and re-run all the above robustness tests. We obtain qualitatively similar results across regressions. We therefore conclude that our finding that underwriters discount IPO prices to favor commission-paying investors is not driven by other major mechanisms documented in the literature.

5.5 Evidence on initial returns

Our hypotheses postulate that underwriters are more likely to set a higher offer price when the orders from mutual funds that pay commissions to them are concentrated around high prices in the demand schedules. These hypotheses are supported by evidence on underwriters' favoritism on (commission-paying) mutual funds in IPO pricing, which is documented in subsection 5.2 and 5.3. In this subsection, we further test the implications of underwriters' rent-seeking incentives on IPO initial returns. We conjecture that the initial returns are positively affected by underwriters' favoritism toward investors paying brokerage commissions due to a larger discount from the market clearing price to the offer price, which, in turn, implies a larger distance from the intrinsic value (proxied by the first-day closing price) to the offer price.

5.5.1 Mutual fund bids and initial returns

We use IPO initial returns, *IR*, as the dependent variable in estimating equation (4) to examine the effect of underwriter rent seeking on underpricing. Table 5 reports OLS regression results on the relation between initial returns and the skewness of the demand schedules of different types of investors with a similar specification as in Table 2. Columns (1) and (6) report the results on mutual fund participation with top tercile prices and top quartile prices as the cutoffs to compute the skewness measures in equation (2), respectively. The coefficient estimates on *SkewFund* are negative and significant at the 1% level in both columns. This effect is also economically significant. With a one standard deviation increase in *SkewFund*, initial returns decrease by 7.5% and 5.1%, which could be translated to a decrease of 50.3 and 32.2 million RMB in the money left on the table, respectively. Placebo tests are conducted in columns (2) to (5) and (7) to (10). We don't find consistent evidence that the skewness of other investors' demand schedules has a significant impact on initial returns.

The above results are consistent with our hypothesis H1 that underwriters deliberately set lower offer prices in IPOs to include more orders from mutual funds for share allocation, suggesting a rent-seeking mechanism in the pricing of IPOs.

5.5.2 Rent seeking and initial returns

We replace *Discount* with *IR* in equation (5) to test the effect of brokerage commissions paid by mutual funds to underwriters on initial returns and report the results in Table 6. The skewness of mutual funds that pay commissions to the underwriter is negatively and significantly related to initial returns. The economic impact is also sizable. With a one standard deviation increase in *SkewPayComm*, there is a 4.1% and 3.9% increase in the initial return if the top tercile and the top quartile prices are used as the cutoffs to construct the skewness measures, respectively, which are equivalent to losses of 27.5 and 26.1 million RMB in terms of the money left on the table. Results on *SkewHighComm* are slightly weaker, but consistent with those on *SkewPayComm*. In addition, the coefficient estimates on *Skewfund* are insignificant in columns (2) to (4), and are marginally significant in column (1), suggesting that the effects of mutual fund participation can be explained by the brokerage commissions they pay to the underwriters.

Table 7 reports the results of our robustness checks on the relation between mutual fund commissions and initial returns. We follow the specification in Section 5.4 and repeat the robustness tests for *Discount*. We control for the information production effect (proxied by *SkewIndExp* in column (1), *SkewInvRtn* in column (2), and *SkewIPORtn* in column (3)), the stabilization effect (proxied by *SkewHold* in column (4) and *SkewNoFlip* in column (5)), and other effects such as the clientele effect (column (6)), mutual fund size (column (7)), mutual fund history (column (8)), and mutual fund management fee (column (9)) in our regressions. Our results stay qualitatively unchanged after these mechanisms are controlled for.

Our findings on initial returns are consistent with the predictions of the rent-seeking theory. Initial returns are lower when orders from (commission-paying) mutual funds are skewed towards high prices in the demand schedules and higher offer prices are set. These findings contradict the notion that our results are driven by the predictions of the information production theory, which predicts a positive relation between the skewness of mutual funds' demand schedule and initial returns. In other words, if mutual

funds have private information that the intrinsic value of the offering firm is high, they would partially adjust their bidding prices upward for the issue, and be rewarded with larger initial returns.

6. RENT SEEKING AND OFFER PRICE SETTING

In this section, we consider the marginal scenario of the price-setting process to test the rent-seeking theory. Specifically, if underwriters favor mutual funds that pay commissions to them and search for the highest acceptable offer price along the demand schedule to include as many mutual fund orders as possible for IPO share allocations, they would stop at prices levels with large orders from commission-paying investors. So the rent-seeking theory predicts that underwriters are more likely to choose price levels with large orders from mutual funds paying commissions to them as IPO offer prices.

6.1 Empirical framework

We test the effect of mutual fund participation on the probability that a price level is chosen as the offer price by running a price-level conditional logit regression:

$$Sel = a + bDmdFund + cDemand + dElasticity + eSdemand + fDisc + \varepsilon \quad (6)$$

where *Sel* is a selection dummy that equals one if a price level is chosen by the underwriter as the offer price, and zero otherwise. For a price level *p* in the demand schedule, our main independent variable of interest, *DmdFund*, represents the percentage of orders in shares from mutual funds with price *p* out of total demand with that price. *Demand* is defined as the number of shares demanded divided by the number of shares offered at price *p*, which measures the increase in demand when underwriters choose *p* rather than the price above it. *Elasticity* is the demand elasticity calculated as the percentage change in demand divided by the percentage change in price from the price level immediately above *p* to price *p*. The total demand eligible for allocation, *Sdemand*, and the discount from the market clearing price, *Disc*, reflecting underwriters' tradeoff between quantity and price when pricing IPOs, are also controlled for in the regression. Details on the construction of these variables are provided in Appendix B. Note that we

use the conditional logit model for estimation, that is, deal-specific characteristics are controlled for in this setting.

Mutual fund orders at price p could be decomposed into orders from (large) commission-paying mutual funds and those from mutual funds that pay no (small) commissions. So we can test the effect of brokerage commissions on the probability that a price is chosen as the offer price with the following equation:

$$Sel = a + bDmdComm + cDmdFund + dDemand + eElasticity + fSdemand + gDisc + \varepsilon \quad (7)$$

where *DmdComm* is the percentage of orders in shares from commission-paying mutual funds out of the demand from all mutual funds at a price level *p*. We construct two versions of *DmdComm*. The first one, *DmdPayComm*, is based on whether the mutual funds' families pay above-zero commissions to the underwriter in the year prior to the issue; and the second one, *DmdHighComm*, is based on whether the commissions paid by the mutual funds' families rank in the top half among all mutual funds bidding for the issue in the most recent year. Other variables are defined similarly as in equation (6).

6.2 Results

6.2.1 Mutual fund bids and IPO price-setting

Column (1) in Table 8 reports the conditional logit regression results estimating equation (6) on the relation between mutual fund orders at a price level and the probability that the price level is chosen as the offer price. The coefficient estimate on *DmdFund* is 1.04, which is significant at the 10% level. This finding suggests that, with one standard deviation increase in *DmdFund*, the odds ratio that the price is chosen as the offer price increases by 42.7%. Thus, we find a positive effect of mutual fund orders, which is statistically significant and economically sizable and supports our rent-seeking hypothesis. We observe significant coefficient estimates on *Demand* and *Elasticity*, which are greater than 1, suggesting that underwriters prefer price levels at which there are large increases in demand and have high demand-price elasticity as the offer prices. The coefficient estimate on *Sdemand* is significant and greater than 1,

and that on *Disc* is significant and smaller than 1, suggesting that underwriter balance price and demand when choosing offer prices, which is consistent with our intuition.

Columns (2) to (5) in Table 8 report the results of placebo tests in which other types of institutional bidders are examined. There is no significant evidence showing that orders from other types of investors (i.e., investment banks, insurance companies, trust firms, and financial firms) have any influence on underwriters' selection of offer prices.

6.2.2 Rent seeking and IPO price-setting

Next, we test whether the effect of mutual funds' orders is driven by the brokerage commissions they pay to underwriters, which is suggested by our hypothesis H2. Table 9 reports the conditional logit regression results estimating equation (7). The coefficient estimate on *DmdPayComm*, the demand variable based on whether mutual funds pay commissions to underwriters, is greater than one and significant at the 1% level, as shown in column (1). The second demand variable based on the ranking of the amount of commissions, *DmdHighComm*, is also greater than 1 and significant at the 1% level. The economic magnitudes involved are sizable as well. With a one standard deviation increase in *DmdPayComm* (*DmdHighComm*), the odds ratio that the price level will be chosen as the offer price increases by 49.6% (41.2%). Moreover, the coefficient estimate on *DmdFund* is smaller than one in column (1) and insignificant in column (2), suggesting that the positive relation between the selection probability and mutual fund participation we observed in Table 8 is at least partly explained by the brokerage commissions. That is, it is the orders from commission-paying mutual funds that make the underwriters to choose a particular price as the offer price.

