Institutional Reform, Collusion, and the Unraveling of China's Initial Public Offerings *

Meng Miao, Tianyue Ruan, and Xiao Yan†

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Abstract

This paper examines how institutional features in the reform to establish the registration system for China's initial public offering (IPO) market inadvertently fostered collusion among institutional investors, ultimately undermining the effectiveness of the reform. While the registration system abolished the IPO pricing cap, the initial reform kept the rule from the previous approval system to exclude 10% highest bids in IPO auctions. As both high and low bids would be excluded while winning IPO allocation is perceived to be highly profitable due to substantial IPO underpricing, strategic coordinating to bid similarly low prices emerges as the optimal bidding strategy for investors. Analyzing 2.5 million investor bids from 1,458 IPOs between 2017 and 2023, we find that extreme degree of bid concentration remained even after the registration system replaced the approval system. After regulators adjusted the high-bid exclusion threshold to 3% in 2021, bid concentration decreased over 80%, confirming that the observed bidding coordination is institutionally driven. Our broker-fund network analysis with 543 members shows that investors with higher centrality have greater bidding success, implying collusion is facilitated by existing business networks. We also rule out alternative explanations, such as the use of similar pricing formulas, as plausible explanations for our finding. This collusion-driven market weakness in gathering information about less transparent firms could be a major factor influencing the underperformance of China's IPO reform.

Keywords: Social Network, IPO Underpricing, Bid Rigging, Institutional Investor, Pricing Efficiency

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†Miao: Renmin University of China, email: miaomeng@ruc.edu.cn. Ruan: National University of Singapore, email: tianyue.ruan@nus.edu.sg. Yan: Renmin University of China, email: yanxiao1999@ruc.edu.cn.

1 Introduction

Market-oriented reforms are often seen as a panacea for enhancing competition and efficiency, yet the reform to establish the registration system for China's initial public offering (IPO) market unveils a troubling paradox: institutional designs intended to unleash market vitality can instead become breeding grounds for collusion (Acemoglu and Verdier, 2000; Hatfield et al., 2020). First introduced in 2019, China's registration system aimed to promote market-driven, competitive IPO pricing. Yet, the initial surge of the reform was soon replaced by fraud allegations and market stagnation, with IPO activity nearly evaporating by 2024. We find that this crisis stems from the legacy of a seemingly neutral rule from the approval system, the 10% high-bid exclusion rule, which removes the highest 10% of bids in IPO auctions. Originally designed to curb speculation, this mechanism evolved under the new system into a driver of collusion, especially among institutional investors with extensive informational networks, who coordinated uniform bids. This undermined IPO pricing efficiency, enabled subpar firms to list, and eroded market confidence. While the literature extensively examines the benefits of market reforms (Rajan and Zingales, 1998; Foster et al., 2008), little attention has been paid to how institutional flaws reshape investor behaviors and undermine reform goals (Goldstein and Knight, 2023). This paper, through China's unique case, unravels the complex costs of marketization and offers fresh insights into institutional design.

Fueled by its fast-growing economy, China's IPO market has been among the largest globally over the past decade. The registration-based reform to established the long-anticipated registration system was expected to reduce the uncertainty and delays caused by administrative reviews, implement market-driven pricing mechanisms through competitive auctions, and enhance the efficiency of both listing and pricing (Bond et al., 2010; Davydenko et al., 2012; Kilenthong and Townsend, 2021). This improvement would allow previously excluded high-tech and pharmaceutical firms to go public, fostering innova-

tion. However, the reform remains unfinished, as elements of the approval system, such as the 10% high-bid exclusion rule, continue to shape market dynamics.

Before the 2019 pilot of the registration system, IPO pricing was effectively government-controlled under the approval system with a strict price-to-earnings ratio (P/E) cap of 23 (Qian et al., 2024). To further curb speculative bidding, regulators mandated that up to 10% of the highest bids are excluded from the IPO auctions. In the initial transitions to the registration system, the 10% high-bid exclusion rule was maintained while the strict P/E cap of 23 was abolished. As both high and low bids would be excluded while winning IPO allocation is perceived to be high profitable due to high expected IPO underpricing, institutional investors have strong incentives to coordinate their bids to bid similarly low prices (to avoid exclusion due to bids being too high), despite the lack of a natural pricing benchmark. This form of strategic coordination would result in bids clustering around a narrow range and artificially low offer prices, leading to systematic underpricing and ultimately distorting capital allocation efficiency.

Using more than 2.5 million bids in approximately 1,500 IPO auctions between 2017 and 2023, we examine the effects of regulatory reforms on investors' bidding behaviors. A comparison of the approval and registration IPO systems shows that while the registration system induced some bid dispersion, bid clustering remained prominent. In the initial phase of the registration system with the 10% high-bid exclusion rule, nearly 80% of submitted bids fall within 1% of the final IPO prices. This is surprisingly high, considering it is not far from the 96% level observed during the approval system, where investors used the P/E cap of 23 as natural pricing benchmarks and submitted bids narrowly clustered around default price levels. The impact of the exclusion rule became even clearer when the threshold was adjusted to 3% in September 2021, leading to greater bid dispersion, with only 12.6% of bids bidding within 1% of the final IPO price. This behavior suggests that investors strategically coordinate their bids in response to the high-bid exclusion rule. Furthermore, we find that final bid values deviate from the Benford's Law

(Benford, 1938; Cong et al., 2023), suggesting possible signs of artificial coordination.

We further examine the mechanisms behind investor coordination in IPO pricing, with a particular focus on the role of different types of investors (Aghion et al., 2013). We find that institutional investors, especially mutual funds and brokerages, tend to submit more concentrated bids than individual investors. This finding suggests that institutional investors, leveraging their market influence and informational advantages, can effectively coordinate bidding behavior to increase their allocation success rate (Baker and Wurgler, 2002; Ortner et al., 2024).

The coordination among investors can occur in various ways. Firstly, they may use the common pricing models to value the IPO firms. Another possibility is that investors inform each other about the bidding prices through various connections. Our subsequent analyses show strong evidence for the second possibility. First, we explore a series of possible pricing formulas based on our conversations with practitioners, particularly the widely rumored benchmark issuance price, which is said to be the average price-to-earnings (PE) ratio of existing companies in the same industry multiplied by a fixed factor less than 1. We find this formula unlikely, as the ratio between the issuance prices of listed companies and those already listed in the industry keeps fluctuating. Moreover, we discover that many investors, during a series of bids, sometimes managed to hit the target price and at other times missed it. This pattern is unlikely to occur if institutional investors use a common pricing formula.

Moreover, using commission-based transaction data, we construct a measure of investors' network centrality and show that investors with higher centrality are more likely to engage in price collusion. These highly connected investors coordinate with other institutions to form aligned bidding strategies, allowing them to dominate IPO allocations (Bajo et al., 2016). However, after the implementation of a stricter 3% high-price exclusion policy, investors became less concerned about bid exclusion, leading to greater bid dispersion and reducing the opportunity for network-based coordination. This shift enhances

the price discovery function and improves fairness and transparency.

Further analysis explores the underlying channels through which broker networks facilitate price collusion, including quid pro quo arrangements, information advantages, and strategic equilibrium mechanisms. Our evidence indicates that the primary channel is a quid pro quo dynamic: when IPOs exhibit greater underpricing and lower price-to-earnings ratios, investors are more inclined to engage in collusive bidding. Firms with lower implied valuations offer higher expected excess returns, attracting concentrated bids from networked investors seeking to maximize their chances of successful allocation. Additionally, we find that analysts' positive ratings and an increase in fund participation significantly strengthen the likelihood of network-based price collusion, highlighting how institutional investors manipulate information and market sentiment to attract broader investor participation and secure IPO profits (Ljungqvist et al., 2006). Notably, when firms face heightened regulatory scrutiny, bidding concentration decreases, suggesting that investors adjust their behavior to avoid attracting regulatory attention. We further rule out alternative explanations, including investors' professional experience, information extraction capabilities, and the possibility that bid concentration results purely from market equilibrium dynamics.

We conclude by discussing the practical consequences of investor collusion during the pricing process. Investor collusion can lead to decreased bid dispersion. More importantly, such collusion would reduce the IPO offer price, resulting in IPO underpricing, which could be exploited by issuers for spinning (Loughran and Ritter, 2004). Our findings reveal that when those within the top 1% of the final bids increased their price by one unit, overall bid diversity decreased by 1.7%. Furthermore, the level of IPO underpricing decreased by 84 basis-point. This demonstrates that investor collusion has a detrimental impact on the pricing system, potentially reducing its efficiency.

This paper makes several key contributions to the literature: First, we extend the understanding of IPO pricing under China's registration issuance system by revealing the

strategic evolution of investor behaviors in the IPO auctions. Existing studies primarily focus on information asymmetry between issuers and underwriters (Loughran and Ritter, 2004) or model the book-building process as a unidirectional information revelation mechanism (Benveniste and Spindt, 1989), overlooking how horizontal interactions among investors reshape pricing power. Our findings demonstrate that institutional investors do not behave independently but instead form implicit collusion through broker networks, challenging the conventional "issuer-led" paradigm (Ljungqvist et al., 2003). Furthermore, we find that partial regulatory changes paradoxically reinforce strategic coordination among investors with strong broker network connections.

Second, we underscore the role of social networks as an informal institution that shapes price discovery (Xu, 2011). While prior literature predominantly focuses on the vertical relationships between firms and external stakeholders (Pagano and Röell, 1998; Huang et al., 2021), our study focuses on horizontal interactions among institutional investors. We show that social networks among institutional investors facilitate coordinated bidding and influence allocation outcomes. Empirically, we provide evidence that investors form "cartels" through brokerage networks and use commission-splitting agreements as incentive-compatible tools for collusion. This perspective highlights how network-based collusion can override competitive market forces in IPO pricing, demonstrating that investor behavior is often driven by strategic coordination rather than independent decision-making.

While prior research has examined how variations in regulatory enforcement across agencies or market participants influence market efficiency (Agarwal et al., 2014; Garicano and Rayo, 2016; Roth, 2018), these studies primarily focus on differences in implementation rather than inherent weaknesses in the system itself, our findings suggest that the issue extends beyond enforcement to the design of the system itself (Myerson, 2008). Specifically, we document how structural loopholes create unintended incentives for investor coordination, undermining the intended benefits of market-oriented pricing

reforms.

2 Institutional Setting and Data Sources

2.A Stock Market Landscape and the Initial Public Offering (IPO) Process in China

China's stock market consists of three primary market segments: the Main Board, ChiNext, and the STAR Market. The Main Board, which includes both the Shanghai Stock Exchange (SSE) Main Board and the Shenzhen Stock Exchange (SZSE) Main Board, serves as the listing platform for established firms with stable earnings. By contrast, ChiNext and the STAR Market target high-growth and innovative enterprises, albeit with distinct industry focuses and listing criteria. ChiNext, launched in 2009 and managed by SZSE, resembles NASDAQ's growth enterprise segment, primarily serving small and medium-sized enterprises (SMEs) with high growth potential. In contrast, the STAR Market, established in 2019 under the SSE, aligns more closely with NASDAQ's technology sector, explicitly catering to high-tech industries such as semiconductors, biotechnology, and artificial intelligence. As of December 2024, ChiNext hosts 1,363 listed firms with a total market capitalization exceeding RMB 12 trillion, while the STAR Market comprises 581 firms, accounting for 11% of all listed companies in China.

Firms seeking to go public in China go through a multi-stage process, including pre-listing guidance, regulatory filing, roadshows, issuance, and final listing. Under the approval system, although any firm that satisfies the listing requirements can apply for an IPO, it needs to obtain approval from the Public Offering Review Committee (PORC) of the China Securities Regulatory Commission (CSRC) before it can go public; the number of shares and the amount raised also need to be approved by the PORC. Under the approval system, access to the public equity market is a privilege and a limited resource; hence, connections, especially political connections, play an important role (Francis et al., 2009; Fan et al., 2014; Chen et al., 2017). The approval system also raises concerns about regulatory capture (Dixit, 2009), as firms with close ties to PORC members exhibited a

higher likelihood of securing approval. Moreover, powerful PORC members have incentives to engage in illicit activities. Over time, documented cases of collusion and misconduct emerged, where committee members exploited their positions to leak confidential review information in exchange for illicit gains, severely undermining market fairness.[1]

The approval system stands in stark contrast to the registration system in the US, in which any company is permitted to go public as long as it meets listing and disclosure requirements. Chinese regulators have contemplated the possibility of changing to a US-style registration system since 2014. The newly created STAR Market was the first to implement the registration system on July 22, 2019, followed by ChiNext on August 24, 2020. After the pilots of the registration system in the STAR and ChiNext markets, in February 2023, China formally announced the full-scale adoption of the registration system, extending it to the Main Board.

The registration system eliminates PORC's approval authority, shifting IPO review responsibilities to the stock exchanges (SSE and SZSE) while removing administrative restrictions on IPO pricing and offering size. Before the transition to the registration system, IPO prices under the approval system were subject to a window guidance price-to-earnings (P/E) cap of 23 (Qian et al., 2024).[2] The transition to the registration system breaks away from the pricing cap and increases the autonomy in IPO pricing.

The registration system makes the auction-based pricing mechanism more important.

[1] A well-known case involved Feng Xiaoshu, a former member of the PORC for the ChiNext market. While serving in the PORC, Feng leveraged his position to obtain insider information about companies preparing to go public. Using accounts registered under his spouse and associates, he acquired pre-IPO shares at discounted prices and later sold them post-listing for illicit gains. The case involved RMB 248 million in illegal profits, which were fully confiscated, and he was further fined RMB 251 million and permanently banned from the securities market. Another high-profile case involved Yao Gang, who served as a CSRC Party Committee Member and Vice Chairman, directly overseeing IPO and refinancing approvals. Yao exploited his position to access non-public information, trading stocks through proxy accounts and intervening in IPO approval processes. He facilitated listings and refinancing for multiple firms in exchange for substantial bribes. Ultimately, he was sentenced to 18 years in prison and fined RMB 11 million for corruption and abuse of power.

[2] On January 12, 2014, the CSRC issued the Measures to Strengthen IPO Regulation, which required issuers to determine their industry classification and reference the most recent one-month static average P/E ratio published by China Securities Index Co., Ltd. as a pricing benchmark. This effectively established an implicit 23× P/E ceiling in the A-share IPO market. Source: https://www.gov.cn/gongbao/content/2014/content_2679356.htm.

