The Behavior of Institutional Investors in IPO Markets and the Decision of Going Public Abroad

by

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Declaration

I declare that this thesis is composed by myself. None part of this thesis has been submitted for any other degree or professional qualification. The work presented in Chapter 3 and Chapter 4 are based on co-authored working papers with Professor Seth Armitage and Dr. Ufuk Gucbilmez. Chapter 3 is based on a working paper titled *Does Experience Affect the Behavior of Institutional Investors in IPO Markets?* Chapter 4 is based on a working paper titled *Do Institutional Investors Truthfully Reveal Private Information in a Quasi-Bookbuilding IPO Mechanism?* The work presented in Chapter 5 is based on a working paper for which I am the single author.

Signature:

Date:

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Abstract

This thesis comprehensively studies three questions. First of all, I use a unique set of institutional investor bids to examine the impact of personal experience on the behavior of institutional investors in an IPO market. I find that, when deciding to participate in future IPOs, institutions take into account initial returns of past IPOs in which they submitted bids more than IPOs which they merely observed. In addition, initial returns from past IPOs in which institutions' bids were qualified for share allocation were given more consideration than IPOs for which unqualified bids were submitted. This phenomenon is consistent with reinforcement learning. I also find that institutions do not distinguish the returns that are derived from random events. Furthermore, institutions become more aggressive bidders after experiencing high returns in recent IPOs, conditional on personal participation or being qualified for share allocation in those IPOs. This bidding behavior provides additional evidence of reinforcement learning in IPO markets.

Secondly, I merge the dataset of institutional investor bids with post-IPO institutional holdings data to examine whether institutional investors such as fund companies reveal their true valuations through bids in a unique quasi-bookbuilding IPO mechanism. I find that fund companies do truthfully disclose their private information via bids, despite these being without guaranteed compensation. My results contribute to the existing literature by providing new evidence on the information compensation theory and have implications for the IPO mechanism design.

Finally, I explore the impact on firm valuation of going public abroad using a sample of 136 Chinese firms that conducted IPOs in the US during the period of 1999-2012. I find that US-listed Chinese firms have higher price multiples and experience less underpricing than their domestic-listed peers. The valuation premium stays consistent when a firm's characteristics and listing cost are being controlled. These findings are consistent with the theories of foreign listing. Moreover, I find

that high-tech Chinese firms with a high growth rate but low profitability are more likely to issue shares in the US, particularly for specific industries such as semiconductors, software and online business services. This industry clustering is interpreted as an incentive to access foreign expertise through listing abroad.

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List of Abbreviations

ADR	American Depositary Receipt
AMEX	American Stock Exchange
BNY	Bank of New York
CBRC	China Banking Regulatory Commission
CNY	Chinese Yuan
CSRC	China Securities Regulatory Commission
ETF	Exchange Traded Fund
FSB	Financial Stability Board
GAAP	Generally Accepted Accounting Principles
GEM	Growth Enterprises Market
IPO	Initial Public Offering
LSE	London Stock Exchange
NN	Nearest Neighbor
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
OTC	Over-the-Counter
PORTAL	Private Offerings, Resale, and Trading through Automated Linkages
PSM	Propensity Score Matching
QFII	Qualified Foreign Institutional Investor
QIB	Qualified Institutional Buyer
SBF	Societe des Bourses Francaises
SDC	Securities Data Company
SEC	Securities and Exchange Commission
SEO	Seasoned Equity Offering
SIC	Standard Industrial Classification
SME	Small and Medium Enterprise
SOE	State-Owned Enterprise
SSE	Shanghai Stock Exchange
SZSE	Shenzhen Stock Exchange
T1B	Thomson One Banker

Chapter 1

1. Introduction

In line with the tremendous economic development in the past decades, China's equity market experienced a rapid growth and has become a conspicuous force in global financial markets. By the end of April 2015, there were 2,721 firms listing on China's stock exchanges and the total market capitalization reached US$ 9,073 billion, ranking the second worldwide.[1] With respect to the initial public offering (IPO), China is one of the most energetic primary markets. During 2014, 215 firms undertook IPOs on China's stock exchanges with a total raised capitals of US$ 11.393 million.[2] Using the sample of Chinese IPOs, this thesis investigates three research questions:

1. Does experience affect the behavior of institutional investors in IPO markets?
2. Do institutional investors truthfully reveal private information in a quasi-bookbuilding IPO mechanism?
3. Whether US-listed Chinese firms can obtain higher valuations than their domestic-listed counterparts in IPOs?

This thesis focuses on China's equity market not only because its raising power but also the unique characteristics of this market that enables me to conduct tests which have not been done. To provide a better understanding of the research context, I introduce the institutional background of China's equity market in Chapter 2. In general, the background chapter presents the history and current status of China's two stock exchanges and three listing boards; IPO approval systems, pricing and allocation mechanism; and institutional investors in China's equity market.

In Chapter 3, I use a unique set of Chinese bookbuilding data to explore the impact of experience on the behavior of institutional investors in IPO markets. The data includes 19,151 bids submitted by 353 institutions in 214 IPOs which took place

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[1] Source: World Federation of Exchanges.

[2] Source: World Federation of Exchanges.

on ChiNext, a new board of Shenzhen Stock Exchange launched in late 2009. I identify that the experience does affect institutions' future investment decisions. More specifically, when deciding to participate[3] in future IPOs, institutions take into account initial returns of past IPOs in which they submitted bid more than IPOs which they merely observed. In addition, initial returns from past IPOs in which institutions' bids were qualified for share allocation were given more consideration than IPOs for which unqualified bids were submitted.[4] I also find that institutions do not distinguish the returns that are derived from random events. Furthermore, institutions become more aggressive bidders when they experienced high returns in recent IPOs, conditional on personal participation or being qualified for share allocation in those IPOs.

The revealed bidding behaviors are consistent with Camerer and Ho's (1999) hybrid model which recognizes that both actual and forgone payoff play roles in the decision-making process but to different extents. More importantly, the behaviors are consistent with reinforcement learning which refers to a strengthening of the behavior through experience. This study contributes to the literature in two ways. Firstly, it provides evidence that reinforcement learning also contributes to the learning process of *institutional* investors. Such learning behavior is only documented for *individual* investors in the extant literature (Kaustia and Knüpfer, 2008; Chiang et al., 2011). Secondly, this research is conducted in a novel setting where different types of returns are generated from a unique IPO mechanism. The multiple types of returns enable me to explicitly disentangle reinforcement learning from the competitive theory of Bayesian learning.

In Chapter 4, I examine institution's bidding and trading behavior to answer the question of whether or not institutional investors truthfully reveal private information in China's bookbuilding IPO mechanism. Although bookbuilding is widely regarded as a price discovery mechanism and prevalent in the global capital markets, limited

[3] Herein, "participate" means submit bid(s) but not necessarily acquire shares in particular IPOs.

[4] Detailed description about the qualification for allocation will be given in due course.

research has been conducted that explicitly tests the fundamental question of *whether or not the information being used for pricing is reliable.* In the literature, researchers extensively study how public and private information is used by underwriters. For example, empirical research normally uses the degree of price adjustment (Hanley, 1993; Loughran and Ritter, 2002; Bradley and Jordan, 2002) to identify whether the bids are informative or not. However, even though price adjustment may indicate that bids are *informative*, this does not mean that the information is *true*. Therefore, in this research, I specifically investigate the question of whether institutional investors truthfully reveal their information (honest valuation) to underwriters in bookbuilding process.

I use the bidding and trading data of 63 fund companies in 410 Chinese IPOs between November 2010 and September 2012 as a search sample. According to my results, fund companies will purchase more shares from the secondary market if they bid a high price or subscribed a large amount of shares during the bookbuilding process. Meanwhile, I document that fund companies' investment decisions are based on a comparison of the bid prices they submitted during the IPO and the after-market share price. These findings indicate that fund companies truthfully disclose their private information (honest valuation) via bids, which is consistent with the conclusion of Cornelli and Goldreich (2003). However, the IPO mechanism being tested in my research is not attached with a discretionary allocation but underwriters have the discretion power in the research setting of Cornelli and Goldreich (2003). Moreover, my results also provide evidence for the theoretical models developed by Biais et al. (2002) and Biais and Faugeron-Crouzet (2002) as their models illustrate that both the bookbuilding mechanism and the *Offre a Prix Minimum* [5], an auction-like IPO method, have information elicitation and price discovery functions although the latter is not embedded with a discretionary allocation.

On the other hand, my findings contrast with those of Benveniste and Wilhelm

[5] This method is commonly used in France and formerly called *Mise en Vente*.

(1990) as they posited that information gathering is impossible when allocation discretion is restricted. According to my findings, I argue that the compensation for revealing information can be replaced by the IPO design such as through a unique qualification system and lottery-based allocation mechanism. Moreover, my findings show that investors truthfully reveal their information in the primary market rather than trade on their information in the secondary market. This is consistent with the conclusion of Busaba and Chang (2010) that informed investors should reveal their information in the primary market in exchange for underpricing compensation, rather than to strategically trade until the issued shares start trading in the secondary market because the former practice generates a higher profit. Therefore, my research contributes to the literature by providing new empirical evidence on the information compensation theory.

This research also has implications for the IPO mechanism design. For the bookbuilding mechanism tested in this research, its allocation rule is specified and publicly available in advance. It also offers institutional investors an equal chance to obtain IPO shares. In addition, this mechanism avoids the free-rider problem as the highest bids are not prioritized in allocation. Moreover, detailed bid information is disclosed to the public, making the process more transparent. Although this mechanism raises some concern over effective information extraction, my results suggest that institutions still truthfully reveal information even if there are no guaranteed means of compensation such as favored allocation. The incentives of revealing information could stem from the mechanism design. Specifically, institutions will not be qualified for the allocation process if their bid prices are lower than the offer price, and the chance of obtaining shares will not increase significantly even if an excessively high price is submitted. Hence, my findings imply that this relatively fair and transparent bookbuilding mechanism is able to exert the same price discovery function as opaque alternatives.

In Chapter 5, I examine that whether US-listed Chinese firms obtain higher valuation than their domestic-listed counterparts in IPOs. Among the extensive literature on foreign listing, the vast majority focuses on foreign cross-listing, particularly among developed countries. Cross-listing, sometimes called dual-listing or inter-listing, refers to the behavior of firms that make their shares tradable on at least one foreign exchange following an IPO in their domestic markets. Several theories such as bonding theory, market segmentation theory and improvement of information environment theory are used to explain the phenomenon of cross-listing. In contrast to the decline in cross-listing activity, there is a growing trend that firms bypass their domestic markets and directly undertake an IPO on a foreign stock exchange (Caglio et al., 2013), which is defined as a foreign IPO in the literature. However, studies on foreign IPOs are limited when comparing with the large amount of research on cross-listing. Therefore, it is not clear whether the explanations for cross-listing phenomenon are applicable to foreign IPOs or not.

Building upon the theories derived from the cross-listing research, I investigate the impact of foreign IPOs on the valuation of Chinese firms using a sample of 136 US-listed Chinese firms and their domestic-listed peers during the period of 1999-2012. Specifically, price multiples (price-to-book ratio and price-to-sales ratio) and underpricing are used as the proxies for valuation. After controlling for firm characteristics, I find that US-listed Chinese firms have higher price multiples and experience less underpricing than domestic-listed Chinese firms. The empirical results support the hypothesis that Chinese firms that conduct IPOs in the US can obtain a higher valuation. This finding is consistent with the conclusion of Sundaram and Logue (1996) and Doidge et al. (2004) who discovered that a valuation premium exists for foreign firms cross-listing in the US. Therefore, my research contributes to the literature by providing evidence that theories derived from cross-listing research can also be used to aid explanations of the foreign IPO phenomenon. In addition, I find that high-tech firms with high growth speed but low profitability are more likely to list their shares in the US, particularly for firms that belong to semiconductors and the software industry. Industry clustering implies that accessing foreign expertise is also an important incentive for Chinese firms to conduct IPOs in the US, and is consistent with the argument of Allen and Gale (1999) who claim that the US equity market has the ability to evaluate the prospects of innovative firms.

In summary, the remainder of this thesis is structured as follows. In Chapter 2, the institutional background of China's equity market is introduced. Chapter 3 explores whether or not experience affects the behavior of institutional investors in IPO markets. Chapter 4 studies the question of whether institutional investors truthfully reveal private information in a unique bookbuilding IPO mechanism. Finally, I investigate the valuation premium of US-based Chinese IPOs in Chapter 5. Chapter 6 draws conclusions.

Chapter 2

2. The Institutional Background of China's Equity Market

2.1. The History and Development of the Chinese Equity Market

2.1.1. Two Exchanges and Three Boards

Representing an important part of its reform and opening-up policy, China established its stock market at the beginning of the 1990s. The Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) were founded in China's two main economic and financial centers in 1990 and 1991 respectively. When the SSE started trading, there were only eight listed firms with 60 million outstanding shares in total. This has grown considerably in the 25 years since, with the number of listed firms has now reached 1,049 and 1,672 for the SSE and SZSE respectively. By the end of April 2015, the total market capitalization of these two markets reached US$ 9,073 billion, making China the second largest market worldwide.[6]

In the first decade following the establishment of China's capital markets, the two exchanges significantly promoted the development and reform of state-owned enterprises (SOEs) by facilitating SOEs' accessing to the equity market. As a result, the operating efficiency and corporate governance of these cumbersome SOEs have been improved markedly. Currently, there are three different boards in China: the main board, the Small and Medium Enterprise (SME) board and the ChiNext board. Nearly all of the listed SOEs went public in the main board as they are the main driving force behind China's economic development.

As private enterprises gradually began to take up a crucial position in China's economy, the SME board was built on the SZSE in 2004 to advance the private economy. However, there has been almost no difference in terms of the listing requirements for the main board and the SME board. The choice between listing in the main board or SME board is mainly driven by the size of the listing firm.

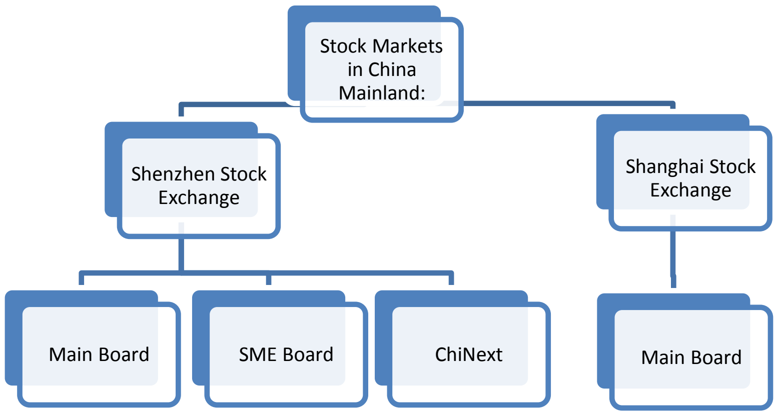
[6] Source: World Federation of Exchanges.

Essentially, the SME board was not a Growth Enterprises Market (GEM) in the real sense, but a preparation for the future GEM board. At the time of writing, 749 firms are listed in the SME board with a market capitalization of CNY 10,314 billion.[7]

In order to build a multi-layered market and provide capital to innovative and technology firms, in October 2009, the SZSE launched the ChiNext board (GEM board) which is regarded as the Chinese NASDAQ. As a supplement to the other two boards, the establishment of ChiNext not only alleviates the financing difficulty of startup enterprises but also promotes the venture capital investment. Considering the strict listing requirements of the main board and the SME board, ChiNext opens a new and relatively easy channel for the exit of venture capitalists. By the end of May 2015, the number of listing firms in the ChiNext board had increased to 458 from an initial 28. Figure 2.1 illustrates the structure of China's stock market.

Figure 2.1 The structure of China's stock market.

This figure illustrates the structure of China's two stock exchanges and three boards.



In terms of requirements, listing in ChiNext is easier than in the main board and the SME board. Table 2.1 elaborates upon the listing criteria for the three different boards. Despite the relatively low listing threshold, firms listing in ChiNext are subject to more stringent supervision, particularly for information disclosure. Overall, the main board is for large and mature firms with stable operation and profitability; the SME board caters to mature but relatively small firms; and the ChiNext board targets startup and innovative firms.

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[7] Source: the official website of the SZSE.

Table 2.1 The listing criteria of three boards in China's stock market

This table illustrates the essential listing criteria for the main board, SME board, and ChiNext board.

	Main Board and SME Board	ChiNext
Length of operation	≥ 3 years	≥ 3 years
Profitability	3 consecutive years with total profits not less than CNY 30 million **AND** Either the total net cash flow is not less than CNY 50 million or the total revenue is not less than CNY 300 million for the past 3 years	2 consecutive years with total profits not less than CNY 10 million **Or** the most recent year with total profits not less than CNY 5 million, total revenue not less than CNY 50 million, revenues growth rate not less than 30% in the past 2 years
Total capitalization	Not less than CNY 30 million before the issuance and not less than CNY 50 million after the issuance	Not less than CNY 30 million after the issuance
Major business	No significant change in the past 3 years	No significant change in the past 2 years
Owner	No change in the past 3 years	No change in the past 2 years
Board members and management team	No significant change in the past 3 years	No significant change in the past 2 years
Proportion of intangible assets	Less than 20% of the net assets	No specific requirement

2.1.2. A-Shares, B-Shares, H-Shares, Red Chip Shares, N-Shares, L-Shares, S-Shares

A-shares are shares that trade on the SSE and SZSE. Before the introduction of Qualified Foreign Institutional Investor (QFII)[8] in November 2002, only the citizen of mainland China could purchase and trade A-shares. In February 1992, Shanghai

[8] Detailed introduction about QFII will be provided in the following institutional investor section.

Electro Vacuum became the first Chinese firm to issue shares to foreign investors[9] via a special channel. This special type of share, widely known as the B-share, is quoted in CNY but traded in foreign currency. The birth of the B-share met the demands of foreign investors to some extent. Unlike A-shares, B-shares were only available for purchase by foreign investors before 2001.[10] In general, A-shares and B-shares are issued by Chinese firms to mainland and foreign investors respectively.

In line with China's economic development, Chinese firms not only issue shares to foreign investors through B-shares but also have direct access to international capital markets. Depending on the listing location, there are H-shares, N-shares and S-shares. H-shares refer to the shares issued in the Hong Kong stock exchange by Chinese firms registered in mainland China. In July 1993, Tsingtao Brewery became the first H-share listing firm. For Chinese firms that are listed in Hong Kong but are registered overseas, these are normally called red chip shares. Analogously, N-shares, L-shares and S-shares represent the different types of shares issued by Chinese firms in New York, London and Singapore. In Chapter 5 of this thesis, I explore the motivation that prompts Chinese firms to bypass the domestic market and list on foreign stock exchanges.

2.2. China's IPO System

2.2.1. IPO Systems

Following the establishment of China's stock markets, the Administrative-Based Approval System (Quota System) was applied until 2001. This system is normally used in emerging and immature markets as it can maintain relative market stability. Under this system, the Chinese central government firstly determines the aggregate issuance volume based on the national economic plan and the market conditions, and then allocates the quotas to local governments. Thereafter, based on the quota, local governments select the issuing candidates and recommend them to the China

[9] Herein, foreign investors also include Hong Kong, Macao and Taiwan citizens.

[10] After 19 February 2001, investors of mainland China are allowed to purchase B-shares.

Securities Regulatory Commission (CSRC) for further review and approval. It can be clearly seen that the prerequisite for issuing shares is to obtain the quota. However, the procedures of quota allocation and final approval are not sufficiently transparent, which leads to an opportunity for rent-seeking. On the other hand, the role played by underwriters is distorted. Instead of guaranteeing the quality of the issuers, underwriters typically put their best efforts into helping companies to obtain the issuing quotas. Overall, the administration of government takes over the market function and becomes the determinant factor in the Administrative-Based Approval System.

In March 2001, the Administrative-Based Approval System was formally replaced by the Sponsor-Based Approval System. There are fundamental differences between these two systems. Firstly, the Sponsor-Based Approval System canceled the quota mechanism. However, the quota mechanism was not fully abolished until 2004. Between 2001 and 2004, the quota was actually granted to underwriters instead of local governments. Secondly, the new system enhances the rights and responsibilities of underwriters. Specifically, along with the CSRC, underwriters are entitled to recommend issuers and have the right to veto those unqualified issuing applications. In addition, they can even have an impact on the issuing size, issuing method and offer price. Meanwhile, the underwriters will take responsibility and face penalties when they are not diligent in the issuing process. For example, the sponsor’s right will be suspended for a certain period if illegal practices are revealed. In the worst cases, the certificate for sponsorship can be revoked.

Currently, the Sponsor-Based Approval System is still being used for IPOs in China. However, scholars and practitioners are advocating a transition from the Sponsor-Based Approval System to the Registration-Based System. The latter will apparently ensure that the market fully exerts its functions. For instance, once a firm meets the listing requirements, this firm would be allowed to issue shares, but the success of issuance will be entirely determined by the market. To provide a better understanding, Table 2.2 illustrates a comparison between the three IPO systems.

Table 2.2 The comparison of three IPO systems in China

This table compares the Administrative-Based Approval System, the Sponsor-Based Approval System and the Registration System.

	Administrative-Based Approval System	Sponsor-Based Approval System	Registration System
Quota	Yes	No	No
Listing requirements	Yes	Yes	Yes
Sponsor	Local government	Underwriter	Underwriter
Examiner	CSRC	CSRC/ Underwriter	Underwriter
Decision maker	CSRC	CSRC/ Underwriter	CSRC/ Underwriter
Degree of market-orientation	None	Partially	Fully

2.2.2. IPO Pricing Methods

Several pricing methods were attempted for China's IPOs as the Chinese stock market developed. Before July 1999, the offer price was calculated by specific formulae. Although various formulas were employed in different periods, the earnings per share of the issuing firm and a P/E ratio suggested by the CSRC[11] were the determinant factors. Consequently, issuers and underwriters did not have any influence on the offer price.

Form July 1999 to 2001, the offer price was set based on the negotiations among issuing firms, underwriters and institutional investors. Specifically, institutional investors subscribed the issuing shares according to the initial filing range set by the issuer and underwriter. Thereafter, the offer price was decided on the basis of market demand and could be outside the initial filing range. This was the first attempt by the authorities to apply a market-oriented pricing mechanism in China's primary market. However, the offer price still needed to be approved by the CSRC which owned the

[11] The P/E ratio is normally determined by the comparable listing firms and ranges between 13 and 20 at that time.

right to modify the offer price eventually if the price was regarded as inappropriate.

Since 2001, the authorities have reinstated a very strict control over the offer price due to a slump in the Chinese market. They attributed the underperformance of IPOs to the high offer price caused by the market-oriented pricing mechanism. Although the offer price was still nominally based on the negotiations between the issuer and underwriter, issuers and underwriters can only set the price according to the following two stipulations. First, the range between the lower and upper end of the initial filing range should be around 10%. Secondly, the P/E ratio was not allowed to exceed 20. In practice, the P/E ratio was normally around 18 at that time.

In 2005, the CSRC introduced a new inquiry mechanism through which offer price was purely set by the issuer and underwriter according to the market demand without the approval of the CSRC. The new approach consists of two steps: preliminary inquiry and cumulative bidding inquiry. The former helps to set the filing range based on the information collected from particular institutions while the latter is used to set the final offer price according to institutional investors' subscription. For further specification, the CSRC published the *Measures for the Administration of Securities Issuance and Underwriting* in September 2006, designating the institutional investors who can participate in the inquiry process. They included securities companies, fund companies, insurance companies, qualified foreign institutional investors (QFIIs), trust companies, finance companies and other institutional investors affirmed by the CSRC. Detailed introductions about these institutions will be provided in Section 2.3 of this chapter.

At present, institutions recommended by the leading underwriter and particular individual investors are entitled to participate in the inquiry process as well. Simultaneously, issuers and underwriters are also allowed to directly set the offer price based on the outcomes of preliminary inquiry without the cumulative bidding inquiry. Notably, they can still go through both of the processes if they prefer to do so. In Chapter 4 of this thesis, I investigate whether the current IPO pricing method used in China can effectively fulfill the price discovery function.

2.2.3. Offline-Offering and Online-Offering

Offline-offering and online-offering are the two separate IPO tranches for institutional and individual investors respectively. Before May 2012, the fraction of institutional offering was capped at 20% of the total issuing shares. A new rule that became effective in May 2012[12] requires the issuers to sell at least 50% of the shares in the institutional offering with a claw back to the retail offering when the latter is heavily oversubscribed. Currently, the proportion for institutional offering tranche has been increased to 60%. In the event that the total number of shares after an IPO is more than 400 million, at least 70% of the issuing shares should be offered to the institutions.

The essential function of institutional offering is to set the offer price through the inquiry process which is similar in manner to the bookbuilding method used in the US. The lead underwriter conducts a roadshow to promote the issue and collects information on institutional demand. In particular, institutional investors submit limit bids that specify the prices and quantities. The bid amounts are submitted in multiples of a minimum quantity and capped by the total number of shares in the institutional offering. Based on the order book and other factors such as market conditions, the underwriter and issuer set the offer price. According to the rules stipulated by the CSRC, only the bids that are at or above the offer price will be qualified for the following allocation process. To mitigate the impact of overbid, the latest regulation[13] also requests that at least the top 10% high-price bids should be excluded from the allocation.