Following the strategies we adopted in Section 5, we run robustness tests to rule out other mechanisms that may affect our results on choosing the offer price. Proxies for these effects are constructed with the same method we use to calculate *DmdPayComm*. For example, the industry expertise measure for the information production effect, *DmdIndExp*, is defined as the percentage of orders in shares from mutual funds with holdings in the same industry of the IPO firm ranking in the top half

among all bidding mutual funds. We provide details on constructing these proxies in Appendix B. In Table 10 we find that our results on choosing the offer price are robust to controlling for proxies for information production, market stabilization, the clientele effect, mutual fund size, mutual fund history, and mutual fund management fee.

7. UNDERWRITER CHARACTERISTICS AND THE EFFECTS OF RENT SEEKING

We have shown robust evidence that underwriters favor mutual funds in pricing IPOs for brokerage commissions by discounting the offer price and choosing the price level at which mutual fund orders cluster as the offer price. In this section, we explore how our main findings are affected by underwriter characteristics.

Specifically, we argue that if an underwriter relies more on the brokerage commission revenue, the effects of underwriters' rent-seeking incentives would be more pronounced on price discounting, initial returns, and price setting. A typical underwriter in our setting balances two relationships when pricing IPOs: the relationship with offering firms and the relationship with brokerage clients. The offering firms prefer a higher offer price, which would also generate more underwriting commissions for the underwriters. Meanwhile, investors prefer a lower offer price, though they would pay brokerage commissions to reward the underwriter in the long run. It is hence reasonable to conjecture that if an underwriter relies more on the brokerage business, it would put more weight on the interests of brokerage clients due to two reasons. First, the brokerage business represents a more important source of revenue for the underwriter. Second, the underwriter has closer business relationships with investors, which makes it more convenient for the underwriter and the investors to arrange profit sharing mechanisms.

We measure the importance of brokerage business to an underwriter by the total amount of brokerage commissions it received in the year prior to the IPO, and define a *TopBroker* dummy that equals one if the underwriter ranks in the top tercile (the largest tercile) in terms of brokerage commissions among all underwriters, and zero otherwise. To test the impact of an underwriter's

brokerage business on its favoritism towards mutual funds, we interact *TopBroker* with the variables of interest: *Discount*, *IR* (equation (5)), and *Sel* (equation (7)).

Panel A in Table 11 reports the Tobit regression results on *Discount* with the interaction terms *SkewPayComm*TopBroker* and *SkewHighComm*TopBroker* as key independent variables of interest. Columns (1) and (2) show that with the top tercile prices as the cutoff for calculating skewness measures, the coefficient estimates on the interaction terms are negative and significant at the 10% and 1% level, respectively. We find similar results in columns (3) and (4), where an alternative quartile cutoff is used. Our findings suggest that the effects of rent seeking on price discounting are more pronounced for underwriters that are top brokers.

Panel B reports the regression results on *IR* with similar specifications in Panel A. As shown in columns (3) and (4), if we use top quartile as the cutoff to calculate the skewness measures, the coefficient estimates on the interaction terms, *SkewPayComm*TopBroker* and *SkewHighComm*TopBroker*, are negative and significant at the 5% level, suggesting that the effects of rent seeking on initial returns are more pronounced for top brokers. Results with the top tercile cutoff are insignificant but with a sign consistent with our conjecture.

Panel C reports the price-level conditional logit regressions results on the probability a price is selected as the offer price following equation (7). We interact the *TopBroker* dummy with the fraction of demand from (high) commission-paying mutual funds (*DmdPayComm* and *DmdHighComm*) to test whether the size of brokerage business affects underwriters' rent seeking. The coefficient estimate in column (1) on *DmdPayComm*TopBroker* is positive and significant at the 5% level, which suggests that top brokers favor commission-paying mutual funds to a larger degree. The estimate for *DmdHighComm*TopBroker* is insignificant but with a positive sign in column (2).

In general, we find evidence consistent with the notion that rent-seeking incentives are stronger for underwriters that are top brokers. They discount the offer price to a greater extent to include more orders from commission-paying mutual funds for allocation, which are associated with larger initial returns.

They are also more likely to choose price levels at which there are more demand from commission-paying mutual funds as the offer price.

8. ALTERNATIVE EXPLANATIONS

In the analyses presented so far in this paper, we have shown that a strong and robust relation exists between brokerage commissions paid to IPO underwriters and IPO offer prices. We interpret these findings as underwriters deliberately lowering the IPO offer price to include more orders from their profit-sharing brokerage clients for IPO share allocation, which is consistent with the predictions of the rent-seeking theory. An alternative explanation of our findings, however, is that underwriters may give advice or leak information to the institutional investors that they want to favor to bid a somewhat higher price to get more IPO share allocations. That is, investors use brokerage commissions to "tip" underwriters for the confidential book-building information and take advantage of other investors.

However, this tipping mechanism, while it may be plausible occasionally in some individual IPOs, is unlikely to be sustainable across all IPOs in our sample. It is hard to rationalize such behavior in practice. First, in case the offer prices are set higher due to such high-price bids, it is not only costly for institutional investors, but will favor offering firms and underwriters as well. In fact, this mechanism implies that institutional investors are paying underwriters for receiving lower IPO returns. Second, it is illegal for underwriters to leak information about their books to investors during the pricing process. If the information leakage is caught by the CSRC or other market participants, underwriters may incur huge costs, including large fines, suspension or revocation of investment banking licenses, loss of investor clients, damaged reputation, and even lawsuits. It is hard to believe that the profits from tipping would justify such potentially large costs.

We next do additional tests, attempting to rule out this alternative tipping explanation of our results. To conduct these tests, we make use of a unique institutional feature of Chinese stock markets. In China, every year the CSRC issues a compliance rating for all underwriters based on their capital adequacy, corporate governance and legal compliance, risk monitoring, and some other indicators. If the

illegal tipping mechanism works, its effect on IPO pricing should be less pronounced among underwriters with higher rating scores and hence smaller risk of violating regulations. If, however, we observe similar results on brokerage commissions regardless of whether the underwriter has a high or low compliance rating score, the tipping explanation is less likely to hold.

We follow the specifications in Section 7 and replace the *TopBroker* dummy with a *Compliance* dummy that equals one if an underwriter is rated as an AA bank (the highest rating) by the CSRC in the year prior to the IPO, and zero otherwise. In the regressions with the dependent variable being *Discount* and *IR* in equation (5), the main variable of interest is the interaction term, *SkewPayComm*Compliance*; in the conditional logit regressions with the dependent variable of S*el* in equation (7), the variable of interest is *DmdPayComm*Compliance*. If the tipping mechanism holds, we expect the coefficients on these interaction terms to have the signs opposite to those of *SkewPayComm* and *DmdPayComm*, suggesting a less pronounced tipping effect for more compliant underwriters.

We report the results in Appendix C. We do not find significant results consistent with the predictions of the tipping explanation. First, the coefficient estimates on *SkewPayComm* and *DmdPayComm* are qualitatively unchanged after controlling for *Compliance* and the interaction terms (see Tables 3, 6, and 9 for the baseline results), suggesting that our main results are robust after we take underwriters' propensity for conducting illegal activities into account. Second, the coefficient estimate(s) on the interaction terms have the same sign as the commission measures across all regressions. All estimates are insignificant except in column (2) in Panel A. These results are inconsistent with the predictions of the tipping explanation. In untabulated analyses, we use another commission measure, *SkewHighComm*, and an alternative proxy that captures an underwriter's violation cost, its ranking in the underwriting league table, in various regressions. We do not find any evidence supporting the tipping explanations in these tests either.

Finally, it should be noted that, while our findings cannot be explained by the tipping mechanism, we are not claiming that lowering the offer price is the only way to favor commission-paying investors. Our objective in this paper is to provide evidence that there exists an important (and legal) way through

which IPO underwriters are able to favor certain institutions by lowering IPO offer prices, making more of their orders qualify for pro rata share allocations.

9. CONCLUSION

In this paper, we have examined the effects of underwriters' rent-seeking incentives on IPO pricing. Using a unique dataset containing investor bidding information for 175 Chinese IPOs, we find that underwriters exhibit strong favoritism towards mutual funds that pay brokerage commissions to them when pricing IPOs. Specifically, because Chinese underwriters do not have discretionary share allocation rights in IPOs, they favor and compensate commission-paying mutual funds by setting IPO offer prices in such a way as to make more orders from these mutual funds eligible for share allocations based on a *pro rata* basis, which in turn increases IPO initial returns. Underwriters are also more likely to choose price levels at which there are more orders from commission-paying mutual funds as the IPO offer price. The effects of rent seeking are more pronounced when an underwriter is a top player in the brokerage business, which means that the underwriter cares more about the interests of bidding investors rather than that of the issuing firm, and is therefore more eager to establish a profit-sharing mechanism with these investors. This study fills the void in the literature on how agency problems affect IPO price setting by showing that underwriters deliberately lower IPO offer prices in return for receiving brokerage commissions. Our paper also sheds new light on how IPO shares are bid for and priced; and how shares are allocated in practice using detailed information on underwriter's order books. Overall, our findings provide significant support for the theoretical analysis of Fulghieri and Spiegel (1993) in that we are able to show empirically that an important factor that drives IPO pricing and share allocation is the desire of IPO underwriters to reward their clients from their non-IPO underwriting businesses by giving them greater share allocations in underpriced IPOs.