There are two primary methods for pricing IPOs. Fixed-price offering allows the issuer and underwriter to set the IPO price in advance, without investor participation in the price discovery process. The auction method involves soliciting bids from institutional investors and qualified individual investors, typically starting with an initial price range and adjusting based on demand.[3] Under the approval system, the strict P/E cap of 23 served as a natural pricing benchmark, and bids in IPO auctions are mostly uninformative: Most bids are at or slightly above 23 times earnings per share to ensure that they are among valid bids. Under the registration system, there is no natural pricing benchmark; accurate valuation and informed bidding hence become more important.[4]

2.B High Bid Exclusion Rules in the IPO Auctions

In response to a series of incidents of inflated IPO prices and subsequent busts, the CSRC introduced a series of measures in 2012 to strengthen oversight of IPO pricing. A key component of these measures was the high-bid exclusion mechanism, designed to prevent speculative bidding and excessive valuations. Under this policy, stock exchanges systematically excluded up to 10% of the highest bids in IPO auctions.[5]

In the initial transitions to the registration system, the 10% high-bid exclusion rule was maintained [6] while the strict P/E cap of 23 was abolished. As both high and low

[3] As Qian et al. (2024) note, the auction method is often referred to as "book-building" or "investor inquiry" in Chinese media and official documents. However, because the underwriters do not have allocation discretion, it is in act an auction mechanism.

[4] The STAR Market requires securities firms to participate in strategic placements through co-investment, where they passively accept the IPO price, a test of their pricing ability. The interests of investment subsidiaries and issuers are not aligned in this case, as excessively high pricing could lead to losses on the co-invested portion. Therefore, securities firms must balance the interests of both investors and issuers. On January 28, 2019, the CSRC introduced the STAR Market's co-investment system for securities firms, which was further expanded to the ChiNext market on April 27, 2020, with special provisions for co-investment participants.

[5] In an effort to reform IPO pricing and allocation mechanisms, the CSRC introduced new rules requiring issuers and lead underwriters to exclude the highest bids submitted by institutional investors before finalizing the offering price. Specifically, at least 10% of the total bid volume must be removed before determining the final issue price based on the remaining bids. Source: https://www.gov.cn/gongbao/content/2014/content_2620292.htm.

[6] Source: *Shanghai Stock Exchange Guidelines for the Issuance and Underwriting of STAR Market Stocks*, available at https://www.pkulaw.com/chl/f1fb25eba774b4edbdfb.html. The SZSE had a similar high-bid exclusion rule in place for the ChiNext when the registration system was rolled out to ChiNext.

bids would be excluded while winning IPO allocation is perceived to be high profitable due to high expected IPO underpricing, institutional investors have strong incentives to coordinate their bids to bid similarly low prices (to avoid exclusion due to bids being too high), despite the lack of a natural pricing benchmark. This form of strategic coordination would result in bids clustering around a narrow range and artificially low offer prices, leading to systematic underpricing and ultimately distorting capital allocation efficiency.

Anecdotal evidence suggests that this form of strategic coordination is widespread. For instance, in 2020, Zejing Pharmaceutical, the first unprofitable firm to list on the STAR Market, experienced significant pricing distortions. Institutional investors clustered their bids at low price levels, resulting in an offer price of RMB 16.62 per share. However, on its first trading day, the stock surged 109.33%, reflecting a clear misalignment between its IPO price and true market valuation. A similar pattern emerged in Longteng Optoelectronics, which went public in the same year. Priced at RMB 1.22 per share, the stock recorded a 308.9% first-day return, with regulatory reports attributing this anomaly to collusive bidding by institutional investors who intentionally suppressed IPO prices.

In response, regulators swiftly implemented corrective measures. On July 9, 2021, the CSRC issued guidelines aimed at tightening oversight of investment banks and institutional investors, introducing stricter bid evaluation requirements. Recognizing that the existing high-bid exclusion rule—originally designed to curb excessive IPO pricing—had unintended consequences, regulators revised the policy in September 2021. Specifically, the SSE reduced the high-bid exclusion ratio from "no less than 10%" to "no more than 3%" for the STAR market.[7] The SZSE, which oversees ChiNext, implemented the same adjustment in September 2021.[8]

In the most recent expansion of the registration system to the Main Board in 2023, the

[7]Source: *Shanghai Stock Exchange Guidelines for the Issuance and Underwriting of STAR Market Stocks (2021 revision)*, available at https://www.pkulaw.com/chl/0d10a35acd86218cbdfb.html.

[8]Source: *Shenzhen Stock Exchange Rules for the Issuance and Underwriting of ChiNext Market Stocks (2021 revision)*, available at https://lawinfochina.com/display.aspx?id=36740&lib=law.

high-bid exclusion thresholds are set to range between 1% and 3%[9]. We provide a brief summary of the major policy changes across the market segments over time in Table 1.

2.C Data Sources

Our sample covers A-share IPOs from 2017 to 2023; spanning the transition from the approval system to the registration system. We compile data from a variety of sources including the China IPO Issuance Database, IPO prospectuses, transaction commission data, and the China Stock Market & Accounting Research (CSMAR) database. We exclude observations with missing issuance dates, incomplete key variables, or internal employee subscriptions to minimize data inconsistencies. After multiple rounds of data cleaning and refinement, our final dataset comprises 1,458 IPOs, 33,854 investors, and 2,534,023 valid bids. Additionally, to mitigate the influence of extreme values, we apply a 1% two-sided winsorization to continuous firm-level variables and investor bidding data, ensuring the robustness of our empirical results. We describe the construction of variables in the subsequent sections on bid concentration and bid coordination.

3 Bid Concentration

3.A Investors and Bids in IPO Auctions

We focus on IPO auctions (also known as the "investor inquiry process" in the Chinese context), where qualified investors submit bids for IPO allocations. Institutional investors, including mutual funds, securities firms, and other professional institutions, are the primary participants in these auctions. Individual investors are also eligible to participate; however, they must meet the same capital requirements as institutional investors. Specifically, before submitting bids during the inquiry process, their fund balance must

[9]Source: *Shanghai Stock Exchange Self-Regulatory Committee's Advocacy for Smooth IPO Issuance under the Comprehensive Implementation of the Registration-Based System*, available at https://www.sse.com.cn/lawandrules/guide/stock/fxcxyw/gztz/c/c_20230320_5718253.shtml.

be no less than 0.1% of their total assets across both securities and fund accounts[10].

Inquiry outcomes in the IPO pricing process vary depending on investor bidding behavior and the IPO pricing mechanism. Investors may submit valid bids that fall within the final offer price range, securing IPO allocations, or their bids may be excluded due to high-price elimination, invalid submissions, or insufficient bidding prices. A key outcome variable in the analysis of IPO pricing is successful IPO subscription, denoted as `IPO_subscribing`, which captures whether an investor secured an IPO allocation. Following bid submission, only investors whose bids fall within the determined offer price range qualify for allocation. Bids that are excessively high or low risk exclusion, directly influencing an investor's likelihood of participating in the final IPO distribution.

One of the central objectives of this study is to examine price clustering patterns in IPO pricing that cannot be fully explained by traditional pricing models. We construct several measures for bid clustering. First, we create indicators that equal one if an investor's bid falls within $\pm 1\%$, $\pm 3\%$, and $\pm 10\%$ of the final IPO price, and zero otherwise.

Second, we create indicators that equal one if an investor's bid is exactly identical to the single first common bid, one of the 4 most common bids, and one of the 8 most common bids. As the second set of measures are closely linked to the measures of market concentration and market power in industrial organization, we follow the norm in that literature to denote these variables as CR1, CR4, and CR8.

3.B Evidence for Substantial Concentration

We begin by documenting the extent of bid clustering in IPO auctions, as summarized in Table 2. Across the entire sample period, 59% of investors, on average, submitted identical bids, highlighting a substantial degree of price concentration. The clustering tendency becomes even more pronounced when considering the top four or eight most common

[10] Additionally, their brokerage account's month-end fund balance must also meet this 0.1% threshold as of the last trading day of the previous month. Source:https://www.cs.ecitic.com/newsite/tzzjy/zt/fxjs_21945/202308/P020230804607045611844.pdf

bid prices, which collectively accounted for 72.5% and 86.5% of all bids, respectively. This striking level of bid concentration suggests that a vast majority of investors submitted bids at highly similar price levels, implying a lack of independent price discovery and a strong reliance on common valuation benchmarks rather than firm-specific fundamentals. The fact that nearly 85% of bids were concentrated in just a few price points indicates that investors were either anchoring their bids to prevailing market conventions or engaging in strategic bidding behavior to maximize their chances of allocation.

Under the approval system, bid clustering was particularly extreme, with 97.4% of investors submitting the exact same bid. This uniformity was primarily driven by regulatory constraints, most notably the fixed 23× price-to-earnings (P/E) multiple rule, which effectively predetermined IPO offer prices. In this environment, investors had little incentive to conduct independent valuations, as pricing was largely dictated by regulatory guidelines rather than market-driven mechanisms. As a result, 95.9% of bids fell within ±1% of the final IPO price. This extreme homogeneity in bidding behavior underscores the fact that the auction process failed to serve its intended function as a price discovery mechanism.

With the transition to the registration system, bid concentration declined significantly, reflecting greater flexibility in price setting. Under the 10% high-bid exclusion rule, the fraction of investors submitting the most common bid dropped to 33.4%. While this decline suggests an improvement in price differentiation, clustering remained substantial, with over 82% of bids still falling within ±1% of the IPO price. The systematic removal of the top 10% of bids may have led investors to adopt a conservative bidding strategy, deliberately avoiding high bids to ensure their orders remained within the allocation range. This behavior implies that rather than facilitating greater price discovery, the exclusion rule may have encouraged tacit collusion or herding behavior among investors.Under the 3% high-bid exclusion rule, bid dispersion increased further. The fraction of bids at the most common price dropped to 9.5%, and clustering within ±1% of the IPO price fell

to 22.8%, suggesting a meaningful reduction in price concentration. This shift implies that tightening the exclusion rule effectively discouraged excessive bid clustering and enhanced price differentiation.

The transition from an approval to a registration system not only transformed IPO pricing mechanisms but also had profound implications for both IPO underpricing and institutional investor participation. Under the approval system, IPO underpricing was relatively moderate, averaging 43.4%. However, following the shift to the registration system with the 10% high-bid exclusion rule, underpricing surged dramatically to 219%. While this period saw a reduction in bid concentration, the exclusion of high bids introduced a new distortion—systematic underpricing due to artificial price suppression. By eliminating the top 10% of bids, the exclusion rule effectively constrained the final offer price, preventing it from fully reflecting market demand and leading to substantial first-day price jumps as prices adjusted post-listing.

The increased pricing flexibility under the registration system also incentivized greater institutional participation, with institutional investor bids rising sharply to 50.8%. However, despite their increased presence, bid clustering remained prevalent, suggesting that institutional investors may have engaged in tacit coordination, privately aligning their bids around a predetermined price level to influence the final offer price. Given the exceptionally high underpricing observed during this period, it is possible that institutional investors deliberately coordinated bids at artificially low prices to secure IPO allocations at a discount, thereby maximizing their first-day gains, reinforcing pricing distortions in the IPO market.[11]

Further evidence of this phenomenon is illustrated in Figure 1, which plots the cumulative distribution function (CDF) of bid prices. Under the approval system, bids were almost entirely clustered around the final offer price, with over 90% of investors submitting bids within a narrow range, indicating that investors largely anchored their bids to

[11]Internet Appendix Tables IA.1, IA.2, and IA.3 report summary statistics for the three market segments separately and confirm the same patterns.

regulatory-imposed valuation benchmarks rather than conducting independent assessments. With the transition to the registration system, pricing flexibility improved to some extent. However, bid clustering remained persistently high, suggesting that the pricing mechanism still failed to fully incorporate relevant market information into the price-setting process.

Figure IA.2 presents a kernel density estimation (KDE) plot, illustrating the distribution of bid prices. While the registration system reduced the extreme bid concentration observed under the approval system, the kurtosis of the bid distribution remains significantly higher than that of a normal distribution. This further supports the existence of persistent bid clustering in the market. Such a pattern reflects investor coordination and strategic behavior, rather than independent judgments based on the intrinsic value of individual firms.

However, a potential alternative explanation for such concentrated bidding patterns is behavioral biases, rather than deliberate collusion among investors. To assess whether bids reflect authentic investor valuations or unnatural digit preferences, we employ Benford's Law, which describes the expected frequency distribution of leading digits in naturally occurring numerical datasets. Under Benford's distribution, lower digits (e.g., 1 and 2) should appear more frequently as the leading digit, with frequencies decreasing for higher digits. Figure 2 illustrates deviations in the distribution of both the leading digit and the first digit after the decimal point of investors' bids. Empirical results strongly reject conformity to Benford's distribution at conventional significance levels, indicating notable deviations from a naturally occurring random distribution of digits.

3.C Why Are Bids So Concentrated?

In the previous section, we documented a persistent high concentration of IPO bids in China's stock market, even after significant market-oriented reforms. According to standard market-oriented theories, investors' bids should reflect heterogeneous beliefs and

independently assessed valuations, resulting in dispersed bid distributions. Contrary to this expectation, our empirical evidence consistently shows that a large proportion of investor bids cluster narrowly around the IPO offer price. Such concentrated bidding behavior cannot be solely attributed to informational efficiency or homogeneous investor valuations. Instead, this phenomenon likely reflects strategic coordination or implicit collusion among institutional investors, raising substantial concerns about market integrity and competitive bidding dynamics.

To formally examine whether this strategic bid concentration benefits institutional investors by increasing their probability of winning IPO allocations, we estimate the following regression specification:

$$Bid_Outcome_{i,j,t} = \gamma_i + \lambda_{m(i),t} + \beta \times Bid_Measure_{i,j,t} + \theta X_{i,j,t} + \varepsilon_{i,j,t} \tag{1}$$

Here, the dependent variable, $Bid_Outcome_{i,j,t}$, equals one if investor j successfully obtains IPO shares from IPO firm i at time t, and zero otherwise. The main explanatory variable, $Bid_Measure_{i,j,t}$, captures whether investor j's bid corresponds to the concentrated bid prices observed in the IPO. We consider a few different ways to construct the measure: indicator variables corresponding to the investor's bid matching the modal bid price, one of the 4 most common bid prices, and one of the 8 most common bid prices; and indicator variables corresponding to the investor's bid falling within a narrow range $\pm 1\%$, $\pm 3\%$, and $\pm 10\%$ around the final IPO offer price). $X_{i,j,t}$ denotes time-varying investor-level controls. Specifically, we control for investor experience, measured as the number of IPO auctions an investor has participated till the current IPO. This variable accounts for potential experience-related biases, as more experienced investors are likely to be more familiar with market pricing mechanisms and may submit more precise bids. By including it, we control for the potential influence of investor experience on bidding strategies and pricing outcomes.