Prior to November 2010, the share allocation was on a pro-rata basis when the issuances were oversubscribed, so that all qualified institutions (i.e. their bids at or above the offer price) were guaranteed to receive shares according to the qualified amounts. Currently, the share allocation is conducted on a lottery basis. Institutional

[12] The decree No.78 became effective on May 18, 2012. The majority of IPOs in my sample take place before this date.

[13] *Opinions on Further Deepening the IPO System Reform* was released on 30 Nov 2013.

investors who are qualified for the allocation will be given different numbers of tickets that are in proportion to their qualified amounts. Thereafter, the tickets are drawn from a pool to decide how many shares are allocated to which institutions. Although the institutional offering method is officially named bookbuilding, it is, to some extent, different from the widely perceived definition. The core feature of bookbuilding is that underwriters can exercise total discretion in both share pricing and allocation. Therefore, the institutional offering in China is a quasi-bookbuilding mechanism as underwriters only have discretion on setting the offer price but not on share allocation. A more detailed description and examples regarding the lottery-based allocation will be provided in due course. In the past, institutions obtaining shares from IPOs cannot immediately sell the allocated shares because there was an enforced lock-up period which typically lasted three months. After May 2012, the compulsory lock-up period was canceled.

Once the offer price is decided via the institutional offering, individual investors start subscribing issuing shares. Unlike institutions, individual investors submit quantity-only bids. In other words, they only inform of the number of shares they would like to purchase without any involvement in the price discovery. Today, the maximum subscribed amount of individual investors is determined by their current holding positions in the secondary market. In other words, the more shares they are holding, the more IPO shares they can subscribe. This method aims to reduce speculation in the primary market and the impact of large-scale IPOs on market stability. With respect to the share allocation to individual investors, it is also determined by the aforementioned ballot process.

2.2.4. The Shutdown of China's IPO Market

Since the establishment of Chinese stock exchanges, the IPO market has been suspended several times. Following the turn of the century, three long-running shutdowns happened. From May 2005 to June 2006, the CSRC froze all of the IPOs to facilitate the so-called "share-split structure reform". In the past, Chinese firms had a unique share-split structure that separated the shares into tradable and non-tradable categories. The former category was normally held by public investors, while the latter was mainly possessed by the government. To solve this issue, from April 2005, the authorities launched the “share-split structure reform” to make the non-tradable shares tradable. It could have been anticipated that this transformation would lead to a slump as a great deal of new shares flooded the market. Therefore, the IPO market was closed down until June 2006 when the reform was more or less completed. Notably, despite the reform, a certain amount of shares are still not tradable even now.

Another shutdown took place between December 2008 and July 2009. On 16 October 2007, the SSE Composite Index achieved the history-highest point of 6,124. However, due to the global financial crisis in 2008 and the large number of ongoing IPOs during that period, the market index dropped to 1,679 by the end of November 2008. Consequently, the government had to suspend all new IPOs in order to maintain market stability.

Owing to the underperformance of the market, China’s IPO market was closed in November 2012 once again. In addition, the CSRC used the suspension period to carefully check the quality of IPO candidates. This market shutdown lasted for more than one year until the Guangdong Xinbao Electrical Appliances Holdings Co.,Ltd undertook an IPO in January 2014. However, the long-running shutdown also caused a severe problem in that nearly 900 Chinese firms sat on the IPO waiting list during the worst phase. Although the pressure of accumulated IPOs was somewhat relieved after the market reopened, there were still 647 firms waiting for the approval of undertaking IPOs by January 2015. From the cases of IPO market shutdown, it is seen that the authorities still tightly control the stock market despite the Sponsor-Based Approval IPO System being applied in China.

2.3. Institutional Investors in China

2.3.1. General Introduction for Chinese Institutional Investors

In Chapter 3 and 4 of this thesis, I study the learning and bidding behavior of the Chinese institutional investors. Therefore, a description about the Chinese institutional investors is provided in this section. The Chinese government advocated the development of professional institutional investors to keep China's equity market robust and stable. Before 1997, securities companies were the main institutional investors in China's stock market. Since then, securities investment funds have entered the Chinese equity market and have become the most predominant institutional investors. In line with the evolution of the Chinese equity market, other institutional investors such as insurance companies, trust companies, social security funds and QFIIs have also participated in the market and made tremendous contributions to China's capital market.

Unlike developed markets, such as the UK and US, the Chinese equity market is dominated by retail investors rather than institutional investors. Despite the development of Chinese institutional investors, the market capitalization of institutional investors' shareholdings is still below that of retail investors. By the third quarter of 2014, the investment of retail investors accounted for 51.90% of the total market capitalization. Moreover, retail investors, on average, generate around 80% of the annual trading volume of the whole market.[14] The major institutional investors in China's equity market are as follows: securities companies, funds (private and public offering funds), insurance companies, QFIIs, trust companies, social security funds and finance companies. In the following section, I will introduce these institutional investors individually.

[14] Li, Z & Cheng,S. 2015. The Chinese Stock Market Volume I (A retrospect and Analysis from 2002), Palgrave Macmillan.

2.3.2. Different Types of Institutional Investors

2.3.2.1. Securities Companies

Securities companies were the main institutional investors when China's equity market was initiated. They invest in the market typically via asset management businesses or proprietary trading. In the asset management business, securities companies provide financial services to investors by investing the entrusted funds in the financial market. Furthermore, the asset management business can be divided into three different types based on number of clients and the purpose of the investment: Target asset management for single client; collective asset management for multiple clients; and exclusive asset management business for a specific purpose. However, in 2003, the issuance of new asset management business was suspended by the CSRC due to disorder in the market. As more detailed regulations grew effective[15], the asset management business was allowed to reopen in 2005. Since then, the business has entered a high-growth era. Based on the statistics of the Securities Association of China, the entrusted funds under the management of securities companies reached CNY 7.97 trillion, with a net income of CNY 12.43 billion by the end of 2014.

Proprietary trading refers to the trading behavior conducted by securities companies using their own capital instead of clients' funding. In this sense, securities companies are exposed to higher risk in proprietary trading than in the asset management business. However, the aggregate scale of proprietary trading is much lower, specifically it was CNY 0.84 trillion by the end of 2014.[16] Initially, the boundary between these two businesses was very blurred. It was not unusual for securities companies to divert clients' funding for the use of proprietary trading. In addition, supervision on proprietary trading was poor as the profit and loss were

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[15] The *Trial Implementation of Securities Company Clients Asset Management Business* was published in September 2003. *The Notifications on Securities Company Doing Collective Asset Management* was issued in 2004.

[16] Source: Securities Association of China.

normally treated as off-balance sheet items. In recent years, several regulations came into effect[17], making the proprietary trading business comparatively well-regulated.

2.3.2.2. Fund Companies

China's security investment fund coincided with the establishment of the SSE and SZSE. In October 1991, Wuhan Securities Investment Fund and Shenzhen Nanshan Venture Capital Fund were set up, symbolizing the formation of the first investment funds in China. Two years later, Zibo Township Enterprise Fund listed on the SSE and became the first exchange-listed investment fund. At that time, there were only 70 funds in total, with total asset value of CNY 4 billion.[18] However, these funds are not securities investment funds in the real sense as the pooled money is mainly invested in industries rather than securities. On 7 April 1998, Jingtai fund and Kaiyuan fund both listed on the SSE and SZSE. They became the first two standard securities investment funds.

According to the issuing target, funds can be classified into two types, namely public offering funds and private offering funds. The most typical public offering fund is the mutual fund. In contrast with private offering funds, mutual funds raise capital from public investors and comply with stringent regulations. In 1998, closed-end funds were formally initiated in China's equity market but only with a value of CNY 10 billion. Three years later, with the establishment of Hua An Innovation Investment Fund, open-end funds were introduced to the market as well. Afterwards, listed open-end funds and exchange traded funds (ETFs) also appeared in the Chinese equity market. During the past decade, public offering funds experienced a rapid growth in terms of the diversification and market shares. By the

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[17] *Guidelines for Securities Company Securities Proprietary Trading Business* was issued in 2005. *The Regulations of Securities Company Risk Control Indicator* was effective in 2008. *Regulations of the Investment Scope and Other Matters of Securities Company Securities Proprietary Trading Business* was revised in in 2012.

[18] Li, Z & Cheng,S. 2015. The Chinese Stock Market Volume I (A retrospect and Analysis from 2002), Palgrave Macmillan.

first quarter of 2015, the net asset value of public offering funds in China amounted to CNY 5.241 trillion which was mainly invested in the stock market. Among them, CNY 1.581 trillion was managed by stock-investment funds, accounting for 30.15% of the public offering funds, making the public offering fund the top institutional shareholder in the Chinese stock market. On the other hand, the market shares of public offering funds are highly concentrated, demonstrated by the fact that the top 10 fund companies control 51.10% of the total assets under management.[19] In Chapter 4 of this thesis, I investigate the bidding and trading behavior of China's funds in the primary and secondary market.

With respect to private offering funds, these only privately offer to a particular group of investors and are not subject to official supervision. The hedge fund is the most common form of private offering fund. Unlike public offering funds, the private offering funds appeared in the Chinese equity market quite late. In 2004, the Pure Heart issued by SZITC Trust Co. Ltd was launched and became the first private offering fund in the country. In China, a private fund investor normally invests not less than CNY 1 million, but the aggregate size of private offering is relatively small with its scale between CNY 50 million and CNY 1 billion. Moreover, private offering funds are not only managed by fund companies but also trust and bond companies[20], which is quite different from the public offering funds as they are solely under the management of fund companies. By 2006, there were only 11 private offering funds in China, but this number increased radically to 10,883 with total assets under management amounting to CYN 1.99 trillion by the first quarter of 2015. Similar to public offering funds, the investments on stock are predominant as CYN 1.01 trillion is shared by the stock-investment private offering funds.[21]

[19] Source: Asset Management Association of China.

[20] The revised *Securities Investment Fund Law*, being effective in 2013, excluded the involvement of trust companies in private offering funds.

[21] Source: Asset Management Association of China.

2.3.2.3. Insurance Companies

Before 1999, insurance companies were not allowed to invest in securities as their investment products are only limited to bank deposits, state bonds and other government-approved items. When China's *Securities Law* was revised in 1999, it permitted indirect investment on the securities market but had to be no higher than 5% of the insurance fund's portfolio. Since 2004, insurance funds were further encouraged to invest in China's stock market when the *Temporary Measures of Insurance Funds Outbound Investment*, *Temporary Measures of Insurance Funds Stocks Investment* was published, allowing insurance funds to directly invest in stocks. Meanwhile, the restriction on the percentage of equity investment was also loosened. An insurance fund could now invest up to 100% of its portfolio on equity. To ensure liquidity and safety, despite the regulatory relaxation, the investment style of insurance funds is relatively conservative as bonds and bank deposits are still the major investment channel for insurance funds. According to the statistics in 2013, bonds and bank deposits accounted for 45% and 31% respectively of the portfolios of insurance funds, and the proportion for equity investment was only 12%. However, as the total assets of the insurance companies reached CNY 10.16 trillion by the end of 2014[22], insurance companies are the second largest institutional investors in China's equity market ranking behind funds.

2.3.2.4. Qualified Foreign Institutional Investors (QFIIs)

For the purpose of attracting foreign investors, the QFII system was introduced to China's capital market in November 2002 when the *Temporary Regulations of Inbound Investment by Qualified Foreign Investors* was officially published. The program permits certain licensed foreign investors to participate in China's stock market. On 9 July 2003, UBS Warburg became the first QFII to purchase shares in the Chinese equity market. However, the admission standard was rather strict and

[22] Source: China Insurance Regulatory Commission.

many constraints were imposed on the investment of QFIIs. Initially, if a foreign fund company wanted to be eligible for QFII, it must have had at least five years of investment experience and managing assets valued at no less than US$ 10 billion. Regarding the investment constraints, one example is that QFIIs cannot possess more than 10% of the shares of one listed Chinese firm. In 2012, the CSRC relaxed the admission standard and investment constraints to some extent. For example, the minimum investment experience was lowered to two years from five. In line with the development of the Chinese capital market, by the first quarter of 2015, the number of QFIIs had reached 279 with a total investment quota of US$ 72.149 billion.[23]

2.3.2.5. Social Security Funds

Social security funds are national strategic reserves under the administration of the National Social Security Funds Committee. Different from the traditional security investment fund, social security funds are not issued to private investors as one of its main purposes is to authorize professional institutions to manage pensions submitted by employees and provide income after their retirement. Besides, the social security funds also include cash and securities assets generated through reducing the holding of state-owned shares, capital allotted by the central government, as well as capital and investment income from other sources with the approval of the State Council. Due to the nature of social security funds, their investment is highly regulated and relatively conservative. Social security funds formally began direct investment on equities after purchasing CNY 10 billion shares of the Communications Bank of China in June 2004. Currently, the proportion of security investment is stipulated to be no more than 40% of the portfolio which is double the initial threshold of 20%. By the end of 2014, the total assets under the management of social security funds had reached CNY 1.235 trillion.[24]

[23] Source: State Administration of Foreign Exchange.

[24] Source: National Council for Social Security Fund.

2.3.2.6. Trust Companies

Trust companies are the trustees that manage the entrusted property of clients for the benefit of the beneficiary. Compared with other financial institutions, one of the most important advantages for a trust is the flexibility of the investment channel. A trust company can invest in money markets, equity markets, real estate, or even art and wine. However, this flexibility brings a risk of investing in cash-strapped industries. China's trust industry experienced a fast but rough growth until the issuance of China's *Trust Law* in 2001. Before 2001, the growth was mainly based on the duplication of bank's credit business and an overheating economy. After a slow development between 2000 and 2006, the trust industry re-accelerated from 2007 because of the boom in the coal mining industry and real estate, which raised concern about so-called shadow banking. According to the monitoring of the Financial Stability Board (FSB), trusts in China have experienced a remarkable growth of 290% since 2010 for an annual average of 57%. Despite the tremendous increase in the trust industry, its investment proportion in the stock market is less than 3%, standing at CNY 300 billion as of the second quarter of 2013. In 2014, the China Banking Regulatory Commission (CBRC) issued the *Guidelines on risk supervision of the trust sector* so as to control the risks of trust investment. As a result of this government intervention, the expansion has been showing signs of slowing down. According to the statement of the China Trustee Association, trust assets under management increased 6.4% to CNY 12.48 trillion in the second quarter of 2014, which is the slowest growth since the first quarter of 2012.

2.3.2.7. Finance Companies

In China, finance companies are non-bank financial institutions that are affiliated to large enterprises and provide financial management services to enterprises for their technological innovation, new product development and sales. Finance companies have gradually become a new force in China’s stock market. For example, particular finance companies, such as Minmetals Finance Company and China Petroleum Finance Company, frequently appear in the top 10 shareholders of listed companies. However, finance companies’ investment in the equity market is still relatively low. According to the statistics of China National Association of Finance Companies, the total assets of finance companies amounted to CNY 2.789 trillion by the end of 2014, but the proportion of equity investment is less than 8%.

Chapter 3

3. Does Experience Affect the Behavior of Institutional Investors in IPO Markets?

3.1. Introduction

Finance literature has been showing an increasing interest toward the investor learning processes and the impact of these processes on investment decisions. Bayesian learning and reinforcement learning are the two leading theories on an agent's learning behavior. Reinforcement learning refers to a strengthening of the behavior through experience (Dinsmoor, 2004). Investors who are reinforcement learners pay more attention to the personally experienced payoffs than forgone payoffs, and not necessarily to the model that generates those payoffs. On the other hand, Bayesian learning theory premises that investors keep track of forgone outcomes as well as personally experienced outcomes, and then form their beliefs based on the updated information (Grosskopf et al., 2006). Therefore, the fundamental distinction between these two theories is that reinforcement learners value the outcomes that are personally experienced more than the outcomes that are merely observed, whereas Bayesian learners value these two different types of outcome equally.

In this research, I use a unique set of bookbuilding data to explore the impact of experience on institutions' investment behaviors in the context of a new IPO market. The data includes 19,151 bids submitted by 353 institutions in 214 IPOs which took place on ChiNext, a new board of Shenzhen Stock Exchange launched in late 2009. I first investigate whether institutions take into account the initial returns of past IPOs when deciding to participate[25] in future IPOs. The fact that an institution chooses to invest (or not to invest) in an IPO generates both experienced and forgone initial

[25] In this paper, "participate" means submit bid(s) but not necessarily acquire shares in particular IPOs.

returns and provides an ideal setting to test Bayesian and reinforcement learning theories.

In ChiNext, not all of the institutions that submit bids in an IPO are qualified for the following share allocation, which produces the return of qualified bids and the return of unqualified bids[26] (Detailed definitions are given in the Appendix A). Moreover, shares are allocated via ballot in oversubscribed issues[27], which forms the return of allocated and unallocated shares. These two categories of special payoffs provide an additional setting to examine Bayesian and reinforcement learning theories. In the order book, the specific bid price from each institution can be scrutinized. Therefore, I also examine the influence of an institution's past experience on its future bid aggressiveness i.e. the tendency to bid at a high price.

My first main finding is that institutions take into account initial returns of the IPOs in which they participated in the past when deciding to participate in future IPOs. However, they put: (i) more weight on payoffs they experienced than those they observed; and (ii) greater attention on the return of qualified bids than that of unqualified bids. This behavior is associated with reinforcement learning. Moreover, I demonstrate that institutions equally assess the returns that are derived from random events, for example the returns of allocated and unallocated shares that are determined by ballot-based allocation in the IPO context. Finally, I identify that institutions will bid more aggressively if they have previously experienced high returns in recent IPOs, but this is conditional on personal participation or being qualified for share allocation in those IPOs. This finding provides additional evidence of reinforcement learning in the IPO market.

This study contributes to the understanding of the learning behavior of investors in two ways. First, I provide evidence that reinforcement learning also contributes to

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[26] The bids are submitted before the offer price is set, and once the offer price is set those that remain below the offer price do not qualify the following ballot-based allocation.

[27] All of the 214 IPOs in my research sample are oversubscribed, i.e. ballot-based allocation mechanism is applied throughout the sample.

the learning process of *institutional* investors. Such learning behavior is only documented for *individual* investors (Kaustia and Knüpfer, 2008; Chiang et al., 2011). The lack of empirical finding for institutional investors could be due to the fact that research focuses are confined to the individual investors. To fill this gap, I specifically shed light on the learning behavior of institutional investors in this research.

Secondly, this research is conducted in a novel setting where new types of returns are generated from a unique IPO mechanism. The multiple types of returns enable me to explicitly disentangle reinforcement learning from Bayesian learning and explore the impact of experience to different degrees. My results are consistent with the hybrid model of Camerer and Ho (1999), recognizing that both actual and forgone payoff play roles in the decision-making process but to different extents.

My research is closely related to two other papers that study the learning behavior of investors in new IPO markets. Kaustia and Knüpfer (2008) studied the bids submitted by individual investors in Finnish IPOs and found that their learning behavior is consistent with reinforcement learning. However, they did not examine the learning behavior of institutional investors. Following Kaustia and Knüpfer (2008), Chiang et al. (2011) studied winning bids in Taiwanese IPO auctions. Besides the positive relationship between past returns and the likelihood of participating in future IPOs, they found that individual investors' auction selection ability deteriorates as they become more experienced. Based on this downward trend, they concluded that individual investors are engaged in reinforcement learning rather than Bayesian learning. They investigated the behavior of institutional investors as well but found little sign of such reinforcement learning.

This paper differs from Kaustia and Knüpfer (2008) and Chiang et al. (2011) in a number of ways. First of all, the analysis in Kaustia and Knüpfer (2008) is exclusively based on individual investors and the work of Chiang et al. (2011) is only partially based on institutional investors. Secondly, I test the Bayesian and reinforcement theories in a novel way by decomposing initial returns into two parts:

experienced versus forgone returns. Since the essential disparity between Bayesian learning and reinforcement learning is the various weights apportioned to experienced payoffs and forgone payoffs, this setting is ideal for testing whether the behavior of institutional investors is consistent with these theories. On the contrary, Chiang et al. (2011) identified investors' learning patterns as reinforcement learning without explicitly identifying personally experienced and forgone payoffs. They posited that individual investors are subject to reinforcement learning based on the finding that investors' selection ability deteriorates as they gain more experience. However, Sargent (2008) argues that judgment errors exist but do not violate rationality. Therefore, the underperformance when institutions have more experience does not necessarily imply reinforcement learning. Thirdly, the unique share allocation mechanism in this setting differs from the one in Chiang et al. (2011), which enables further decomposition of experienced returns and generates the return of qualified and unqualified bids, and the return of allocated shares and unallocated shares. Further analyses on these returns provide complementary evidence for an institution's learning behavior. Essentially, my research contributes to the literature by providing new evidence on the learning behavior of institutional investors, who are considered to be better informed and sophisticated investors (Michaely and Shaw, 1994; Badrinath et al., 1995; Cohen et al., 2002; Nagel, 2005; Chiang et al., 2010) under a different IPO mechanism.

The remainder of this chapter is organized as follows. The related literature is reviewed in Section 3.2. In Section 3.3, I discuss the institutional features of ChiNext. Section 3.4 describes the data. The test of the relationship between past experience and future bidding frequency is elaborated upon in Section 3.5. Section 3.6 presents the tests regarding the decision to bid in an upcoming IPO. Section 3.7 explores the impact of experience on future bid aggressiveness. Finally, Section 3.9 provides a conclusion.

3.2. Literature Review

3.2.1. Reinforcement Learning

The original idea of reinforcement learning, the law of effect, is attributed to Thorndike (1911). Through a famous experiment named the "puzzle box"[28], he investigated the learning process of animals and found that behaviors that generate good outcomes are likely to be repeated in the future. Building upon the law of effect, Skinner (1938) and Zeiler (1968) formally established the concept of reinforcement learning in the psychological realm after observing the response of "reinforced" animals such as rats and pigeons. Specifically, they focused on the probability and the speed of the animal's responses. To quantify the observed learning behavior in experiments, Bush and Mosteller (1951) firstly developed a mathematical model for reinforcement learning. Their model illustrates the impact of experimental variables, such as the amount of reward and work, on the probability of the reinforced learner's response.

Decades later, this psychological theory was introduced to the economic research. Cross (1973) successfully incorporated a learning process to the traditional economic model, which promoted studies on the decisions of firms and the corresponding market reaction. Arthur (1991) designed an algorithm to replicate the decision-making process of human beings. He found that there exists a "learning time" that is driven by the payoff structure and the frequency of trials. The impact of frequency suggests that the learning behavior is reinforced by the outcome of actions that are being taken frequently. Furthermore, some papers came to the conclusion that reinforcement learning models have greater explanation power on experimental data than those belief-based learning models (Mookherjee and Sopher, 1994; 1997; Chen and Tang, 1998).

[28] In the experiment, a cat was placed inside a box. The cat was able to escape from the box only when it hit the lever. As a reward, food was provided when the cat got out. Afterwards, the cat was put into the box repeatedly and it hit the lever increasingly quick.

Roth and Erve, two economists, contribute markedly to the understanding of reinforcement learning as well. Roth and Erev (1995) used one-parameter reinforcement learning models to trace the behaviors observed in three extensive-form games. The behaviors of players converge to the perfect equilibrium as they acquire more experience in two of the three games they tested. Furthermore, the learning behavior is initially apparent and turns out to be weak as experience increases. However, it is also worth noting that the models of Roth and Erev (1995) do not take into account the payoff information from actions that players did not choose, which is a key feature of reinforcement learning. To improve the descriptive and predictive power, Erev and Roth (1998) further built a three-parameter reinforcement learning model by incorporating more psychological components. Specifically, the new model considers the generalization effect which makes players not only choose actions that generate favorable outcomes in the past but also those that are *similar* to the chosen actions. Moreover, the three-parameter model controls the fact that recent experience has a larger impact than preceding experience. To obtain a better understanding of reinforcement learning, Erev and Roth (1999) also successfully applied this learning theory in cognitive game theory context.

In the learning process, it is very intuitive that agents are more likely to choose actions that generate payoffs above their aspiration level and less likely to opt for those that yield payoffs below their aspiration level. Previous literature on reinforcement learning tended to treat the aspiration level as fixed. The reinforcement learning model of Börgers and Sarin (2000) shows that decision makers would adjust their aspiration levels to the actually reinforced payoffs. Such adjustment, however, could either improve or harm the decision maker's long-term performance, depending on the problem context and the initial aspiration level.

3.2.2. Bayesian Learning

Researchers not only pay attention to reinforcement learning but also construct theoretical models to investigate the Bayesian learning process. Grossman et al.

(1977) modeled an information generation process that incorporates a Bayesian learning mechanism. Specifically, they explored the impact of experience on the level of new drug consumption and found a positive relationship. Therefore, the authors concluded that individuals and firms learn from experience when they enter unknown markets. More importantly, the learners, Bayesian learners, are not passive about information obtained from their experiences but actively update the information and adjust their behaviors accordingly.