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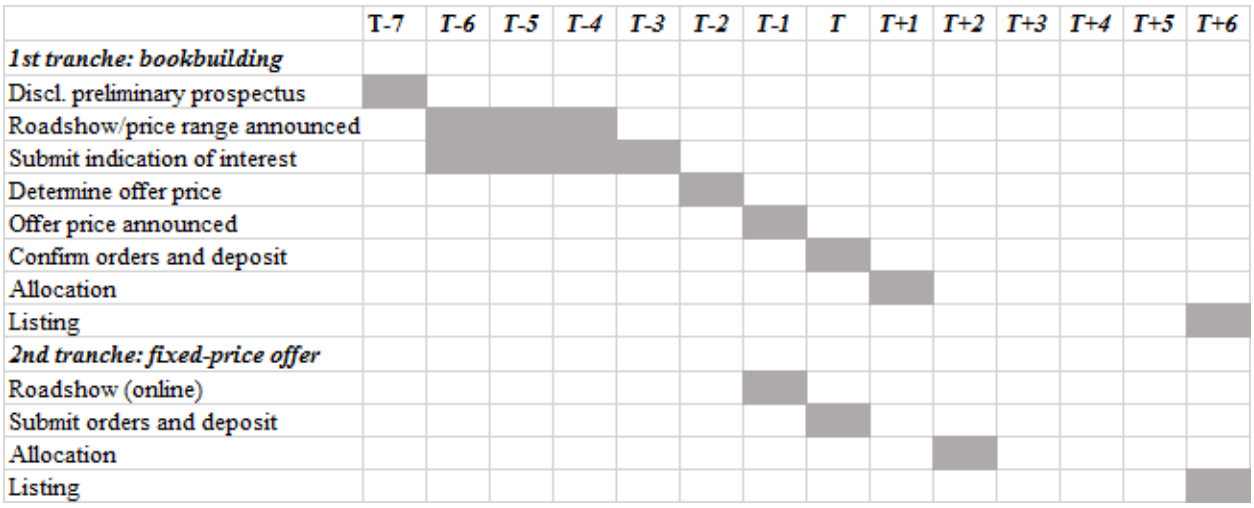
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Figure 1
The structure and timeline of a typical Chinese IPO



* *T* denotes the official issuance/offering date.

Table 1

Summary statistics.

This table reports summary statistics for characteristics on the offers, bidding patterns, and investor participation. The sample consists of 175 Chinese IPOs between October 2011 and October 2012.

Panel A: Deal Characteristics

Market	N. Deals	Shares Offered (millions)	Bookbuild Shares (%)	Proceeds (billion RMB)	Firm Age (years)	VC-backed (%)	Distance (%)	Distance>0 (%)	Initial Return (%)
CHINext	78	2.28	6.43	0.47	10.62	66.67	8.92	89.74	22.00
SME	71	3.72	5.78	0.63	10.70	50.70	8.52	88.73	28.87
MAIN	26	13.95	5.53	1.43	11.47	57.69	6.04	92.31	39.00
All	175	4.60	6.03	0.67	10.78	58.86	8.33	89.71	27.31

Panel B: Bidding Characteristics

Market	N. Bids	N. Inst.	N. Bidders	Total Demand	Bookbuild Demand	Offer/Bidding Price	Price STD%	Elasticity at offer price	Order Concen.
CHINext	86.60	45.64	79.22	42.69	20.94	0.91	15.16	63.01	3.44
SME	95.92	46.30	84.17	50.39	23.60	0.89	15.26	72.85	4.10
MAIN	144.08	56.88	115.12	28.55	18.38	0.93	15.49	30.88	3.76
All	98.92	47.58	86.56	43.71	21.64	0.90	15.25	62.23	3.76

Panel C: Investor Participation Characteristics

Investor Type	N. Bids	N. Inst.	N. Bidders	Demand in Shares (%)	Demand in Dollars (%)	Eligible Shares (%)	Bid Size (million shares)	Bid Size (million RMB)	Allocation (%)
Fund	7,681	61	484	42.35	44.75	43.01	5.50	74.15	42.83
Inv. bank	4,327	75	211	22.97	23.39	24.81	5.30	68.80	25.50
Insurance	1,617	12	116	12.92	10.53	9.36	7.98	82.91	7.68
Trust	882	26	42	5.73	5.53	6.58	6.49	79.74	6.86
Financial	630	25	27	4.09	3.76	3.85	6.47	76.02	4.04
Other	2,174	149	243	11.93	12.03	12.39	5.48	70.41	13.10
All	17,311	348	1,123	100.00	100.00	100.00	5.77	73.51	100.00

Table 2

Investor participation and deliberate underpricing.

This table reports deal-level Tobit regression results on the relation between the skewness of investor demand schedules and the pricing discount from market clearing price. The sample consists of 175 Chinese IPOs priced below the market clearing price between October 2011 and October 2012. The dependent variable is the percentage discount from the market clearing price, calculated by (market clearing price – offer price)/market clearing price*100. The skewness for an investor type's demand schedules is calculated as (demand with top 1/3 prices from investor/total demand from investor)/(demand with top 1/3 prices/total demand) for Panel A, and with top 1/4 prices for Panel B. See Appendix B for definitions of variables. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Top 1/3					*Panel B: Top 1/4*				
Y =	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Discount%	*Fund*	*Inv. Bank*	*Insurance*	*Trust*	*Financial*	*Fund*	*Inv. Bank*	*Insurance*	*Trust*	*Financial*
SkewInvs	-2.045***	1.930***	0.582	0.166	-0.139	-1.612***	1.328***	-0.016	-0.216	-0.040
	(0.776)	(0.662)	(0.882)	(0.235)	(0.324)	(0.567)	(0.375)	(0.679)	(0.158)	(0.232)
SkewDemand	-0.112***	-0.110***	-0.153***	-0.123***	-0.122***	-0.148***	-0.148***	-0.195***	-0.153***	-0.169***
	(0.021)	(0.021)	(0.037)	(0.021)	(0.021)	(0.023)	(0.023)	(0.043)	(0.024)	(0.024)
Assets	0.266	-0.266	2.079**	0.310	0.187	0.028	-0.455	2.381***	0.114	0.009
	(0.550)	(0.531)	(0.855)	(0.551)	(0.587)	(0.526)	(0.516)	(0.854)	(0.544)	(0.553)
TDemand	0.040***	0.045***	0.018	0.042***	0.038***	0.042***	0.045***	0.026**	0.040***	0.034***
	(0.007)	(0.007)	(0.011)	(0.007)	(0.008)	(0.007)	(0.007)	(0.011)	(0.007)	(0.007)
NIns	0.094***	0.074***	0.185***	0.094***	0.089***	0.102***	0.092***	0.147***	0.094***	0.104***
	(0.027)	(0.026)	(0.047)	(0.027)	(0.028)	(0.026)	(0.026)	(0.046)	(0.027)	(0.027)
LargeIns	0.002	0.021	-0.036	0.019	0.038	0.009	0.024	0.055	0.020	0.044
	(0.027)	(0.027)	(0.075)	(0.028)	(0.029)	(0.027)	(0.026)	(0.080)	(0.027)	(0.028)
HighBids	0.430***	0.363***	0.557***	0.407***	0.464***	0.407***	0.321***	0.540***	0.420***	0.431***
	(0.086)	(0.085)	(0.201)	(0.091)	(0.088)	(0.080)	(0.081)	(0.191)	(0.087)	(0.084)
IPORtn	0.864***	0.787***	-0.036	0.664***	0.798***	1.047***	0.903***	-0.298	0.840***	0.912***
	(0.246)	(0.242)	(0.442)	(0.248)	(0.249)	(0.236)	(0.229)	(0.446)	(0.239)	(0.234)
MktRtn	-0.312***	-0.262***	-0.155	-0.235***	-0.215***	-0.377***	-0.312***	-0.104	-0.275***	-0.233***
	(0.076)	(0.074)	(0.145)	(0.076)	(0.079)	(0.075)	(0.070)	(0.144)	(0.074)	(0.074)
MktVola	-8.496***	-8.249***	2.411	-8.998***	-11.270***	-10.185***	-9.741***	3.833	-10.619***	-12.386***
	(2.898)	(2.892)	(4.987)	(2.909)	(2.971)	(2.801)	(2.776)	(4.918)	(2.874)	(2.862)

Exchange	-0.921	0.425	-3.306*	-1.990	-0.342	-1.085	0.092	-2.969	-1.511	-0.481
	(1.353)	(1.355)	(1.857)	(1.420)	(1.434)	(1.321)	(1.296)	(1.804)	(1.410)	(1.366)
Constant	-2.592	-4.130	0.404	1.648	-0.870	-7.551	-7.548	4.408	-3.568	-5.643
	(6.112)	(6.181)	(11.038)	(6.200)	(6.153)	(5.618)	(5.531)	(11.098)	(5.774)	(5.616)
Year, under., and ind. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	175	175	103	167	163	175	175	103	167	163
Pseudo R^2	0.322	0.324	0.193	0.325	0.328	0.329	0.333	0.197	0.328	0.339

Table 3

Rent seeking and deliberate underpricing.