We include IPO firm fixed effects γ_i to control for observed and unobserved heterogeneity in the cross-section of IPO firms. This set of fixed effects essentially remove the impact of issuer characteristics that may affect IPO auction bidding and pricing. The year fixed effects, $\lambda_{m(i),t}$, further neutralize the impacts of common trends. As the three market segments have different listing rules, we include a separate set of time fixed effects for each market segment (hence the subscript $m(i)$) for a cleaner identification.

Table 3 presents comprehensive evidence regarding the relationship between IPO bid concentration and investors' allocation outcomes. Across all specifications, we consistently find that greater bid concentration significantly enhances investors' probability of successfully receiving IPO allocations.

Column (1) shows that investors whose bids exactly match the modal bid price (CR1) are 47.5 percentage points more likely to receive an allocation, suggesting that bidding at the most common price point confers a considerable advantage. Columns (4)–(6) extend this analysis using alternative measures of bid concentration, capturing progressively broader price ranges around the final offer price. The results indicate that investors bidding within $\pm$1%, $\pm$3%, and $\pm$10% of the final offer price are 59.4, 50.5, and 45.9 percentage points more likely, respectively, to receive an allocation. Notably, the magnitude of these effects declines as the bid-price range widens, reinforcing the pattern that tighter bid concentration yields greater IPO allocation advantages.

These findings suggest that concentrated bidding is not merely a reflection of informational consensus among investors but potentially involves strategic bidding coordination or implicit collusion. If investors deliberately align their bids to enhance allocation success, this could weaken the competitive bidding process, distort price discovery, and reduce market transparency.

3.D Bid Concentration Hurts IPO Firms

We proceed to investigate the effect of bid concentration on IPO firms, exploring its broader implications for IPO market outcomes. Specifically, we examine the outcome of IPO i in time t using the following regression specification:

$$IPO_Outcome_{i,t} = \gamma_{s(i)} + \lambda_{m(i),t} + \beta \times Concentration_Measure_{i,t} + \theta X_{i,t} + \varepsilon_{i,j,t} \quad (2)$$

The main explanatory variable, $Concentration_Measure_{i,t}$, captures whether the degree of bid concentration in this IPO. We focus on the fraction of bids within the narrow range $\pm 1\%$ around the final IPO offer price.[12] In this IPO-level regression, the IPO firm-level control variables ($X_{i,t}$) include return on assets (ROA), leverage (Lev), book-to-market ratio (BM), firm size (Size), and accounting firm quality (Big4). These variables capture key financial and governance attributes of IPO firms, helping isolate the independent effect of investor behavior on IPO pricing dynamics. We include industry fixed effects $\gamma_{s(i)}$ to control for observed and unobserved industry heterogeneity. As in the previous bid-level regression specification (equation (1)), we include market segment specific year fixed effects $\lambda_{m(i),t}$ to control for markeg segment specific time trends.

Table 4 presents our findings. Column (1) indicates that a one-percentage-point increase in bid concentration raises the proportion of effective bids by approximately 12.53 percentage points. This result suggests that investors strategically cluster their bids within a narrow price range, potentially reflecting coordinated or herding behavior aimed at increasing individual allocation probabilities. Column (2) further highlights the detrimental implications for IPO issuers by showing that higher bid concentration significantly reduces bid-price diversity. Specifically, a one-percentage-point increase in bid concentration is associated with an approximate 1.7% decline in bid-price diversity. This loss of pricing diversity implies a reduction in competitive bidding pressures, severely con-

[12] We obtain similar estimates if we examine alternative measures of bid concentration.

straining independent valuation judgments and undermining efficient price discovery processes. Consequently, issuers may fail to achieve fair and market-driven IPO valuations.

Column (3) examines the relationship between bid concentration and IPO underpricing, revealing that higher bid concentration substantially amplifies initial IPO returns (underpricing). Specifically, the results imply that a one-percentage-point increase in bid concentration corresponds to an 84 basis-point increase in first-day returns. Greater underpricing imposes direct economic costs on issuing firms by transferring wealth from issuers to strategic bidders, reflecting potential implicit collusion among investors, thereby undermining the fairness and efficiency of the IPO market.

Finally, Column (4) investigates offline auction participation, finding that higher bid concentration significantly increases the proportion of effective offline subscriptions. Increased offline participation, particularly under concentrated bidding conditions, raises concerns about potential collusion or rent-seeking behavior among institutional and strategic investors. This scenario may further exacerbate price coordination, distorting the competitive equilibrium and adversely affecting market fairness, transparency, and efficiency.

4 Bid Coordination

In the previous analysis, we documented that investors who engage in highly concentrated bidding can significantly improve their IPO allocation outcomes. This chapter further investigates the phenomenon of investor bid concentration, focusing specifically on identifying which types of investors are more prone to bid clustering and exploring the underlying factors contributing to coordinated or potentially collusive bidding behaviors.

4.A Investor Identity and Collusive Bidding

We first examine differences in bid concentration between institutional investors and retail investors across various regulatory regimes. Figure 3 illustrates changes in the distri-

bution of bid-price deviations relative to the final IPO issuance price for both institutional and retail investors, categorized into two distinct regulatory periods: the approval system and the registration system.

Figure 3 clearly demonstrates that during the approval system—characterized by the "23-times earnings" fixed pricing rule—there was minimal difference in bidding patterns between institutional and retail investors. Both groups' bids were tightly clustered around the offering price, primarily due to regulatory constraints rather than independent valuation assessments. However, as the market transitioned to the registration system, notable differences emerged between these investor types. Under these conditions, approximately 60% of institutional investors managed to place their bids precisely within a narrow 1% range of the actual issuing price, whereas fewer than 10% of retail investors achieved similar accuracy.

Importantly, this discrepancy likely does not merely reflect institutional investors' superior analytical capabilities or informational advantages under new regulatory environments. Instead, it suggests the existence of coordinated behaviors or implicit collusion among institutional investors. Institutions typically have greater resources to facilitate information sharing, allowing them to converge more accurately on the anticipated issuing price. Consequently, this collective strategy amplifies bid concentration and secures allocation advantages. Institutional investors strategically align their bids closely, not necessarily reflecting genuine market consensus on firm valuation, but possibly representing coordinated actions aimed at influencing IPO pricing outcomes to their advantage.

Moreover, extending the analysis to bids placed within a broader range (from 1% to 10% around the issuing price), we continue to observe significantly higher bid concentration among institutional investors relative to retail investors. This pattern further supports our suspicion that institutional bid clustering extends beyond rational market consensus, reinforcing the possibility of implicit coordination or collusion among institutional market participants.

To further examine the relationship between investor identity and bid concentration, we conduct additional empirical analyses, as reported in Table 5. Column (1) presents a baseline comparison between institutional and retail investors. The results indicate that institutional investors are 11.3 percentage points more likely than retail investors to submit bids within a ±1% range around the final IPO offer price. However, this difference is not statistically significant, suggesting that, in the aggregate, institutional and retail investors exhibit broadly similar bidding behaviors when regulatory differences are not accounted for. While this result implies that institutional investors do not inherently prefer bid clustering, it does not capture how specific regulatory structures influence their strategic incentives.

Column (2) explores this distinction by comparing bid concentration under the approval and registration systems. The approval system was characterized by significant regulatory intervention in price formation, most notably through the implicit 23-times price-to-earnings (P/E) ratio rule, which effectively capped IPO valuations. Because this pricing convention was widely recognized and followed by market participants, institutional investors had little opportunity to use bid concentration as a strategic tool. Regardless of their informational advantage, they had no meaningful incentive to cluster bids, as the final offer price was largely predetermined by regulatory norms rather than market-driven price discovery. This explains why institutional investors under the approval system show no significant difference from retail investors in bid concentration patterns, with the coefficient estimate close to zero.

In contrast, the transition to a registration system eliminated the 23-times P/E constraint and transferred price-setting discretion from regulators to the market. This shift introduced greater uncertainty in IPO pricing, incentivizing institutional investors to coordinate their bids strategically. The results indicate that under the registration system, institutional investors are 6.88 percentage points more likely than retail investors to submit concentrated bids, with the effect significant at the 10 percent level. The introduction

of market-driven pricing mechanisms increased the benefits of bid clustering, as institutional investors sought to influence pricing outcomes and enhance their allocation probabilities.

Column (3) further examines institutional bidding behavior within the registration system by comparing periods with different bid exclusion thresholds. Specifically, we distinguish between an initial regime with a 10 percent exclusion rule, under which extreme bids (both high and low) were removed from the price-setting calculation, and a later regime that tightened this threshold to 3 percent. Under the 10 percent exclusion rule, institutional investors were 86.8 percentage points more likely than retail investors to submit bids within the 1% range. This substantial effect indicates that when the risk of being excluded from pricing calculations was high, institutional investors responded by clustering their bids around an expected price level to minimize the likelihood of disqualification.

However, under the stricter 3 percent exclusion rule, institutional investors' relative advantage declined significantly, reducing their tendency to engage in bid clustering. This shift likely reflects the fact that a narrower exclusion threshold reduced the risks associated with bid misalignment, thereby encouraging greater price dispersion. With fewer investors facing the threat of having their bids discarded, incentives for excessive bid concentration—especially among institutional investors—diminished. As a result, market bid diversity improved, weakening the previously substantial competitive advantage institutional investors derived from bid clustering. This finding underscores the role of regulatory design in shaping IPO market competitiveness, suggesting that as exclusion thresholds tighten, strategic coordination among institutional investors becomes less effective, fostering a more dispersed and competitive bidding environment.

To better understand how investor identity influences IPO bid concentration, we distinguish between fund investors and other institutional investors, examining how their bidding behaviors vary under different IPO regulatory regimes. Given the differences

in their investment strategies, risk management approaches, and access to market information, it is likely that these two groups respond differently to shifts in IPO pricing mechanisms.

Column (1) of Table IA.4 presents the baseline comparison of bid concentration across different investor types. Consistent with the main findings, fund investors are more likely to adopt concentrated bidding strategies, reinforcing their systematic role in IPO pricing. In contrast, other institutional investors do not exhibit statistically significant differences from retail investors, suggesting that bid clustering is not a universal institutional strategy. To further explore how IPO pricing regimes influence institutional bidding behavior, we distinguish between the approval and registration systems. Under the approval system, fund investors continue to play a prominent role in bid concentration, while other institutional investors display similar or even slightly lower bid concentration levels compared to retail investors. This finding aligns with the rigid pricing constraints of the approval system, where price-setting discretion is limited.

In contrast, under the registration system, institutional investors as a whole exhibit higher bid concentration than retail investors. This shift likely reflects greater incentives for strategic coordination, as institutional investors—particularly non-fund institutions—may have stronger ties to fund investors and thus greater opportunities to engage in aligned bidding behavior. The increased transparency and market-driven pricing under the registration system may have reinforced institutional coordination mechanisms, leading to more concentrated bidding patterns across investor groups.

4.B Measuring Broker Network

Among the various market participants, brokerage firms and mutual funds play a particularly significant role in shaping capital market efficiency. The structure of relationships between these institutions can influence IPO pricing efficiency through mechanisms such as information sharing, resource complementarity, and strategic coordination. Specifi-

cally, brokerage firms serve as intermediaries in capital markets, providing mutual funds with trading services, research support, and underwriting opportunities. Meanwhile, mutual funds—often acting as key institutional investors in IPOs—rely on brokerage firms for both access to market information and execution services. The strength of these interactions may shape pricing outcomes by affecting how efficiently information is transmitted and incorporated into the IPO bidding process.

Following the network construction methodology of Bajo et al. (2016), this study develops a broker-fund network centrality measure based on transaction commission data.[13] Specifically, we model brokerage firms and mutual funds as nodes, with commission flows representing weighted edges in the broker-fund relationship network. Each edge in this network signifies an established business relationship between a mutual fund and a brokerage firm, arising from either brokerage services or underwriting activities. By employing a network-based approach to analyze these relationships, we assess the extent of information integration between brokers and funds and examine its influence on bidding behavior. A higher network centrality score indicates that an institutional investor occupies a more prominent position within the network, suggesting stronger connections with other institutional investors and greater informational influence. Internet Appendix Figure IA.1 presents a visualization of selected broker-fund network structures.

Following the existing literature on networks, we construct five different centrality measures, namely degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, and the PageRank centrality. We describe the technical details on how we construct these measures in Internet Appendix Section IA.2.

[13]Transaction commissions refer to the fees paid by mutual funds to brokerage firms for executing trades on their behalf. These fees, typically calculated as a percentage of the total trade value, serve as a key indicator of business relationships between brokers and fund managers.

4.C Broker Network and Collusive Bidding

To better understand variations in IPO bidding behavior among institutional investors and identify potential mechanisms driving coordinated or collusive bidding strategies, we further examine investor heterogeneity within the institutional investor category. Specifically, this section investigates how institutional investor networks—formed through shared brokerage relationships and joint participation in IPO offerings—affect bid concentration and allocation success. Table IA.5 presents detailed regression results exploring the relationship between investor network centrality and bid concentration.

The empirical findings indicate that institutional investor networks significantly influence IPO bidding behavior. Investors occupying central positions within brokerage networks exhibit higher bid concentration compared to those at the periphery or outside the network. In particular, the results suggest that institutional investors with greater network centrality are approximately 0.3 percentage points more likely to submit bids within a narrow $\pm 1\%$ range around the final IPO offer price. This finding highlights the potential for network-driven coordination, where centrally positioned investors may leverage their market influence to align bidding strategies.

Columns (2)–(6) further explore the relationship between network centrality and IPO bidding outcomes using different centrality measures from network theory, including closeness centrality, betweenness centrality, degree centrality, eigenvector centrality, and PageRank centrality. Across specifications, the results consistently indicate that institutional investors in more central network positions exhibit stronger bid concentration and greater allocation success. This suggests that occupying a central position within investor networks enhances the ability to coordinate bidding behavior, increasing investors' influence over IPO pricing outcomes and allocation mechanisms.

Furthermore, the observed effects remain robust across different IPO pricing regimes. As shown in Table 6, network centrality continues to play a significant role in institutional bidding strategies. Under the previous 10% high-bid exclusion rule and registration sys-

tem, brokerage networks significantly amplified the advantage of centrally positioned investors, enabling them to submit more concentrated bids and achieve higher IPO allocation success. The heightened risk of bid exclusion under this regime likely incentivized investors to coordinate their bids, leveraging network relationships to align pricing strategies and avoid disqualification. However, following the implementation of the stricter 3% high-bid exclusion rule, the strength of network effects diminished substantially. The narrower exclusion threshold reduced the probability of bid rejection, thereby weakening investors' incentives for coordinated bidding.