The model of Blume and Easley (1982) shows that traders constantly update their information in order to obtain an equilibrium price, which is consistent with Bayesian learning. Specifically, traders give more weight to models that generate a better estimation and abandon inferior models. Crawford (1995) and Crawford and Broseta (1998) presented learning models in the context of coordination games and suggested that players revise their strategies according to the analysis of their experience in repeated games. Boylan and El-Gamal (1993) studied Bayesian learning based on a comparison between two learning models in nine experiments. Their study shows that players update their beliefs according to Bayes' rules while making decisions. Following Boylan and El-Gamal (1993), Cheung and Friedman (1997) also built upon the Bayesian learning model for the behavior observed in laboratory experiments. Their model suggests that agents would treat the payoffs from chosen and unchosen actions equally if the information regarding a forgone payoff is available.

Mahani and Bernhardt (2007) established a Bayesian learning model that is able to reconcile several empirical regularities: Most speculators lose money; large speculators outperform small speculators; trading intensity is positively driven by past performance; most novice traders lose money and stop speculating; and past and future performance are positively correlated. In a similar way, Linnainmaa (2011) developed a structural model showing that investors rationally learn from active trading. Moreover, Linnainmaa provided empirical evidence for his model as investors start trading with a small amount of money but increase their trading frequency and volume if the past performance was successful, and quit if the performance was poor.

On the other hand, it has also been found that the reinforcement learning and Bayesian learning are not necessarily mutually exclusive. Camerer and Ho (1999) established a hybrid model that incorporates the elements of reinforcement and Bayesian learning. Specifically, the model considers the impact of actual and forgone payoff simultaneously and shows that both play differently weighted roles in the decision-making process. The laboratory experiment of Charness and Levin (2005) also provided evidence that reinforcement and Bayesian learning can affect the decision-making process at the same time. They found that the probability of making a mistake is low when these two forces are aligned, but is quite high when they oppose each other.

3.2.3. Learning Behavior of Individual Investors

The empirical evidence suggests that individual investors are subject to the reinforcement learning as they replicate the trading behaviors that generate pleasure (Barber and Odean, 2011). Kaustia and Knüpfer (2008) and Chiang et al. (2011) revealed that individual investors are more likely to subscribe shares in future IPOs if they previously had a favorable experience in the IPO market; the investors' returns decrease as they participate in more IPOs. On the other hand, Choi et al. (2009) discovered that personally experienced high returns in 401(k) accounts prompt individual investors to increase their 401(k) savings rates, while volatile returns in the past decrease the savings rates. Using trading data from two brokers, Strahilevitz et al. (2011) found that individual investors repurchase stocks previously sold for a gain, and evade stocks previously sold for a loss or stocks that had an increase in price after a prior sale. The authors posited that this trading pattern is due to reinforcement learning. Similarly, Huang (2012) demonstrated that individual investors are more likely to purchase stocks from a given industry that generated abnormal returns in previous investments. This correlation is pronounced for the more recent investment experiences. Using vast Indian trading data, De et al. (2010) showed that individual investors increase trading frequency when they earned positive returns in recent trades. Furthermore, the sign of the return (positive or negative) is more influential than the scale of the gains or losses. Malmendier and Nagel (2011) used a comprehensive survey data to study the impact of past macroeconomic shocks on an individual investor's future risk taking. They found that individual investors are more likely to invest in the stock market and become less risk averse if they have experienced high stock market returns in the past. In addition, they also found that the more recent the experiences are, the stronger the effect it has. On the other hand, a positive impact of personal experience on individual's inflation expectation was demonstrated by Malmendier and Nagel (2013) as well. Specifically, they found that personal experience is more influential than other observable historical data. Using Indian data, Campbell et al. (2013) concluded that individual investors learn from personal participation in the stock market according to the findings that the longer the period since an account was opened, (1) the better this account's performance; (2) the higher the tendency to purchase value stocks and stocks with low turnover; (3) the less likely it is to suffer from excessive trading and disposition effect. In summary, the aforementioned research provides extensive evidence that individual investors are subject to the reinforcement learning.

Other papers also demonstrate the learning behavior of individual investors, albeit no explicit reference to either reinforcement or Bayesian learning is made in those papers. The model constructed by Gervais and Odean (2001) suggests that traders excessively attribute past successes to their own abilities and therefore become overconfident. With more experiences, however, traders will obtain a better assessment of their abilities. Based on the trading records of 1,511 Chinese investors, Feng and Seasholes (2005) investigated the disposition effect, termed by Shefrin and Statman (1985), that investors are reluctant to realize losses and more likely to realize gains. They discovered that trading experience can mitigate the disposition effect. Such a self-learning pattern was also documented by Dhar and Zhu (2006). Furthermore, Nicolosi et al. (2009) and Seru et al. (2010) revealed that individual investors do learn about their trading abilities through active trading rather than by observing fictitious trades. In particular, the trading abilities of some investors improve as they gain more experience, while others cease trading once they realize that their trading skills are inferior. On the other hand, Barber et al. (2014) studied the behavior of day trading (buy and sell the same stock within a day) using Taiwanese data from 1992 to 2006. Consistent with Seru et al. (2010), they documented that day traders with poor performance are more likely to quit the market and normally begin with a small investment and increase as they gain more experiences. However, the overall return of day traders is negative, which is not consistent with the rational learning model. Therefore, the authors concluded that "learning by trading" is not necessarily a rational and profitable behavior.

3.2.4. Learning Behavior of Institutional Investors

In the extant literature, very few papers specifically focus on the learning behavior of institutional investors. Chiang et al. (2011) explored the learning behavior of institutional investors, using the bidding data of 1,232 institutional investors in the Taiwanese stock market. Unlike individual investors, institutions' decisions to participate in future IPOs are not influenced by their past returns. Besides, the experiences neither significantly improve nor deteriorate their investment performance. Therefore, it was concluded that the behaviors of institutional investors are not consistent with either reinforcement or Bayesian learning. Using age as a proxy for experience, Greenwood and Nagel (2009) revealed that, during the technology bubble period, inexperienced fund managers displayed "chasing behavior" whereby inexperienced fund managers increased their holdings on technology stocks if technology stocks generated high returns in the last quarter. Such chasing behavior was not found from experienced fund managers. Kempf et al. (2013) showed that a learning by doing phenomenon exists for fund managers. Instead of age or tenure, they used the number of negative shocks for a given industry over a fund manager's career as the proxy for the experience of the fund manager in that industry. In other words, a fund manager has different experiences across different industries. Based on the new measurement, it was found that mutual fund managers outperform by 1.5% per quarter in industries that they have more experience than those in which they do not have experience.

The shortage of research on institutions' learning behavior could be due to institutions being widely regarded as sophisticated investors (Michaely and Shaw, 1994; Badrinath et al., 1995; Cohen et al., 2002; Nagel, 2005; Chiang et al., 2010). However, institutional investors actually suffer from behavioral bias as well. Using a Taiwanese dataset between 2001 and 2006, Chou and Wang (2011) found that institutions have the propensity to buy more shares if they experienced high returns in the past. This finding is interpreted as the behavior bias of overconfidence. Although institutional investors are also subject to behavior biases, the extent is found to be lower than for individuals. Using an Australian dataset, Brown et al. (2006) revealed that the behavioral bias of disposition effect exists for both institutional and retail investors. However, institutional investors and those with more trading experiences are less susceptible to the disposition effect. Consistent results have also been found in other markets, such as the Taiwanese stock market (Barber et al., 2007) and Korean stock index futures market (Choe and Eom, 2009). Using 46,969 Chinese brokerage accounts data, Chen et al. (2007) found that investors not only display the disposition effect but also overconfidence and representativeness bias (have excessive belief based on past returns). However, institutional investors are less prone to these behavioral biases than individual investors.

3.3. Institutional Background

Aiming to promote the innovative small and mid-sized enterprises (SMEs) and to perfect the structure of China's capital market, ChiNext[29], a new exchange board affiliated with the Shenzhen Stock Exchange, was launched in 2009. The first batch of 28 SMEs started trading on ChiNext on 30 October 2009. At the time of writing, there are 484 firms listed on ChiNext.

ChiNext IPOs include separate tranches for institutional and individual investors. For a long period following the launch of ChiNext, the fraction of shares which issuers could sell in the institutional offering was capped at 20%. A new rule that became effective in May 2012[30] requires issuers to sell at least 50% of the issuing shares in the institutional offering with a claw back to the retail offering when the latter is heavily oversubscribed.

The essential function of institutional offering is to set the offer price. In my sample, bookbuilding is used as the primary pricing mechanism whereby the lead underwriter conducts a roadshow to promote the issue and collects data about institutional demand. In particular, institutional investors submit limit bids that specify prices and quantities. For each investment account[31], an institution is allowed to bid for up to three different prices with a tick size of CNY 0.01. The bid amounts are submitted in multiples of a minimum quantity and capped by the total number of shares in the institutional offering. Based on the order book and other factors such as market conditions, the underwriter and the issuing firm set the offer price. According to the rules set by the CSRC, only the bids that are at or above the offer price qualify for the following lottery-based allocation.[32]

My sample starts from November 2010 when ballot was initially introduced as

[29] ChiNext can be regarded as the Chinese equivalent of NASDAQ or Alternative Investment Market (AIM).

[30] The decree No.78 became effective on May 18, 2012. The majority of IPOs in my sample took place before this date.

[31] An investment account refers to the investment product under the management of an institution. Institutions can submit bids through several investment accounts in a single IPO.

[32] If one institution has multiple investment accounts and only part of the bids are qualified, this institution is still eligible to take part in the allocation, but with lower qualified amount compared to its total bid amount.

the allocation method for institutional offering in ChiNext. I assume that institutions have to start learning in order to be fully comfortable with this new mechanism.[33] The process of allocation is best explained by a real example. One of the issuers in my sample offered 8 million shares to institutions at an offer price of CNY 21.09.[34] In this IPO, 42 institutions submitted bids during bookbuilding with the total demand of 232 million shares. Overall, 23 out of the 42 institutions were eligible for the allocation as their bid prices were not less than CNY 21.09 and the total qualified amount[35] was 103.2 million shares. Since the minimum bid amount for institutions in this IPO was 0.8 million shares, 10 tickets (8 million shares supply / 0.8 million shares per ticket) out of 129 tickets (103.2 million shares demand / 0.8 million shares per tickets) were drawn in the lottery. The number of tickets held by each institution is determined by their qualified amounts. For instance, one institution in this IPO has a qualified amount of 4 million shares, but only 0.8 million subscribed shares are qualified for another institution. As a consequence, they received five tickets and one ticket respectively. It is worth noting that institutions with more qualified bids have a higher probability of receiving an allocation, 0.0388 versus 0.0078 in this example. At the end of the ballot, two institutions had two winning tickets and received 1.6 million shares, while six institutions had only one winning ticket and obtained 0.8 million shares. The remaining 15 institutions with qualified bids did not obtain any shares having not been chosen randomly from the ballot.

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33 Although the lottery-based allocation mechanism was used in retail offering for individual investors before, institutions still need to learn from the beginning as they have very different characteristics such as investment policy comparing with individuals.

34 The issuing firm of this IPO is Yantai Zhenghai Magnetic Material Co., Ltd (Ticker: 300224).

35 Qualified amount refers to the number of shares that are qualified for the following lottery-based share allocation. When one institution submits several bids with different prices, for example, three different prices P1, P2, P3 ($P1 > P2 > P3$) with bid amount of Q1, Q2, Q3 and the offer price is P, if $P > P1$, this institution cannot participate allocation; if $P1 \geq P > P2$, the amount being qualified for allocation is Q1; if $P2 \geq P > P3$, the amount being qualified for allocation is Q1+Q2; if $P3 \geq P$, the amount being qualified for allocation is Q1+Q2+Q3.

3.4. Data and Descriptive Statistics

To investigate the learning behavior of institutions, I study the IPOs that took place on ChiNext between November 2010 and September 2012. One reason for choosing November 2010 as the starting date of my sample is that the new IPO mechanism[36] was introduced during this month meaning that I can investigate institutions' learning processes. Another reason is that the detailed bidding information, such as bid price and amount, cannot be observed before November 2010. On the other hand, there was no IPO on ChiNext after September 2012 since the authority shut down the IPO market.[37] In total, 353 unique institutions submitted 19,151 bids in 214 IPOs that took place during this sample period.

The data on bids is hand-collected from official documents that issuing firms have to share with the public. From these documents, I can obtain the institution name, investment account name, bid price, bid quantity, quantity qualified for ballot, and quantity allocated. I use the institution name as an identifier to track each institution's bidding history.[38]

Table 3.1 provides summary statistics about bids submitted by the 353 institutions in the 214 IPOs. On average, an institution participated in 30 IPOs during the sample period, whereas the median is only 8. The large difference between the mean and the median, or the skewness, implies that some institutions are quite active in the IPO market. For example, funds and security firms are quite active in the IPO

[36] Prior to November 2010, the share allocation was on a pro-rata basis, such that all institutions with qualified bids (i.e. bids at or above the offer price) were guaranteed to receive some shares in the issue.

[37] The IPO market was re-opened in January 2014.

[38] I identify the changes in names of institutions, such that an institution which changes its name during the sample period is not treated as a new institution. The cases of changing names are identified using multiple resources: the corporate information search engine of State Administration for Industry & Commerce of the People's Republic of China (http://gzhd.saic.gov.cn/gszj/qyj/listGg.jsp); the list of ChiNext listed firms (obtained from the official website of the Shenzhen Stock Exchange); The official website of the China Securities Regulatory Commission (http://www.csrc.gov.cn/pub/newsite/);Baidu.com, the largest Chinese language-search engine (http://www.baidu.com/).

market with mean participating times of 63 and 54 respectively. A plausible explanation for their active participation is that these two types of institutions may have more information than other institutions. As a result, they have more confidence to make investments in the IPO market. For the bid amount, Table 3.1 also shows that fund firms are the most aggressive institutions. They usually subscribe 5.78 million (median: 5.17 million) shares worth CNY 126.86 million (median: CNY 109.83 million) in one IPO. Meanwhile, I find the bid sizes of trusts and finance firms are also considerable although they do not participate in IPOs very often.

With respect to the IPO data, listing date, offer price, closing price on the first trading day, the number of shares issued and gross proceeds are obtained from the official website of the SZSE. In addition, I collected data from the Securities Data Company (SDC) and cross checked the information. Table 3.2 presents the descriptive statistics for the 214 IPOs in my sample. The mean unadjusted initial return, which is defined as the percentage change between the offer price and the closing price on the first trading date, is 22.60%. Derrien and Womack (2003) pointed out that the lag between the IPO day[39] and the first trading day leads to greater underpricing. Therefore, I account for market-related movements between the IPO day and trading day. Specifically, I adjust the initial return by subtracting the percentage change of Shenzhen A-Share Stock Price Index during the waiting period (13.84 days on average). The mean and median of the adjusted initial returns are 23.17% and 16.22% respectively. Table 3.2 also shows that, on average, 49 institutions submit bids in an IPO, the order book contains 89 bids, and the amount of shares demanded by institutions (mean: 246.80 million) far exceeds the amount of shares offered (mean: 5.13 million). Even if I use the proportion of issued shares relative to qualified shares to measure the chance of receiving a share allocation, the probability is as low as 9.27%. This implies that the IPOs in my sample are heavily oversubscribed.

[39] IPO day is the day on which offer price is set.

Table 3.1 Descriptive statistics of institutions

The descriptive statistics about bids submitted by 353 institutions in 214 IPOs are presented according to their types. Recommendation refers to the institutional investors being independently recommended to participate in IPOs by the lead underwriter. Security refers to security firms. Fund includes mutual fund and Chinese national social security fund. Trust stands for trust companies. Finance represents the companies that provide financial services. QFII stands for qualified foreign institutional investors who are permitted to invest in the Chinese capital market. Insurance refers to insurance companies. One bid is defined as an offer with specific price and quantity via an institution's investment account. The number of bids submitted by one institution in an IPO is the sum of bids from all of the institution's investment accounts. If an institutional investor submitted at least one bid in an IPO, the frequency of participation is counted as once regardless of whether the bid(s) is (are) eligible for the following allocation. The bid value equates to bid quantity multiplies by the corresponding bid price. The mean values are reported and medians are presented in parentheses.

Institution Type	Count	Percent	Frequency of Participation	Number of bids submitted in an IPO	Number of shares demanded in an IPO (in millions)	Bid value in an IPO (in CNY million)
Recommendation	100	28.33%	8.35 (3.00)	1.12 (1.00)	1.96 (1.01)	43.64 (23.34)
Security	78	22.10%	53.65 (38.00)	1.24 (1.12)	3.46 (3.26)	82.24 (84.98)
Fund	61	17.28%	63.05 (42.00)	2.09 (1.75)	5.78 (5.17)	126.86 (109.83)
Unknown	60	17.00%	1.65 (1.00)	1.21 (1.00)	1.83 (0.99)	36.91 (22.20)
Trusts	26	7.37%	28.27 (10.00)	1.29 (1.00)	3.71 (3.24)	95.39 (87.81)
Finance	22	6.23%	32.32 (19.50)	1.12 (1.00)	4.42 (3.88)	106.53 (98.69)
QFII	4	1.13%	5.25 (4.50)	1.25 (1.00)	2.07 (2.15)	71.58 (68.30)
Insurance	2	0.57%	20.00 (20.00)	1.01 (1.01)	1.66 (1.66)	49.01 (49.01)
All	353	100%	29.67 (8.00)	1.34 (1.00)	3.21 (2.25)	73.49 (54.05)

Table 3.2 Descriptive statistics of IPOs

This table presents descriptive statistics for the 214 IPOs in my sample. The unadjusted initial return is defined as the percentage change between the offer price and the closing price on the first trading date. Market return is the market index return between the IPO day and listing day. Adjusted initial return is calculated as the unadjusted initial return minus the corresponding market return. The probability of obtaining shares is estimated by the proportion of issued shares relative to shares qualified for ballot-based allocation.

	Mean	P25	Median	P75	SD
Unadjusted initial return (%)	22.60	2.05	16.17	32.67	29.55
Number of days between the IPO and listing day	13.84	12	13	14	2.75
Market return (%)	-0.57	-3.78	-0.78	2.37	4.29
Adjusted initial return (%)	23.17	2.83	16.22	35.60	28.37
Number of institutions per IPO	48.93	36	45	56	18.64
Number of bids per IPO	89.49	58.00	76.50	111.00	49.12
Number of shares (in millions) demanded in bookbuilding	264.80	113.85	171.05	298.40	368.36
Number of shares (in millions) eligible for lottery	129.69	36.85	68.38	117.30	316.30
Number of shares (in millions) allocated in lottery	5.13	3.39	4.22	6.00	3.27
Probability of obtaining shares in lottery (%)	9.27	3.94	6.18	11.56	9.78

3.5. Past Returns and the Future Bidding Frequency

3.5.1. Hypotheses Development and Methodology

In order to have a better understanding of the behavior of investors, it is crucial to know how investors learn, i.e. the impact of past experience on their future decisions. When making investment decisions, some investors (Reinforcement learners) pay more attention to personally experienced outcomes than observing other's experiences without personal involvement. Reinforcement learners tend to repeat behaviors that have generated favorable results in the past and switch actions if the previous decisions caused unfavorable outcomes. There are also investors (Bayesian learners) who pay equal attention to their own and other's experiences. Specifically, Bayesian learners not only repeat their-own successful actions but also give equal consideration on other's experiences. Therefore, we test the two competitive learning mechanisms, Bayesian learning and reinforcement learning, to reveal how investors learn, which will provide empirical evidence to the learning behavior of institutional investors and the relationship between investor sentiment and IPO demand. The fundamental distinction between Bayesian learning and reinforcement learning is the distinct weights allocated to experienced payoffs versus forgone payoffs. Therefore, the primary objective is to decompose institutions' past returns into different components and test how institutions take into account each type of return when making future investment decisions.

Following Chiang et al. (2011), I divide the sample into two periods based on the number of IPOs. Periods 1 and 2 include 107 IPOs each. The aim is to explore whether an institution's experience in period 1 affects its behavior in period 2. For each institution, the participating frequency in period 1 N_{p1} and period 2 N_{p2} is counted. Meanwhile, I calculate the frequency of observing (forgoing) IPOs N_o[40] for period 1. Because of the unique IPO mechanism, one institution is only able to enter

[40] One IPO is classified as under observation for one institution if this institution does not submit any bids in that IPO.

the allocation process in some of the participated IPOs, unless its bids are at or above the corresponding offer price every time. Therefore, I also compute the frequency of submitting bids but being unqualified for allocation N_u[41] and the frequency of submitting bids and being qualified bids N_q. As introduced before, even though institutions are qualified for share allocation, it is not guaranteed that they will obtain shares eventually. Within those qualified bids, the frequency of receiving shares N_w and the frequency of not receiving shares N_l are obtained for each institution as well. The relationships among these count variables are as follows:

$$N_o + N_{p1} = N_o + N_u + N_q = N_o + N_u + N_l + N_w = 107 \qquad (3.1)$$

3.5.1.1. Experienced Return versus Forgone Return

To distinguish Bayesian learning from reinforcement learning, it is necessary to know how institutions' future decisions are influenced by the experienced payoff which is measured by the adjusted initial return of IPOs in which institutions submitted bids, and the forgone payoff which is the adjusted initial return of IPOs observed by institutions. The average adjusted initial return of the 107 IPOs in period 1 is *A* = 20.40%. Herein, the constant *A* can be decomposed into two components: (1) average observed return $\bar{R}_o$[42] and (2) average experienced return $\bar{R}_e$[43]. Regarding the magnitude of impact on future behavior, it could depend on the frequency of participation and observation. In other words, the greater frequency of participation in period 1, the more influence the experienced returns have and vice versa. Therefore, I weigh observed return and experienced return by the scaled times of

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[41] Unqualified bids are those that are lower than the offer price such that not being eligible to participate in share allocation.

[42] $\bar{R}_o = \frac{\sum_{i=1}^{N_o} r_i}{N_o}$ where r_i is the adjusted initial return for IPO_i that institutions only observed.

[43] $\bar{R}_e = \frac{\sum_{i=1}^{N_{p1}} r_i}{N_{1p}}$ where r_i is the adjusted initial return for IPO_i in which institution submitted bids. If institutions did not participate in any IPO in period 1, I set $\bar{R}_e = 0$.

observation $\frac{N_o}{107}$ and participation $\frac{N_{p1}}{107}$ respectively, such that $A = \frac{N_o}{107}\bar{R}_o + \frac{N_{p1}}{107}\bar{R}_e$. In the following analysis, $O \equiv \frac{N_o}{107}\bar{R}_o$ is a measure of observed return and $E \equiv \frac{N_{p1}}{107}\bar{R}_e$ is a measure of experienced return. To investigate the extent to which an institution's future decisions are driven by O and E, I construct the following regression model:

$$\text{(3.2)} \qquad \mathrm{Ln}\left(1 + N_{p2}\right) = \beta_o O + \beta_e E + \beta_p \mathrm{Ln}\,(1 + N_{p1}) + e$$

Since N_{2p} is positively skewed, i.e. there are many low-frequency participants, Ln $\left(1 + N_{p2}\right)$ is used as the dependent variable, which captures an institution's future participating tendency. O and E are the main variables of interest as they capture forgone and experienced payoffs respectively. In addition to past experiences, inherent investment propensity can affect an institution's bidding frequency as well. For instance, some institutions have an information advantage, which makes them more likely to participate in IPOs. In Table 3.1 , it has already been found that some institutions are exceedingly active in the IPO market. Therefore, Ln $(1 + N_{p1})$ is added to control an institution's inherent investment tendency. More importantly, Ln $(1 + N_{p1})$ controls those unobservable institution-specific factors that affect their participating frequency.

Econometrically, the regression model (3.2) is subject to perfect multicollinearity because $\mathrm{A} = O + E$ and A is a constant number. Hence, $\mathrm{A} - E$ is substituted for O to eliminate the problem of perfect multicollinearity.[44] Then Equation (3.2) takes on the following format:

$$\text{(3.3)} \qquad \mathrm{Ln}\left(1 + N_{p2}\right) = \beta_o(\mathrm{A} - E) + \beta_e E + \beta_p \mathrm{Ln}(1 + N_{p1}) + e$$

[44] The algorithm is quite similar to the concept of dummy variable.

$$(3.4) \qquad = \beta_o \mathrm{A} + (\beta_e - \beta_o)E + \beta_p \mathrm{Ln}(1 + N_{p1}) + e$$

where $\beta_o \mathrm{A}$ is the regression intercept as A is constant[45].

Hypothesis 1a: Institutions are subject to reinforcement learning, i.e. the impact of experienced return is greater than the observed return ($\beta_e - \beta_o > 0$).

Hypothesis 1b: Institutions are subject to Bayesian learning, i.e. the impact of experienced return is the same as the observed return ($\beta_e - \beta_o = 0$).

3.5.1.2. Decomposition of Experienced Return

When participating in an IPO, institutions are eligible for the share allocation only if they have at least one qualified bid, i.e. bids that remain at or above the offer price. Referring to the reinforcement learning, the return of unqualified bids can be regarded as the forgone payoff because institutions abandon these revenues via bidding at such a low price. In contrast, the return generated from qualified bids can be considered as the personally experienced return. If institutions' behaviors are consistent with reinforcement learning, the past return of qualified bids[46] should matter more than past return of unqualified bids[47] when they make a future investment decision. Therefore, I test whether institutions take into account the return of qualified bids more than that of unqualified bids. To do so, the weighted-average experienced return in period 1 E is further split into weighted-average return of unqualified bids U and weighted-average return of qualified bids Q, where $U = \frac{N_u}{107}\bar{R}_u$[48] and $Q = \frac{N_q}{107}\bar{R}_q$[49]. Similar to Section 3.5.1.1, the scaled times of

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[45] The estimate of β_o can easily be obtained by dividing the intercept estimate by A=20.40%.