This table reports deal-level Tobit regression results on the relation between the skewness of the demand schedule of mutual funds whose families pay commissions to underwriters and the pricing discount from the market clearing price. The sample consists of 175 Chinese IPOs priced below the market clearing price between October 2011 and October 2012. The dependent variable is the percentage discount from the market clearing price, calculated by (market clearing price – offer price)/market clearing price*100. The skewness of the demand schedule of commission-paying mutual fund is calculated as (demand with top 1/3 prices from (above median) commission-paying mutual funds/total demand from (above median) commission-paying mutual funds)/(demand with top 1/3 prices/total demand) for Panel A, and with top 1/4 prices for Panel B. Other variables are defined as in Table 2. See Appendix B for definitions of variables. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Top 1/3		*Panel B: Top 1/4*	
Y = Discount%	(1)	(2)	(3)	(4)
SkewPayComm	-3.313**		-2.142***	
	(1.279)		(0.711)	
SkewHighComm		-0.935		-0.756*
		(0.611)		(0.414)
SkewFund	1.412	-1.203	0.478	-0.999
	(1.519)	(0.949)	(0.907)	(0.656)
SkewDemand	-0.098***	-0.112***	-0.132***	-0.146***
	(0.022)	(0.021)	(0.023)	(0.023)
Assets	0.123	0.240	-0.114	-0.062
	(0.547)	(0.548)	(0.518)	(0.525)
TDemand	0.044***	0.041***	0.045***	0.041***
	(0.007)	(0.007)	(0.007)	(0.007)
NIns	0.081***	0.090***	0.087***	0.101***
	(0.027)	(0.027)	(0.027)	(0.026)
LargeIns	0.007	0.001	0.006	0.006
	(0.027)	(0.027)	(0.026)	(0.026)
HighBids	0.415***	0.419***	0.376***	0.386***
	(0.085)	(0.086)	(0.080)	(0.081)
IPORtn	0.818***	0.811***	0.937***	0.985***
	(0.248)	(0.247)	(0.238)	(0.237)
MktRtn	-0.282***	-0.300***	-0.346***	-0.367***
	(0.076)	(0.076)	(0.074)	(0.074)
MktVola	-7.769**	-7.947***	-8.123***	-9.354***
	(2.975)	(2.909)	(2.890)	(2.819)
Exchange	-0.449	-0.656	-0.673	-0.935
	(1.359)	(1.359)	(1.312)	(1.315)
Constant	-2.330	-1.315	-5.862	-6.084
	(6.103)	(6.146)	(5.614)	(5.639)
Year, under., and ind. FE	YES	YES	YES	YES
Observations	172	174	172	174
Pseudo R^2	0.327	0.323	0.336	0.331

Table 4

Robustness tests: rent seeking and deliberate underpricing.

This table reports deal-level Tobit regression results on the relation between the skewness of demand from mutual funds whose families pay commissions to underwriters and the pricing discount from market clearing price, controlling for other mutual fund characteristics. The sample consists of 175 Chinese IPOs priced below the market clearing price between October 2011 and October 2012. The control variable for a characteristic is the skewness of demand from mutual fund of which the characteristic ranks in the top half among mutual funding bidding for the deal, calculated with the demands with top 1/3 prices as in Table 3. Other variables are defined as in Table 3. See Appendix B for definitions of variables. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	With controls for other fund characteristics, Control = Skew-								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Y = Discount%	*IndExp*	*InvRtn*	*IPORtn*	*Hold*	*NoFlip*	*NIPO*	*Assets*	*History*	*Fee*
SkewPayComm	-3.423***	-3.184**	-3.336**	-3.480***	-3.369**	-3.342**	-3.349**	-2.606*	-3.258**
	(1.286)	(1.275)	(1.292)	(1.279)	(1.281)	(1.344)	(1.279)	(1.351)	(1.293)
SkewFund	1.033	0.667	1.331	0.511	0.969	1.382	1.056	-1.037	1.606
	(1.600)	(1.653)	(1.647)	(1.661)	(1.669)	(1.578)	(1.626)	(2.194)	(1.659)
SkewDemand	-0.097***	-0.099***	-0.098***	-0.100***	-0.099***	-0.098***	-0.099***	-0.105***	-0.097***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Assets	0.114	0.277	0.113	0.049	0.071	0.122	0.179	0.110	0.134
	(0.546)	(0.552)	(0.553)	(0.547)	(0.553)	(0.548)	(0.554)	(0.544)	(0.548)
TDemand	0.045***	0.043***	0.044***	0.043***	0.044***	0.044***	0.045***	0.042***	0.044***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
NIns	0.078***	0.088***	0.081***	0.085***	0.081***	0.080***	0.079***	0.087***	0.081***
	(0.027)	(0.028)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
LargeIns	0.009	-0.000	0.008	0.008	0.007	0.007	0.006	0.008	0.007
	(0.027)	(0.028)	(0.028)	(0.027)	(0.027)	(0.028)	(0.027)	(0.027)	(0.027)
HighBids	0.421***	0.404***	0.416***	0.419***	0.415***	0.415***	0.417***	0.421***	0.413***
	(0.086)	(0.085)	(0.086)	(0.085)	(0.085)	(0.085)	(0.085)	(0.085)	(0.086)
IPORtn	0.817***	0.832***	0.816***	0.801***	0.822***	0.819***	0.838***	0.795***	0.827***
	(0.247)	(0.252)	(0.248)	(0.247)	(0.247)	(0.248)	(0.250)	(0.246)	(0.250)
MktRtn	-0.279***	-0.310***	-0.281***	-0.269***	-0.279***	-0.283***	-0.286***	-0.277***	-0.286***
	(0.076)	(0.080)	(0.077)	(0.076)	(0.076)	(0.077)	(0.076)	(0.076)	(0.077)
MktVola	-7.858**	-7.289**	-7.731**	-7.676**	-7.843**	-7.779**	-8.227***	-7.855***	-7.767**
	(2.973)	(2.995)	(2.991)	(2.961)	(2.974)	(2.979)	(3.066)	(2.956)	(2.975)

Exchange	-0.436	-0.762	-0.413	-0.161	-0.285	-0.445	-0.596	-0.360	-0.448
	(1.357)	(1.372)	(1.389)	(1.370)	(1.382)	(1.360)	(1.379)	(1.351)	(1.359)
Control	0.462	0.602	0.101	1.006	0.481	0.068	0.594	1.636	-0.217
	(0.619)	(0.769)	(0.800)	(0.770)	(0.757)	(1.004)	(0.977)	(1.064)	(0.744)
Constant	-2.080	-3.183	-2.366	-2.419	-2.330	-2.335	-2.279	-1.919	-2.656
	(6.103)	(6.162)	(6.109)	(6.074)	(6.096)	(6.104)	(6.097)	(6.068)	(6.203)
Year, under., and ind. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	172	171	172	172	172	172	172	172	172
Pseudo R^2	0.327	0.329	0.327	0.328	0.327	0.327	0.327	0.329	0.327

Table 5

Investor participation and initial returns.