4.D Heterogeneity Analysis

In previous sections, we documented that institutional investors—particularly those with strong brokerage-fund network ties—are more likely to engage in coordinated bidding strategies. A key question remains: how is this collusion formed, and what underlying mechanisms drive it?

To examine how institutional investors coordinate bidding behavior in IPOs, we consider two potential mechanisms: (i) the economic incentives for collusion and (ii) the risks of profit-sharing with outsiders. Institutional investors may engage in coordinated bidding when high expected returns or structural advantages make collusion profitable, but they also face the risk that outsiders—investors not within their network—could observe and replicate their bidding strategies, diluting the benefits of collusion.

Collusive behavior is a well-documented phenomenon in financial markets, particularly in environments characterized by information asymmetry and limited competition. Investors often coordinate through shared brokerage relationships, repeated interactions, and information-sharing networks to influence price outcomes and improve their allocation success. Theoretical models suggest that when the expected gains from coordination are high—such as in IPOs with substantial underpricing—investors have stronger incentives to align their bids strategically (Avery and Zemsky, 1998). Empirical research

further supports the idea that institutional investors leverage information advantages to reinforce their market position, often leading to systematic distortions in price discovery and allocation fairness (Cornelli and Goldreich, 2001).

Economic Incentives for Collusion To examine the economic benefits of collusion, we assess two factors: IPO underpricing (a proxy for expected IPO profitability) and issuance costs (which capture coordination incentives among issuers, underwriters, and investors).

In IPO markets, high expected returns create strong incentives for institutional investors to engage in coordinated bidding. When IPO underpricing is substantial, investors benefit more from securing allocations, motivating them to align bids and reinforce their control over pricing outcomes. In such cases, brokerage networks facilitate information sharing and collusion, allowing connected investors to coordinate pricing strategies and increase bid concentration. Columns (1)–(2) of Table 7 show that when IPO underpricing is high, institutional investors are more likely to exploit network relationships and information sharing to coordinate bidding, thereby increasing their chances of winning IPO allocations. This effect is particularly pronounced under the registration-based pricing system, where the role of investor networks in price formation is more significant. The results indicate that under high IPO underpricing, institutional investors' reliance on network relationships increases from 36% to 50%,representing a relative increase of approximately 39%.

Another key economic driver is the cost structure of IPO issuance. Higher underwriting fees often signal closer collaboration between issuers, underwriters, and institutional investors, potentially encouraging coordinated bidding. In such cases, issuers actively engage with investors through broker networks to foster market consensus, increasing IPO demand and stabilizing prices. This strategic alignment can lead to a self-reinforcing cycle, where investors benefit from both greater allocation success and higher underpricing profits, reinforcing their incentives to participate in network-driven coordination.

Columns (3)–(4) demonstrate that IPOs with higher issuance costs exhibit significantly greater bid concentration among brokerage-network investors. This suggests that investors leverage their brokerage-based relationships and resources to align their bidding strategies with issuers' interests, significantly improving their IPO allocation success.

The Risk of Exposure to Outsiders While the potential gains from collusion are high, institutional investors also face the risk that outsiders—investors who are not part of their network—may observe and imitate their strategies, thereby reducing the profits from collusion. If too many investors align their bids with the coordinated strategy, the price advantage diminishes, making it harder for network members to extract rents from the IPO process.

High-tech IPOs provide a natural setting to examine this dynamic. Due to their innovation-driven business models and uncertain future cash flows, high-tech firms typically face greater information asymmetry, which naturally increases institutional investors' reliance on brokerage networks for information-sharing and strategic coordination. In contrast, traditional industries rely more on publicly available financial disclosures, potentially weakening the role of network-driven advantages. Columns (5)–(6) present regression results based on an industry classification of IPOs. The findings indicate that institutional investors within brokerage networks exhibit significantly higher bid concentration and IPO allocation success for high-tech IPOs compared to traditional sectors. This confirms that when information asymmetry is greater, brokerage networks amplify their role in enhancing pricing efficiency and allocation advantages for connected investors.

Similarly, geographic factors influence exposure risks. Firms headquartered in major financial centers such as Beijing, Shanghai, and Shenzhen provide institutional investors with better access to local information advantages, but they also attract a broader set of sophisticated market participants who may monitor and react to collusive bidding patterns. In contrast, IPOs from firms in smaller or less scrutinized markets may allow in-

stitutional investors to coordinate more effectively without the risk of profit-sharing with external investors. Columns (7)–(8) show that investors in financial centers leverage local information barriers and brokerage-network advantages to effectively coordinate bids and enhance allocation outcomes. However, the presence of wider market scrutiny and enhanced information availability in these regions may also mitigate collusion risks, as a larger pool of market participants can access credible pricing signals, reducing reliance on network-based coordination.

4.E Addressing the Alternative Explanation of Convergence in Equilibrium

In IPO markets, the concentration of investor bids is shaped by a combination of market mechanisms, investor behavior, and institutional constraints. Traditional game theory suggests that in a well-informed and competitive market, investors gradually refine their bidding strategies over multiple rounds of interaction, converging toward an equilibrium price—often aligning with regulatory thresholds. A classic example is the "guessing game" framework, where iterative strategic adjustments lead participants to settle on a stable equilibrium outcome (Nagel, 1995).

A potential alternative channel we consider is that IPO bidding may follow a similar process, where investors incrementally adjust their bids through multiple rounds of price discovery, theoretically leading to a stable equilibrium price. In this view, as investors gain more bidding experience, their behavior should become more rational, ultimately stabilizing around a specific price point. Such price convergence is often interpreted as a hallmark of market efficiency (Bolton and Harris, 1999).

However, existing literature highlights that in markets characterized by information asymmetry and binding institutional constraints, investors may engage in strategic coordination or information-sharing, thereby distorting price distribution and preventing equilibrium convergence (Loughran and Ritter, 2004). Given this context, we examine whether game-theoretic equilibrium mechanisms can explain the observed concentration

of investor bids—particularly whether institutional investors leverage their network ties to influence this process.

To explore this hypothesis, we first provide a graphical analysis of the relationship between an investor's bidding frequency and their bid percentile rank. As shown in Figure 4, despite an increase in bidding experience, investors' bid percentiles exhibit substantial dispersion and fail to converge toward a stable value. Table 8 further investigates whether institutional investor identity affects bid percentiles.

To empirically test the possibility of equilibrium convergence in bidding behavior, we classify investors into four experience-based groups: those with 0–10 bids, 10–100 bids, 100–200 bids, and more than 200 bids. Figure IA.3 presents the density distribution of investor bids relative to the industry price-to-earnings (P/E) multiple across these experience categories. Strikingly, we observe highly consistent bidding patterns regardless of cumulative bidding experience, with bids persistently clustering within the 0–1 range of the industry P/E ratio. This persistent concentration suggests that bidding behavior remains systematically clustered rather than converging toward an equilibrium driven by experience.

A closer examination reveals two distinct peaks at 0.2 to 0.4 times the industry P/E ratio, indicating significant clustering around these valuation points. Column (2) of Table 8 confirms that institutional investor identity does not significantly influence the likelihood of bidding within this narrow P/E range.

Next, we examine whether regulatory constraints systematically influence investor bidding behavior, with a particular focus on the requirement that IPO firms attain a minimum market capitalization of RMB 1 billion upon listing. In theory, this threshold could discourage investors from collectively submitting excessively low bids, as a concentrated cluster of such bids might prevent the IPO from reaching the required capitalization level, ultimately leading to its failure[14].

[14]A notable example is Shangwei New Materials, whose IPO faced significant challenges due to investor bids being overly concentrated at the lower end of the price range. As a result, the final offering price was

Column (3) of table 8 tests whether institutional investors' bids tend to cluster around the market capitalization cutoff. The coefficient on Institutional Investor × Approval is negative but statistically insignificant, indicating that institutional investors do not systematically place bids near the RMB 10 billion threshold under the approval system. Similarly, the coefficient on Institutional Investor × Registration is also small and insignificant, suggesting that the transition to a registration system has not altered this bidding pattern. These results further challenge the game-theoretic equilibrium explanation, suggesting that the observed concentration of bids is not driven by the need to meet external regulatory thresholds.

5 Conclusion

This study investigates investor bid concentration, brokerage networks, and implicit price collusion in the context of IPO allocation, emphasizing how recent regulatory reforms have influenced pricing behavior in China's equity markets. Specifically, we analyze the transition from an approval IPO system to a registration-based IPO system, as well as subsequent policy changes regarding high-price exclusion thresholds, to understand their impact on investor bidding strategies and IPO allocation outcomes. By systematically examining the role of brokerage-fund networks in facilitating concentrated bidding, this research provides novel insights into the microstructure dynamics of IPO price formation.

Our analysis reveals several key empirical findings. First, we document robust evidence of implicit price collusion among investors, as demonstrated by persistently high bid-price concentration in China's IPO markets. Under the approval system characterized by the stringent "23 times P/E ratio" regulatory constraint, bid concentration was extraordinarily high, with over 90% of investors submitting identical or nearly identical bids. Although the shift toward a registration system modestly reduced bid concen-

set at just RMB 2.49 per share, bringing the firm's market capitalization at listing to RMB 10.04 billion. Had the offering price been merely one cent lower, the company would have failed to meet the minimum market capitalization requirement and been unable to go public,Both investors and the issuing firm would have incurred substantial losses in such a scenario.

tration, significant coordination persisted under the initial 10% high-bid exclusion rule, indicating continued investor collusion and inefficiencies in the pricing mechanism.

Subsequently, the regulatory reform tightening the high-price exclusion threshold from 10% to 3% significantly decreased bid concentration. However, this improvement mainly corrected issues stemming from previous market-oriented reforms, suggesting that earlier policies inadvertently intensified strategic coordination and price collusion among institutional investors. Thus, while the stricter 3% rule enhanced market efficiency by mitigating investor collusion, its necessity highlights fundamental shortcomings embedded within prior regulatory designs that encouraged strategic bidding behavior detrimental to fair IPO pricing.

Second, we find that bid concentration is not uniformly distributed among investors. Institutional investors, especially those embedded within brokerage-fund networks, uniquely engage in concentrated bidding strategies. Such strategic bidding is particularly pronounced in IPOs characterized by greater profitability and lower external visibility. Institutional investors leverage their information networks and relationships to achieve precise bidding, thereby disproportionately benefiting from IPO allocation outcomes.

Collectively, our findings underscore the critical role regulatory frameworks play in shaping investor incentives and behaviors in IPO markets. Effective policy measures—particularly those aimed at limiting implicit collusion and promoting transparency—are essential not only for addressing unintended consequences of prior reforms but also for fostering genuinely competitive bidding, improved price discovery, and allocative efficiency in IPO markets.

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Figure 1: **Cumulative Density Function of Investors' Bid Price Proximity to IPO Offering Prices Across Different Chinese IPO Systems**

This figure presents the cumulative density functions (CDFs) of investors' bid prices during the IPO price discovery process under different regulatory frameworks in Chinese stock markets. The horizontal axis measures the relative proximity of bid prices to the final IPO offering price, with smaller values indicating bids that are more closely clustered around the offering price. The figure compares bid distributions across two IPO regimes: the approval system and the registration system. Within the registration system, we further distinguish between bid concentrations before and after the implementation of the 3% price deviation reform. The vertical line at zero represents cases where bid prices exactly match the final IPO offering price.

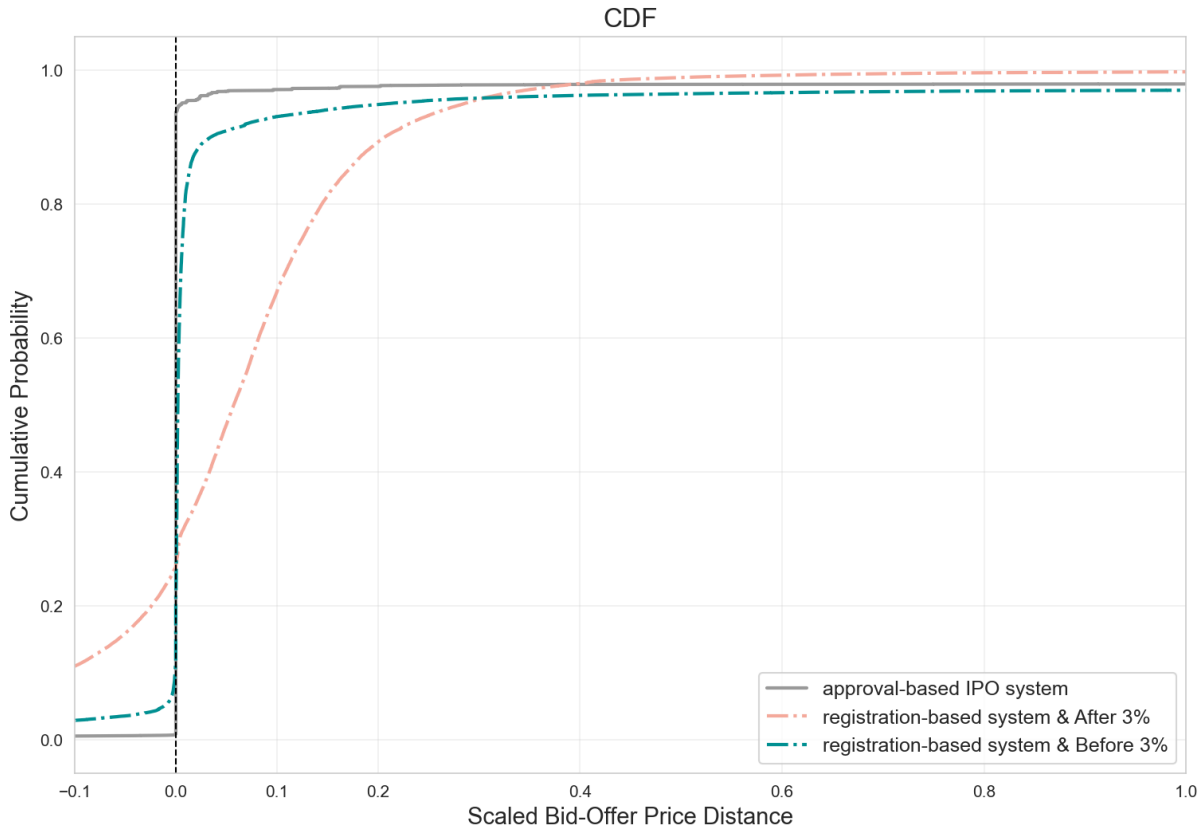


Figure 2: **Bids and the Benford's Law**

This figure presents a comparative analysis of the distributions of the first digit (top row) and the first decimal digit (bottom row) of investors' bid prices under the approval and registration IPO regimes in Chinese stock markets. In each panel, observed frequencies are benchmarked against theoretical proportions predicted by the Benford's Law, and a chi-square (χ^2) goodness-of-fit test is conducted. The reported χ^2 statistics and corresponding p-values indicate statistically significant deviations from the expected Benford distribution, suggesting potential pricing irregularities or inefficiencies in the IPO price inquiry process.