[46] Return of qualified bids is defined as the adjusted initial return of an IPO in which institutions' bids are qualified for share allocation.

[47] Return of unqualified bids is defined as the adjusted initial return of an IPO in which bids are unqualified for share allocation.

[48] $\bar{R}_u = \frac{\sum_{i=1}^{N_u} r_i}{N_u}$ where r_i is the adjusted initial return for IPO_i that institutions participated in but were not qualified for share allocation.

qualification $\frac{N_q}{107}$ and unqualification $\frac{N_u}{107}$ are used to control the frequency effect due to fact that the returns of qualified bids would exert more impact if one institution had more qualified bids in the past and vice versa. Based on this decomposition, $\mathrm{A} = O + E = O + U + Q$ and O is replaced by $\mathrm{A} - U - Q$ in order to avoid the perfect multicollinearity problem. Therefore, the following OLS regression (3.7) is used to study the impact of U and Q:

(3.5) $$\mathrm{Ln}\left(1 + N_{p2}\right) = \beta_o O + \beta_u U + \beta_q Q + \beta_p \mathrm{Ln}\left(1 + N_{p1}\right) + e$$

(3.6) $$= \beta_o(\mathrm{A} - U - Q) + \beta_u U + \beta_q Q + \beta_p \mathrm{Ln}\left(1 + N_{p1}\right) + e$$

(3.7) $$=\beta_o \mathrm{A} + (\beta_u - \beta_o)U + (\beta_q - \beta_o)Q + \beta_p \mathrm{Ln}\left(1 + N_{p1}\right) + e$$

Hypothesis 2: Institutions' behaviors are consistent with reinforcement learning, i.e. the return of qualified bids has stronger impact than the return of unqualified bids on the decision of participating in future IPOs ($\beta_q > \beta_u$).

3.5.1.3. Further Decomposition of Return for Qualified Bid

Although institutions' bids are qualified for share allocation in one IPO, whether they can obtain shares or not is determined by the lottery-based allocation. As described above, the return of qualified bids can be realized only when institutions receive shares. Hence, I further decompose the return of qualified bid Q into the return of unallocated shares L and the return of allocated shares W. More specifically, L is the adjusted initial return of IPOs in which institutions were qualified for share allocation but did not receive shares; W is the adjusted initial return of IPOs in which institutions were qualified for share allocation and received an allocation eventually. Herein, $L = \frac{N_l}{107} \bar{R}_l$[50] and $W = \frac{N_w}{107} \bar{R}_w$[51]. Ultimately, I have $\mathrm{A} = O +$

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[49] $\overline{\mathrm{R}}_\mathrm{q} = \frac{\sum_{\mathrm{i}=1}^{N_q} \mathrm{r_i}}{N_q}$ where $\mathrm{r_i}$ is the adjusted initial return for $\mathrm{IPO_i}$ that institutions participated in and were qualified for share allocation.

[50] $\overline{\mathrm{R}}_\mathrm{l} = \frac{\sum_{\mathrm{i}=1}^{N_l} \mathrm{r_i}}{N_l}$ where $\mathrm{r_i}$ is the adjusted initial return for $\mathrm{IPO_i}$ that institutions were qualified but did not receive shares eventually.

$E = O + U + Q = O + U + W + L$. Since the random event of the ballot, rather than institutions' own investment decisions, determines the returns for allocated and unallocated shares, institutions should not differentiate between these two types of returns if they are rational. In this test, I regress $\text{Ln}\left(1 + N_{p2}\right)$ on L and W with the controlling of observed return and the return for unqualified bids.

(3.8) $\text{Ln}\left(1 + N_{p2}\right) = \beta_o O + \beta_u U + \beta_L L + \beta_L W + \beta_p \text{Ln}\left(1 + N_{p1}\right) + e$

(3.9) $= \beta_o(\text{A} - U - L - W) + \beta_u U + \beta_l L + \beta_w W + \beta_p \text{Ln}\left(1 + N_{p1}\right) + e$

(3.10) $= \beta_o \text{A} + (\beta_u - \beta_o)U + (\beta_l - \beta_o)L + (\beta_w - \beta_o)W + \beta_p \text{Ln}\left(1 + N_{p1}\right) + e$

Hypothesis 3: The returns of allocated and unallocated shares have equivalent impact on institutions' future investment decisions if institutions behave rationally, i.e. $\beta_w = \beta_l$.

3.5.2. Empirical Results

In this section, I run the regression models (Equation (3.4), Equation (3.7), and Equation (3.10)) developed in Section 3.5.1 to investigate the learning behavior of institutional investors. Results are exhibited in Table 3.3. Recall Equation (3.4), the constant term in model 1 of Table 3.3 represents the impact of observed return on institutions' future investment decisions. I find the effect of constant is positively significant, i.e. institutions will participate in more IPOs in period 2 if they observed high IPO returns in period 1. Compared with observed return, experienced return exerts a greater effect on institutions' future decisions because the coefficient of E is positive and significant at the 1% level.[52] Economically, an institution's participating frequency increases 15.125% when they experienced additional 1% IPO returns in

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[51] $\overline{\text{R}}_\text{w} = \frac{\sum_{\text{i}=1}^{N_W} \text{r}_\text{i}}{N_w}$ where r_i is the adjusted initial return for IPO_i that institutions were qualified and got shares.

[52] In fact, the coefficient of E in model 1 is the coefficient difference between E and O in Equation (3.2).

the past, but the investment propensity only increases by 3.647%[53] when they observed the same amount of incremental observed return.

It is a fact that institutions are more likely to conduct investment if they have abundant funding. Therefore, I add the logarithm of net assets[54] by the end of the 2010 fiscal year to measure institutions' funding availability.[55] The result for controlling of funding availability is presented in model 4 of Table 3.3. While the number of observations drops to 170, the result is still qualitatively consistent with that of model 1. Based on the two models, I conclude that institutions are subject to reinforcement learning since the experienced payoff matters more than forgone payoff ($\beta_e - \beta_o > 0$) when institutions make their future decisions. Hypothesis 1a is sustained.

In model 2 of Table 3.3 , I examine the effect of return generated from qualified and unqualified bids. The coefficients of U and Q in model 2 are actually $\beta_u - \beta_0$ and $\beta_q - \beta_0$ in Equation (3.5). In the last row, I show the p-value of t-test that compares the coefficient between U and Q. The p-value of 0.013 indicates that β_q is significantly higher than β_u[56]. In other words, institutions' future decisions are affected by the return of qualified bids more than by unqualified bids. This result is economically significant as well. Institutions will participate in an additional 19.998% IPOs if 1% returns growth for qualified bids occurred in the past. But the future participating frequency will only rise by 10.319% if the 1% additional return comes from unqualified bids. Compared with qualified bids, the return of unqualified bids

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53 3.647=0.774/20.40%, where 20.40% is the average adjusted initial return of the 107 IPOs in period 1.

54 The definition of net assets is the total asset minus total liability. The net assets data of funds, security firms and trusts are collected from Fund Research Center of China Galaxy Securities Company, Securities Association of China and Baidu.com respectively. For the other types of institutions, I collect the net assets data from annual reports.

55 The period 2, the second period results from the division of my sample, starts in 2011. Therefore, I use the data in the year-end of 2010 as predictor for future behavior.

56 Although the t-test compares the equality of $\beta_u - \beta_0$ and $\beta_q - \beta_0$, it actually test whether β_u is equal to β_q as β_0 is same in both parts.

can be regarded as forgone payoff due to the fact that the low bid prices (lower than the offer price) make some institutions lose the chance to obtain the issuing shares. Therefore, reinforcement learning is also supported in model 2. Meanwhile, the intercept term is still positively significant, i.e. observed return matters in institutions' learning processes. However, observed return is less important than the return of both unqualified and qualified bids based on the coefficient of U and Q, which is consistent with the finding in model 1. The result including funding size is shown in model 5 from which I get a similar result to model 2. Therefore, Hypothesis 2 is justified.

In model 3 of Table 3.3, I investigate whether the return of allocated and unallocated shares has the same impact on institutions' future investment decisions. The coefficient of L and W in model 3 is $\beta_l - \beta_o$ and $\beta_w - \beta_o$. The p-value of equality test between these two coefficients is 0.711, which implies β_l and β_w are not statistically different to each other. In model 6, it can be seen that the coefficient of 12.643 is quite close to the coefficient of 11.057. These results imply that institutions treat the return of allocated and unallocated shares without a tremendous difference. Thus, Hypothesis 3 is supported. Much like the previous results, the impact of return for unqualified bids, unallocated and allocated shares on institutions' future decisions are more influential than the observed return as the coefficient of U, L and W are all positively significant. According to the six models in Table 3.3, I confirm that the behaviors of institutions are affected by past investment experience and they are subject to reinforcement learning because of the following impact gradation of different returns: experienced return (E) > observed return (O); return of qualified bid (Q) > return of unqualified bid (U). These results provide empirical evidence for the hybrid model of Camerer and Ho (1999) in which both actual and forgone payoff influence the decision-making process but with different weights. Moreover, I also find that institutions equally take into account the returns that are derived from random events. This finding exhibits the rational aspect of institutional investors as they are not blindly driven by favorable outcomes of a random event.

Table 3.3 Effect of past returns on future decision

This table presents OLS regression results. N_{p1} and N_{p2} are the participating frequency in the periods 1 and 2 respectively. E is the weighted-average adjusted initial return of IPOs in which institutions submitted bids. U is the weighted-average adjusted initial return of IPOs in which an institution submitted bids but its bids were unqualified for share allocation. Q is the weighted-average adjusted initial return of IPOs in which an institution submitted bids and its bids were qualified for share allocation. L is the weighted-average adjusted initial return of IPOs in which institutions were qualified for share allocation but did not receive shares. W is the weighted-average adjusted initial return of IPOs in which institutions were qualified for share allocation and received an allocation eventually. For model 4 – model 6, I add funding availability to my regression model. Variable definitions are in Section 3.5.1. Robust t-values for eliminating heteroscedasticity are reported in parentheses. The last row demonstrates the p-value of the t-test that compares the equality of paired coefficient. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: Log $(1+N_{p2})$						
Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log $(1+N_{p1})$	0.251***	0.253***	0.251***	0.203*	0.204*	0.202*
	(3.69)	(3.77)	(3.69)	(1.89)	(1.90)	(1.87)
E	15.125***			9.855***		
	(8.36)			(4.42)		
U		10.319***	10.350***		7.644***	7.657***
		(4.25)	(4.27)		(3.01)	(3.01)
Q		19.998***			12.261***	
		(7.02)			(3.92)	
L			20.658***			12.643***
			(5.52)			(3.33)
W			17.788***			11.057**
			(3.02)			(2.22)
Funding availability				0.221***	0.217***	0.217***
				(4.39)	(4.27)	(4.25)
Constant	0.744***	0.744***	0.745***	0.533**	0.543 **	0.541**
	(9.39)	(9.42)	(9.41)	(2.08)	(2.11)	(2.09)
Obs.	353	353	353	170	170	170
R-sq	57.35%	57.82%	57.83%	53.36%	53.58%	56.62%
Comparisons of coefficients		U and Q	L and W		U and Q	L and W
p-value		0.013**	0.711		0.192	0.799

3.5.3. Robustness Tests

There are other potential regression techniques that can be applied to my models which use count data as a dependent variable, such as negative binomial regression, zero-inflated negative binomial, Poisson regression, and zero-inflated Poisson regression. Negative binomial regression is used for over-dispersed count data, which is when the variance of a dependent variable is much higher than the mean. Poisson regression is more suitable when the data is not over-dispersed, i.e. the variance of the dependent variable does not exceed the mean. With respect to zero-inflated negative binomial and zero-inflated Poisson regression, both of them deal with the situation that dependent variable has excessive zeros.

From the descriptive statistics, I know the variance of N_{p2} is 247.70 which is much higher than the mean of 10.07. Therefore, Poisson regression is not appropriate for my analysis. I also implement the Likelihood-ratio test for alpha=0. The result suggests that alpha is significantly different from zero, i.e. negative binomial is better than Poisson regression. Therefore, I re-run the six models in Table 3.3 using standard and zero-inflated negative binomial with Vuong closeness test[57]. The z-value of Vuong test is not significantly different from zero, indicating that standard negative binomial is more suitable for my models. The results of standard negative binomial regression are displayed in Table 3.4. It can be seen that the results are qualitatively similar to those shown in Table 3.3.

[57] Negative binomial regression is more preferred when the z-value of Vuong test is not significantly different from zero.

Table 3.4 Effect of past returns on future decision (negative binomial)

This table presents the results of standard negative binomial regression. N_{p1} and N_{p2} are the participating frequency in the periods 1 and 2 respectively. E is the weighted-average adjusted initial return of IPOs in which institutions submitted bids. U is the weighted-average adjusted initial return of IPOs in which an institution submitted bids but its bids were unqualified for share allocation. Q is the weighted-average adjusted initial return of IPOs in which an institution submitted bids and its bids were qualified for share allocation. L is the weighted-average adjusted initial return of IPOs in which institutions were qualified for share allocation but did not obtain shares. W is the weighted-average adjusted initial return of IPOs in which institutions were qualified for share allocation and received an allocation eventually. For model 4 – model 6, I add funding availability to my regression model. Variable definitions are in Section 3.5.1. Robust t-values for eliminating heteroscedasticity are reported in parentheses. The last row demonstrates the p-value of t-test that compares the equality of paired coefficient. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: N_{p2}

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log $(1+N_{p1})$	0.409*** (3.90)	0.405*** (3.87)	0.402*** (3.83)	0.222* (1.80)	0.219* (1.78)	0.221* (1.80)
E	10.068*** (4.48)			7.494*** (3.38)		
U		6.261** (2.45)	6.306** (2.48)		6.405*** (2.62)	6.403*** (2.61)
Q		14.355*** (4.42)			8.819*** (3.15)	
L			15.145*** (3.70)			8.214** (2.58)
W			11.891** (2.19)			10.614** (2.29)
Funding availability				0.140*** (2.61)	0.138** (2.57)	0.137** (2.53)
Constant	0.929*** (4.89)	0.930*** (4.90)	0.930*** (4.90)	1.278*** (3.41)	1.284*** (3.43)	1.289*** (3.42)
Obs.	353	353	353	170	170	170
Pseudo R-sq	8.87%	8.94%	8.95%	6.70%	6.71%	6.72%
Comparisons of coefficients		U and Q	L and W		U and Q	L and W
p-value		0.029**	0.647		0.389	0.648

One could argue that my results are driven by the division point of the two periods. Therefore, I split the sample in another way by which period 1 is extended by one additional month.[58] Based on the new division point, period 1 covers 118 IPOs from November 2010 to August 2011 and period 2 consists of 96 IPOs from September 2011 to September 2012. I implement the same tests as before and the alternative results are displayed in Table 3.5. We can see that the variable of *E* is positively significant, which indicates that the impact of experienced return is larger than observed return. Moreover, model 2 of Table 3.5 shows that the return of qualified bids is more meaningful than the return of unqualified one. Therefore, the results based on alternative division point also support the conclusion that institutional investors are subject to reinforcement learning.

[58] I also contract the period 1 by one month. The results are qualitatively similar to those of other period divisions.

Table 3.5 Effect of past returns on future decision (alternative division)

This table presents OLS results with alternative period division. I extend the period 1 that measures institutions' experiences by one additional month. N_{p1} and N_{p2} are the participating frequency in the periods 1 and 2 respectively. E is the weighted-average adjusted initial return of IPOs in which institutions submitted bids. U is the weighted-average adjusted initial return of IPOs in which an institution submitted bids but its bids were unqualified for share allocation. Q is the weighted-average adjusted initial return of IPOs in which an institution submitted bids and its bids were qualified for share allocation. L is the weighted-average adjusted initial return of IPOs in which institutions were qualified for share allocation but did not receive shares. W is the weighted-average adjusted initial return of IPOs in which institutions were qualified for share allocation and obtained an allocation eventually. For model 4 – model 6, I add funding availability to my regression model. Variable definitions are in Section 3.5.1. Robust t-values for eliminating heteroscedasticity are reported in parentheses. The last row demonstrates the p-value of t-test that compares the equality of paired coefficient. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: Log $(1 + N_{P2})$

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log $(1 + N_{p1})$	0.271***	0.273***	0.273***	0.253**	0.254**	0.254**
	(8.65)	(4.37)	(4.28)	(2.40)	(2.43)	(2.38)
E	12.595***			7.652***		
	(7.79)			(3.77)		
U		8.100***	8.100***		4.926**	4.924*
		(3.49)	(3.49)		(1.97)	(1.97)
Q		17.224***			10.666***	
		(6.90)			(3.63)	
L			17.214***			10.804***
			(4.97)			(2.79)
W			17.253***			10.279**
			(2.96)			(2.15)
Funding availability				0.204***	0.199***	0.200***
				(3.93)	(3.81)	(3.78)
Constant	0.652***	0.652***	0.652***	0.414	0.426	0.425
	(8.65)	(8.68)	(8.65)	(1.58)	(1.62)	(1.61)
Obs.	353	353	353	170	170	170
R-sq	57.11%	57.60%	57.60%	52.37%	52.77%	52.77%
Comparisons of coefficients		U and Q	L and W		U and Q	L and W
p-value		0.013**	0.996		0.117	0.936

3.6. The Decision to Bid for a Forthcoming IPO

3.6.1. Hypotheses Development and Methodology

In the preceding section, I investigated the impact of past experience on an institution's future bidding frequency by dividing the sample into two periods, which is a method borrowed from Kaustia and Knüpfer (2008) and Chiang et al. (2011). In practice, however, institutions have to make a decision on whether to participate in, or only observe, a forthcoming IPO. In this section, I take a further step to study which factors affect an institution's investment decision on submitting bids for an upcoming IPO.

Each time an IPO takes place, the institution decides whether or not to bid. Therefore, the data has a panel structure with 353 (institutions) × 214 (IPOs) = 75,542 observations, whereby IPOs are ordered according to the issue date. If there are multiple IPOs on the same day[59], they are then ordered by their stock ticker[60]. Clearly, the decision to bid in an IPO can only be affected by the outcomes of IPOs that have already taken place. Thus, the *last* IPO is defined as the most recent IPO whose first trading day (the day on which institutions know the initial return) is before the upcoming IPO's bidding date (the day on which institutions submit bids).

In China, institutions are allowed to submit bid(s) for an ongoing IPO through a three-day window, which is typically the three days prior to the day that the offer price is settled. Based on the data, however, I cannot know the exact date when an institution placed a bid. To deal with this shortcoming, I conduct three separate analyses using the potential three days as the bidding day. Since the results of the three independent tests are qualitatively the same, hereafter, I only report results based on the second bidding day, i.e. two days before the day that offer price is settled.

Once the order of the IPO sequence is settled, I can ascertain the adjusted initial

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[59] For the sample period, there are typically three IPOs issued at a time every week since the Chinese IPO market is highly regulated by the CSRC.

[60] Stock ticker is the unique official identification number pertaining to each of the listing firm.

returns for IPOs prior to the ongoing IPO_i and denote them as r_{i-j}. Besides, I can also track whether a particular institution submitted bids in past IPOs. The dummy variable of bid_{i-j} is used to indicate institutions' participating history, where bid_{i-j} equals 1 if at least one bid was submitted in IPO_{i-j} and 0 otherwise. To explore the relationship between the experiences in previous IPOs and an institution's future participating decision, I regress the participating decision variable of bid_i on r_{i-j}, bid_{i-j} and the interaction term $r_{i-j} * bid_{i-j}$, with the control of IPO-specific characteristics. The variable of bid_{i-j} is used to control an institution's inherent participating propensity as it has been shown in Table 3.1 where some institutions are more likely to submit bids in IPOs than others. On the other hand, IPO-specific characteristics could affect the institution's decision as well. For example, institutions may be prone to invest in IPOs with fast growth or high profitability. Specifically, I use IPO proceeds to measure IPO size; net profit margin[61] as the proxy for profitability; sales growth[62] to gauge the growth rate; and the Hi-tech dummy to indicate whether an issuing firm belongs to the Hi-tech industry or not.

More importantly, interaction terms are variables of interest since they disentangle reinforcement learning from Bayesian learning. Specifically, if the interaction terms are significantly positive, it means the returns of past IPOs in which institutions submitted bids matter more than those they simply observed. If so, this result implies reinforcement learning. Alternatively, Bayesian learning is indicated if institutions attach the same weight to the two types of returns, i.e. interaction terms do not matter. Hence, I have the following hypothesis:

Hypothesis 4a: Institutions are subject to reinforcement learning i.e. institutions are more likely to participate in a forthcoming IPO when they participated in

[61] Net profit margin is defined as net income/ net sales or revenues.

[62] It is calculated as the sales growth from the year before IPO to the IPO year.

recent IPOs and experienced high returns. (Interaction terms are positively significant).

Hypothesis 4b: Institutions are subject to Bayesian learning i.e. Participation of past high-return IPOs does not increase the likelihood of participating in a forthcoming IPO (Interaction terms are not significant).

In the tests, I consider up to five previous IPOs, i.e. $\mathrm{IPO}_{\mathrm{i}-5}$ to $\mathrm{IPO}_{\mathrm{i}-1}$ because the influence of IPOs earlier than $\mathrm{IPO}_{\mathrm{i}-5}$ is significantly weaker (not reported). In Table 3.6, I present the descriptive statistic regarding the number of days between $\mathrm{IPO}_{\mathrm{i}}$ and $\mathrm{IPO}_{\mathrm{i}-\mathrm{j}}$[63]. The most recent three IPOs are normally one week before the ongoing IPO with the median of 6, 6, and 7 respectively. For the fourth and fifth most recent IPOs, there typically is a time gap of around two weeks based on the median of 13. This pattern is mainly because the Chinese IPO market is highly regulated by the CSRC.

Moreover, I notice that an institution's attrition matters because institutions may quit the IPO market for a while without participating in, or observing, any IPOs. When attrition exists, the regression results will be biased if I still include those IPOs taking place during the attrition period in my analysis. To avoid this issue, I exclude all of the IPOs completed before the first IPO in which one particular institution submitted a bid and those conducted after the last IPO in which this institution submitted a bid. As a result, the panel data become $353 \times \mathrm{N}_{\mathrm{i}}$, where N_{i} depends on the number of IPOs left after this exclusion and varies across institutions.

[63] The number of observations for $\mathrm{IPO}_{\mathrm{i}-1}$, $\mathrm{IPO}_{\mathrm{i}-2}$, and $\mathrm{IPO}_{\mathrm{i}-3}$ are 205 because 9 out of the 214 IPOs do not have any past IPOs whose first trading days is before the ongoing IPO's bidding day. The observations for $\mathrm{IPO}_{\mathrm{i}-4}$ and $\mathrm{IPO}_{\mathrm{i}-5}$ are 202 since there are 12 out of 214 IPOs do not have the last fourth and fifth IPO that meet time series criterion regarding first trading day and bidding day.

Table 3.6 Descriptive statistics of the number of days between $\mathrm{IPO_i}$ and $\mathrm{IPO_{i-j}}$

This table presents the descriptive statistics for the number of days between $\mathrm{IPO_i}$ and $\mathrm{IPO_{i-j}}$ which is measured by the difference between $\mathrm{IPO_i}$'s second bidding date and $\mathrm{IPO_{i-j}}$'s trading date. The definition of the second bidding date is the second day on which institutions can submit bids for a particular IPO. Trading date is the day on which one particular IPO starts trading on ChiNext.

Number of Days between $\mathrm{IPO_i}$ and $\mathrm{IPO_{i-j}}$	N	Min	P25	Mean	Median	P75	Max
$\mathrm{IPO_{i-1}}$	205	1	5	6.73	6	7	21
$\mathrm{IPO_{i-2}}$	205	1	5	8.44	6	10	34
$\mathrm{IPO_{i-3}}$	205	1	6	10.56	7	13	42
$\mathrm{IPO_{i-4}}$	202	1	10	14.53	13	18	55
$\mathrm{IPO_{i-5}}$	202	3	11	16.30	13	21	55

3.6.2. Empirical Results

Table 3.7 presents the logistic panel regression results with fixed-effects for institutions. The heterogeneity of the institutions could also affect their participating decision. Therefore, I use the fixed-effects to control those time-invariant factors such as size and reputation.[64] Model 1 of Panel A considers the impact of the three most recent IPOs, and IPO_{i-4} and IPO_{i-5} are added in models 2 and 3 respectively. In Panel A, I find that the coefficients of $\mathrm{bid_{i-j}}$ are all positively significant at 1% or 5% level, which indicates that institutions are more likely to submit bids in a future IPO if they participated in recent IPOs. In other words, the inherent participation propensity affects an institution's investment decision. Furthermore, the coefficients of $\mathrm{r_{i-j}}$ are not significant in the three models except $\mathrm{r_{i-4}}$ in models 2 and 3, and $\mathrm{r_{i-5}}$ in model 3. However, the impact of $\mathrm{r_{i-j}}$ becomes positively significant when they interact with the dummy variable $\mathrm{bid_{i-j}}$, for example

[64] I admit that institution's characteristics vary over time, but the sample period is two years which is too short for an institution's characteristics, such as reputation, to change substantially.