This table reports deal-level OLS regression results on the relation between the skewness of investor demand and IPO initial returns. The sample consists of 175 Chinese IPOs priced below the market clearing price between October 2011 and October 2012. The dependent variable is IPO initial return, calculated by (first-day closing price – offer price)/offer price*100. Skewness and other variables are defined as in Table 2. See Appendix B for definitions of variables. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A :Top 1/3					*Panel B: Top 1/4*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Y = IR%	*Fund*	*Inv. Bank*	*Insurance*	*Trust*	*Financial*	*Fund*	*Inv. Bank*	*Insurance*	*Trust*	*Financial*
SkewInvs	-14.365***	-3.646	5.968*	0.218	3.091	-7.985***	-1.269	0.816	0.273	2.069
	(3.906)	(4.812)	(3.060)	(0.855)	(2.057)	(2.084)	(2.269)	(2.069)	(0.605)	(1.120)
SkewDemand	0.166	0.124	-0.121	0.141	0.141	-0.037	-0.056	-0.427	-0.060	-0.052
	(0.116)	(0.109)	(0.127)	(0.088)	(0.099)	(0.184)	(0.181)	(0.354)	(0.171)	(0.194)
Elasticity	-0.022*	-0.025*	-0.039	-0.025*	-0.027**	-0.020**	-0.022*	-0.039	-0.022*	-0.026**
	(0.010)	(0.012)	(0.039)	(0.011)	(0.010)	(0.008)	(0.010)	(0.039)	(0.010)	(0.008)
Assets	7.336	5.587	7.556	5.128	6.080	6.060	5.351	7.202	4.725	6.083
	(5.452)	(5.927)	(11.032)	(6.542)	(6.674)	(5.096)	(5.689)	(10.522)	(6.026)	(6.494)
TDemand	0.805***	0.821***	0.824***	0.817***	0.796***	0.809***	0.816***	0.812***	0.813***	0.805***
	(0.061)	(0.062)	(0.063)	(0.068)	(0.068)	(0.060)	(0.064)	(0.077)	(0.067)	(0.065)
NIns	-0.376	-0.438*	-0.441	-0.413*	-0.411*	-0.327	-0.387	-0.383	-0.361	-0.358
	(0.230)	(0.223)	(0.301)	(0.219)	(0.213)	(0.253)	(0.259)	(0.410)	(0.258)	(0.249)
LargeIns	-0.267**	-0.246**	-0.178	-0.229*	-0.238	-0.215***	-0.208**	-0.113	-0.203**	-0.230*
	(0.085)	(0.106)	(0.158)	(0.116)	(0.129)	(0.045)	(0.064)	(0.064)	(0.069)	(0.103)
HighBids	1.495**	1.472**	1.464	1.541**	1.609**	1.067**	1.085***	1.139	1.123**	1.313***
	(0.463)	(0.563)	(0.843)	(0.603)	(0.625)	(0.334)	(0.241)	(0.638)	(0.349)	(0.349)
IPORtn	-5.763**	-6.850**	-8.105*	-6.821**	-6.950**	-6.192*	-7.067**	-8.572*	-7.160**	-7.427**
	(2.429)	(2.437)	(3.907)	(2.769)	(2.308)	(3.009)	(2.654)	(4.120)	(2.999)	(2.786)
MktRtn	-0.160	0.352	0.758	0.342	0.403	0.042	0.437	0.951	0.429	0.527
	(0.509)	(0.448)	(0.749)	(0.415)	(0.432)	(0.724)	(0.525)	(0.795)	(0.468)	(0.610)
MktVola	85.940***	79.740**	62.088**	87.223**	87.225***	83.327**	81.080***	63.268**	88.474**	90.066**
	(25.447)	(24.656)	(20.284)	(26.830)	(24.014)	(25.373)	(23.684)	(21.180)	(27.634)	(27.716)

Exchange	20.680	23.185	21.909	26.716*	21.935	21.654*	23.012	21.452	26.417*	21.856
	(11.724)	(12.976)	(17.499)	(13.851)	(14.019)	(11.616)	(13.296)	(20.226)	(13.969)	(14.917)
Reputation	4.009	3.126	3.442	4.106	4.012	3.240	2.483	1.887	3.638	3.752
	(7.734)	(6.741)	(5.411)	(7.483)	(6.907)	(7.160)	(6.494)	(5.225)	(7.887)	(6.408)
Constant	49.008	77.039	130.981*	59.635	62.243	63.261	84.647	152.034	73.578	78.044
	(37.937)	(47.665)	(64.074)	(42.929)	(35.717)	(54.698)	(50.989)	(81.882)	(48.943)	(49.410)
Year and ind. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	175	175	103	167	163	175	175	103	167	163
R^2	0.777	0.763	0.806	0.769	0.772	0.768	0.761	0.808	0.768	0.770

Table 6

Rent seeking and initial returns.

This table reports deal-level OLS regression results on the relation between the skewness of demand from mutual funds whose families pay commissions to underwriters and IPO initial returns. The sample consists of 175 Chinese IPOs priced below the market clearing price between October 2011 and October 2012. The dependent variable is IPO initial return, calculated by (first-day closing price – offer price)/offer price*100. Skewness and other variables are defined as in Table 3. See Appendix B for definitions of variables. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Top 1/3		*Panel B: Top 1/4*	
Y = IR%	(1)	(2)	(3)	(4)
SkewPayComm	-7.183***		-4.645***	
	(1.141)		(0.527)	
SkewHighComm		-4.773		-5.182**
		(2.997)		(1.605)
SkewFund	-9.415*	-11.236	-2.883	-2.488
	(4.714)	(8.456)	(3.170)	(3.570)
SkewDemand	0.168	0.150	-0.044	-0.085
	(0.101)	(0.141)	(0.195)	(0.195)
Elasticity	-0.025*	-0.023**	-0.023**	-0.021**
	(0.011)	(0.010)	(0.008)	(0.009)
Assets	6.722	6.841	5.868	5.620
	(6.204)	(5.656)	(6.001)	(5.136)
TDemand	0.810***	0.805***	0.818***	0.806***
	(0.056)	(0.064)	(0.055)	(0.062)
NIns	-0.354	-0.361	-0.327	-0.310
	(0.233)	(0.224)	(0.266)	(0.251)
LargeIns	-0.276***	-0.255***	-0.242***	-0.219***
	(0.049)	(0.066)	(0.020)	(0.028)
HighBids	1.385**	1.401*	0.937**	0.842*
	(0.438)	(0.615)	(0.284)	(0.441)
IPORtn	-5.765*	-5.916**	-6.031	-6.119*
	(2.846)	(2.471)	(3.419)	(3.052)
MktRtn	-0.070	-0.104	0.062	0.004
	(0.635)	(0.529)	(0.835)	(0.719)
MktVola	87.594***	88.103***	84.118***	84.695***
	(20.585)	(25.031)	(17.988)	(25.141)
Exchange	21.670	22.079	21.772	22.271*
	(13.561)	(12.009)	(14.494)	(11.728)
Reputation	3.742	4.238	2.203	2.748
	(6.754)	(8.180)	(5.378)	(7.418)
Constant	48.765	51.701	59.758	61.736
	(42.231)	(39.456)	(63.954)	(56.538)
Year and ind. FE	YES	YES	YES	YES
Observations	172	174	172	174
R^2	0.782	0.778	0.773	0.772

Table 7

Robustness tests: rent seeking and initial returns.

This table reports deal-level OLS regression results on the relation between the skewness of demand from mutual funds whose families pay commissions to underwriters and IPO initial returns, controlling for other mutual fund characteristics. The sample consists of 175 Chinese IPOs priced below the market clearing price between October 2011 and October 2012. The dependent variable is IPO initial return, calculated by (first-day closing price – offer price)/offer price*100. Skewness, control and other variables are defined as in Table 6. See Appendix B for definitions of variables. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	With controls for fund other characteristics, Control = Skew-								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Y = IR%	*IndExp*	*InvRtn*	*IPORtn*	*Hold*	*NoFlip*	*NIPO*	*Assets*	*History*	*Fee*
SkewPayComm	-4.398***	-5.130**	-4.844**	-5.278***	-5.293**	-4.713***	-5.230**	-6.675*	-4.457***
	(0.666)	(1.548)	(1.552)	(1.364)	(1.439)	(0.907)	(1.564)	(2.962)	(1.018)
SkewFund	-5.488	-14.727*	0.231	-15.136	-12.918*	-21.019	-3.309	-3.312	0.652
	(3.353)	(6.775)	(5.437)	(10.213)	(6.372)	(14.758)	(3.812)	(6.767)	(4.800)
SkewDemand	0.194	0.171	0.233*	0.192	0.191	0.154	0.194	0.200	0.213
	(0.110)	(0.140)	(0.113)	(0.105)	(0.108)	(0.083)	(0.105)	(0.123)	(0.124)
Elasticity	-0.020**	-0.020**	-0.024**	-0.021	-0.020*	-0.023	-0.023**	-0.022*	-0.016**
	(0.008)	(0.008)	(0.009)	(0.012)	(0.009)	(0.013)	(0.009)	(0.011)	(0.006)
Assets	8.067	8.618	8.438	8.084	8.125	7.945	7.840	8.726	9.474
	(6.081)	(5.677)	(6.460)	(6.476)	(6.540)	(6.435)	(6.394)	(7.064)	(7.009)
TDemand	0.843***	0.846***	0.851***	0.845***	0.846***	0.840***	0.839***	0.855***	0.847***
	(0.051)	(0.057)	(0.052)	(0.052)	(0.051)	(0.056)	(0.048)	(0.040)	(0.049)
NIns	-0.404	-0.401	-0.439	-0.409	-0.416	-0.388	-0.404	-0.424	-0.424
	(0.244)	(0.239)	(0.259)	(0.248)	(0.244)	(0.258)	(0.232)	(0.240)	(0.229)
LargeIns	-0.260***	-0.292***	-0.345***	-0.292***	-0.285***	-0.260***	-0.224***	-0.271***	-0.223***
	(0.017)	(0.055)	(0.042)	(0.066)	(0.053)	(0.032)	(0.050)	(0.033)	(0.017)
HighBids	1.319***	1.342**	1.439***	1.444***	1.431***	1.292***	1.364***	1.369***	1.386***
	(0.272)	(0.504)	(0.305)	(0.370)	(0.357)	(0.258)	(0.307)	(0.282)	(0.335)
IPORtn	-1.275***	-1.200***	-1.106***	-1.242***	-1.231***	-1.267***	-1.320***	-1.187***	-1.083***
	(0.143)	(0.130)	(0.132)	(0.142)	(0.142)	(0.144)	(0.154)	(0.157)	(0.229)
MktRtn	-0.625**	-0.704*	-0.693**	-0.573**	-0.588**	-0.593**	-0.533*	-0.675*	-0.838**
	(0.240)	(0.305)	(0.243)	(0.233)	(0.227)	(0.242)	(0.248)	(0.283)	(0.265)