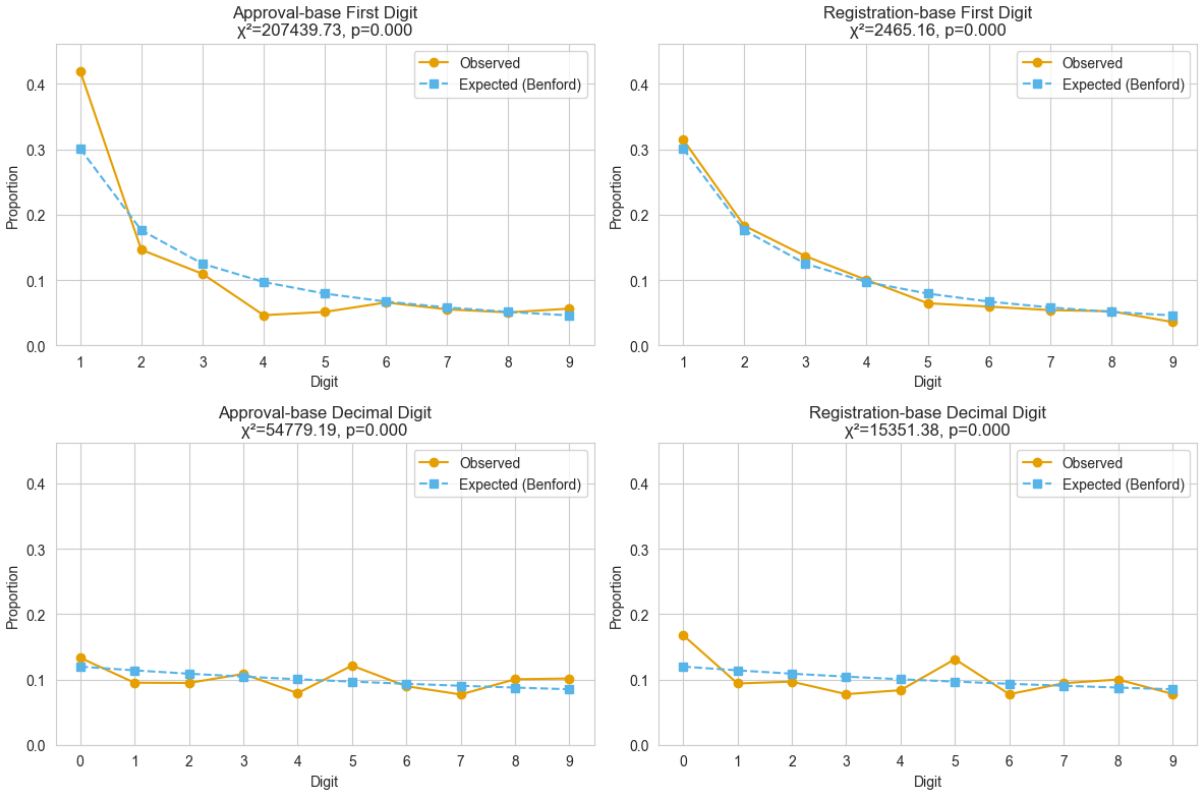


Figure 3: **Concentration of Institutional versus Retail Investors' Bids**

This figure examines the degree of bid clustering around the final IPO offering price for institutional and retail investors under different IPO regulatory frameworks. The left panel represents the approval system, while the right panel corresponds to the registration system. The horizontal axis indicates different price ranges (±1%, ±2%, ±3%, ±5%, ±10%) and reflects the proportion of bids that fall within each interval. The vertical axis represents the cumulative proportion of bids within these ranges, with higher values indicating stronger clustering of bids around the offering price.

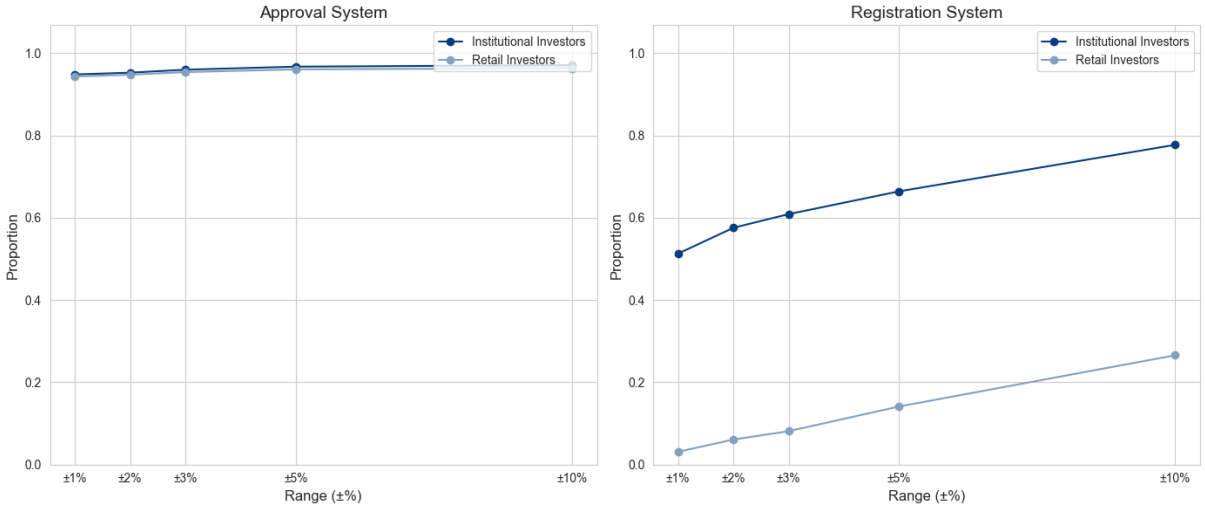


Figure 4: **Investor Bid Frequency and Equilibrium in Bid Percentile Position**

This figure illustrates the relationship between an investor's bid count and the percentile rank of their bid within the overall distribution of bids. Each gray dot represents an individual bid, while the red line depicts the locally smoothed trend. The x-axis denotes the cumulative number of bids submitted by an investor, while the y-axis indicates the percentile position of the bid relative to all bids in the IPO.

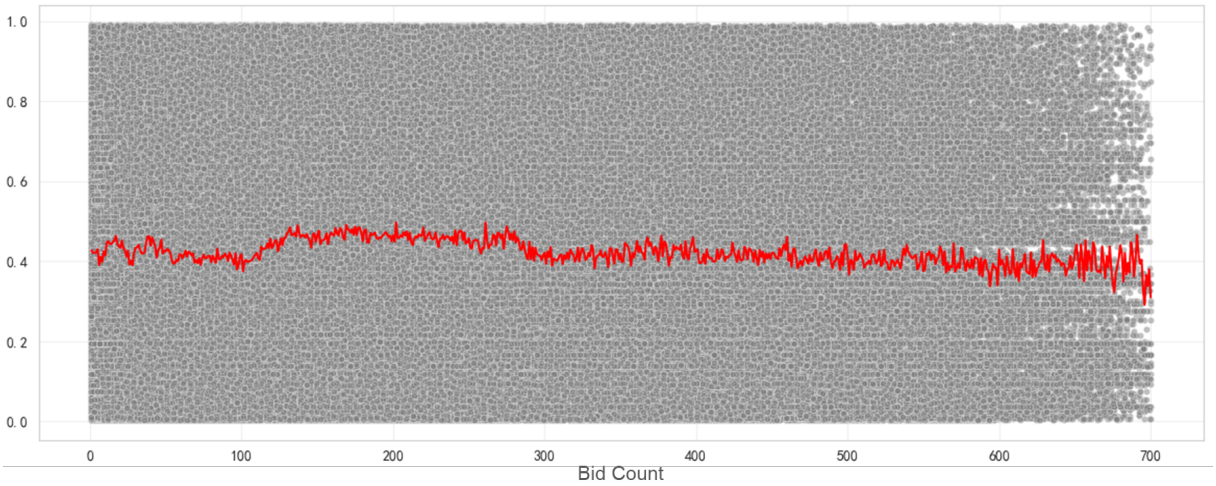


Table 1: **Summary of Stock Market Boards and Key Policy Reforms in China**

This table summarizes the key characteristics and regulatory developments of China's three major stock market boards: the Main Board (SSE & SZSE), ChiNext (SZSE), and STAR Market (SSE). The comparison covers market focus, listing requirements, investor eligibility, IPO approval mechanisms, pricing methods, and price restrictions before and after the adoption of the registration system.

Board	**Main Board (SSE & SZSE)**	**ChiNext (SZSE)**	**STAR Market (SSE)**
Launch Year	SSE: 1990, SZSE: 1991	2009	2019
Market Focus	Large, mature enterprises	High-growth SMEs	Hard-tech industries (AI, biotech, semiconductors)
Listing Criteria	Higher financial and profitability thresholds	Lower profitability requirements	Flexible listing rules, no profitability requirement
Investor Eligibility	No special threshold	2 years of experience, assets $\geq$ 10M RMB	2 years of experience, assets $\geq$ 50M RMB
Regulatory Framework	Approval-Based $\rightarrow$ Registration-Based	Approval-Based $\rightarrow$ Registration-Based	Directly launched under Registration-Based System
Registration-Based Reform Implementation	2023/02/17	2020/08/24	2019/07/22
IPO Review Authority			
Before Reform	IPOs reviewed by CSRC Public Offering Review Committee (PORC)	IPOs reviewed by CSRC Public Offering Review Committee (PORC)	Always Exchange-Based Review
After Reform	IPOs reviewed by SSE & SZSE; CSRC only registers approvals	IPOs reviewed by SZSE; CSRC only registers approvals	IPOs reviewed by SSE; CSRC only registers approvals
Pricing Mechanism			
Before Reform	Fixed-price issuance	Fixed-price issuance	Always Market-Based Pricing
After Reform	Fixed-price,book-building,auction-based	Fixed-price,book-building,auction-based	Fixed-price,book-building,auction-based
Price Restrictions			
Before Reform	Implicit 23$\times$ P/E cap;10% high-price exclusion(2013)	Implicit 23$\times$ P/E cap;10% high-price exclusion(2013)	No P/E cap from inception
After Reform	3% (2023)	10% high-price exclusion (2019), revised to 3% (2021)	10% high-price exclusion (2019), revised to 3% (2021)

Table 2: **Summary of IPO-level statistics.**

This table summarizes key statistics on price clustering, institutional investor participation, and IPO underpricing under different regulatory regimes in China's stock market. The data are categorized into four periods: (i) Approval-Based System, (ii) Registration-Based System with 10% High-Bid Exclusion, (iii) Registration-Based System with 3% High-Bid Exclusion, and (iv) All Periods Combined. The first set of rows presents the degree of price clustering, measured by the fraction of bids concentrated at the most common bid price and the top four or eight most common bid prices. The table also reports the proportion of bids falling within $\pm 1\%$, $\pm 3\%$, and $\pm 10\%$ of the IPO offering price. The second set of rows reports the institutional investor participation rate, capturing the fraction of bids submitted by institutional investors across different regulatory periods. The final section presents the degree of IPO underpricing, calculated as the percentage difference between the first-day closing price and the IPO offering price.

	Obs.	Mean	Std. Dev.	25%	50%	75%
All time:						
Fraction(Most common bid price), %	1,458	59.0	41.5	12.3	65.7	99.6
Fraction(4 most common bid prices), %	1,458	72.5	35.1	37.1	96.5	100.0
Fraction(8 most common bid prices), %	1,458	86.5	22.8	83.1	100.0	100.0
Fraction(bids $\pm 1\%$ of IPO price), %	1,458	72.3	39.7	25.6	96.0	99.8
Fraction(bids $\pm 3\%$ of IPO price), %	1,458	78.1	34.7	76.8	97.0	99.8
Fraction(bids $\pm 10\%$ of IPO price), %	1,458	88.0	21.7	90.4	98.1	99.8
Fraction(institutional investors), %	1,458	38.6	18.3	23.7	36.5	53.2
IPO underpricing (%)	1,455	93.7	125.1	44.0	44.0	94.6
Approval based system:						
Fraction(Most common bid price), %	706	97.4	8.6	99.1	99.6	99.8
Fraction(4 most common bid prices), %	706	99.6	3.1	100.0	100.0	100.0
Fraction(8 most common bid prices), %	706	99.8	1.8	100.0	100.0	100.0
Fraction(bids $\pm 1\%$ of IPO price), %	706	95.9	16.5	99.4	99.8	99.9
Fraction(bids $\pm 3\%$ of IPO price), %	706	97.0	13.0	99.5	99.8	99.9
Fraction(bids $\pm 10\%$ of IPO price), %	706	98.1	8.9	99.7	99.8	99.9
Fraction(institutional investors), %	706	25.9	12.0	17.5	24.4	32.2
IPO underpricing (%)	706	43.4	3.8	44.0	44.0	44.0
Registration based system with 10% high bid exclusion:						
Fraction(Most common bid price), %	415	33.4	20.0	17.4	30.7	45.7
Fraction(4 most common bid prices), %	415	67.0	23.6	47.3	74.0	87.8
Fraction(8 most common bid prices), %	415	82.1	17.7	71.1	88.9	95.6
Fraction(bids $\pm 1\%$ of IPO price), %	415	80.1	27.2	81.4	92.1	95.1
Fraction(bids $\pm 3\%$ of IPO price), %	415	90.2	16.5	91.9	94.7	96.7
Fraction(bids $\pm 10\%$ of IPO price), %	415	95.2	8.0	95.1	96.7	98.1
Fraction(institutional investors), %	415	50.8	15.8	39.1	52.9	64.9
IPO underpricing (%)	415	219.0	172.4	101.7	179.5	272.4
Registration based system with 3% high bid exclusion:						
Fraction(Most common bid price), %	334	9.5	21.4	2.7	3.4	4.5
Fraction(4 most common bid prices), %	334	22.0	23.2	11.7	14.0	18.4
Fraction(8 most common bid prices), %	334	63.6	30.7	35.7	51.4	100.0
Fraction(bids $\pm 1\%$ of IPO price), %	334	12.6	24.0	2.7	5.2	9.0
Fraction(bids $\pm 3\%$ of IPO price), %	334	22.8	23.8	8.7	14.5	26.0
Fraction(bids $\pm 10\%$ of IPO price), %	334	57.5	24.5	38.2	59.8	77.6
Fraction(institutional investors), %	334	50.2	13.7	39.8	48.9	60.9
IPO underpricing (%)	334	44.5	62.7	0.1	32.5	64.9