$r_{i-1} * \mathrm{bid}_{\mathrm{i}-1}$ in models 1, 2 and 3, and $r_{i-3} * \mathrm{bid}_{\mathrm{i}-3}$ in model 1. I interpret the impact of interaction terms to mean that the returns on IPOs in which institutions submitted bid has more impact on the participating decision than those of observed IPOs. For example, when holding all other variables at certain values, the coefficient 0.3460 of $r_{i-1} * \mathrm{bid}_{\mathrm{i}-1}$ in model 3 means that, if institutions participated in the last IPO, a one-unit increase for the initial return of the last IPO prompts the odds ratio of subscribing the forthcoming IPO to grow by an additional 1.41 times ($e^{0.3460}$). Therefore, it provides support for reinforcement learning since the theory posits that the experienced payoffs matter more than the forgone payoffs. Besides, the results also indicate that the more recent the past IPOs are, the more impact they have on the future participating decision. With respect to the IPO-specific variables, I document that institutions are more likely to subscribe to shares of non-hi-tech firms with high profitability and fast growth rate.

Panel B of Table 3.7 illustrates the results of alternative tests in which I use the dummy variables of $\mathrm{qlf}_{\mathrm{i-j}}$ to replace $\mathrm{bid}_{\mathrm{i-j}}$. Herein, $\mathrm{qlf}_{\mathrm{i-j}}$ equals 1 if an institution is qualified for the share allocation and 0 otherwise.[65] If one institution submits multiple prices for an IPO, I assign the dummy variable as 1 as long as at least one bid meets the offer price. In Panel B, I can see that most of the $\mathrm{qlf}_{\mathrm{i-j}}$ are positively significant. This implies that institutions are keen on submitting bids in the upcoming IPO if they were qualified for share allocation in previous IPOs. This behavior is in line with the fact that human beings' future decisions can be positively motivated by good experiences.

Furthermore, r_{i-1} and r_{i-2} are not influential in models 1-3 of Panel B but the interaction term of $r_{i-1} * \mathrm{qlf}_{\mathrm{i}-1}$ and $r_{i-2} * \mathrm{qlf}_{\mathrm{i}-2}$ are positively significant in all of the three models. It implies that the returns of IPOs in which institutions were

[65] $\mathrm{qlf}_{\mathrm{i-j}}$ =0 involves the both cases that institution did not submit bid in that IPO and that an institution submitted bid but was not qualified for the allocation.

Table 3.7 Impact of past returns on participating decision

This table presents the results of logistic panel regression with fixed-effects. The dependent variable $\mathrm{bid_i}$ is dummy variable which equals to 1 if an institution submits a bid in $\mathrm{IPO_i}$ and 0 otherwise. $\mathrm{r_{i-j}}$ is the adjusted initial returns for $\mathrm{IPO_{i-j}}$. $\mathrm{bid_{i-j}}$ indicates an institution's participating history, where $\mathrm{bid_{i-j}}$ equals 1 if at least one bid was submitted in $\mathrm{IPO_{i-j}}$ and 0 otherwise. $\mathrm{qlf_{i-j}}$ measures whether institution were qualified for share allocation in the past IPOs, where it is equal to 1 if at least one bid is qualified and 0 otherwise. *ln(proceeds)* is the natural logarithm of total IPO proceeds. *Profitability* is measured by the net profit margin. *Growth rate* is gauged by the sales growth rate. The dummy variable of *Hi-tech* equals 1 if the issuing firm belongs to the hi-tech industry and 0 otherwise.***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: $\mathrm{bid_i}$							
Panel A				Panel B			
Independent variables	Model 1	Model 2	Model 3	Independent variables	Model 1	Model 2	Model 3
r_{i-1}	-0.0378	-0.1100	-0.0416	r_{i-1}	0.0588	0.0234	0.0732
	(-0.39)	(-1.08)	(-0.40)		(0.71)	(0.26)	(0.82)
r_{i-2}	0.0582	-0.0277	0.0354	r_{i-2}	0.0399	-0.0436	0.0084
	(0.66)	(-0.30)	(0.38)		(0.52)	(-0.54)	(0.10)
r_{i-3}	0.0253	-0.0268	0.0197	r_{i-3}	0.0582	-0.0117	0.0141
	(0.33)	(-0.34)	(0.25)		(0.86)	(-0.17)	(0.20)
r_{i-4}		0.3602***	0.3679***	r_{i-4}		0.2687***	0.2753***
		(3.59)	(3.67)			(3.01)	(3.08)
r_{i-5}			-0.2323***	r_{i-5}			-0.1735***
			(-3.62)				(-3.17)
$\mathrm{bid_{i-1}}$	0.4414***	0.3598***	0.3523***	$\mathrm{qlf_{i-1}}$	0.2334***	0.1312**	0.1267*
	(8.79)	(6.99)	(6.81)		(3.59)	(1.98)	(1.90)
$\mathrm{bid_{i-2}}$	0.4028***	0.3304***	0.3232***	$\mathrm{qlf_{i-2}}$	0.1672***	0.1248**	0.1208**
	(9.47)	(7.55)	(7.33)		(3.18)	(2.31)	(2.24)
$\mathrm{bid_{i-3}}$	0.2928***	0.2356***	0.2282***	$\mathrm{qlf_{i-3}}$	0.3499***	0.3329***	0.3346***
	(6.52)	(5.15)	(4.97)		(6.51)	(6.10)	(6.13)
$\mathrm{bid_{i-4}}$		0.3347***	0.3111***	$\mathrm{qlf_{i-4}}$		0.3016***	0.2859***
		(7.22)	(6.61)			(4.98)	(4.69)
$\mathrm{bid_{i-5}}$			0.0939**	$\mathrm{qlf_{i-5}}$			0.0609
			(2.28)				(1.17)
$r_{i-1} * \mathrm{bid_{i-1}}$	0.2414*	0.3624**	0.3460**	$r_{i-1} * \mathrm{qlf_{i-1}}$	0.3134*	0.4724***	0.4598**
	(1.73)	(2.56)	(2.44)		(1.75)	(2.60)	(2.53)
$r_{i-2} * \mathrm{bid_{i-2}}$	0.0873	0.0625	0.0436	$r_{i-2} * \mathrm{qlf_{i-2}}$	0.5087***	0.4758***	0.4436***
	(0.72)	(0.50)	(0.35)		(3.55)	(3.25)	(3.03)
$r_{i-3} * \mathrm{bid_{i-3}}$	0.2143**	0.1711	0.1408	$r_{i-3} * \mathrm{qlf_{i-3}}$	0.1200	0.1076	0.0889
	(2.08)	(1.64)	(1.33)		(0.98)	(0.87)	(0.71)

Table 3.7 – Continued

$r_{i-4} * \mathrm{bid}_{i-4}$		-0.0554	-0.0802	$r_{i-4} * \mathrm{qlf}_{i-4}$		0.1563	0.1574
		(-0.38)	(-0.54)			(0.79)	(0.79)
$r_{i-5} * \mathrm{bid}_{i-5}$			0.1305	$r_{i-5} * \mathrm{qlf}_{i-5}$			0.1561
			(1.38)				(1.34)
ln(proceeds)	0.0404	-0.0106	-0.0341	*ln(proceeds)*	0.0814***	0.0222	0.0044
	(1.40)	(-0.36)	(-1.13)		(2.86)	(0.76)	(0.15)
Profitability	1.0034***	1.0787***	1.1390***	*Profitability*	0.9995***	1.0696***	1.1095***
	(7.73)	(8.18)	(8.58)		(7.78)	(8.19)	(8.45)
Growth Rate	0.2861***	0.2886***	0.2919***	*Growth Rate*	0.2787***	0.2754***	0.2800***
	(5.30)	(5.28)	(5.34)		(5.23)	(5.10)	(5.18)
Hi-tech	-0.0952***	-0.0900**	-0.0976***	*Hi-tech*	-0.0969***	-0.0892**	-0.0947***
	(-2.61)	(-2.46)	(-2.66)		(-2.69)	(-2.46)	(-2.61)
Obs.	37,968	37,422	37,422	Obs.	37,968	37,422	37,422
Groups	305	303	303	Groups	305	303	303
Pseudo R-sq	3.28%	3.33%	3.41%	Pseudo R-sq	1.48%	1.62%	1.67%

qualified for share allocation are more influential than those institutions to have only observed, or participated in but not qualified for share allocation. Economically, ceteris paribus, the coefficient of 0.4598 in model 3 of Panel B represents that the odds ratio of submitting bids in a forthcoming IPO is expected to grow by an additional 58.38% ($e^{0.4598}$) when a one-unit increase for the initial return of the last IPO and institutions participated in that IPO. Although the variables of $\mathrm{r}_{\mathrm{i}-4}$ and $\mathrm{r}_{\mathrm{i}-5}$ have significant impact on the possibility of future participation, it does not fail the conclusion of reinforcement learning. The results of $\mathrm{r}_{\mathrm{i}-4}$ and $\mathrm{r}_{\mathrm{i}-5}$ only indicate that past returns have impact on future participating decision when experienced and observed returns are not explicitly distinguished. However, the way I distinguish reinforcement learning and Bayesian learning is to test whether the participation of high-return IPOs in the past will generate incremental influence on future participating decision, i.e. whether the interaction terms have significantly additional effect. In conclusion, the results of Table 3.7 provide additional support for reinforcement learning.

In conclusion, an institution's participation decision in the IPO market is consistent with reinforcement learning. Institutions are more likely to submit bids in an upcoming IPO if they experienced high initial returns in recent IPOs in which they were personally involved rather than those they merely observed. This pattern is consistent with the finding of Seru et al. (2010) that individual investors gain experience by actively trading rather than observing hypothetical trades. Based on the results in Sections 3.5 and 3.6, I conclude that an institution's learning behavior is persistent for both aggregate and single IPO level.

3.7. Past Returns and Bid Aggressiveness in the Following IPO

3.7.1. Hypotheses Development

With respect to the learning behavior, it is also valuable to explore whether institutions' bid aggressiveness is influenced by past investment outcomes. According to reinforcement learning theory, if one institution experienced a favorable outcome in the past, this institution would be avid to acquire shares in the next IPO. In such a case, a high price would be bid. In this section, therefore, I examine whether institutional investors' bid aggressiveness is positively affected by past investment outcome. If so, this test will provide extra evidence for reinforcement learning. Chiang et al. (2011) found that institutional investors will bid less aggressively if they have experienced a high return before. However, institutions are not found to be subject to reinforcement learning in their research. In Sections 3.5 and 3.6, it has been revealed that institutions are reinforcement learners. As a result, they should bid more aggressively in order to obtain shares after experiencing a high return. Particularly in this research context, institutional investors are qualified for shares allocation only if their bids are not less than the offer price. Therefore, I propose the following hypothesis:

> **Hypothesis 5**: Institutional investors (reinforcement learners) will bid more aggressively after experiencing high returns in past IPOs.

3.7.2. Methodology

I use the panel data employed in Section 3.6 to explore institutional investors' bid aggressiveness. Bid aggressiveness is defined as the quantity-weighted bid price / midpoint of the filing range, where weight is based on the amount of shares an institution subscribes under a particular price; filing range is the price interval being proposed by the lead underwriter during preliminary inquiry.

$$\text{Bid Aggressiveness} = \frac{\sum_{i=1}^{n} \frac{subscribed\ amount\ of\ bid\ price_i}{total\ subcribed\ amount} * bid\ price_i}{(upper\ end\ of\ filing\ range + lower\ end\ of\ filing\ range)/2}$$

If one institution does not submit any bid in a specific IPO, I let this institution's bid aggressiveness in that IPO equal 0. For the 353 institutions in my sample, the mean and median of bid aggressiveness are 23.54% and 0%[66] respectively with the standard deviation of 40.80%.

Similar to the models in Panel A of Table 3.7 , the dummy variable of bid_{i-j} is used to control institutions' inherent tendency of participation; the interaction term $r_{i-j} * \mathrm{bid}_{i-j}$ is added to distinguish the returns of IPOs in which institutions were personally involved and those they merely observed. The only difference is that the dependent variable is bid aggressiveness instead of bid_i.

According to the characteristics of reinforcement learning, the reinforcement learner replicates the behavior that generated a favorable outcome in the past. In my research context, given institutions are reinforcement learners, they should bid more aggressively to become qualified for shares allocation once again when they were qualified in past IPOs and experienced high returns. Put another way, bid aggressiveness will not be affected if an institution was not qualified for the allocation in past IPOs even if it generated a very high initial return. This is because the strength of reinforcement is weak when institutional investors have little personal

[66] In general, institutions choose few IPOs to participate, i.e. they do not submit bid in most of the upcoming IPOs. Therefore, the median equals 0 as most of the observations' bid aggressiveness is zero.

involvement in past IPOs. Based on the aforementioned argument, interactive effect may exist between past investment outcome and qualification dummy as well. Therefore, I also replace $\mathrm{bid_{i-j}}$ and $\mathrm{r_{i-j} * bid_{i-j}}$ by $\mathrm{qlf_{i-j}}$ and $\mathrm{r_{i-j} * qlf_{i-j}}$ respectively in the alternative test.

3.7.3. Empirical Results

Panel A of Table 3.8 reports the results of regressing bid aggressiveness in $\mathrm{IPO_i}$ on $\mathrm{r_{i-j}}$, $\mathrm{bid_{i-j}}$, and $\mathrm{r_{i-j} * bid_{i-j}}$ with fixed-effects for institutions. First of all, $\mathrm{bid_{i-j}}$ are positively significant in all of the three models, which implies that frequent participants in the IPO market also bid aggressively. A plausible explanation for this finding is that these regular participants are more knowledgeable about the IPO market and therefore have confidence to bid a high price for the IPOs they recognize as “hot”.

The interaction term $\mathrm{r_{i-j} * bid_{i-j}}$ are the variables of interest. In the three models of Panel A, it can be seen that the $\mathrm{r_{i-1} * bid_{i-1}}$ and $\mathrm{r_{i-2} * bid_{i-2}}$ significantly affect an institution’s bid aggressiveness in a positive way but the impact of $\mathrm{r_{i-1}}$ and $\mathrm{r_{i-2}}$ are insignificant. It means that only the returns of IPOs in which institutions submit bids influence an institution’s future bid aggressiveness. With regard to the economic meaning, based on model 3, the bid aggressiveness will be increased by 2.89% if institutions personally experienced an additional 21.53%[67] initial returns in the last IPO. In addition, we can see that the interaction terms are insignificant and present lower coefficients for the $\mathrm{r_{i-3} * bid_{i-3}}$, $\mathrm{r_{i-4} * bid_{i-4}}$, and $\mathrm{r_{i-5} * bid_{i-5}}$. This pattern hints that the relatively recent experiences have a greater impact on an institution’s future bid behavior than more distant experiences. Furthermore, the results also suggest that institutions bid more aggressively in the IPOs of large non-hi-tech firms with high profitability and fast growth rate.

[67] 21.53% is the standard deviation of $\mathrm{r_{i-1}}$.

Panel B of Table 3.8 demonstrates the results of alternative tests in which the personally involved experience is upgraded to being qualified for share allocation. Firstly, most of the qlf_{i-j} are positively significant in the three models, which suggests that bid aggressiveness is one of the institution's inherent characteristics because aggressive institutions will keep bidding aggressively in the upcoming IPO. Secondly, the interaction term indicates that past investment outcomes have a significantly positive impact on bid aggressiveness but on the condition of being qualified for share allocation in the two most recent IPOs. This result differentiates reinforcement learning from Bayesian learning as the past investments do not particularly matter when the returns of unqualified and qualified bids are mixed up, but it becomes influential or more powerful when I explicitly distinguish between these two types of returns. Besides, similar to the results in Panel A, the impact of past returns starts shrinking from the IPO_{i-3}.

According to the results in Table 3.8, the behaviors in bid aggressiveness also suggest that institutions are engaged in reinforcement learning as they replicate the behavior (bid high prices to become qualified) after experiencing a favorable outcome (personally involved in IPOs and received high initial return). The conclusion is in contrast with the finding of Chiang et al. (2011) that institutional investors bid less aggressively after experiencing a high return. However, the result is consistent with the conclusion of Chuang and Lee (2006) that market gains make investors trade more aggressively in subsequent periods.

Table 3.8 Impact of past returns on bid aggressiveness

This table presents the results of panel regression with fixed-effects. The dependent variable is bid aggressiveness which is defined as the quantity weighted bid price / midpoint of the filing range. $\mathrm{r_{i-j}}$ is the adjusted initial returns for $\mathrm{IPO_{i-j}}$. $\mathrm{bid_{i-j}}$ indicates an institution's participating history, where $\mathrm{bid_{i-j}}$ equals 1 if at least one bid was submitted in $\mathrm{IPO_{i-j}}$ and 0 otherwise. $\mathrm{qlf_{i-j}}$ measures whether institutions were qualified for share allocation in the past IPOs, where it equals 1 if at least one bid is qualified and 0 otherwise. *ln(proceeds)* is the natural logarithm of total IPO proceeds. *Profitability* is measured by the net profit margin. *Growth rate* is gauged by the sales growth rate. The dummy variable of *Hi-tech* equals 1 if the issuing firm belongs to hi-tech industry and 0 otherwise. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: Bid Aggressiveness in $\mathrm{IPO_i}$

Panel A				Panel B			
Independent variables	Model 1	Model 2	Model 3	Independent variables	Model 1	Model 2	Model 3
r_{i-1}	0.0108	0.0070	0.0171	r_{i-1}	0.0359***	0.0395***	0.0491***
	(0.79)	(0.52)	(1.22)		(2.84)	(2.98)	(3.55)
r_{i-2}	0.0006	-0.0081	0.0009	r_{i-2}	-0.0018	-0.0121	-0.0033
	(0.05)	(-0.68)	(0.08)		(-0.16)	(-1.05)	(-0.28)
r_{i-3}	0.0101	0.0030	0.0094	r_{i-3}	0.0134	0.0017	0.0065
	(1.04)	(0.30)	(0.97)		(1.48)	(0.18)	(0.72)
r_{i-4}		0.0323**	0.0317**	r_{i-4}		0.0251**	0.0255**
		(2.49)	(2.42)			(2.05)	(2.06)
r_{i-5}			-0.0283***	r_{i-5}			-0.0284***
			(-3.95)				(-4.16)
$\mathrm{bid_{i-1}}$	0.0663***	0.0476***	0.0454***	$\mathrm{qlf_{i-1}}$	0.0419**	0.0174	0.0160
	(5.62)	(4.21)	(4.05)		(2.49)	(1.10)	(1.00)
$\mathrm{bid_{i-2}}$	0.0644***	0.0505***	0.0488***	$\mathrm{qlf_{i-2}}$	0.0252*	0.0153	0.0142
	(6.85)	(5.59)	(5.53)		(1.79)	(1.14)	(1.07)
$\mathrm{bid_{i-3}}$	0.0595***	0.0488***	0.0470***	$\mathrm{qlf_{i-3}}$	0.0668***	0.0628***	0.0627***
	(6.10)	(4.92)	(4.74)		(4.55)	(4.27)	(4.26)
$\mathrm{bid_{i-4}}$		0.0529***	0.0486***	$\mathrm{qlf_{i-4}}$		0.0551***	0.0511***
		(4.72)	(4.44)			(3.59)	(3.48)
$\mathrm{bid_{i-5}}$			0.0197**	$\mathrm{qlf_{i-5}}$			0.0196
			(2.38)				(1.47)
$r_{i-1} * \mathrm{bid_{i-1}}$	0.1038***	0.1346***	0.1343***	$r_{i-1} * \mathrm{qlf_{i-1}}$	0.1047**	0.1424***	0.1395***
	(3.51)	(4.72)	(4.66)		(2.28)	(3.16)	(3.09)
$r_{i-2} * \mathrm{bid_{i-2}}$	0.0543**	0.0432*	0.0420*	$r_{i-2} * \mathrm{qlf_{i-2}}$	0.1450***	0.1348***	0.1289***
	(2.12)	(1.76)	(1.71)		(4.27)	(4.10)	(3.95)
$r_{i-3} * \mathrm{bid_{i-3}}$	0.0305	0.0157	0.0135	$r_{i-3} * \mathrm{qlf_{i-3}}$	0.0239	0.0168	0.0118
	(1.53)	(0.78)	(0.67)		(0.83)	(0.59)	(0.42)

Table 3.8 – Continued

$r_{i-4} * \mathrm{bid}_{i-4}$		0.0221	0.0200	$r_{i-4} * \mathrm{qlf}_{i-4}$		0.0695	0.0709
		(0.75)	(0.68)			(1.43)	(1.47)
$r_{i-5} * \mathrm{bid}_{i-5}$			0.0027	$r_{i-5} * \mathrm{qlf}_{i-5}$			0.0209
			(0.16)				(0.87)
ln(proceeds)	0.0272***	0.0167***	0.0132**	*ln(proceeds)*	0.0328***	0.0208***	0.0176***
	(5.13)	(3.19)	(2.56)		(5.66)	(3.70)	(3.16)
Profitability	0.1465***	0.1536***	0.1622***	*Profitability*	0.1508***	0.1571***	0.1642***
	(8.51)	(8.85)	(9.20)		(8.35)	(8.70)	(8.97)
Growth Rate	0.0561***	0.0568***	0.0576***	*Growth Rate*	0.0547***	0.0545***	0.0554***
	(7.92)	(8.02)	(8.21)		(7.22)	(7.20)	(7.37)
Hi-tech	-0.0154***	-0.0141***	-0.0154***	*Hi-tech*	-0.0156***	-0.0136***	-0.0147***
	(-3.52)	(-3.20)	(-3.50)		(-3.51)	(-3.01)	(-3.29)
Constant	-0.0573*	-0.0032	0.0146	Constant	-0.0618*	0.0024	0.0197
	(-1.74)	(-0.10)	(0.46)		(-1.71)	(0.07)	(0.57)
Obs.	38,005	37,456	37,456	Obs.	38,005	37,456	37,456
Groups	339	336	336	Groups	339	336	336
R-sq within	4.95%	4.84%	4.92%	R-sq within	2.84%	3.01%	3.09%
R-sq between	11.45%	9.79%	9.08%	R-sq between	13.37%	14.39%	12.81%
R-sq overall	18.49%	19.36%	19.75%	R-sq overall	9.15%	10.69%	11.14%

3.8. Learning Behaviors of Different Types of Institutions

As stated in Section 2.3.2, different types of institutional investors could present distinct learning behaviors. Therefore, I replicate the tests of Table 3.3, Table 3.7 and Table 3.8 for each of the seven types of institutions[68] to investigate the impact of past returns on their future participating decisions and bid aggressiveness. However, I only got valid results for security companies, funds and recommended institutional investors as they have sufficient numbers of observation for multivariate tests. As showed in Table 3.1, there are only 26 trust companies, 22 finance companies, 4 QFII and 2 insurance companies in my research sample. Their sample sizes are not big enough to conduct aforementioned multivariate tests.

The results for security companies, shown in Table 3.9 – Table 3.11, are generally consistent with the full sample result of Table 3.3, Table 3.7 and Table 3.8. Specifically, Table 3.9 displays that the impact of experienced returns *E* is significant and higher than observed returns. In addition, the return of qualified bids *Q* is more meaningful than the return of unqualified bids *U*. With respect to security company's decision of participating in a forthcoming IPO, the interactions terms of $\mathrm{r}_{\mathrm{i}-1} * \mathrm{bid}_{\mathrm{i}-1}$, $\mathrm{r}_{\mathrm{i}-3} * \mathrm{bid}_{\mathrm{i}-3}$, $\mathrm{r}_{\mathrm{i}-2} * \mathrm{qlf}_{\mathrm{i}-2}$ and $\mathrm{r}_{\mathrm{i}-3} * \mathrm{qlf}_{\mathrm{i}-3}$ in Table 3.10 are positively significant, indicating that high level of personal involvement in hot IPOs generates more reinforcing effect for future investment decision. Similar effect is also documented in Table 3.11 where the interactions terms of $\mathrm{r}_{\mathrm{i}-1} * \mathrm{bid}_{\mathrm{i}-1}$, $\mathrm{r}_{\mathrm{i}-3} * \mathrm{bid}_{\mathrm{i}-3}$ and $\mathrm{r}_{\mathrm{i}-2} * \mathrm{qlf}_{\mathrm{i}-2}$ have positively significant effect on bid aggressiveness. Therefore, I conclude that security companies are subject to reinforcement learning. On the other hand, the results of recommended institutions are qualitatively similar with security firms, which imply that recommended institutions are also reinforcement learners[69].

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[68] Securities companies, fund companies, recommended institutional investors, insurance companies, QFII, trust companies, finance companies.

[69] I do not present the results of recommended institutions due to the similarity with security firms. The results will be provided upon request.