MktVola	43.699***	43.279**	37.042***	41.972***	41.562***	43.369***	42.856***	43.785***	46.108***
	(4.188)	(16.340)	(4.587)	(3.741)	(4.442)	(3.274)	(4.544)	(3.352)	(3.427)
Exchange	19.854	18.989	17.879	20.003	19.583	19.762	19.830	18.542	18.533
	(13.089)	(11.872)	(14.541)	(13.130)	(13.984)	(13.919)	(13.951)	(15.166)	(13.761)
Reputation	5.940	4.801	6.573	5.160	5.238	5.372	5.943	4.973	5.831
	(7.577)	(9.569)	(6.995)	(6.658)	(6.835)	(7.220)	(7.095)	(6.770)	(7.105)
Control	-7.592	2.056	-12.342***	2.177	0.357	8.637	-10.892***	-7.378	-12.504
	(6.882)	(1.870)	(1.065)	(4.844)	(1.590)	(10.510)	(1.709)	(8.895)	(8.031)
Constant	-12.931**	-11.923	-8.744	-9.877*	-9.749*	-10.668*	-9.075*	-14.307	-22.856*
	(5.052)	(29.176)	(4.769)	(4.477)	(4.377)	(5.245)	(4.415)	(9.355)	(11.622)
Year and ind. FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	172	171	172	172	172	172	172	172	172
R^2	0.781	0.780	0.783	0.777	0.777	0.779	0.781	0.779	0.786

Table 8

Investor participation and determination of offer price.

This table reports price-level conditional logistic regression results on the relation between investor participation and the probability that a price level is selected as the offer price. The sample consists of 5,436 price levels below the market clearing price from the demand schedules of 175 Chinese IPOs between October 2011 and October 2012. The dependent variable is a selection dummy that equals one if a price level is selected as the offer price, and zero otherwise. Columns (1) to (5) report results with the fraction of demand in shares from mutual funds, investment banks, insurance companies, trust firms, and financial firms as the main independent variable, respectively. See Appendix B for definitions of variables. Odds ratios are reported. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Y = Sel	*Fund*	*Inv. bank*	*Insurance*	*Trust*	*Financial*
DmdInvs	1.004*	0.997	1.003	1.000	0.998
	(0.002)	(0.002)	(0.004)	(0.003)	(0.006)
Demand	1.113***	1.115***	1.118***	1.119***	1.119***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Elasticity	1.001**	1.001**	1.001**	1.001**	1.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sdemand	1.033***	1.033***	1.033***	1.033***	1.033***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Disc	0.875***	0.874***	0.874***	0.875***	0.875***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Deal FE	YES	YES	YES	YES	YES
Observations	5,436	5,436	5,436	5,436	5,436
Pseudo R^2	0.191	0.190	0.188	0.188	0.188

Table 9

Rent seeking and determination of offer price.

This table reports price-level conditional logistic regression results on the relation between the participation of mutual funds paying commission to underwriters and the probability that a price level is selected as the offer price. The sample consists of 5,436 price levels below the market clearing price from the demand schedules of 175 Chinese IPOs between October 2011 and October 2012. The dependent variable is a selection dummy that equals one if a price level is selected as the offer price and zero otherwise. Columns (1) and (2) report results with the fractions of demand from mutual funds by whose fund families the commissions paid to the underwriters are above zero and rank in the top half among all mutual funds bidding for the deals as main independent variables. See Appendix B for definitions of variables. Odds ratios are reported. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Y = Sel	(1)	(2)
DmdPayComm	1.017***	
	(0.003)	
DmdHighComm		1.007***
		(0.002)
DmdFund	0.991***	1.000
	(0.003)	(0.002)
Demand	1.068**	1.101***
	(0.028)	(0.028)
Elasticity	1.001**	1.001**
	(0.000)	(0.000)
Sdemand	1.035***	1.032***
	(0.010)	(0.010)
Discount	0.866***	0.874***
	(0.013)	(0.013)
Deal FE	YES	YES
Observations	5,436	5,436
Pseudo R^2	0.223	0.199

Table 10

Robustness tests: Rent seeking and determination of offer price.

This table reports price-level conditional logistic regression results on the relation between the participation of mutual funds paying commissions to underwriters and the probability that a price level is selected as the offer price, controlling for other mutual fund characteristics. The sample consists of 5,436 price levels below the market clearing price from the demand schedules of 175 Chinese IPOs between October 2011 and October 2012.The control variable for a characteristic is calculated as the fraction of demand from mutual fund of which the characteristic ranks in the top half among all mutual funds bidding for the deal. Other variables are defined as in Table 9. See Appendix B for definitions of variables. Odds ratios are reported. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	With controls for other fund characteristics, Control =Dmd-								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Y = Sel_Dummy	*IndExp*	*InvRtn*	*NIPO*	*IPORtn*	*Hold*	*NoFlip*	*Assets*	*History*	*Fee*
DmdPayComm	1.015***	1.016***	1.016***	1.015***	1.016***	1.016***	1.016***	1.013***	1.016***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
DmdFund	0.990***	0.991***	0.991***	0.990***	0.991***	0.990***	0.990***	0.989***	0.991***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Demand	1.067**	1.067**	1.066**	1.066**	1.068**	1.067**	1.063**	1.063**	1.068**
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Elasticity	1.001**	1.001**	1.001**	1.001**	1.001**	1.001**	1.001**	1.001**	1.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sdemand	1.034***	1.035***	1.035***	1.035***	1.035***	1.035***	1.034***	1.034***	1.034***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Discount	0.865***	0.866***	0.866***	0.865***	0.866***	0.866***	0.866***	0.864***	0.866***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
DmdControl	1.005**	1.002	1.002	1.004*	1.000	1.002	1.003	1.008***	1.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Deal FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,436	5,436	5,436	5,436	5,436	5,436	5,436	5,436	5,436
Pseudo R^2	0.226	0.223	0.223	0.225	0.223	0.223	0.224	0.232	0.223

Table 11

The effects of underwriter characteristics.

This table reports regression results on the effects of underwriter brokerage revenues on the relation between mutual fund commissions paid to underwriters and IPO pricing. *TopBroker* is a dummy variable that equals one if an underwriter's total commission revenue ranks in the top tercile among all underwriters, and zero otherwise. Other variables and statistics in Panel A, Panel B, and Panel C are as defined in Table 3, Table 6, and Table 9, respectively. See Appendix B for definitions of variables. Odds ratios are reported in Panel C. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: the effects on deliberate underpricing

	Top 1/3		*Top 1/4*	
Y = Discount%	(1)	(2)	(3)	(4)
*SkewPayComm*TopBroker*	-2.368*		-1.996*	
	(1.403)		(1.108)	
SkewPayComm	-3.005**		-2.110***	
	(1.248)		(0.691)	
*SkewHighComm*TopBroker*		-3.349***		-1.266*
		(0.899)		(0.697)
SkewHighComm		0.055		-0.352
		(0.634)		(0.456)
TopBroker	-5.860	-4.052	-5.886*	-6.271*
	(3.643)	(3.432)	(3.379)	(3.347)
SkewFund	2.988*	-0.230	2.059*	-0.436
	(1.725)	(0.920)	(1.183)	(0.677)
SkewDemand	-0.092***	-0.110***	-0.122***	-0.142***
	(0.021)	(0.020)	(0.023)	(0.023)
Assets	0.123	0.379	-0.153	-0.144
	(0.537)	(0.523)	(0.506)	(0.512)
TDemand	0.043***	0.038***	0.045***	0.039***
	(0.007)	(0.007)	(0.007)	(0.007)
NIns	0.086***	0.106***	0.090***	0.114***
	(0.026)	(0.026)	(0.026)	(0.026)
LargeIns	0.004	-0.012	0.004	0.004
	(0.027)	(0.026)	(0.026)	(0.026)
HighBids	0.426***	0.436***	0.404***	0.404***
	(0.083)	(0.081)	(0.079)	(0.079)
IPORtn	0.778***	0.779***	0.829***	0.898***
	(0.241)	(0.234)	(0.234)	(0.233)
MktRtn	-0.263***	-0.287***	-0.305***	-0.330***
	(0.075)	(0.073)	(0.073)	(0.074)
MktVola	-7.175**	-6.870**	-6.626**	-7.664***
	(2.918)	(2.760)	(2.850)	(2.799)
Exchange	-0.690	-1.086	-0.734	-0.976
	(1.352)	(1.297)	(1.291)	(1.293)