Table 3: **Bid Clustering and IPO Share Allocation Probability**

This table examines the relationship between bid clustering and the likelihood of winning an IPO share allocation. The dependent variable is a binary indicator that equals one if investor j receives an IPO allocation in IPO i and zero otherwise. The key independent variables capture different levels of bid clustering. Column (1) considers whether the investor's bid matches the most common bid price, while Columns (2) and (3) extend this measure to include bids among the four most common and eight most common bid prices, respectively. Columns (4) to (6) focus on the proximity of bids to the final IPO offering price, identifying bids that fall within $\pm 1\%$, $\pm 3\%$, and $\pm 10\%$ of the offering price. All specifications include controls for investor characteristics and incorporate IPO fixed effects and market-by-year fixed effects to account for unobserved heterogeneity across IPOs and market conditions. Standard errors, reported in parentheses, are clustered at the IPO level. Statistical significance is denoted by $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	$\mathbb{1}$(Investor j wins allocation in IPO i)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Investor bid is						
most common bid price)	0.475***					
	(0.0249)					
1 of the 4 most common bid prices)		0.373***				
		(0.0142)				
1 of the 8 most common bid prices)			0.336***			
			(0.0154)			
$\pm 1\%$ of IPO price)				0.594***		
				(0.0222)		
$\pm 3\%$ of IPO price)					0.505***	
					(0.0222)	
$\pm 10\%$ of IPO price)						0.459***
						(0.0214)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
IPO FEs	Yes	Yes	Yes	Yes	Yes	Yes
Market $\times$ Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.290	0.222	0.206	0.286	0.261	0.248
Observations	2,534,023	2,534,023	2,534,023	2,534,023	2,534,023	2,534,023

Table 4: **The Impact of Bid Clustering on Issuer Costs in IPOs**

This table examines the impact of bid clustering on key IPO outcomes related to issuing firms' costs. The main independent variable measures the fraction of bids falling within ±1% of the IPO offering price, capturing the degree of bid concentration. Column (1) reports the relationship between bid clustering and the proportion of investors who receive IPO allocations (Winners (%)), measured at the IPO level as the fraction of investors allocated shares relative to the total number of bidding investors. Column (2) examines the effect on bid dispersion, which captures the diversity of submitted prices and reflects the degree of competition and information aggregation in the IPO pricing process. Column (3) evaluates the impact on IPO underpricing, calculated as the percentage difference between the first-day closing price and the IPO offering price. Column (4) assesses the relationship between bid clustering and the proportion of shares allocated through offline placement, which refers to institutional investor participation in IPO subscriptions outside the exchange-based online trading system, where pricing flexibility is typically greater. All specifications include controls for firm and deal characteristics, as well as industry fixed effects and market-by-year fixed effects to account for unobserved heterogeneity. Standard errors, reported in parentheses, are clustered at the IPO level. Statistical significance is denoted by $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	(1) Winners (%)	(2) Bid dispersion	(3) IPO underpricing	(4) Auctions (%)
Fraction(bids ±1% of IPO price), %	12.53***	-1.701***	84.28***	5.340***
	(1.705)	(0.0877)	(13.83)	(1.419)
Controls	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
Market × Year FEs	Yes	Yes	Yes	Yes
R^2	0.600	0.873	0.447	0.707
Observations	1,160	1,160	1,160	1,160

Table 5: **Institutional Investor and Bid Clustering in IPOs**

This table examines the relationship between institutional investor status and the likelihood of submitting a clustered bid, measured by whether an investor's bid falls within ±1% of the IPO offering price. The key independent variable is a binary indicator for institutional investors, interacted with different IPO regulatory regimes to assess how institutional bidding behavior varies across market conditions.Column (1) estimates the baseline relationship between institutional investor status and bid clustering across all periods. Column (2) introduces interactions between institutional investor status and two broad IPO regulatory frameworks: approval and registration systems. Column (3) further differentiates the registration system by distinguishing between the 10% high-bid exclusion rule and the later 3% high-bid exclusion rule, allowing for a more granular analysis of institutional bidding behavior under different pricing restrictions. All specifications include controls for investor characteristics, as well as IPO fixed effects and market-by-year fixed effects to account for unobserved heterogeneity in IPO pricing and market conditions. Standard errors, reported in parentheses, are clustered at the IPO level. Statistical significance is denoted by $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	$\mathbb{1}$(Investor j's bid is $\pm$1% of IPO price)		
	(1)	(2)	(3)
$\mathbb{1}$(Institutional investor)	0.00113		
	(0.00104)		
$\mathbb{1}$(Institutional investor)			
$\times$ $\mathbb{1}$(Approval)		-0.000509	-0.000402
		(0.000713)	(0.000712)
$\mathbb{1}$(Institutional investor)			
$\times$ $\mathbb{1}$(Registration)		0.0688*	
		(0.0354)	
$\mathbb{1}$(Institutional investor)			
$\times$ $\mathbb{1}$(Registration, 10%)			0.868***
			(0.0331)
$\mathbb{1}$(Institutional investor)			
$\times$ $\mathbb{1}$(Registration, 3%)			-0.00711***
			(0.00275)
Controls	Yes	Yes	Yes
IPO FEs	Yes	Yes	Yes
Market $\times$ Year FEs	Yes	Yes	Yes
R^2	0.782	0.783	0.786
Observations	2,534,023	2,534,023	2,534,023

Table 6: **Network Centrality and Bid Clustering in IPOs**

This table examines the relationship between investors' network centrality and their likelihood of submitting a clustered bid, measured by whether an investor's bid falls within ±1% of the IPO offering price. The key independent variables capture different aspects of an investor's position within the fund-broker network, interacting various network centrality measures with IPO regulatory regimes to assess how an investor's connectivity and influence in the network relate to bidding behavior.Each column employs a different network centrality measure: Column (1) uses network presence, Column (2) uses closeness centrality, Column (3) uses degree centrality, Column (4) uses betweenness centrality, Column (5) uses eigenvector centrality, and Column (6) uses PageRank centrality. These measures reflect different dimensions of an investor's position, influence, and access to information within the fund-broker network.The interaction terms differentiate between IPO regulatory environments, including the approval system, the registration system with a 10% high-bid exclusion rule, and the registration system with a 3% high-bid exclusion rule, allowing for an analysis of how network centrality affects bid clustering under different market structures. All specifications include investor-level controls, as well as IPO fixed effects and market-by-year fixed effects to account for unobserved heterogeneity across IPOs and market conditions. Standard errors, reported in parentheses, are clustered at the IPO level. Statistical significance is denoted by $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	$\mathbb{1}$(Investor j's bid is $\pm$1% of IPO price)					
	(1) Use network presence as measure	(2) Use closeness centrality as measure	(3) Use degree centrality as measure	(4) Use betweenness centrality as measure	(5) Use eigenvector centrality as measure	(6) Use PageRank centrality as measure
Network measure						
$\times$ $\mathbb{1}$(Approval)	0.00268	0.00744	0.0371*	0.0802**	0.0476*	0.361*
	(0.00184)	(0.00477)	(0.0192)	(0.0355)	(0.0256)	(0.195)
Network measure						
$\times$ $\mathbb{1}$(Registration, 10%)	0.00848***	0.0276***	0.196***	0.244***	0.310***	0.931***
	(0.00303)	(0.00780)	(0.0272)	(0.0548)	(0.0376)	(0.301)
Network measure						
$\times$ $\mathbb{1}$(Registration, 3%)	0.000208	0.00123	0.00650	0.00386	0.0159	-0.0706
	(0.00179)	(0.00458)	(0.0180)	(0.0577)	(0.0256)	(0.262)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
IPO FEs	Yes	Yes	Yes	Yes	Yes	Yes
Market $\times$ Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.782	0.782	0.783	0.782	0.783	0.782
Observations	2,534,023	2,534,023	2,534,023	2,534,023	2,534,023	2,534,023

Table 7: **Economic Incentives and Constraints in Bid Coordination**

This table examines two key factors that may drive coordinated bidding behavior among investors: (i) the economic incentives for collusion and (ii) the risks of profit-sharing with outsiders. The dependent variable in all specifications is a binary indicator equal to one if investor j's bid falls within ±1% of the IPO offering price, capturing the extent of bid clustering. The primary independent variable is PageRank centrality, which reflects an investor's prominence within the fund-broker network. Columns (1)–(4) distinguish IPOs based on underpricing and issuance costs, while Columns (5) and (6) examine IPOs in high-tech industries versus other sectors. Columns (7) and (8) compare IPOs conducted in financial centers—defined as cities with stock exchanges (Beijing, Shanghai, and Shenzhen)—against those in other regions. All specifications include controls for investor characteristics, as well as IPO fixed effects and market-by-year fixed effects to account for unobserved heterogeneity in IPO pricing and market conditions. Standard errors, reported in parentheses, are clustered at the IPO level. Statistical significance is denoted by $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	$\mathbb{1}$(Investor j's bid is $\pm$1% of IPO price)							
	IPO underpricing		Inssuance cost		High-tech industry		Financial center	
	(1) High	(2) Low	(3) High	(4) Low	(5) Yes	(6) No	(7) Yes	(8) No
PageRank centrality								
$\times$ $\mathbb{1}$(Approval)	0.360	0.385	0.485	0.265	0.0681	0.443**	0.734	0.178
	(0.276)	(0.270)	(0.346)	(0.204)	(0.403)	(0.222)	(0.500)	(0.155)
PageRank centrality								
$\times$ $\mathbb{1}$(Registration)	0.500**	0.497	0.771***	-0.305	0.893*	0.465**	0.344	0.644**
	(0.242)	(0.319)	(0.227)	(0.392)	(0.472)	(0.220)	(0.332)	(0.255)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IPO FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market $\times$ Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.747	0.823	0.829	0.598	0.763	0.786	0.805	0.765
Observations	1,308,536	1,225,487	1,265,372	1,268,651	504,552	2,029,471	853,153	1,680,870

Table 8: **Institutional Investors' Strategic Bidding and IPO Pricing Dynamics**

This table examines whether institutional investors strategically place bids within a ±1% range of the final IPO offering price, potentially reflecting repeated-game dynamics in the IPO pricing process. Columns (1)–(3) report regression results using different dependent variables. Column (1) captures the bidder's percentile rank within the overall bid distribution. Column (2) indicates whether bids fall within a specific relative price-to-earnings (P/E) valuation range (0.2–0.4 times the industry average P/E). Column (3) measures the investor's proximity to the critical 10-billion RMB market capitalization threshold. All specifications include controls for investor characteristics, as well as IPO fixed effects and market-by-year fixed effects to account for unobserved heterogeneity in IPO pricing and market conditions. Standard errors, reported in parentheses, are clustered at the IPO level. Statistical significance is denoted by $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	$\mathbb{1}$(Investor j's bid is $\pm 1\%$ of IPO price)		
	(1) Bid percentile	(2) $\mathbb{1}$(Within relative P/E range)	(3) Distance from 10B market cap cutoff
$\mathbb{1}$(Institutional investor)			
$\times$ $\mathbb{1}$(Approval)	0.0234	-0.000326	-1.636
	(0.0208)	(0.000422)	(1.013)
$\mathbb{1}$(Institutional investor)			
$\times$ $\mathbb{1}$(Registration)	0.00988	-0.0121	-0.370
	(0.0314)	(0.0161)	(0.400)
Controls	Yes	Yes	Yes
IPO FEs	Yes	Yes	Yes
Market $\times$ Year FEs	Yes	Yes	Yes
R^2	0.405	0.982	0.000429
Observations	2,520,895	2,534,023	2,534,023

Internet Appendix

Institutional Reform, Collusion, and the Unraveling of China's Initial Public Offerings

This Internet Appendix contains supplementary material.

IA.1 Additional Results on Bid Concentration

Tables IA.1, IA.2, and IA.3 expand the pooled summary statistics in Table 2 in the main paper into the three separate market segments. A summary of the major policy changes over time across the three market segments is provided in Table 1.

IA.2 Details on network measures

IA.2.1 Degree Centrality

Degree centrality is one of the most intuitive and widely used measures in social network analysis, capturing the number of direct connections a given node has with other nodes. In the broker-fund network, degree centrality quantifies the extent of a brokerage firm's direct relationships with mutual fund institutions, reflecting its fundamental influence in capital market information acquisition and dissemination. Specifically, a higher degree centrality indicates that a brokerage firm has established direct business or trading relationships with a larger number of mutual funds, thereby granting it broader network resources and greater control over market information.

To quantify degree centrality, we first construct an undirected adjacency matrix X. Suppose the total number of institutions in the network is N, including both brokerage firms and mutual funds. The adjacency matrix X is an $N \times N$ matrix, where each element X_{ij} (or equivalently X_{ji} in an undirected network) is assigned a value of 1 if institution i and institution j have at least one transaction or business relationship during the observation period, and 0 otherwise. The degree centrality of node i is then given by:

$$d_i = \sum_{j \neq i} X_{ij} \tag{IA.1}$$

where d_i represents the row sum (or equivalently, the column sum) of the adjacency matrix X. This value directly reflects the number of direct connections an institution has within the network. One of the key advantages of degree centrality is its simplicity and computational efficiency, making it a fundamental measure for describing network char-

acteristics and conducting preliminary analyses in academic research. Generally, brokerage firms with higher degree centrality are better positioned to acquire and disseminate market information, making them more likely to gain insights into market trends and investor preferences. This, in turn, may provide them with a competitive advantage in underwriting, IPO pricing, and capital raising activities.

However, degree centrality has certain limitations. First, it only considers the number of direct connections a node has, without accounting for the broader network structure, indirect relationships, or potential information flow pathways. As a result, it may not fully capture a node's true influence within the network. Second, degree centrality is typically computed under the assumption of an undirected network, meaning it does not account for the directionality or varying strength of connections, which may limit its ability to accurately reflect the actual dynamics of information transmission. Additionally, the raw degree centrality measure does not account for differences in network size, making cross-network or intertemporal comparisons potentially biased.

To address these limitations, we adopt a normalized degree centrality measure, which adjusts for network size by dividing each institution's degree centrality d_i by the maximum possible number of connections $(N-1)$:

$$d_i^{\text{norm}} = \frac{\sum_{j \neq i} X_{ij}}{N-1} \tag{IA.2}$$

This normalization eliminates the influence of network size, allowing for more accurate and objective comparisons across networks of different scales, facilitating both cross-sectional and longitudinal empirical analyses. However, as a single measure, degree centrality remains limited in capturing the full complexity of network structures. Therefore, in subsequent sections, we introduce additional centrality measures—including eigenvector centrality, betweenness centrality, and structural holes—to provide a more comprehensive and precise characterization of brokerage firms' positions and informational advantages within the broker-fund network.