Table 3.9 Effect of past returns on future decision (security companies)

This table presents OLS regression results for security companies. N_{p1} and N_{p2} are the participating frequency in the periods 1 and 2 respectively. E is the weighted-average adjusted initial return of IPOs in which institutions submitted bids. U is the weighted-average adjusted initial return of IPOs in which an institution submitted bids but its bids were unqualified for share allocation. Q is the weighted-average adjusted initial return of IPOs in which an institution submitted bids and its bids were qualified for share allocation. L is the weighted-average adjusted initial return of IPOs in which institutions were qualified for share allocation but did not receive shares. W is the weighted-average adjusted initial return of IPOs in which institutions were qualified for share allocation and received an allocation eventually. For model 4 – model 6, I add funding availability to my regression model. Variable definitions are in Section 3.5.1. Robust t-values for eliminating heteroscedasticity are reported in parentheses. The last row demonstrates the p-value of the t-test that compares the equality of paired coefficient. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: Log $(1+N_{p2})$						
Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log $(1+N_{p1})$	-0.025 (-0.17)	-0.026 (-0.18)	-0.025 (-0.17)	-0.041 (-0.27)	-0.046 (-0.30)	-0.047 (-0.30)
E	14.601*** (4.65)			13.357*** (4.11)		
U		11.161*** (3.28)	11.098*** (3.19)		9.067** (2.52)	9.117** (2.47)
Q		19.260*** (3.75)			19.019*** (3.55)	
L			18.852*** (3.00)			19.400*** (2.94)
W			21.203 (1.37)			17.192 (1.04)
Funding availability				0.204* (1.78)	0.223* (1.94)	0.224* (1.91)
Constant	1.808*** (6.29)	1.796*** (6.22)	1.796*** (6.18)	1.201** (2.42)	1.125** (2.26)	1.122** (2.22)
Obs.	78	78	78	76	76	76
R-sq	43.85%	44.70%	44.71%	45.11%	46.44%	46.45%
Comparisons of coefficients		U and Q	L and W		U and Q	L and W
p-value		0.168	0.898		0.117	0.910

Table 3.10 Impact of past returns on participating decision (security companies)

This table presents the results of logistic panel regression with fixed-effects for security companies. The dependent variable $\mathrm{bid_i}$ is dummy variable which equals to 1 if an institution submits a bid in $\mathrm{IPO_i}$ and 0 otherwise. $\mathrm{r_{i-j}}$ is the adjusted initial returns for $\mathrm{IPO_{i-j}}$. $\mathrm{bid_{i-j}}$ indicates an institution's participating history, where $\mathrm{bid_{i-j}}$ equals 1 if at least one bid was submitted in $\mathrm{IPO_{i-j}}$ and 0 otherwise. $\mathrm{qlf_{i-j}}$ measures whether institution were qualified for share allocation in the past IPOs, where it is equal to 1 if at least one bid is qualified and 0 otherwise. *ln(proceeds)* is the natural logarithm of total IPO proceeds. *Profitability* is measured by the net profit margin. *Growth rate* is gauged by the sales growth rate. The dummy variable of *Hi-tech* equals 1 if the issuing firm belongs to the hi-tech industry and 0 otherwise.***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: $\mathrm{bid_i}$							
Panel A				Panel B			
Independent variables	Model 1	Model 2	Model 3	Independent variables	Model 1	Model 2	Model 3
r_{i-1}	-0.3125*	-0.2825*	-0.2362	$\mathrm{r_{i-1}}$	0.0438	0.1668	0.2172
	(-1.95)	(-1.66)	(-1.38)		(0.33)	(1.17)	(1.50)
r_{i-2}	0.1453	0.1203	0.1534	$\mathrm{r_{i-2}}$	0.0947	0.0802	0.1217
	(0.98)	(0.78)	(0.98)		(0.77)	(0.62)	(0.92)
r_{i-3}	-0.2136*	-0.2463*	-0.2196*	$\mathrm{r_{i-3}}$	-0.1511	-0.2322**	-0.2378**
	(-1.67)	(-1.90)	(-1.67)		(-1.38)	(-2.09)	(-2.12)
r_{i-4}		0.0558	0.0586	r_{i-4}		-0.0616	-0.0565
		(0.34)	(0.35)			(-0.43)	(-0.39)
r_{i-5}			-0.1305	r_{i-5}			-0.0762
			(-1.25)				(-0.89)
$\mathrm{bid_{i-1}}$	0.5094***	0.4258***	0.4061***	$\mathrm{qlf_{i-1}}$	0.4453***	0.3086***	0.2721**
	(6.29)	(5.11)	(4.83)		(4.26)	(2.87)	(2.52)
$\mathrm{bid_{i-2}}$	0.5359***	0.4521***	0.4391***	$\mathrm{qlf_{i-2}}$	0.1943**	0.1741*	0.1602*
	(7.78)	(6.34)	(6.13)		(2.23)	(1.95)	(1.79)
$\mathrm{bid_{i-3}}$	0.2844***	0.2274***	0.2094***	$\mathrm{qlf_{i-3}}$	0.3062***	0.2819***	0.2775***
	(3.91)	(3.07)	(2.80)		(3.55)	(3.21)	(3.16)
$\mathrm{bid_{i-4}}$		0.2763***	0.2444***	$\mathrm{qlf_{i-4}}$		0.2917***	0.2241**
		(3.64)	(3.16)			(2.94)	(2.22)
$\mathrm{bid_{i-5}}$			0.1300*	$\mathrm{qlf_{i-5}}$			0.3670***
			(1.91)				(4.12)
$r_{i-1} * \mathrm{bid_{i-1}}$	0.6661***	0.7264***	0.7195***	$r_{i-1} * \mathrm{qlf_{i-1}}$	0.1622	0.2829	0.2475
	(2.95)	(3.15)	(3.11)		(0.57)	(0.97)	(0.85)
$r_{i-2} * \mathrm{bid_{i-2}}$	0.1253	0.0894	0.0780	$r_{i-2} * \mathrm{qlf_{i-2}}$	0.6667***	0.6247***	0.5726**
	(0.63)	(0.44)	(0.38)		(2.84)	(2.59)	(2.37)
$r_{i-3} * \mathrm{bid_{i-3}}$	0.4858***	0.4098**	0.3805**	$r_{i-3} * \mathrm{qlf_{i-3}}$	0.5304***	0.5211***	0.4632**
	(2.88)	(2.38)	(2.19)		(2.71)	(2.65)	(2.33)

Table. 3.10 – Continued

$r_{i-4} * \mathrm{bid}_{i-4}$		0.2468	0.2335	$r_{i-4} * \mathrm{qlf}_{i-4}$		0.3690	0.4159
		(1.02)	(0.96)			(1.14)	(1.28)
$r_{i-5} * \mathrm{bid}_{i-5}$			0.0923	$r_{i-5} * \mathrm{qlf}_{i-5}$			-0.1754
			(0.60)				(-0.87)
ln(proceeds)	0.0325	-0.0323	-0.0480	*ln(proceeds)*	0.1284***	0.0456	0.0321
	(0.69)	(-0.67)	(-0.98)		(2.83)	(0.98)	(0.68)
Profitability	0.9767***	1.0286***	1.0679***	*Profitability*	0.9293***	0.9735***	1.0135***
	(4.64)	(4.81)	(4.96)		(4.52)	(4.64)	(4.81)
Growth Rate	0.3949***	0.3953***	0.3963***	*Growth Rate*	0.4044***	0.3949***	0.3888***
	(4.51)	(4.46)	(4.47)		(4.75)	(4.57)	(4.49)
Hi-tech	-0.0303	-0.0178	-0.0205	*Hi-tech*	-0.0522	-0.0338	-0.0364
	(-0.51)	(-0.30)	(-0.35)		(-0.91)	(-0.58)	(-0.63)
Obs.	12,838	12,667	12,667	Obs.	12,838	12,667	12,667
Groups	76	76	76	Groups	76	76	76
Pseudo R-sq	6.24%	6.00%	6.06%	Pseudo R-sq	2.50%	2.59%	2.76%

Table 3.11 Impact of past returns on bid aggressiveness (security companies)

This table presents the results of panel regression with fixed-effects for security companies. The dependent variable is bid aggressiveness which is defined as the quantity weighted bid price / midpoint of the filing range. $\mathrm{r_{i-j}}$ is the adjusted initial returns for $\mathrm{IPO_{i-j}}$. $\mathrm{bid_{i-j}}$ indicates an institution's participating history, where $\mathrm{bid_{i-j}}$ equals 1 if at least one bid was submitted in $\mathrm{IPO_{i-j}}$ and 0 otherwise. $\mathrm{qlf_{i-j}}$ measures whether institutions were qualified for share allocation in the past IPOs, where it equals 1 if at least one bid is qualified and 0 otherwise. *ln(proceeds)* is the natural logarithm of total IPO proceeds. *Profitability* is measured by the net profit margin. *Growth rate* is gauged by the sales growth rate. The dummy variable of *Hi-tech* equals 1 if the issuing firm belongs to hi-tech industry and 0 otherwise. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: Bid Aggressiveness in $\mathrm{IPO_i}$

Panel A				Panel B			
Independent variables	Model 1	Model 2	Model 3	Independent variables	Model 1	Model 2	Model 3
r_{i-1}	-0.0115	-0.0030	0.0061	r_{i-1}	0.0471*	0.0729***	0.0837***
	(-0.40)	(-0.11)	(0.22)		(1.91)	(2.89)	(3.17)
r_{i-2}	0.0055	0.0013	0.0089	r_{i-2}	0.0019	-0.0022	0.0077
	(0.25)	(0.06)	(0.39)		(0.08)	(-0.10)	(0.34)
r_{i-3}	-0.0138	-0.0191	-0.0139	r_{i-3}	-0.0114	-0.0260	-0.0256
	(-0.75)	(-1.04)	(-0.80)		(-0.67)	(-1.56)	(-1.59)
r_{i-4}		0.0012	0.0010	r_{i-4}		-0.0130	-0.0119
		(0.05)	(0.04)			(-0.56)	(-0.51)
r_{i-5}			-0.0225*	r_{i-5}			-0.0212*
			(-1.87)				(-1.72)
$\mathrm{bid_{i-1}}$	0.0894***	0.0644***	0.0595***	$\mathrm{qlf_{i-1}}$	0.0806***	0.0447*	0.0379*
	(4.71)	(3.57)	(3.38)		(3.23)	(1.97)	(1.69)
$\mathrm{bid_{i-2}}$	0.0899***	0.0712***	0.0682***	$\mathrm{qlf_{i-2}}$	0.0405*	0.0339	0.0299
	(5.71)	(4.77)	(4.72)		(1.68)	(1.46)	(1.30)
$\mathrm{bid_{i-3}}$	0.0627***	0.0504***	0.0461**	$\mathrm{qlf_{i-3}}$	0.0562**	0.0505*	0.0486*
	(3.67)	(2.82)	(2.56)		(2.10)	(1.92)	(1.85)
$\mathrm{bid_{i-4}}$		0.0543***	0.0471***	$\mathrm{qlf_{i-4}}$		0.0665***	0.0526**
		(3.08)	(2.73)			(2.82)	(2.42)
$\mathrm{bid_{i-5}}$			0.0304**	$\mathrm{qlf_{i-5}}$			0.0741***
			(2.04)				(3.14)
$r_{i-1} * \mathrm{bid_{i-1}}$	0.1588***	0.1861***	0.1877***	$r_{i-1} * \mathrm{qlf_{i-1}}$	0.0689	0.1078	0.1003
	(2.80)	(3.48)	(3.50)		(0.90)	(1.49)	(1.39)
$r_{i-2} * \mathrm{bid_{i-2}}$	0.0680	0.0592	0.0570	$r_{i-2} * \mathrm{qlf_{i-2}}$	0.1709***	0.1604***	0.1512***
	(1.51)	(1.40)	(1.35)		(3.16)	(2.92)	(2.76)
$r_{i-3} * \mathrm{bid_{i-3}}$	0.0559*	0.0357	0.0330	$r_{i-3} * \mathrm{qlf_{i-3}}$	0.0792	0.0726	0.0620
	(1.67)	(1.08)	(1.00)		(1.64)	(1.51)	(1.32)

Table 3.11 – Continued

$r_{i-4} * \mathrm{bid}_{i-4}$		0.0519	0.0515	$r_{i-4} * \mathrm{qlf}_{i-4}$		0.0860	0.0967
		(1.02)	(1.02)			(1.13)	(1.33)
$r_{i-5} * \mathrm{bid}_{i-5}$			-0.0003	$r_{i-5} * \mathrm{qlf}_{i-5}$			-0.0374
			(-0.01)				(-0.80)
ln(proceeds)	0.0283***	0.0145	0.0110	*ln(proceeds)*	0.0424***	0.0243**	0.0211**
	(3.09)	(1.56)	(1.22)		(3.82)	(2.25)	(2.01)
Profitability	0.1608***	0.1660***	0.1746***	*Profitability*	0.1645***	0.1677***	0.1769***
	(4.72)	(4.91)	(5.09)		(4.49)	(4.62)	(4.80)
Growth Rate	0.0747***	0.0757***	0.0761***	*Growth Rate*	0.0775***	0.0762***	0.0754***
	(6.24)	(6.39)	(6.51)		(5.71)	(5.72)	(5.74)
Hi-tech	-0.0087	-0.0064	-0.0072	*Hi-tech*	-0.0117	-0.0076	-0.0085
	(-1.23)	(-0.89)	(-1.00)		(-1.59)	(-1.02)	(-1.13)
Constant	-0.0577	0.0187	0.0353	Constant	-0.0979	0.0022	0.0169
	(-1.03)	(0.34)	(0.66)		(-1.46)	(0.03)	(0.27)
Obs.	12,841	12,670	12,670	Obs.	12,841	12,670	12,670
Groups	78	78	78	Groups	78	78	78
R-sq within	8.83%	8.35%	8.46%	R-sq within	4.28%	4.46%	4.75%
R-sq between	49.61%	51.08%	51.01%	R-sq between	45.53%	48.83%	48.62%
R-sq overall	20.36%	20.74%	21.06%	R-sq overall	9.52%	10.94%	11.62%

Table 3.12 – Table 3.14 illustrate the results of fund companies. In Table 3.12, it can be seen that the variable of E is not significant and the variables of Q and U exhibit equal impact on participating frequency, which is consistent with Bayesian learning. Table 3.13 shows very weak evidence of reinforcement learning, where only the interaction term $\mathrm{r}_{\mathrm{i}-1} * \mathrm{qlf}_{\mathrm{i}-1}$ is positively significant when deciding whether submit bid in a forthcoming IPO. For bid aggressiveness, however, the behavior of fund companies are consistent with reinforcement learning as $\mathrm{r}_{\mathrm{i}-1} * \mathrm{bid}_{\mathrm{i}-1}$and $\mathrm{r}_{\mathrm{i}-1} * \mathrm{qlf}_{\mathrm{i}-1}$ are both positively significant in the six models of Table 3.14. Based on the mixed results, it seems that fund companies are subject to Bayesian learning when deciding whether participate in IPOs, but follow reinforcement learning in terms of bid aggressiveness.

Based on the tests for different types of institutions, I conclude that different institutional investors exhibit distinct learning behaviors. In addition, they could also learn in different ways for various types of investment decisions.

Table 3.12 Effect of past returns on future decision (fund companies)

This table presents OLS regression results for fund companies. N_{p1} and N_{p2} are the participating frequency in the periods 1 and 2 respectively. E is the weighted-average adjusted initial return of IPOs in which institutions submitted bids. U is the weighted-average adjusted initial return of IPOs in which an institution submitted bids but its bids were unqualified for share allocation. Q is the weighted-average adjusted initial return of IPOs in which an institution submitted bids and its bids were qualified for share allocation. L is the weighted-average adjusted initial return of IPOs in which institutions were qualified for share allocation but did not receive shares. W is the weighted-average adjusted initial return of IPOs in which institutions were qualified for share allocation and received an allocation eventually. For model 4 – model 6, I add funding availability to my regression model. Variable definitions are in Section 3.5.1. Robust t-values for eliminating heteroscedasticity are reported in parentheses. The last row demonstrates the p-value of the t-test that compares the equality of paired coefficient. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: Log $(1 + N_{p2})$

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log $(1 + N_{p1})$	0.445***	0.445***	0.455***	0.329**	0.327**	0.334**
	(2.71)	(2.68)	(2.72)	(2.19)	(2.16)	(2.18)
E	4.179			3.698		
	(1.44)			(1.54)		
U		4.026	4.201		3.036	3.074
		(1.21)	(1.28)		(0.99)	(1.00)
Q		4.329			4.304	
		(1.42)			(1.57)	
L			1.352			2.745
			(0.38)			(0.83)
W			11.367***			7.930**
			(2.86)			(2.06)
Funding availability				0.306***	0.309***	0.305***
				(3.48)	(3.45)	(3.33)
Constant	1.550***	1.550***	1.555***	0.234	0.223	0.242
	(4.59)	(4.55)	(4.53)	(0.55)	(0.51)	(0.54)
Obs.	61	61	61	60	60	60
R-sq	63.47%	63.47%	64.19%	70.96%	70.99%	71.18%
Comparisons of coefficients		U and Q	L and W		U and Q	L and W
p-value		0.904	0.038*		0.695	0.264

Table 3.13 Impact of past returns on participating decision (fund companies)

This table presents the results of logistic panel regression with fixed-effects for fund companies. The dependent variable $\mathrm{bid_i}$ is dummy variable which equals to 1 if an institution submits a bid in $\mathrm{IPO_i}$ and 0 otherwise. $\mathrm{r_{i-j}}$ is the adjusted initial returns for $\mathrm{IPO_{i-j}}$. $\mathrm{bid_{i-j}}$ indicates an institution's participating history, where $\mathrm{bid_{i-j}}$ equals 1 if at least one bid was submitted in $\mathrm{IPO_{i-j}}$ and 0 otherwise. $\mathrm{qlf_{i-j}}$ measures whether institution were qualified for share allocation in the past IPOs, where it is equal to 1 if at least one bid is qualified and 0 otherwise. *ln(proceeds)* is the natural logarithm of total IPO proceeds. *Profitability* is measured by the net profit margin*. Growth rate* is gauged by the sales growth rate. The dummy variable of *Hi-tech* equals 1 if the issuing firm belongs to the hi-tech industry and 0 otherwise.***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: $\mathrm{bid_i}$							
Panel A				Panel B			
Independent variables	Model 1	Model 2	Model 3	Independent variables	Model 1	Model 2	Model 3
r_{i-1}	0.1025	-0.2237	-0.1766	r_{i-1}	0.1406	-0.1835	-0.1673
	(0.61)	(-1.26)	(-0.99)		(1.00)	(-1.19)	(-1.08)
r_{i-2}	0.2388	0.0208	0.0583	r_{i-2}	0.1891	-0.0232	0.0100
	(1.60)	(0.13)	(0.37)		(1.42)	(-0.17)	(0.07)
r_{i-3}	0.1930	0.1257	0.1571	r_{i-3}	0.2728**	0.2160*	0.2331**
	(1.46)	(0.95)	(1.17)		(2.40)	(1.90)	(2.02)
r_{i-4}		0.9225***	0.9223***	r_{i-4}		0.8420***	0.8280***
		(5.33)	(5.33)			(5.48)	(5.36)
r_{i-5}			-0.1441	r_{i-5}			-0.1106
			(-1.34)				(-1.17)
$\mathrm{bid_{i-1}}$	0.2468***	0.2015**	0.1999**	$\mathrm{qlf_{i-1}}$	-0.0279	-0.0755	-0.0663
	(2.96)	(2.36)	(2.34)		(-0.26)	(-0.70)	(-0.62)
$\mathrm{bid_{i-2}}$	0.3263***	0.2894***	0.2841***	$\mathrm{qlf_{i-2}}$	0.1478*	0.1018	0.1186
	(4.67)	(4.07)	(3.95)		(1.79)	(1.21)	(1.40)
$\mathrm{bid_{i-3}}$	0.2508***	0.2207***	0.2172***	$\mathrm{qlf_{i-3}}$	0.3160***	0.3130***	0.3207***
	(3.42)	(2.96)	(2.91)		(3.68)	(3.60)	(3.68)
$\mathrm{bid_{i-4}}$		0.2893***	0.2738***	$\mathrm{qlf_{i-4}}$		0.3065***	0.3181***
		(3.82)	(3.57)			(3.26)	(3.37)
$\mathrm{bid_{i-5}}$			0.0743	$\mathrm{qlf_{i-5}}$			-0.1565**
			(1.11)				(-1.97)
$r_{i-1} * \mathrm{bid_{i-1}}$	0.2026	0.3397	0.3359	$r_{i-1} * \mathrm{qlf_{i-1}}$	0.3857	0.5887**	0.5775*
	(0.88)	(1.46)	(1.43)		(1.32)	(2.00)	(1.96)
$r_{i-2} * \mathrm{bid_{i-2}}$	-0.2591	-0.3011	-0.2985	$r_{i-2} * \mathrm{qlf_{i-2}}$	0.0615	-0.0087	-0.0423
	(-1.29)	(-1.47)	(-1.44)		(0.27)	(-0.04)	(-0.18)
$r_{i-3} * \mathrm{bid_{i-3}}$	0.1017	0.0910	0.0868	$r_{i-3} * \mathrm{qlf_{i-3}}$	-0.2337	-0.2320	-0.2287
	(0.60)	(0.53)	(0.51)		(-1.18)	(-1.17)	(-1.14)

Table 3.13 – Continued

$r_{i-4} * \mathrm{bid}_{i-4}$		-0.1806 (-0.75)	-0.1974 (-0.82)	$r_{i-4} * \mathrm{qlf}_{i-4}$		-0.0368 (-0.12)	-0.0551 (-0.18)
$r_{i-5} * \mathrm{bid}_{i-5}$			0.0229 (0.15)	$r_{i-5} * \mathrm{qlf}_{i-5}$			0.2461 (1.38)
ln(proceeds)	0.0281 (0.57)	-0.0003 (-0.01)	-0.0185 (-0.36)	ln(proceeds)	0.0379 (0.77)	0.0032 (0.06)	0.0003 (0.01)
Profitability	1.2149*** (5.38)	1.3174*** (5.75)	1.3641*** (5.91)	Profitability	1.2149*** (5.41)	1.2972*** (5.68)	1.3132*** (5.71)
Growth Rate	0.4371*** (4.75)	0.4712*** (5.07)	0.4734*** (5.09)	*Growth Rate*	0.4289*** (4.68)	0.4588*** (4.96)	0.4655*** (5.03)
Hi-tech	-0.2142*** (-3.42)	-0.2278*** (-3.63)	-0.2341*** (-3.72)	*Hi-tech*	-0.2104*** (-3.38)	-0.2224** * (-3.56)	-0.2264*** (-3.62)
Obs.	10,802	10,664	10,664	Obs.	10,802	10,664	10,664
Groups	59	59	59	Groups	59	59	59
Pseudo R-sq	2.13%	2.60%	2.64%	Pseudo R-sq	1.25%	1.74%	1.78%

Table 3.14 Impact of past returns on bid aggressiveness (fund companies)

This table presents the results of panel regression with fixed-effects for fund companies. The dependent variable is bid aggressiveness which is defined as the quantity weighted bid price / midpoint of the filing range. $\mathrm{r_{i-j}}$ is the adjusted initial returns for $\mathrm{IPO_{i-j}}$. $\mathrm{bid_{i-j}}$ indicates an institution's participating history, where $\mathrm{bid_{i-j}}$ equals 1 if at least one bid was submitted in $\mathrm{IPO_{i-j}}$ and 0 otherwise. $\mathrm{qlf_{i-j}}$ measures whether institutions were qualified for share allocation in the past IPOs, where it equals 1 if at least one bid is qualified and 0 otherwise. *ln(proceeds)* is the natural logarithm of total IPO proceeds. *Profitability* is measured by the net profit margin. *Growth rate* is gauged by the sales growth rate. The dummy variable of *Hi-tech* equals 1 if the issuing firm belongs to hi-tech industry and 0 otherwise. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: Bid Aggressiveness in $\mathrm{IPO_i}$							
Panel A				Panel B			
Independent variables	Model 1	Model 2	Model 3	Independent variables	Model 1	Model 2	Model 3
r_{i-1}	0.0256	-0.0118	-0.0035	r_{i-1}	0.0492**	0.0125	0.0183
	(1.07)	(-0.46)	(-0.13)		(2.22)	(0.49)	(0.68)
r_{i-2}	0.0218	-0.0057	0.0044	r_{i-2}	0.0155	-0.0139	-0.0040
	(0.91)	(-0.23)	(0.17)		(0.70)	(-0.67)	(-0.18)
r_{i-3}	0.0321	0.0212	0.0282	r_{i-3}	0.0434**	0.0319*	0.0368*
	(1.58)	(1.02)	(1.35)		(2.44)	(1.75)	(1.99)
r_{i-4}		0.1044***	0.1026***	r_{i-4}		0.1028***	0.1010***
		(4.07)	(3.99)			(4.25)	(4.07)
r_{i-5}			-0.0290**	r_{i-5}			-0.0287**
			(-2.04)				(-2.25)
$\mathrm{bid_{i-1}}$	0.0341*	0.0259	0.0252	$\mathrm{qlf_{i-1}}$	-0.0035	-0.0155	-0.0139
	(1.86)	(1.48)	(1.44)		(-0.11)	(-0.53)	(-0.46)
$\mathrm{bid_{i-2}}$	0.0544***	0.0464***	0.0460***	$\mathrm{qlf_{i-2}}$	0.0196	0.0084	0.0107
	(3.49)	(3.19)	(3.22)		(0.87)	(0.41)	(0.54)
$\mathrm{bid_{i-3}}$	0.0525***	0.0470***	0.0464***	$\mathrm{qlf_{i-3}}$	0.0691***	0.0659***	0.0672***
	(3.36)	(2.93)	(2.89)		(3.10)	(2.98)	(3.01)
$\mathrm{bid_{i-4}}$		0.0373**	0.0349**	$\mathrm{qlf_{i-4}}$		0.0463*	0.0471*
		(2.24)	(2.11)			(1.90)	(1.92)
$\mathrm{bid_{i-5}}$			0.0112	$\mathrm{qlf_{i-5}}$			-0.0195
			(0.85)				(-1.24)
$r_{i-1} * \mathrm{bid_{i-1}}$	0.1111***	0.1377***	0.1405***	$r_{i-1} * \mathrm{qlf_{i-1}}$	0.1321*	0.1716**	0.1682**
	(2.83)	(3.69)	(3.76)		(1.67)	(2.18)	(2.12)
$r_{i-2} * \mathrm{bid_{i-2}}$	-0.0029	-0.0205	-0.0193	$r_{i-2} * \mathrm{qlf_{i-2}}$	0.0756	0.0543	0.0460
	(-0.07)	(-0.51)	(-0.47)		(1.44)	(1.12)	(0.95)
$r_{i-3} * \mathrm{bid_{i-3}}$	0.0239	0.0154	0.0174	$r_{i-3} * \mathrm{qlf_{i-3}}$	-0.0215	-0.0269	-0.0270
	(0.67)	(0.43)	(0.48)		(-0.47)	(-0.62)	(-0.62)