Constant	-4.571 (5.981)	-5.201 (5.850)	-8.033 (5.523)	-8.783 (5.600)
Year, under., and ind. FE	YES	YES	YES	YES
Observations	172	174	172	174
Pseudo R^2	0.335	0.340	0.344	0.338

Panel B: the effects on initial returns

	Top 1/3		*Top 1/4*	
Y = IR%	(1)	(2)	(3)	(4)
SkewPayComm TopBroker*	-6.832		-9.793**	
	(5.298)		(3.256)	
SkewPayComm	-6.584***		-4.469***	
	(1.101)		(0.468)	
SkewHighComm TopBroker*		-3.747		-6.459**
		(6.536)		(2.590)
SkewHighComm		-3.496		-3.499*
		(2.282)		(1.697)
TopBroker	3.404	1.160	7.303	6.178
	(11.786)	(14.592)	(7.999)	(8.783)
SkewFund	-6.275	-10.520	2.622	-0.402
	(7.226)	(10.298)	(4.717)	(4.511)
SkewDemand	0.179	0.150	-0.026	-0.112
	(0.121)	(0.171)	(0.173)	(0.181)
Assets	7.292	7.266	6.394	5.785
	(6.585)	(5.876)	(6.367)	(5.724)
TDemand	0.809***	0.806***	0.815***	0.795***
	(0.047)	(0.056)	(0.048)	(0.053)
NIns	-0.346	-0.359	-0.307	-0.275
	(0.210)	(0.198)	(0.249)	(0.231)
LargeIns	-0.284***	-0.265**	-0.252***	-0.219***
	(0.071)	(0.083)	(0.030)	(0.047)
HighBids	1.373**	1.371*	0.973***	0.783
	(0.461)	(0.700)	(0.247)	(0.448)
IPORtn	-5.722*	-5.901**	-6.206	-6.350*
	(2.699)	(2.249)	(3.304)	(2.830)
MktRtn	-0.108	-0.137	0.069	-0.002
	(0.652)	(0.555)	(0.868)	(0.718)
MktVola	89.283***	89.623***	88.671***	88.891***
	(22.851)	(25.972)	(20.241)	(25.553)
Exchange	20.504	21.339	20.205	21.058
	(13.579)	(11.777)	(14.651)	(12.356)
Elasticity	-0.024*	-0.023*	-0.024**	-0.022**
	(0.011)	(0.010)	(0.008)	(0.009)
Reputation	5.546	5.584	3.116	2.142
	(11.492)	(12.589)	(9.390)	(11.117)
Constant	42.576	48.570	53.180	59.515
	(39.217)	(38.948)	(59.933)	(52.937)
Year and industry FE	YES	YES	YES	YES
Observations	172	174	172	174
R^2	0.783	0.779	0.775	0.774

Panel C: the effects on offer price determination		
Y = Sel	(1)	(2)
DmdPayComm TopBroker*	1.010**	
	(0.005)	
DmdPayComm	1.012***	
	(0.004)	
DmdHighComm TopBroker*		0.996
		(0.004)
DmdHighComm		1.009***
		(0.003)
DmdFund TopBroker*	0.987**	1.000
	(0.006)	(0.005)
DmdFund	0.996	1.000
	(0.004)	(0.003)
Demand	1.063**	1.101***
	(0.028)	(0.028)
Elasticity	1.001**	1.001**
	(0.000)	(0.000)
Sdemand	1.034***	1.032***
	(0.010)	(0.010)
Discount	0.866***	0.873***
	(0.013)	(0.013)
Deal FE	YES	YES
Observations	5,436	5,436
Pseudo R^2	0.227	0.200

Appendix A
Distribution of IPO pricing distances.

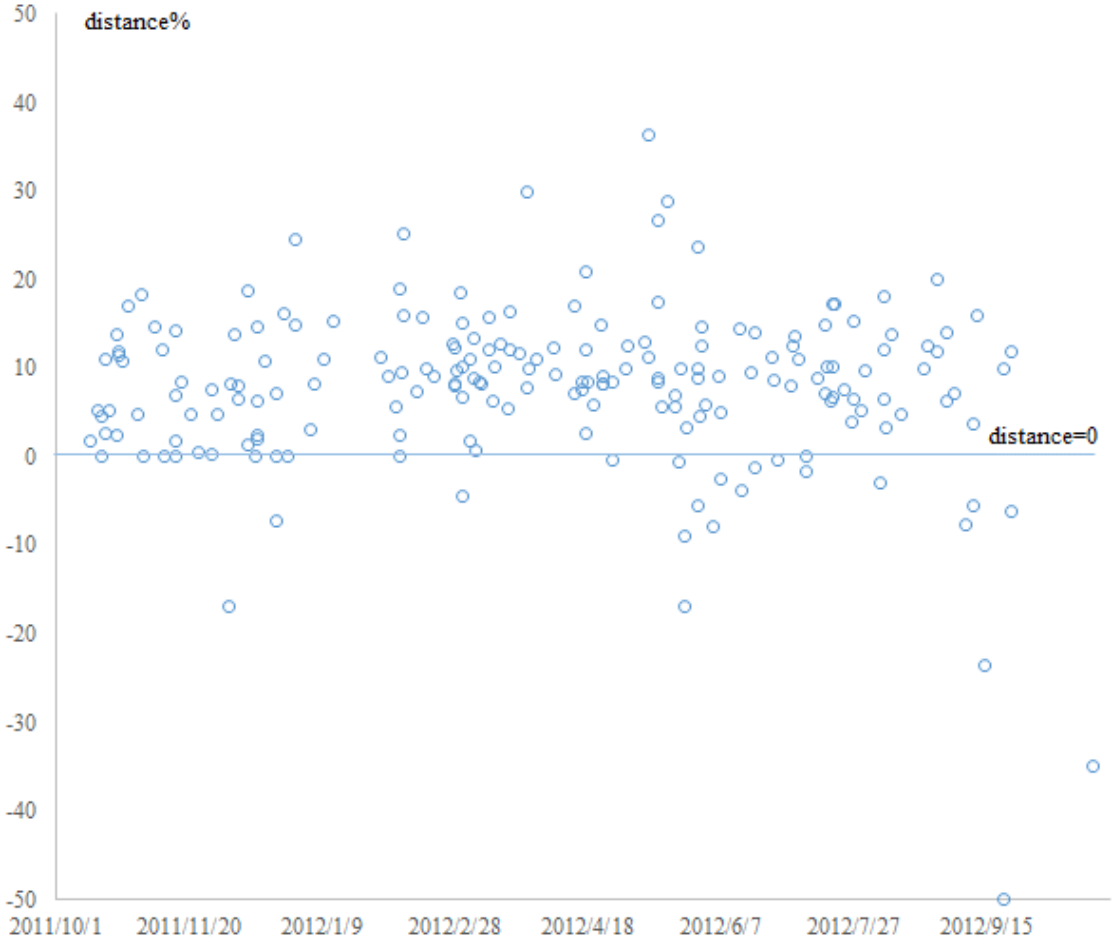


Figure A1
IPO pricing between October 2011 and October 2012.
This figure plots the distances from IPO offer prices to the regulatory price caps for 196 Chinese IPOs between October 2011 and October 2012, defined as (offer price – price cap)/price cap*100. Price caps are calculated as the maximum of the simple average, weighted average, and median of bidding prices from all investors and mutual funds,

Appendix B
Definitions of variables.