IA.2.2 Betweenness Centrality

Betweenness centrality is a key metric in social network analysis that quantifies the extent to which a node acts as a bridge connecting other nodes within a network. Specifically, it measures the frequency or probability with which a given node appears on the shortest paths between pairs of other nodes. In the IPO broker-fund network, intermediaries with high betweenness centrality often occupy strategic positions within the network. These institutions serve as crucial conduits for information flow and resource allocation, en-

abling them to control the transmission of key resources while playing a pivotal role in information dissemination and market coordination.

The betweenness centrality of node i is computed as follows:

$$b_i = \sum_{j<k} \frac{p_{ijk}}{p_{jk}} \tag{IA.3}$$

where p_{ijk} represents the number of shortest paths between nodes j and k that pass through node i, and p_{jk} denotes the total number of shortest paths between j and k. A higher betweenness centrality indicates that a node frequently occupies a central position in the network's information flow, granting it greater control over information dissemination and resource distribution.

However, the computation of betweenness centrality is computationally intensive, particularly in large-scale networks, as it requires identifying shortest paths across all node pairs. As a result, algorithmic optimizations are often necessary to improve computational efficiency.

IA.2.3 Closeness Centrality

Unlike degree centrality, which focuses on the local connectivity of a node, closeness centrality captures a node's global position within the entire network. It evaluates how efficiently a node can access information by measuring the total shortest path distances between the node and all other nodes in the network. A higher closeness centrality indicates that a node is, on average, closer to other nodes, enabling it to receive and disseminate information more rapidly. The formal computation of closeness centrality is given by:

$$C(v) = \frac{n-1}{\sum_{u \neq v} \text{dist}(v,u)} \tag{IA.4}$$

where $\text{dist}(v,u)$ represents the shortest path distance between node v and node u, and n denotes the total number of nodes in the network. A higher closeness centrality implies that the node is, on average, at a shorter distance from other nodes, allowing for faster information diffusion and greater strategic advantage in information transmission.

However, closeness centrality has several limitations. First, in disconnected networks, it fails to accurately reflect the position of isolated nodes or nodes within separate subnetworks. Second, in large-scale networks, the computational complexity increases significantly, making it challenging to obtain quick and precise estimations. Lastly, in networks that are either too sparse or too dense, closeness centrality may lose its discriminative power, making it difficult to differentiate the relative importance of nodes.

IA.2.4 Eigenvector Centrality

Eigenvector centrality extends traditional centrality measures by not only accounting for the number of direct connections a node has but also incorporating the centrality of its neighboring nodes. This metric emphasizes the idea that connections to highly influential nodes contribute more to a node's importance than connections to less central nodes. In the IPO broker-fund network, investors with high eigenvector centrality are not only well-connected but also tend to collaborate with other key players in the network. This enhances their market influence and strengthens their informational advantage.

The eigenvector centrality of an intermediary i, denoted as e_i, is computed as follows:

$$e_i = \frac{1}{\lambda} \sum_{j=1}^{N} x_{ij} e_j \tag{IA.5}$$

where x_{ij} represents the elements of the adjacency matrix, λ is the largest eigenvalue of the adjacency matrix, and e_i is the eigenvector centrality of node i. This formulation effectively weights a node's connections based on the centrality of its neighbors, assigning higher scores to nodes that are linked to more influential counterparts. By incorporating such weighted adjustments, eigenvector centrality provides a more precise representation of a node's true importance within the network.

IA.2.5 PageRank Centrality

The PageRank algorithm was originally proposed by Google co-founders Page and Brin for ranking web pages and analyzing the importance of network nodes. Based on a random walk model, this metric incorporates network topology characteristics and determines a node's final importance using a steady-state probability distribution. Although initially developed for search engines, PageRank has been widely applied in financial network research in recent years to assess the network position and influence of financial institutions.

The PageRank score of a node v is calculated as follows:

$$PR(v) = \frac{1-d}{N} + d \sum_{u \in \text{InNeighbors}(v)} \frac{PR(u)}{\text{outdegree}(u)} \tag{IA.6}$$

where $PR(v)$ represents the PageRank value of node v, reflecting its importance in the network; N is the total number of nodes; d is the damping factor, typically set to 0.85; $\text{InNeighbors}(v)$ denotes the set of nodes linking to v; and $\text{outdegree}(u)$ represents the out-degree of node u. The PageRank values are computed iteratively until the algorithm

converges.

PageRank has significant applications in financial networks. Unlike traditional centrality measures that focus solely on the number of direct connections, PageRank also accounts for the quality of links and the overall network topology. This allows for a more comprehensive evaluation of an institution's influence and importance within capital market networks. While PageRank can be computationally intensive in large-scale networks, the development of modern distributed algorithms has significantly improved computational efficiency, making it one of the key tools for assessing the network position of financial institutions.

Figure IA.1: **Network Structure of the Top 100 Funds and Brokerage Firms Based on Degree Centrality**

This figure visualizes the network structure of the top 100 funds and brokerage firms based on degree centrality, which measures the importance of a node by the number of direct connections it has within the network. Nodes positioned closer to the center exhibit higher centrality, indicating their greater significance in the interconnections among market participants.

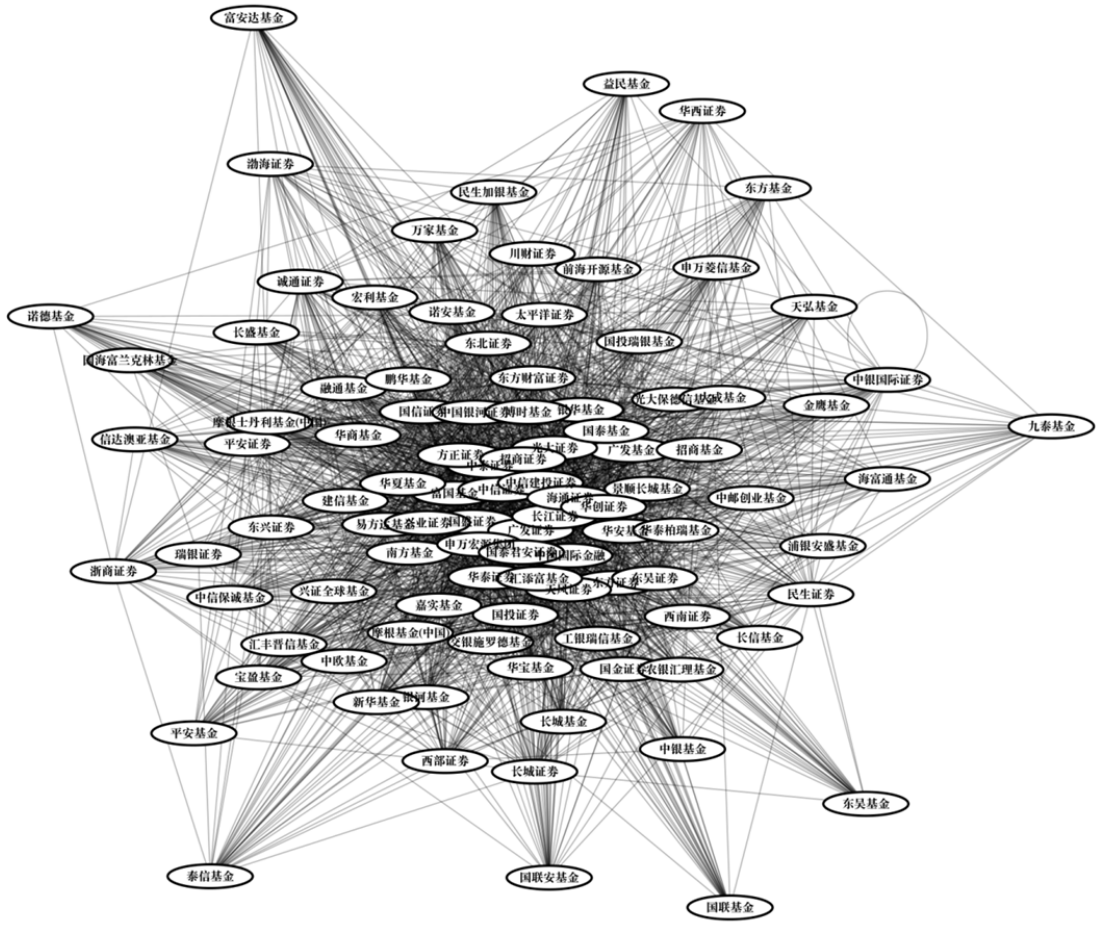


Figure IA.2: **Kernel Density Estimation of Bidding Prices During the IPO Process Across Different Market Periods**

This figure compares the distribution of IPO quoted prices with the corresponding normal distribution (shaded area) across different market periods. The four panels represent: the approval system (top-left), the registration system (top-right), the registration system before the 3% reform (bottom-left), and the registration system after the 3% reform (bottom-right). The kernel density estimates illustrate the clustering patterns of quoted prices in each period, highlighting deviations from normality and potential structural differences in the IPO pricing process under different regulatory frameworks.

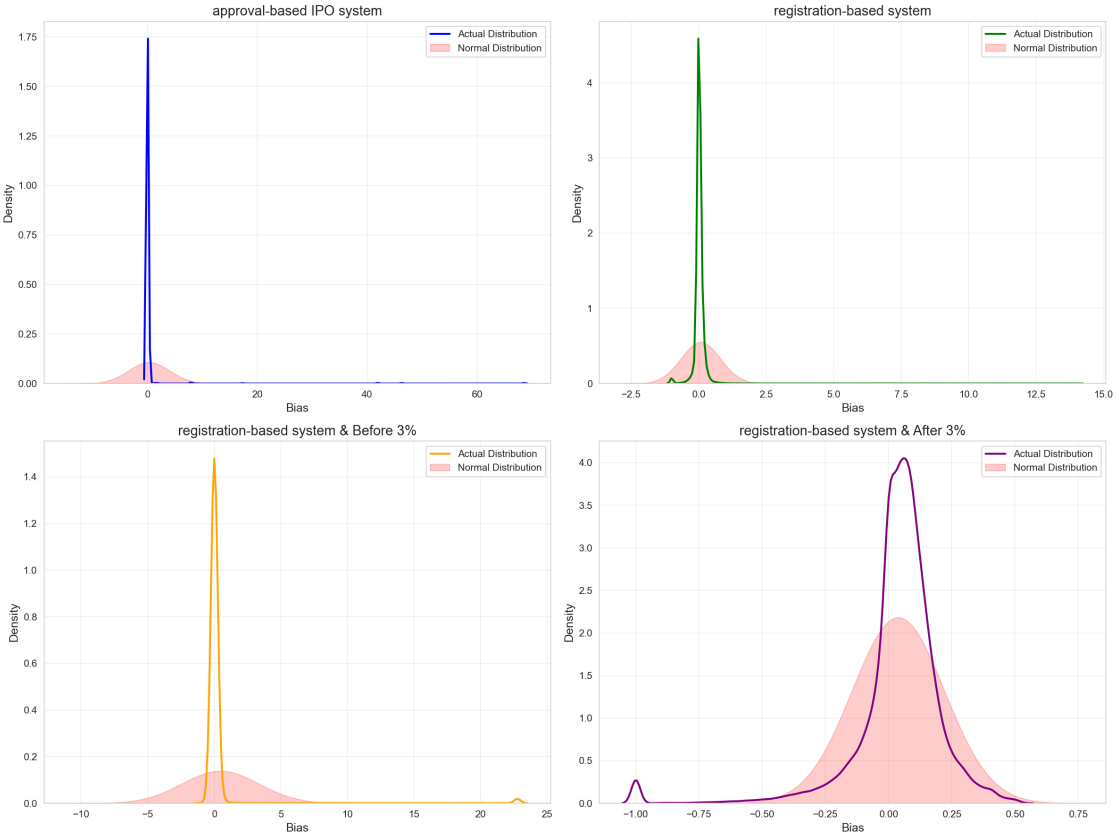


Figure IA.3: **Distribution of Relative P/E Ratios by Investor Bid Frequency**

This figure illustrates the distribution of investors' bid prices relative to industry price-to-earnings (P/E) ratios across different bid frequency groups. The four panels represent investors who have submitted 0-10, 10-100, 100-200, and 200+ bids. The horizontal axis denotes the relative P/E ratio, computed as the bid price divided by the industry-average P/E ratio, while the vertical axis indicates density. The blue line represents the kernel density estimate using an Epanechnikov kernel with varying bandwidths, and the red line represents the normal density distribution.

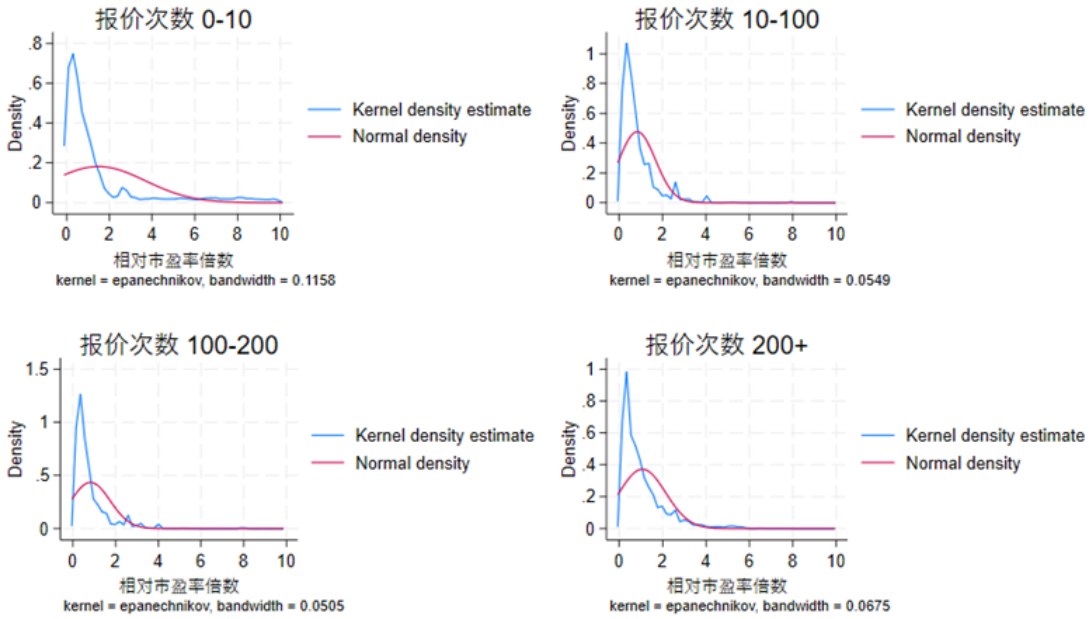


Table IA.1: **IPO-level summary statistics (STAR market)**

This table summarizes key statistics on price clustering, institutional investor participation, and IPO underpricing under different regulatory regimes in the STAR market. The data are categorized into three periods: (i) Registration-Based System with 10% High-Bid Exclusion, (ii) Registration-Based System with 3% High-Bid Exclusion, and (iii) All Periods Combined. The first set of rows presents the degree of price clustering, measured by the fraction of bids concentrated at the most common bid price and the top four or eight most common bid prices. The table also reports the proportion of bids falling within $\pm$1%, $\pm$3%, and $\pm$10% of the IPO offering price. The second set of rows reports the institutional investor participation rate, capturing the fraction of bids submitted by institutional investors across different regulatory periods. The final section presents the degree of IPO underpricing, calculated as the percentage difference between the first-day closing price and the IPO offering price.