Table 3.14 – Continued

$r_{i-4} * \mathrm{bid}_{i-4}$		0.0275	0.0255	$r_{i-4} * \mathrm{qlf}_{i-4}$		0.0700	0.0678
		(0.63)	(0.59)			(0.96)	(0.92)
$r_{i-5} * \mathrm{bid}_{i-5}$			-0.0075	$r_{i-5} * \mathrm{qlf}_{i-5}$			0.0437
			(-0.25)				(1.47)
ln(proceeds)	0.0386***	0.0298***	0.0260***	*ln(proceeds)*	0.0390***	0.0295***	0.0275***
	(4.08)	(3.31)	(2.92)		(4.05)	(3.24)	(3.04)
Profitability	0.2177***	0.2251***	0.2348***	*Profitability*	0.2238***	0.2278***	0.2339***
	(7.65)	(7.53)	(7.66)		(7.44)	(7.23)	(7.24)
Growth Rate	0.0877***	0.0931***	0.0940***	*Growth Rate*	0.0856***	0.0904***	0.0916***
	(6.25)	(6.81)	(6.90)		(5.76)	(6.21)	(6.25)
Hi-tech	-0.0356***	-0.0365***	-0.0381***	*Hi-tech*	-0.0352***	-0.0358***	-0.0368***
	(-3.77)	(-3.82)	(-4.05)		(-3.73)	(-3.72)	(-3.91)
Constant	-0.0914	-0.0527	-0.0328	Constant	-0.0632	-0.0187	-0.0048
	(-1.52)	(-0.92)	(-0.59)		(-1.02)	(-0.32)	(-0.08)
Obs.	10,804	10,666	10,666	Obs.	10,804	10,666	10,666
Groups	61	61	61	Groups	61	61	61
R-sq within	4.09%	4.35%	4.42%	R-sq within	2.98%	3.40%	3.45%
R-sq between	48.14%	49.97%	49.05%	R-sq between	51.57%	54.21%	55.47%
R-sq overall	15.38%	16.73%	17.12%	R-sq overall	6.76%	8.37%	8.15%

3.9. Conclusion

In conclusion, this research elucidates the impact of personal experience on the behavior of institutional investors in an IPO market. In contrast to Chiang et al. (2011), I find that, when deciding to participate in future IPOs, institutions take into serious account the past initial returns of the IPOs in which they were involved: experienced return (E) > observed return (O); return of qualified bid (Q) > return of unqualified bid (U). This finding reveals that investors not only "look to the past" in the secondary market (Nicolosi et al., 2009; Seru et al., 2010), but also recall prior experience when making an investment in the primary market, a relatively low-frequency market. More importantly, the distinct impact of different types of returns provide empirical support for the hybrid model of Camerer and Ho (1999) in which both actual and forgone payoff influence the decision-making process but with different weights. Therefore, I conclude that the learning behavior of institutional investors is consistent with reinforcement learning.

This result is also in agreement with the finding of Seru et al. (2010) that individual investors gain experience by actively trading rather than observing hypothetical trades. Such a result is consistent with the conclusion in the psychology literature stating that personally experienced outcomes have a greater impact on agents' decisions than those without personal involvement (Hertwig et al., 2004; Weber et al., 1993). In addition, I find that institutions equally take into account the returns that are derived from random events rather than their own investment decisions, which shows the rational aspect of institutions. Finally, this research identifies that institutions will bid more aggressively after experiencing a favorable outcome in the IPOs in which they were personally involved, which offers additional support to the learning behavior of reinforcement.

Overall, this paper contributes to the extant literature by providing new evidence on the learning behavior of institutional investors, who are considered to be better informed and sophisticated investors (Michaely and Shaw, 1994; Badrinath et al., 1995; Cohen et al., 2002; Nagel, 2005; Chiang et al., 2010), under a different IPO mechanism. In addition, my results also imply that learning behavior not only exist among amateur investors, such as retail investors, but also among sophisticated investors like institutional investors. However, pure reinforcement learning, without the consideration of others' behaviors, could lead to an underperformance in future investment due to over-confidence. Therefore, my results suggest that institutional investors should have more analysis on others' investment behaviors when making investment decisions, instead of simply replicating successful actions in the past. On the other hand, my research also provides evidence that investor sentiment is an important determinant of IPO waves and pricing patterns, which can be a useful reference for policy makers. For example, the regulators of some developing counties, such as China, want to keep a stable capital market and therefore control the volume of IPO to balance the demand of investors and the supply of new IPOs. Based on my findings, policy makers can analyze the performance of past IPOs, investor's bidding behavior in recent IPOs to forecast the demand for new IPOs and then set corresponding policies to keep the market stable. Moreover, my findings also present that how popular investment styles are formed, which is quite useful for the marketing of financial products.

Chapter 4

4. Do Institutional Investors Truthfully Reveal Private Information in a Quasi-Bookbuilding IPO Mechanism?

4.1. Introduction

Initial public offering (IPO) mechanisms that are widely used in global equity markets include bookbuilding, fixed-price offering, uniform-price auction and discriminatory auction (pay-what-you-bid auction)[70]. Bookbuilding has become the dominant method in many markets because it reduces the risk of IPO failure and the investment risk of investors. More importantly, bookbuilding helps increase the IPO proceeds by promoting new shares via a roadshow (Degeorge et al., 2007; Gao and Ritter, 2010; Jagannathan et al., 2014; Sherman, 2005).

By comparison, fixed-price offerings suffer from the problem of the winner's curse since investors' interests are not considered in advance when setting the offer price (Rock, 1986). As a result, the issuing shares have to be discounted to attract both uninformed and informed investors. However, bookbuilding alleviates the winner's curse problem by using a roadshow through which the underwriter can learn about investors' demand on the issuing shares. Benveniste and Wilhelm (1990) illustrated the conditions under which the cost of collecting information by bookbuilding is lower than the cost of bearing the winner's curse.

Auction mechanisms are perceived as low-cost (Biais et al., 2002; Biais and Faugeron-Crouzet, 2002) and are able to mitigate underpricing (Derrien and Womack, 2003; Kaneko and Pettway, 2003). However, Sherman (2005) pointed out that the main issue with uniform-price auction is its failure to provide rewards for investors who carefully evaluate the issuing shares and reveal their private information. In addition, uniform-price auction inevitably raises the free-rider problem as the highest

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[70] W.R Hambrecht designed a modified Dutch auction mechanism, called OpenIPO, to underwrite equity issues. However, the market share of this method is not very meaningful so far.

bids take priority in share allocation while paying the same price for the issuing shares. Although the free-rider problem is extenuated when the discriminatory auction (pay-what-you-bid auction) is used, discrimination on price could impede the participation of investors who do not possess the skills required to evaluate a new share. Without those investors, there could be a lack of liquidity when the IPO shares start trading.

In short, auction-IPOs suffer from inaccurate pricing due to the free-rider problem and the uncertainty about the number of participants. Therefore, the auction mechanism has been abandoned in most countries where it has been attempted (Jagannathan et al., 2014). However, bookbuilding can help underwriters collect more accurate information on demand and coordinate the number of investors, thereby becoming the dominant issuing method. Although bookbuilding is regarded as a price discovery mechanism and prevalent in the global capital markets, limited research has been conducted that explicitly tests the fundamental question of *whether or not the information being used for pricing is reliable.* In the literature, researchers extensively study how public and private information is used by underwriters. For example, empirical research normally uses the degree of price adjustment (Hanley, 1993; Loughran and Ritter, 2002; Bradley and Jordan, 2002) to identify whether the bids are informative or not. However, even though price adjustment may indicate that bids are *informative*, this does not mean that the information is *true*. For example, the midpoint of an IPO's filing range is US$ 10 and the average bid price submitted by institutions is US$ 15. Based on the high bid price, the underwriter may adjust the offer price to US$ 15 eventually, which is normally viewed as evidence of an effective price discovery in the literature. However, the US$ 15 bid could result from an institution's deliberate inflation rather than the true valuation. Similarly, institutions may also intentionally deflate their bid prices, such as by bidding US$ 5, to make the offer price lower than the true value. Based on the price adjustment, we cannot ascertain whether the bid price is true or being inflated/deflated. Therefore, in this paper, I investigate the fundamental question of whether institutional investors truthfully reveal their information (provide honest valuation) to the underwriter in a quasi-bookbuilding process.

My paper is closely related to the study conducted by Cornelli and Goldreich (2003), but distinct enough in several ways. Most importantly, Cornelli and Goldreich (2003) mainly focus on the issue of how the bid information is being used by the underwriter. In contrast, my research intends to answer the question of whether or not the bid information is reliable. In other words, Cornelli and Goldreich explore the pricing behavior of underwriters whereas I investigate the bidding behavior of bidders. Secondly, although Cornelli and Goldreich can observe the information of the entire order book, 82.5% of the bids are strike bids whereby bidders only specify the total number of requested shares or the aggregate amount of money regardless of the offer price. Put another way, most of the bids are not embedded with the pricing information. However, all of the bids in my sample are limit or step bids[71] that involve bidders' efforts to evaluate the issuing shares. Thirdly, the sample size of 37 IPOs used in Cornelli and Goldreich (2003) is relatively small. In my research, I expand the sample to 410 IPOs.

According to my results, I find that fund companies will purchase more shares from the secondary market if they bid a high price or subscribed a large amount of shares during a quasi-bookbuilding process. Meanwhile, I document that fund companies' investment decisions are also based on a comparison of the bid prices they submitted during the IPO and the after-market share price. These findings indicate that fund companies truthfully disclose their private information (honest valuation) via bids. This conclusion is consistent with Cornelli and Goldreich (2003) although the unique IPO mechanism being used in my research does not have a discretionary allocation. Moreover, my results also provide evidence for the theoretical models developed by Biais et al. (2002) and Biais and Faugeron-Crouzet (2002) as their models illustrate that both the bookbuilding mechanism and the *Offre*

[71] A step bid is a combination of limit bids.

a Prix Minimum[72], an auction-like IPO method, have information elicitation and price discovery functions although the latter is not embedded with a discretionary allocation.

On the other hand, my findings contrast with those of Benveniste and Wilhelm (1990) as they posited that information gathering is impossible when allocation discretion is restricted. According to my findings, I argue that the compensation for revealing information can be replaced by the IPO design such as through a unique qualification system and lottery-based allocation mechanism. Moreover, My findings show that investors truthfully reveal their information in the primary market rather than trade on their information in the secondary market. This is consistent with the conclusion of Busaba and Chang (2010) that informed investors should reveal their information in the primary market in exchange for underpricing compensation, rather than to strategically trade until the issued shares start trading in the secondary market because the former practice generates a higher profit. Therefore, my research contributes to the literature by providing new empirical evidence on the information compensation theory.

This research also has implications for the IPO mechanism design. For the bookbuilding mechanism tested in this paper, its allocation rule is specified and publicly available in advance. It also offers institutional investors an equal chance to obtain IPO shares. In addition, this mechanism avoids the free-rider problem as the highest bids are not prioritized in allocation. Moreover, detailed bid information is disclosed to the public, making the process more transparent. Although this mechanism raises some concern over effective information extraction, my results suggest that institutions still truthfully reveal information even if there are no guaranteed means of compensation such as favored allocation. The incentives of revealing information could stem from the mechanism design. Specifically, institutions will not be qualified for the allocation process if their bid prices are lower

[72] This method is commonly used in France and formerly called *Mise en Vente*.

than the offer price, and the chance of obtaining shares will not increase significantly even if an excessively high price is submitted. Hence, my findings imply that this relatively fair and transparent bookbuilding mechanism is able to exert the same price discovery function as opaque alternatives.

The remainder of this paper is structured as follows. In Section 4.2, the literature about bookbuilding is reviewed. I introduce China's IPO mechanism in Section 4.3 and develop hypotheses in Section 4.4. Section 4.5 describes the data and Section 4.6 illustrates the descriptive statistics of the research sample. The methodology is discussed in Section 4.7 and the results are presented in Section 4.8. Section 4.9 examines whether institutions exaggerate their demands. Finally, Section 4.10 delivers a conclusion.

4.2. Literature Review

4.2.1. Theoretical Research about Bookbuilding

Benveniste and Spindt (1989) and Benveniste and Wilhelm (1990) first studied the bookbuilding mechanism from a theoretical perspective and proposed information compensation theory as a way to demonstrate that bookbuilding can reduce uncertainty and the information asymmetries of IPO. Benveniste and Spindt (1989) modeled the bookbuilding process and found that this mechanism is able to induce investors into disclosing their private information. As compensation for revealing positive information, IPO offer prices are revised upwards only partially so that they are still lower than the fair value, leading to the underpricing phenomenon. In addition, they showed that allocation priority is given to an underwriter's frequent investors as compensation for the information revealed. Benveniste and Wilhelm (1990) investigated the consequences when underwriters lose their power of discretion on share allocation and pricing and found that these two constraints reduced the investors' incentive to truthfully reveal private information and therefore lessened the expected proceeds from an IPO due to the winner's curse.

However, Benveniste and Spindt (1989) and Benveniste and Wilhelm (1990) did not reveal the optimal amount of information gathering. To address this question, Maksimovic and Pichler (2006) modeled a mechanism for eliciting information, which shows that it is not necessary to underprice the issuing shares for information extraction if no restriction has been placed on the share allocation between informed and uninformed investors. When minimum allocations are required for informed investors, the issued shares have to be underpriced. They found that the optimal amount of information gathering, measured by the number of investors, has a positive relationship with the risk of the issues, but also on the conditions of the allocation policy.

To compare the performance of different IPO mechanisms, Biais and Faugeron-Crouzet (2002) developed a unified theoretical model for the bookbuilding method, the fixed price auction, the *Offre a Prix Minimum*, and the uniform auction. Their model made the following discoveries: the fixed price method suffers from inefficient pricing and winner's curse; uniform price auction also reveals inefficiencies; and the bookbuilding and *Offre a Prix Minimum* are the optimal mechanisms in terms of information elicitation and price discovery. The optimum of *Offre a Prix Minimum* provides contrary evidence to Benveniste and Wilhelm's (1990) information compensation theory as underwriters in *Offre a Prix Minimum* do not have discretionary powers of allocation but still fulfill a price discovery function. Similarly, the models developed by Bulow and Klemperer (2002) and Parlour and Rajan (2005) also suggest that price discovery is still efficient when the discretionary allocation is replaced by rationing.

Sherman (2005) also developed models for bookbuilding, discriminatory auction and uniform price auction for purposes of comparison. Her models show that bookbuilding is less risky than the two types of auctions because underwriters can manage the offering process through bookbuilding to ensure a reasonable number of investors who will diligently evaluate an IPO. Moreover, the models predict that both bookbuilding and auctioned IPOs display partial adjustment to the public and private information.

Although bookbuilding in the literature is mostly found to be superior, Busaba and Chang (2010) showed, on the contrary, that bookbuilding could be more costly than fixed-price offering when informed investors misrepresent their information in the primary market and then profit from their information through strategically trading in the secondary market. To force informed investors to forgo the potential aftermarket profit, excessive underpricing is needed. Similarly, Kaneko and Pettway (2003) found that the underpricing of bookbuiding IPOs is significantly greater than those of auctioned IPOs, especially during hot market.

4.2.2. Empirical Research about Bookbuilding

With respect to the empirical research, the focus has been concentrated on price discovery (Bertoni and Giudici, 2014; Cornelli and Goldreich, 2003; Hanley, 1993; Ljungqvist and Wilhelm, 2002; Lowry and Schwert, 2004; Bubna and Prabhala, 2011) and share allocation (Aggarwal et al., 2002; Cornelli and Goldreich, 2001; Jenkinson and Jones, 2004; Lee et al., 1999; Ljungqvist and Wilhelm, 2002; Rocholl, 2009; Bubna and Prabhala, 2011)

Cornelli and Goldreich (2003), the most relevant paper to my research, analyzed the order books of 63 equity offerings (37 IPOs and 26 SEOs) in order to examine what information in the order book is used to set the offer price and how the information is reflected in the aftermarket price and found that the bid price submitted by institutional investors heavily affected the offer price. The offer price is set to approximately equal the quantity-weighted average of bid prices. In addition, the oversubscription also influences the offer price, but to a limited extent. Therefore, they concluded that bookbuilding successfully works as an information extraction process. In addition, the authors further distinguished different types of bids and revealed that the offer price is particularly driven by large quantity bids and bids submitted by frequent participants. Taking advantage that the time of submitting bids can be observed in their dataset, Cornelli and Goldreich also demonstrated that information arrives from the beginning of bookbuilding and is refined over time. In addition, they revealed that bids convey the bidder's reaction to public information to the underwriter, indicating that the boundary between public and private information is blurred. With respect to the pricing accuracy, they found that the percentage difference between the offer price and the quantity-weighted average bid price does not have explanatory power on the aftermarket price (measured by underpricing), and interpreted this result as that bid information is accurately used when pricing the IPO shares. On the other hand, the information least used in setting the offer price can predict the first-day return, including the oversubscription ratio and the dispersion of bid prices. Therefore, these two factors are underestimated during the pricing process.

Lowry and Schwert (2004) examined the efficiency of the bookbuilding process by testing the underwriter's treatment of public information. In particular, they tested whether public information is fully incorporated into the initial price range and the final offer price. Based on the statistically, but not economically, significant relationship between the offer-specific characteristics and the price revision, they concluded that underwriters do not fully, but mostly, incorporate public information into the initial price range. A similar relationship was documented between the market return from the filing date to the offer date and the initial return, indicating that the offer price contains almost all public information. Based on these two findings, the Lowry and Schwert concluded that the bookbuilding process is practically efficient.

Previous research has not only studied the price discovery but has also linked price discovery with allocation of shares. Using a large sample of 1,032 IPOs across 37 countries between 1990 and 2000, Ljungqvist and Wilhelm (2002) found that investors that reveal more valuable information, particularly positive information, are allotted more shares in IPOs. This finding is consistent with Benveniste and Spindt's (1989) partial adjustment theory and Hanley's (1993) empirical evidence. More importantly, they found that offer price deviates less from the initial price range when allocation discretion is constrained. The authors interpreted this finding as diminished price discovery when an underwriter's discretion is low, which is in contrast with Biais and Faugeron-Crouzet (2002). Deviating from a focus on offer price revision, Bertoni and Giudici (2014) built upon the work of Ljungqvist and Wilhelm (2002) to study the revision on share allocation among institutional and retail investors. By measuring the adjustment from the pre-announced allocation amount to eventual allotment, they found that IPO shares migrated toward institutional investors if positive information is revealed during a bookbuilding process. In addition, the revision on share allocation is found to interact with offer price revision, and the two modifications are applied simultaneously to reward institutional investors for revealing their private information. Their model also shows that the allocation to institutional investors increases when the upward price adjustment is low. Using 6,527 institutional bids in 42 Indian IPOs, Bubna and Prabhala (2011) investigated the impact of allocation discretion on price discovery and found that IPOs with allocation discretion have lower underpricing than those without allocation discretion. This finding suggests that price discovery improves when underwriters are given allocation power. Furthermore, the authors revealed that allocation discrimination not only exists between institutional and retail investors but also among different institutions. Allocation decisions are made primarily based on the identity of the bidder instead of the bid itself.

On the other hand, Cornelli and Goldreich (2001) specifically studied the share allocation in 39 international equity issues by the bookbuilding method, including 23 IPOs and 16 SEOs and found that underwriters strategically favor limit and step bids and bids with a revision in share allocation. Since offer prices are normally set below its fair value (underpricing) to compensate information discloser (Benveniste and Spindt,1989), Cornelli and Goldreich interpreted the favorable allocation as compensation for providing valuable information. Moreover, large-quantity bids and frequent bidders also get more allocation due to concerns over liquidity and support for cold IPOs respectively. Underwriters also favor insurance companies and pension funds, which could be because these two types of institutions are treated as long-term investors. Building upon Cornelli and Goldreich (2001), Jenkinson and Jones (2004) used 27 European IPOs to study whether long-term shareholders are favored in IPO share allocation and utilized the likelihood of being a long-term investor, derived from a major European privatization IPO, to rank institutions. By doing so, they found that institutions perceived as long-term investors were allocated more shares. In addition, the authors found little evidence that favors are given to informative bids (limit and step bids) in share allocation, which contradicts Cornelli and Goldreich's (2001) conclusion. Furthermore, Rocholl (2009) expanded the IPO allocation sample to both institutional and retail investors, allowing an investigation of why institutional investors obtain a favored allocation compared to retail investors. The results suggest that the favored allocation is due to the institution's superior ability to identify underpriced issues. When further categorizing institutional investors, it was documented that domestic institutional investors receive better allocation because they play supporting roles in cold IPOs. Apart from the relationship between institutional allocation and underpricing, Boehmer et al. (2006) found that institutional investors also receive a greater allocation in IPOs with better long-run performance.

In summary, although theoretical models suggest that investors will truthfully reveal their information when particular benefits such as underpricing, favorable allocation are provided (Benveniste and Spindt, 1989; Sherman and Titman, 2002), rarely does empirical evidence provide the truthfulness of investors' bids as focus is mainly given to price discovery and share allocation.

4.2.3. Critiques on Bookbuilding

Although bookbuilding is widely used in global equity markets, there are extensive controversies over allocation discrimination and the lack of transparency in bookbuilding. First of all, it has been documented extensively that allocation policy normally favors institutional investors compared with individual investors (Aggarwal et al., 2002; Boehmer et al., 2006; Cornelli and Goldreich, 2001; Hanley and Wilhelm, 1995; Ljungqvist and Wilhelm, 2002; Sherman, 2000). However, the discretionary allocation is not only due to the incentive of information revelation, but also rent-seeking behavior. Loughran and Ritter (2002) and Loughran and Ritter (2004) documented that underwriters allocate more underpriced IPO shares to institutional investors in exchange for commission fees. Moreover, Liu and Ritter (2010) revealed that underwriters may engage in *spinning* in which underwriters allot hot IPO shares to corporate executives in return for future underwriting business. Meanwhile, *Laddering* is another rent-seeking behavior in the bookbuilding process (Griffin et al., 2007; Hao, 2007). In practice, institutions (ladderers) secretly promise to purchase extra issuing shares in the secondary market in exchange for a higher allocation in the IPO. Laddering inflates the offer price and underpricing so that both underwriters and institutions can benefit from this behavior.

Jagannathan and Sherman (2005) criticized the dominance of particular investors and the opaque in the allocation process of bookbuilding and hence advocated a hybrid IPO mechanism that preserves the main benefits of bookbuilding, while improving transparency. Specifically, they proposed that the general rules for setting the offer price and allocating shares should be specified in advance, and that a fraction of the allocation should be guaranteed for individual investors. In addition, bids should not only be ranked by bid price but also by additional factors such as timing and quality of investors. Chen et al. (2014) also analyzed the drawbacks of bookbuilding such as the exclusion of retail investors from bookbuilding, expensive commission fees, and having no formal allocation rules. Accordingly, they suggested that the human judgment involved in the IPO process should be replaced largely, but not fully, by a standardized electronic platform.

4.3. China's IPO Mechanism

In China, an IPO includes two tranches, one for institutional investors and another for retail investors. A pre-determined fraction[73] of shares are allotted to retail investors through a public offering, in which retail investors submit quantity-only orders without any involvement in the price-setting process. For the institutional offering, shares are priced and allocated through a quasi-bookbuilding process. Referring to Sherman (2000), China's IPO method that combines both bookbuilding (for institutional investors) and public offering (for individual investors) should be defined as a hybrid IPO mechanism. In this paper, I focus on the institutional offering as it reveals a price discovery.