Variable	Definition
Discount	Discount from the market clearing price *mktclrprc* to the offer price *p*, calculated as (*mktclrprc* - *p*)/*mktclrprc**100
SkewInvs	Adjusted skewness of the demand schedule of investor type *Invs*, calculated as *(demand with top 1/3 (1/4) prices from Invs/total demand from Invs)/(demand with top 1/3 (1/4) prices/total demand). Invs* could be replaced with *Fund, Inv. Bank, Insurance, Trust* and *Financial* to calculate the skewness of demand from mutual funds, investment banks, insurance companies, trust firms, and financial firms, respectively.
SkewDemand	Skewness of the overall demand schedule, calculated as *total demand with top 1/3 (1/4) prices/total demand*100*
TDemand	Total demand in times of shares offered in the full demand schedule
Nins	Number of bidding institutions
Assets	Log of total assets of the offering firm
LargeIns	Number of institutions in the largest bid size decile divided by number of institutions with prices between the clearing price and the offer price
HighBids	The difference between the current clearing price and the clearing price if orders with the 5% highest prices, are removed, divided by the current clearing price
IPORtn	Time-weighted average of IPO underpricing% during the 360 days prior to the issue
MktVola	Standard deviation of daily market returns during the 3 months prior to the offer
MktRtn	Market return for the 3 months prior to the offer
Exchange	Stock exchange dummy that equals one if the new stock is listed on the Shanghai Exchange, and zero if listed on the Shenzhen Stock Exchange
SkewPayComm	Adjusted skewness of the demand schedule of mutual funds whose families pay commissions to the underwriter, calculated as *(demand with top 1/3 (1/4) prices from mutual funds whose family pays commission to the underwriter/total demand from mutual funds whose family pays commission to the underwriter)/(demand with top 1/3 (1/4) prices/total demand)*
SkewHighComm	Adjusted skewness of the demand schedule of mutual funds whose families pay above median commissions to the underwriter among all mutual funds bidding for the deal
SkewInvRtn	Adjusted skewness of the demand schedule of mutual funds ranking in the top half by investment performance among all mutual funds bidding for the deal, measured by Jensen' alpha, calculated as *(demand from mutual funds ranking in the top half by investment performance with top 1/3 (1/4) prices/total demand from mutual funds ranking in the top half by investment performance)/(demand with top 1/3 (1/4) prices/total demand)*
SkewIndExp	Adjusted skewness of the demand schedule of mutual funds ranking in the top half by the fraction of amount they invest in the same industry of the IPO firm
SkewNIPO	Adjusted skewness of the demand schedule of mutual funds ranking in the top half by the number of IPOs they bided for in the most recent 360 days
SkewIPORtn	Adjusted skewness of the demand schedule of mutual funds ranking in the top half by the average 1-year returns of the IPOs they bided for in the most recent 360 days
SkewHold	Adjusted skewness of the demand schedule of mutual funds ranking in the top half by the duration they hold their allocations, as inferred from the most recent two semi-annual reports
SkewNoFlip	Adjusted skewness of the demand schedule of mutual funds ranking in the top half by the fraction of IPOs they did not sell their allocations within 1 month, as inferred from the most recent two semi-annual reports
SkewAssets	Adjusted skewness of the demand schedule of mutual funds ranking in the top half by the size of total assets
SkewHistory	Adjusted skewness of the demand schedule of mutual funds ranking in the top half by the duration since the funds' establishment
SkewFee	Adjusted skewness of the demand schedule of mutual funds ranking in the top half by the

	rate of management fee
Reputation	Underwriter reputation dummy that equal one if the underwriter was awarded as "Best Investment Banks" by the New Fortune magazine in the year prior to the issue
DmdInvs	Fraction of orders in shares from investor type *Invs* orders with price *p*, calculated as *demand from Invs orders with price p/demand from all orders with price p*100. Invs* could be replaced with *Fund, Inv. Bank, Insurance, Trust* and *Financial* to calculate fraction of demand from mutual funds, investment banks, insurance companies, trust firms, and financial firms, respectively.
Demand	Demand from all bidders with price *p*, in times of shares offered
Disc	Discount from market clearing price *mktclrprc* at a price level *p*, calculated as *(mktclrprc-p)/mktclrprc*100*
Sdemand	Total demand from orders with prices not lower than *p*, in times of shares offered
Elasticity	Demand elasticity at a price level *p*, calculated as *(demand/Sdemand)/(-Δp/p)*
DmdPayComm	Fraction of orders in shares from mutual funds by whose fund families the commissions paid to the underwriters are above zero at price level *p*, calculated as *share demand in orders from mutual fund whose family paying commission to the underwriter in the previous year with price p/demand from all mutual funds orders with p*100*
DmdHighComm	Fraction of orders in shares from mutual funds by whose fund families the commissions paid to the underwriters rank in the top half among all mutual funds bidding for the deal at price level *p*
DmdIndExp	Fraction of orders in shares from mutual funds of which the fractions of amount invested in the same industry of the IPO firm rank in the top half among all mutual funds bidding for the deal, at price level *p*
DmdInvRtn	Fraction of orders in shares from mutual funds of which the investment performance, measured by Jensen's alpha, ranks in the top half among all mutual funds bidding for the deal, at price level *p*
DmdNIPO	Fraction of orders in shares from mutual funds of which the numbers of IPOs they bided for in the most recent 360 days rank in the top half among all mutual funds bidding for the deal, at price level *p*
DmdIPORtn	Fraction of orders in shares from mutual funds of which the average 1-year return of IPOs they bided for in the most recent 360 days ranks in the top half among all mutual funds bidding for the deal, at price level *p*
DmdHold	Fraction of orders in shares from mutual funds for which the duration their IPO allocations are held for, as inferred from the most recent two semi-annual reports, rank in the top half among all mutual funds bidding for the deal, at price level *p*
DmdNoflip	Fraction of orders in shares from mutual funds for which the fraction of IPOs they did not sell their allocations within 1 month, as inferred from the most recent two semi-annual reports, rank in the top half among all mutual funds bidding for the deal, at price level *p*
DmdAssets	Fraction of orders in shares from mutual funds of which the amounts of total assets rank in the top half among all mutual funds bidding for the deal, at price level *p*
DmdHistory	Fraction of orders in shares from mutual funds of which the durations in years since establishment rank in the top half among all mutual funds bidding for the deal, at price level *p*
DmdFee	Fraction of orders in shares from mutual funds of which the rates of management fee rank in the top half among all mutual funds bidding for the deal, at price level *p*
TopBroker	A dummy variable that equals one if the underwriter's total commission revenue ranks in the top tercile among all underwriters in the year prior to the offer, and zero otherwise
Compliance	A dummy variable that equals one if an underwriter is rated as an AA bank by the CSRC in the year prior to the offer, and zero otherwise

Appendix C

Tests on the tipping mechanism.

This table reports regression results on the effects of underwriter compliance status on the relation between mutual fund commissions paid to underwriters and IPO pricing. *Compliance* is a dummy variable that equals one if an underwriter is rated as an AA bank by the CSRC, and zero otherwise. Other variables and statistics in Panel A and Panel B are as defined in Table 3, Table 6, and Table 9, respectively. See Appendix B for definitions of variables. Odds ratios are reported in Panel C. Standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: the effects on deliberate underpricing and initial returns

	Discount%		*IR%*	
	Top 1/3	*Top 1/4*	*Top 1/3*	*Top 1/4*
	(1)	(2)	(3)	(4)
*SkewPayComm*Compliance*	-1.522	-2.191*	-8.952	-8.455
	(1.558)	(1.216)	(12.902)	(4.645)
SkewPayComm	-3.033**	-1.863**	-5.964***	-4.174***
	(1.335)	(0.719)	(1.128)	(0.625)
Compliance	2.319	1.923	-4.979	2.324
	(1.741)	(1.233)	(5.576)	(5.857)
SkewFund	-0.682	0.672	5.096	5.669
	(2.846)	(2.603)	(12.826)	(6.114)
SkewDemand	-0.102***	-0.133***	0.177	-0.036
	(0.022)	(0.023)	(0.101)	(0.186)
Assets	0.266	-0.006	7.183	6.024
	(0.552)	(0.517)	(6.354)	(5.956)
TDemand	0.042***	0.044***	0.808***	0.818***
	(0.007)	(0.007)	(0.056)	(0.053)
NIns	0.086***	0.092***	-0.345	-0.319
	(0.027)	(0.026)	(0.232)	(0.255)
LargeIns	0.013	0.018	-0.253***	-0.212***
	(0.029)	(0.028)	(0.017)	(0.037)
HighBids	0.432***	0.402***	1.408**	0.930**
	(0.086)	(0.080)	(0.426)	(0.281)
IPORtn	0.823***	0.930***	-5.791*	-6.152
	(0.248)	(0.238)	(2.944)	(3.553)
MktRtn	-0.284***	-0.347***	-0.092	0.064
	(0.076)	(0.074)	(0.644)	(0.887)
MktVola	-8.358***	-8.467***	88.375***	85.761***
	(2.980)	(2.870)	(20.765)	(18.097)
Exchange	-1.147	-1.169	21.095	21.681
	(1.453)	(1.406)	(13.716)	(14.165)
Elasticity			-0.024**	-0.023**
			(0.009)	(0.008)
Reputation			6.271	4.120
			(6.373)	(4.132)

Constant	-2.969	-8.429	43.308	55.291
	(6.123)	(5.711)	(35.616)	(63.920)
Year, under., and ind. FE	YES	YES	YES	YES
Observations	172	174	172	174
R^2/Pseudo R^2	0.335	0.340	0.774	0.338

Panel B: the effects on offer price determination		
Y = Sel	(1)	(2)
*DmdPayComm*Compliance*	1.008	
	(0.005)	
DmdPayComm	1.012***	
	(0.004)	
DmdHighComm Compliance*		0.999
		(0.005)
DmdHighComm		1.008**
		(0.004)
DmdFund Compliance*	0.984***	0.995
	(0.006)	(0.005)
DmdFund	0.999	1.003
	(0.004)	(0.004)
Demand	1.059**	1.100***
	(0.028)	(0.028)
Elasticity	1.001**	1.001**
	(0.000)	(0.000)
Sdemand	1.035***	1.032***
	(0.010)	(0.010)
Discount	0.865***	0.874***
	(0.013)	(0.013)
Deal FE	YES	YES
Observations	5,436	5,436
Pseudo R^2	0.230	0.200