	Obs.	Mean	Std. Dev.	25%	50%	75%
All time:						
Fraction(Most common bid price), %	441	24.0	22.5	3.7	17.5	40.4
Fraction(4 most common bid prices), %	441	50.3	32.0	16.9	47.4	84.2
Fraction(8 most common bid prices), %	441	75.4	24.8	53.3	86.7	100.0
Fraction(bids $\pm$1% of IPO price), %	441	54.2	41.8	6.3	77.4	94.1
Fraction(bids $\pm$3% of IPO price), %	441	65.5	37.8	20.4	91.2	96.0
Fraction(bids $\pm$10% of IPO price), %	441	81.8	24.0	70.4	95.1	97.7
Fraction(institutional investors), %	441	56.9	14.4	49.9	60.0	66.8
IPO underpricing (%)	441	133.4	149.3	35.8	93.2	186.4
Registration based system with 10% high bid exclusion:						
Fraction(Most common bid price), %	292	33.7	21.0	16.9	33.4	46.6
Fraction(4 most common bid prices), %	292	66.8	24.6	45.1	76.5	88.1
Fraction(8 most common bid prices), %	292	81.9	18.1	69.0	89.9	95.9
Fraction(bids $\pm$1% of IPO price), %	292	77.9	29.9	76.3	92.5	95.6
Fraction(bids $\pm$3% of IPO price), %	292	89.2	18.8	91.2	94.8	97.0
Fraction(bids $\pm$10% of IPO price), %	292	95.1	9.1	95.1	96.9	98.4
Fraction(institutional investors), %	292	55.0	15.7	46.8	58.0	66.7
IPO underpricing (%)	292	185.5	156.1	85.4	139.9	243.0
Registration based system with 3% high bid exclusion:						
Fraction(Most common bid price), %	149	5.1	9.6	2.7	3.3	3.9
Fraction(4 most common bid prices), %	149	17.9	16.4	11.1	13.9	17.4
Fraction(8 most common bid prices), %	149	62.7	30.5	35.5	50.9	100.0
Fraction(bids $\pm$1% of IPO price), %	149	7.9	13.4	2.5	5.0	8.1
Fraction(bids $\pm$3% of IPO price), %	149	19.0	16.5	8.7	13.7	24.4
Fraction(bids $\pm$10% of IPO price), %	149	55.8	23.0	38.2	59.5	72.5
Fraction(institutional investors), %	149	60.7	10.4	55.3	61.6	67.2
IPO underpricing (%)	149	31.2	49.7	-6.9	23.6	54.9

Table IA.2: **IPO-level summary statistics (ChiNext market)**

This table summarizes key statistics on price clustering, institutional investor participation, and IPO underpricing under different regulatory regimes in the ChiNext market. The data are categorized into four periods: (i) Approval-Based System, (ii) Registration-Based System with 10% High-Bid Exclusion, (iii) Registration-Based System with 3% High-Bid Exclusion, and (iv) All Periods Combined. The first set of rows presents the degree of price clustering, measured by the fraction of bids concentrated at the most common bid price and the top four or eight most common bid prices. The table also reports the proportion of bids falling within $\pm$1%, $\pm$3%, and $\pm$10% of the IPO offering price. The second set of rows reports the institutional investor participation rate, capturing the fraction of bids submitted by institutional investors across different regulatory periods. The final section presents the degree of IPO underpricing, calculated as the percentage difference between the first-day closing price and the IPO offering price.

	Obs.	Mean	Std. Dev.	25%	50%	75%
All time:						
Fraction(Most common bid price), %	420	43.9	41.3	3.9	27.4	99.5
Fraction(4 most common bid prices), %	420	59.6	37.6	16.0	69.5	100.0
Fraction(8 most common bid prices), %	420	80.9	25.6	55.8	100.0	100.0
Fraction(bids $\pm$1% of IPO price), %	420	60.5	43.5	6.5	90.6	99.6
Fraction(bids $\pm$3% of IPO price), %	420	66.9	39.3	18.8	94.2	99.6
Fraction(bids $\pm$10% of IPO price), %	420	81.8	25.2	70.6	95.9	99.7
Fraction(institutional investors), %	420	36.0	12.5	27.7	37.6	44.7
IPO underpricing (%)	420	122.4	157.2	44.0	44.0	166.0
Approval based system:						
Fraction(Most common bid price), %	136	98.6	5.7	99.5	99.7	99.8
Fraction(4 most common bid prices), %	136	99.9	0.3	100.0	100.0	100.0
Fraction(8 most common bid prices), %	136	100.0	0.1	100.0	100.0	100.0
Fraction(bids $\pm$1% of IPO price), %	136	98.0	11.8	99.6	99.8	99.9
Fraction(bids $\pm$3% of IPO price), %	136	98.7	8.4	99.7	99.8	99.9
Fraction(bids $\pm$10% of IPO price), %	136	98.8	8.4	99.7	99.9	99.9
Fraction(institutional investors), %	136	24.4	9.9	17.1	24.2	30.4
IPO underpricing (%)	136	44.0	0.0	44.0	44.0	44.0
Registration based system with 10% high bid exclusion:						
Fraction(Most common bid price), %	123	32.7	17.3	18.5	29.6	44.4
Fraction(4 most common bid prices), %	123	67.5	21.2	49.5	70.1	87.0
Fraction(8 most common bid prices), %	123	82.5	16.7	73.2	87.6	95.1
Fraction(bids $\pm$1% of IPO price), %	123	85.3	18.2	86.6	91.3	94.1
Fraction(bids $\pm$3% of IPO price), %	123	92.7	8.5	92.3	94.6	95.8
Fraction(bids $\pm$10% of IPO price), %	123	95.5	4.7	95.1	96.4	97.5
Fraction(institutional investors), %	123	40.9	11.0	33.1	42.9	46.7
IPO underpricing (%)	123	298.4	183.6	179.5	254.1	384.3
Registration based system with 3% high bid exclusion:						
Fraction(Most common bid price), %	161	6.3	12.0	2.7	3.5	4.4
Fraction(4 most common bid prices), %	161	19.6	17.6	12.0	14.2	17.6
Fraction(8 most common bid prices), %	161	63.7	29.8	39.9	51.4	100.0
Fraction(bids $\pm$1% of IPO price), %	161	9.9	18.7	2.8	5.0	8.3
Fraction(bids $\pm$3% of IPO price), %	161	20.4	19.7	8.7	14.4	25.0
Fraction(bids $\pm$10% of IPO price), %	161	56.9	23.8	40.2	59.6	77.0
Fraction(institutional investors), %	161	42.0	8.1	37.4	41.2	45.9
IPO underpricing (%)	161	54.3	72.8	6.8	36.1	76.8

Table IA.3: **IPO-level summary statistics (Main board)**

This table summarizes key statistics on price clustering, institutional investor participation, and IPO underpricing under different regulatory regimes in the main board. The data are categorized into three periods: (i) Approval-Based System, (ii) Registration-Based System with 3% High-Bid Exclusion, and (iii) All Periods Combined. The first set of rows presents the degree of price clustering, measured by the fraction of bids concentrated at the most common bid price and the top four or eight most common bid prices. The table also reports the proportion of bids falling within $\pm$1%, $\pm$3%, and $\pm$10% of the IPO offering price. The second set of rows reports the institutional investor participation rate, capturing the fraction of bids submitted by institutional investors across different regulatory periods. The final section presents the degree of IPO underpricing, calculated as the percentage difference between the first-day closing price and the IPO offering price.

	Obs.	Mean	Std. Dev.	25%	50%	75%
All time:						
Fraction(Most common bid price), %	594	95.6	15.1	98.5	99.6	99.8
Fraction(4 most common bid prices), %	594	98.0	11.8	99.9	100.0	100.0
Fraction(8 most common bid prices), %	594	98.5	10.0	100.0	100.0	100.0
Fraction(bids $\pm$1% of IPO price), %	594	93.9	20.7	99.3	99.7	99.9
Fraction(bids $\pm$3% of IPO price), %	594	95.2	17.6	99.4	99.8	99.9
Fraction(bids $\pm$10% of IPO price), %	594	96.9	12.2	99.6	99.8	99.9
Fraction(institutional investors), %	594	26.9	12.9	18.0	24.9	32.9
IPO underpricing (%)	594	44.0	10.6	44.0	44.0	44.0
Approval based system:						
Fraction(Most common bid price), %	570	97.2	9.2	98.8	99.6	99.8
Fraction(4 most common bid prices), %	570	99.5	3.4	99.9	100.0	100.0
Fraction(8 most common bid prices), %	570	99.8	2.0	100.0	100.0	100.0
Fraction(bids $\pm$1% of IPO price), %	570	95.4	17.4	99.3	99.7	99.9
Fraction(bids $\pm$3% of IPO price), %	570	96.6	13.8	99.4	99.8	99.9
Fraction(bids $\pm$10% of IPO price), %	570	98.0	9.0	99.6	99.8	99.9
Fraction(institutional investors), %	570	26.3	12.4	17.6	24.5	32.4
IPO underpricing (%)	570	43.3	4.2	44.0	44.0	44.0
Registration based system with 3% high bid exclusion:						
Fraction(Most common bid price), %	24	58.8	48.1	3.5	97.1	99.6
Fraction(4 most common bid prices), %	24	63.2	44.3	12.2	99.5	100.0
Fraction(8 most common bid prices), %	24	68.1	38.7	24.2	100.0	100.0
Fraction(bids $\pm$1% of IPO price), %	24	59.1	47.9	3.8	97.3	99.6
Fraction(bids $\pm$3% of IPO price), %	24	61.7	44.9	9.6	97.3	99.6
Fraction(bids $\pm$10% of IPO price), %	24	71.7	33.6	33.9	97.4	99.7
Fraction(institutional investors), %	24	40.2	16.4	29.5	40.2	50.4
IPO underpricing (%)	24	60.8	46.3	44.0	44.0	64.2

Table IA.4: **Bid Clustering Among Fund Investors, Other Institutional Investors, and Retail Investors**

This table examines the relationship between investor type and bid clustering, measured by whether an investor's bid falls within ±1% of the IPO offering price. The key independent variables are binary indicators for fund investors and other institutional investors (including brokerage firms, financial institutions, and corporate investment groups), with retail investors as the baseline. Column (1) estimates baseline differences across investor types, while Columns (2) and (3) introduce interactions with IPO regulatory regimes, distinguishing between approval and registration systems, as well as the 10% and 3% high-bid exclusion rules. All specifications control for investor characteristics, IPO fixed effects, and market-by-year fixed effects. Statistical significance is denoted by $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	$\mathbb{1}$(Investor j's bid is $\pm$1% of IPO price)		
	(1)	(2)	(3)
$\mathbb{1}$(Fund)	0.0104***		
	(0.00157)		
$\mathbb{1}$(Other institutions)	-0.000525		
	(0.00101)		
$\mathbb{1}$(Fund) ×			
$\mathbb{1}$(Approval)		0.00370*	0.00460**
		(0.00195)	(0.00193)
$\mathbb{1}$(Fund) ×			
$\mathbb{1}$(Registration)		0.0816**	
		(0.0354)	
$\mathbb{1}$(Other institutions) ×			
$\mathbb{1}$(Approval)		-0.00124**	-0.00126**
		(0.000601)	(0.000602)
$\mathbb{1}$(Other institutions) ×			
$\mathbb{1}$(Registration)		0.0648*	
		(0.0354)	
$\mathbb{1}$(Fund) ×			
$\mathbb{1}$(Registration, 10%)			0.889***
			(0.0333)
$\mathbb{1}$(Fund) ×			
$\mathbb{1}$(Registration, 3%)			-0.00467
			(0.00306)
$\mathbb{1}$(Other institutions) ×			
$\mathbb{1}$(Registration, 10%)			0.861***
			(0.0334)
$\mathbb{1}$(Other institutions) ×			
$\mathbb{1}$(Registration, 3%)			-0.00766***
			(0.00275)
Controls	Yes	Yes	Yes
IPO FEs	Yes	Yes	Yes
Market × Year FEs	Yes	Yes	Yes
R^2	0.783	0.783	0.786
Observations	2,534,023	2,534,023	2,534,023

Table IA.5: **The Impact of Network Relationships on Bid Clustering**

This table examines the relationship between investors' network relationships and their likelihood of submitting a clustered bid, measured by whether an investor's bid falls within ±1% of the IPO offering price. Column (1) uses network presence, a binary measure indicating whether an investor has established relationships within the network, while Columns (2)–(6) measure network centrality using closeness, degree, betweenness, eigenvector, and PageRank, respectively. All specifications include controls for investor characteristics, as well as IPO fixed effects and market-by-year fixed effects. Standard errors, reported in parentheses, are clustered at the IPO level. Statistical significance is denoted by $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

	$\mathbb{1}$(Investor j's bid is $\pm$1% of IPO price)					
	(1)	(2)	(3)	(4)	(5)	(6)
Network presence	0.00369***					
	(0.00110)					
Closeness centrality		0.0114***				
		(0.00284)				
Degree centrality			0.0722***			
			(0.0112)			
Betweenness centrality				0.113***		
				(0.0249)		
Eigenvector centrality					0.111***	
					(0.0156)	
PageRank centrality						0.441***
						(0.130)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
IPO FEs	Yes	Yes	Yes	Yes	Yes	Yes
Market × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.782	0.782	0.783	0.782	0.783	0.782
Observations	2,534,023	2,534,023	2,534,023	2,534,023	2,534,023	2,534,023