Although the institutional offering is officially named bookbuilding, it is, to some extent, different from what is understood by the term's widely perceived definition. The core difference between standard bookbuilding and other IPO mechanisms is that underwriters can exercise total discretion in the former (Chen et al., 2014; Sherman, 2005). In this sense, the institutional offering in China is a quasi-bookbuilding mechanism which is somewhere between auction and bookbuilding because underwriters only have discretion on setting the offer price but not on share allocation.[74]

The general issuing process for institutions is as follows. The underwriter and issuer organize a roadshow to promote the issuing shares, in which an initial price range is provided to institutional investors as a benchmark for evaluation. Once the roadshow finishes, institutions then submit bids for the ongoing IPO. Each bid contains the price an institution would like to pay and the amount this institution

[73] This fraction could change if a claw-back option is triggered under certain conditions.

[74] For this quasi-bookbuilding mechanism, the underwriter can deliberately allocate shares to particular institutions only when they set the offer price at the market-clearing price, namely the point where demand equals supply. As a result, the institutions with bid price higher or at the offer price will definitely obtain share allocation. In fact, however, even the demand of bids with the highest price is larger than the offering amount. Therefore, there is almost no chance for underwriters to intentionally allocate shares to particular institutors.

subscribes. Thereafter, the underwriter and issuer set the offer price based on the institution's demand. From this perspective, it is a bookbuilding process since underwriters can determine the offer price according to the interests of institutional investors. Upon the completion of pricing, a lottery-based share allocation commences. Specifically, only the bids with bid price higher or at the offer price qualify for the allocation. Institutions are apportioned various numbers of tickets which are in proportion to the amount of qualified bids. Finally, the underwriter draws tickets from the lottery pool to decide which institutions are allocated shares. As the underwriter's discretion on allocation is replaced by the lottery process, the IPO mechanism used in China is a quasi-bookbuilding one with discretion only exercised on setting the offer price.

The quasi-bookbuilding method used in China is very similar to the mechanism of *Offre a Prix Minimum* (formerly called Mise en Vente)[75] used in France. However, Chahine (2007) and Biais and Faugeron-Crouzet (2002) define this French mechanism as an auction-like procedure. Different from China's pricing mechanism, there is no roadshow for *Offre a Prix Minimum*, but rather the underwriter sets a minimum price as a benchmark for the following auction. Afterwards, both institutions and retail investors submit price-quantity bids.

After collecting the bids, Societe des Bourses Francaises (SBF), the authority covering the French market, analyzes the market demand and jointly sets the offer price with the issuer and underwriter. Simultaneously, a maximum price is chosen in order to exclude those bids that are higher than the maximum price. Since every bidder pays a common price for the shares, it seems that the price cap is being used to eliminate free-riders. Finally, shares are allocated to investors whose bid prices are in between the offer price and the maximum price on a pro rata basis.

In summary, there are several differences between the Chinese and French mechanisms. Firstly, the French mechanism does not have a roadshow. Secondly,

[75] More detailed description of this French IPO pircing mechansim can be seen in Derrien and Womack (2003).

unrealistic bids (where the bid price is too high) are excluded from the allocation process for the French mechanism, but no such control is available in China during the sample period.[76] Thirdly, both institutional and individual investors can take part in the pricing process in France, but this is only available for institutions in China. Moreover, French IPOs allot shares on a pro rata basis, but in China a lottery-based method is used[77]. A detailed comparison between the Chinese and French IPO mechanisms is summarized in Table 4.1.

For a better understanding of China's IPO pricing mechanism, I also compare it with the standard bookbuilding method used in the US. Prior to the step of share allocation, the general processes are almost the same for the two markets, but there is one minor difference related to the participants. In the US, only investors invited by the underwater can bid for an IPO. The invited investors include both institutions and some high-net worth retail investors. In China's system, however, institutions can participate in the share pricing process of every IPO as long as they are authorized to do so by the CSRC. During my sample period, Chinese retail investors are not allowed to attend the IPO share pricing.[78] However, it does not mean that Chinese retail investors are excluded from the IPO. In fact, they simply do not get involved in the share pricing, and still have a chance of being allotted IPO shares via a particular tranche for retail investors. The most important distinction between the two mechanisms lies with the share allocation. US underwriters have the discretionary power to decide who will get the IPO shares and how many shares they will eventually obtain. This discretion is widely regarded as compensation for revealing private information (Benveniste and Spindt, 1989; Sherman and Titman, 2002).

[76] The decree No.98 (Decision on Amending the Measures for the Administration of Securities Offering and Underwriting), being effective on Mar 31 2014, also requires underwriters to eliminate those high-price bids but does not specify the criteria. However, this new regulation was not effective during my sample period.

[77] The pro-rata allocation mechanism was also used in China before November 2010.

[78] The decree No.98 (Decision on Amending the Measures for the Administration of Securities Offering and Underwriting), being effective on Mar 31 2014, allows qualified retail investors to participate in the bookbuilding process. Typically, these individuals are High-net worth investors.

Table 4.1 The comparison of IPO mechanisms

This table illustrates a comparison of China's quasi-bookbuilding mechanism with the Offre a Prix Minimum method used in France and the standard bookbuilding method used in the US and India respectively.

	China	France	US	India
Mechanism	Quasi-bookbuilding	Offre a Prix Minimum	Bookbuilding	Bookbuilding
Price set before or after demand	After	After	After	After
Setter of offer price	Underwriter/ issuer	Underwriter/ issuer/SBF	Underwriter/ issuer	Underwriter/ issuer
Market-clearing price	No	No	No	No
Blind bid	Yes	Yes	Yes	Yes
Road show	Yes	No	Yes	Yes
Exclusion of unrealistic bids	No	Yes	No	No
Allocation rule	Lottery	Pro rata	Discretionary	Pro rata
Allocation result	Available	Not available	Not available	Not available
Anonymous bidders	No	No	Yes	Yes
Participants	Institutions	Institutions High-net worth individuals	Institutions Individuals	Institutions Individuals
Live bookbuilding process	No	No	No	Yes

In contrast, Chinese underwriters do not possess the same discretionary power in allocation as in the lottery-based method. In addition, the allocation outcome is disclosed to the public upon the finish of China's IPOs while this is not available in the US. A comparison between quasi- and standard-bookbuilding is illustrated in Table 4.1.

With regards to bookbuilding, the quasi-bookbuilding mechanism improves the transparency and fairness of the IPO process to some extent. First of all, the allocation rule is specified and publicly available in advance, and provides the institutions an equal chance of participation and, ultimately, of being allocated IPO shares. Secondly, the lottery-based method avoids the free-rider problem as the highest bids do not have priority in share allocation. However, it raises concerns over the willingness with which institutions truthfully reveal their private information through bids since there is no guaranteed reward via share allocation. Moreover, detailed bid information is disclosed to the public, which makes the process more transparent.

Another transparent IPO mechanism is the one used in Indian IPO market. The most important feature of the Indian IPO mechanism is the "live" bookbuilding process in which the number of shares that have been subscribed by each investor category (institutional investors and individual investors) and the proportion of subscription to the total issuing amount are published every 30 minutes. The description of Indian bookbuilding is also presented in Table 4.1. Different from China and the US, the share allocation of Indian IPO is on a pro rata basis rather than the discretion of underwriters or lottery.[79] Notably, although bookbuilding method is widely used in India's primary market, issuers are also allowed to choose fixed-price as the issuing method.

4.4. Hypotheses Development

As pointed out by Busaba and Chang (2010), informed investors have an incentive to misrepresent their interests in the primary market when they are able to profit from their private information through strategically trading in the secondary market. On the one hand, institutions could deliberately bid at an extremely high price in the quasi-bookbuilding process. By doing so, it would slightly increase the likelihood of being allocated IPO shares as more bids can be eligible for the lottery-based allocation. However, Cornelli and Goldreich (2003) found that the offer price is set close to the quantity-weighted average price of limit bids and concluded that bid

[79] Since November 2005, the share allocation process has changed to a pro rata method from the underwriter's discretion, which is quite similar to the Dutch auction method.

prices have a strong impact on the offer price. Therefore, an inflated bid price could simultaneously result in an expensive offer price, which is not in the interests of bidders. On the other hand, institutions may intentionally bid a price that is lower than their real valuations. Consequently, the offer price would be undervalued and those dishonest bidders could profit from the mispricing of the IPO shares.

For instance, institutions are assumed to know if the true value of an issuing share is US$ 10 per share, by deceitfully making a bid price of US$ 8 thus eventually forcing the offer price to be set at US$ 8 per share. Once the IPO shares start trading, the share price will revert to its fair value of US$ 10 if the market is efficient. In this case, institutions are able to easily gain US$ 2 per share if they are allocated shares. For those who do not receive IPO shares, they can still profit from purchasing undervalued shares in the secondary market before it fully returns to the true value of US$ 10, for example at US$ 9 per share. In the context of Chinese IPO, however, an unrealistically low bid price will render the institution unqualified for the allocation thereby losing the chance to obtain IPO shares.

Instead *deliberately* fooling the market by inflating or deflating bids, institutions could simply provide a price without diligent efforts since the evaluation of unseasoned shares is costly, as it involves large amount of data collection and analysis (Sherman and Titman, 2002). Moreover, the fact that China's IPO mechanism has no guaranteed compensation for revealing information, such as favored share allocation, could also reduce the incentive to disclose information. According to the above arguments, it is essential to explore whether or not institutions truthfully disclose their information in a relatively transparent and fair, but less discretionary, IPO mechanism.

In my dataset, bid prices and the corresponding bid amounts submitted by each institutional investor can be observed. Therefore, I make use of these two variables to measure an institution's willingness to acquire IPO shares. In theory, the higher the price an institution bids or the more shares it subscribes, the more eager this institution will be to obtain IPO shares. Since IPO shares are heavily oversubscribed in China, the probability of obtaining an allocation is extremely low. Even though some institutional investors are fortunate enough to receive IPO shares, the allotted amounts are often much lower than what they demand.[80] Therefore, institutional investors who have displayed a strong willingness in the quasi-bookbuilding process should purchase shares from the secondary market if their bid prices and bid amounts truthfully reflect their valuations on the issuing shares.[81] In other words, when a positive relationship between the willingness and the following purchasing behavior is observed, institutional investors truthfully reveal their information through bids.

However, the decision of whether or not to make a purchase in the secondary market is not only driven by the institution's valuation (bid price) but also by the after-IPO market conditions. For example, although one institution bids a very high price for one IPO, this institution may not purchase any shares from the secondary market when the share price exceeds its valuation. Similarly, an institution could purchase the issuing shares from the secondary market when the share price is lower than its valuation (bid price) even if its bid price is low. In other words, the secondary market share price can be used as a benchmark to detect whether the bid price is truthful or not. For example, one institution provides a bid at US$ 8 per share. If US$ 8 is the truthful valuation, this institution should not purchase any shares from the secondary market when the after-IPO shares price is higher than US$ 8. Conversely, this institution should buy the issued shares from the secondary market when the share price is lower than the bid price of US$ 8, such as at US$ 7 per share. In summary, two potential trading behaviors (purchase / do not purchase shares from the secondary market) can be observed under two different scenarios (secondary

[80] Among the entire 7,133 institution-IPO observations in my sample, only 57 cases in which the institutions fully got the amount of shares they subscribed in bookbuilding. In average, the gap between subscribed amount and allocated amount for one institution in an IPO is 8.81 million shares.

[81] The unique lottery-based allocation mechanism (no discretionary power) guarantees that institutions' purchasing behaviours are not a result of laddering in which institutions (ladderers) secretly promise to purchase extra issuing shares in the secondary market in exchange for a higher allocation in IPO.

market price benchmark $\geq$ or $<$ bid price). When the secondary-market price benchmark is lower than the bid price, institutions should purchase shares if the bids truthfully reflect their valuations. When the after-IPO share price is higher than, or equal to, institutions' bid prices, they should not purchase shares from the secondary market if the bids truly reflect their valuations. Otherwise, it indicates that institutional investors do not truthfully reveal their information through bids. Therefore, a pair of mutually exclusive hypotheses is developed as follows:

Hypothesis 1a: Institutional investors truthfully reveal their information through bids.

Hypothesis 1b: Institutional investors do not truthfully reveal their information through bids.

Either conclusion (H1a or H1b) will provide implications for the information compensation theory and bookbuilding mechanism design, which is the main contribution of this research. If institutional investors do not truthfully disclose information through bids (H1b), it could be due to the fact that Chinese underwriters cannot use discretionary allocation to compensate information revelation. In a Chinese IPO, shares are allocated to institutional investors based on a unique lottery method in which the underwriter draws tickets to decide the allocation outcome. The lack of allocation discretion may block the potential rewarding channel through which underwriters can deliberately allocate underpriced shares to institutions that submit informative bids, which thus reduces institutions' incentives to disclose information (Benveniste and Spindt, 1989; Hanley, 1993; Ljungqvist and Wilhelm, 2002; Spatt and Srivastava, 1991). Therefore, the conclusion of H1b will provide complementary empirical evidence for the information compensation theory.

Sherman (2005) stated that "*Book building is the primary initial public offering (IPO) method in the United States, but for decades it has generated controversy because it allows shares to be preferentially allocated. Investors complain that they are shut out of the allocation process, calling for changes that will give everyone a* *fair chance*".[82] If Chinese institutions truthfully disclose information through their bids (H1a), it indicates that the relatively fair and transparent allocation mechanism used in China can exert the same price discovery function as opaque mechanisms do. In addition, H1a will also cast doubt on the information compensation theory because institutions still play the price discovery role even if there is no guaranteed compensation such as favored allocation. Therefore, either conclusion (H1a or H1b) will contribute to the information compensation theory and the IPO mechanism design.

4.5. Data

To my knowledge, the IPO bid information is not disclosed to the public in the US and European markets. Only a few researchers can obtain proprietary data from particular investment banks but with a small-size sample, for example Cornelli and Goldreich (2003) and Jenkinson and Jones (2004). Although the data used in Cornelli and Goldreich (2003) also provides detailed bid information such as bid price, 82.5% of the bids are strike bids in which investors only specify the number of demanding shares or the total amount of money they would like to invest regardless of the offer price. In other words, most of the bids do not explicitly reflect investors' valuations on the issuing shares.

While the IPO mechanisms used in particular markets, such as India (Khurshed et al., 2014), allow investors to know the total amount of shares that have been demanded by each of the investor categories (institutional / retail investors), it is not possible to know the bid amount and bid price from each individual entity. Although detailed Indian IPO bidding data was used by Bubna and Prabhala (2011), they obtained the dataset from a proprietary source that confines the sample size to 42 IPOs. However, the information on bid amount and price submitted by each institution is publicly available in the Chinese market as regulations force IPO firms

[82] See page 2 of the paper "Global trends in IPO methods: Book building versus auctions with endogenous entry".

to disclose such data. Therefore, I can use the Chinese data to conduct tests that have not been executed before.

In general, my research data consists of two parts. The first part is the institution's bidding data, which is collected from the order book of Chinese IPO firms. Specifically, I use the Chinese IPOs that took place in the ShenZhen Stock Exchange (ChiNext board + SME board) between November 2010 and September 2012 as my sample. The IPOs in Shenzhen's main board are excluded because all of them took place before November 2010. There are two reasons that this particular sample period is determined. Firstly, bid prices submitted by institutions cannot be observed before November 2010 because the listing firms were not required to disclose such information at that time.[83] Secondly, the Chinese IPO market was closed after September 2012.[84] In sum, 410 IPOs are selected as the research sample.

The second part of the research data is institutional holdings data. The Chinese database, Wind[85], provides the quarterly institutional holdings data of every listing firm, including the name of the institution, the type of institution, the number of holding shares and the proportion of holding shares to the total number of outstanding shares. In this paper, however, I only focus on the fund companies by excluding the other types of institutions[86] due to some limitations of Wind's data. For each listing firm, Wind records the top 10 shareholders of the tradable shares as well as all shareholders who are fund companies. In other words, if one institution is not a fund company and the number of shares it holds is not in the top 10, this institution will not appear in Wind's quarterly holding data even though it owns shares. For fund companies, even if they are not among the top 10 shareholders of

[83] The decree No.69 (*Decision on Amending the Measures for the Administration of Securities Offering and Underwriting*) requires that issuers and the lead underwriter to disclose detailed bidding information after setting the offer price since November 1 2010.

[84] The Chinese IPO market re-opened in Jan 2014. In the year of 2014, 31 and 51 IPOs took place in the SME board and ChiNext board respectively.

[85] Wind is one of the most widely used databases for Chinese research.

[86] The excluded institutions are security firms, trust firms, finance firms, insurance firms and qualified foreign institutional investors.

one particular IPO firm, their holding information is recorded in Wind.

Despite the exclusion of particular institutions, the fund companies are representative for the institutions in my research sample as they account for a large proportion of the full sample. Table 4.2 provides a description of the institutions that submit bids in the sampled 410 IPOs. In terms of the institution-IPO cases, there are 7,133 fund company-IPO cases that account for 34.91% of the full sample. Regarding the number of bids, fund companies submit 18,413 bids in the 410 IPOs, which is 47.59% of the whole sample and ranks first among the institutions.

Table 4.2 The distribution of institution-IPO cases

This table presents the distribution of institution-IPO cases for the eight types of institutions in my research sample.

Type	Number of Institution-IPO Cases	Percentage	Number of Bids	Percentage
Security	7,749	37.92%	10,323	26.68%
Fund	7,133	34.91%	18,413	47.59%
Recommend	1,628	7.97%	1,793	4.63%
Trusts	1,438	7.04%	3,047	7.88%
Finance	1,420	6.95%	1,629	4.21%
Insurance	750	3.67%	3,082	7.97%
Unknown	266	1.30%	351	0.91%
QFII	51	0.25%	52	0.13%
All	20,435	100%	38,690	100%

However, I found that the holding data of fund companies are *mostly* accurate for quarter 1 and quarter 3, but *fully* accurate for quarter 2 and quarter 4. This is because fund companies disclose all of their holding positions in a semi-annual and annual report, but only the top 10 holding positions do so in a quarterly report in March and September. Despite biases existing for the data of quarter 1 and quarter 3, these are not significant. Therefore, in this research, I conduct tests using the data of fund companies in all four quarters.

In the robustness test, I replicate the analyses only using the data of June or December. Based on the aforementioned data filter, the bidding and holding data of 63 fund companies in 410 IPOs are used as the search sample. Among the 410 IPOs, 196 and 214 of them list in the SME and ChiNext boards respectively. Furthermore, the data of IPO-specific characteristics, such as IPO proceeds and P/E ratio, are collected from the Shenzhen Stock Exchange fact books. For the share price information, I also collect the after-market share prices and market index from the Datastream.

4.6. Descriptive Statistics

Table 4.3 presents the summary statistics on the behaviors of the 63 fund companies in the 410 IPOs. On average, a fund company participates in 113 of the total 410 IPOs during the sample period. The low median participating frequency of 82 and the high standard deviation of 101.29 imply that some fund companies are much more active than the others in the IPO market. When fund companies participate in an IPO, they usually submit two bids and subscribe 6.15 million shares worth of CNY 121.34 million.

Table 4.3 Descriptive statistics of fund companies' behaviors in quasi-bookbuilding

This table presents the descriptive statistics on the behaviors of the 63 fund companies in the 410 IPOs. One bid is defined as an offer with a specific price and quantity submitted via a fund. The number of bids submitted by one fund company in an IPO is the sum of bids from all funds under the management of the fund company. If a fund company submits at least one bid in an IPO, the frequency of participation will be counted as once. The bid value is equal to the bid amount multiplied by the corresponding bid price.

	Number of Cases	Mean	Median	SD	Min	Max
Frequency of Participation	63	113.22	82.00	101.29	1.00	336.00
Number of bids submitted in an IPO	63	2.03	1.82	0.89	1.00	5.81
Number of shares demanded in an IPO (in millions)	63	6.15	5.47	4.54	0.61	21.60
Bid value in an IPO (in CNY million)	63	121.34	108.30	92.72	11.35	489.78

Table 4.4 shows the descriptive statistics for the 410 IPOs. The mean unadjusted initial return is 18.58%. On average, there are 12 days between the IPO day[87] and the first trading day. Derrien and Womack (2003) pointed out that the lag between the IPO day and the first trading day leads to greater underpricing. To control the market conditions during the waiting period, the market index return is calculated using the SME-ChiNext 500 index.[88] Therefore, I obtain the adjusted initial return, measured as the unadjusted initial return minus the corresponding market index return, and the mean value is 19.38%. I can see that the underpricing level in the sample period is much lower than that of a decade ago when the fixed-price method was used as the IPO pricing mechanism in China. For instance, Chen et al. (2004) reported an

[87] IPO day is the day on which offer price is set.

[88] SME-ChiNext 500 represents the performance of the top 500 SME and ChiNext board listed firms ranked by total market capitalization, free-float market capitalization and turnovers.

underpricing level of 295% (mean) and 137% (median) for Shenzhen A-share IPOs during the period of 1992-1997. Similar evidence is documented by Chan et al. (2004), Tian (2011), and Lin and Tian (2012). Even compared with the underpricing level in the US market where standard bookbuilding is used, the underpricing level of 19.38% still seems acceptable as Loughran and Ritter (2004) and Ljungqvist (2007) reported an average underpricing of 15-20% for the US market.

As I intend to investigate fund companies' trading behaviors right after the IPO, the after-market share performances are presented in Table 4.4 as well. Specifically, I study the performance between the first trading day and the first quarter-report day, where the first quarter-report day is the first time that listing firms disclose their quarterly reports after the IPO. In my sample, on average, listing firms disclose the first quarterly report in 40 days after their shares start trading. The mean of unadjusted and adjusted return between the first trading day and the first quarter-report day are -10.80% and -5.97%. These two figures indicate the underperformance of the IPO shares in the secondary market.

For the other IPO characteristics, the mean values of IPO proceeds, P/E ratio, profitability and sales growth of the 410 IPO samples are CNY 696.08 million, 45.29, 17.32% and 19.91% respectively. Moreover, Table 4.4 shows that there are normally 45 bids submitted by 17 fund companies with a subscription of 156.23 million shares in one IPO.

Table 4.4 Descriptive statistics of IPOs

This table presents the descriptive statistics for the 410 IPOs in my research sample. The unadjusted initial return is defined as the percentage change between the offer price and the closing price of the first trading day. The market return is calculated using the SME-ChiNext 500 index. The adjusted initial return is calculated as the unadjusted initial return minus the corresponding market return. The first quarter-report day is the first time that listing firms disclose their quarterly reports after an IPO. The unadjusted return between the first trading day and the first quarter-report day is the percentage change between the closing price of the listing day and the closing price of the first quarter-report day. The proxy for profitability is the net margin which is defined as net income / net sales. Sales growth is calculated as the percentage change from the year before the IPO to the IPO year.

	N	Mean	Median	SD
Number of days between the IPO day and the first trading day	410	11.99	12.00	3.13
Unadjusted initial return	410	18.58%	15.42%	24.13%
Market return between the IPO day and the first trading day	410	-0.80%	-1.02%	4.39%
Adjusted initial return	410	19.38%	15.21%	22.89%
Number of days between the first trading day and the first quarter-report day	410	40.26	37.00	26.25
Unadjusted return between the first trading day and the first quarter-report day	410	-10.80%	-9.30%	15.76%
Market return between the first trading day and the first quarter-report day	410	-4.83%	-3.54%	7.09%
Adjusted return between the first trading day and the first quarter-report day	410	-5.97%	-5.97%	12.91%
IPO proceeds (in CNY million)	410	696.08	559.80	465.37
P/E ratio	410	45.29	40.24	21.03
Profitability (net margin)	410	17.32%	14.67%	10.70%
Sales Growth	410	19.91%	18.45%	24.54%
Number of fund companies per IPO	410	17.40	17.00	6.85
Number of bids submitted by fund companies per IPO	410	45.27	39.00	29.59
Number of shares (in millions) demanded by fund companies per IPO	410	156.23	94.05	236.54

4.7. Methodology

There are two ways to identify a unique institution. The first approach is to regard each institution with a disassociated identity as distinct. However, the decisions of two identities may come from a single decision maker. For example, one fund company typically manages several funds. As a result, the investment decision could be made by the fund company rather than by a particular fund manager.

In this research, I use the second approach (the level of fund company) to distinguish between different entities due to the following two reasons. Firstly, I explored the bidding pattern in my sample and found that 70.52% and 65.36% of decisions are made by the fund company[89] in terms of the bid price and bid amount respectively. Secondly, Jenkinson and Jones (2004) also use the second approach in their research. Therefore, I use the same method for the sake of consistency.

In this research, I use Buy_{scale} as the dependent variable to measure a fund company's purchasing behavior between the first trading day and the first quarter-report day. Specifically, $Buy_{scale} = \ln(1 + \text{purchase amount})$, where purchase amount is calculated as the difference between the holding amount on the first report day and the IPO allocation amount. Therefore, if one fund company does not purchase any shares from the secondary market, i.e. purchase amount = 0, then Buy_{scale} equals 0. If one fund company sells the allocated shares, I let $Buy_{scale} = 0$.[90] With regard to willingness to acquire the IPO shares, the bid aggressiveness and bid amount are used as proxies. In one IPO, the aggressiveness of a fund company's bid is defined as the quantity-weighted bid price / the midpoint of IPO initial price range. I use the quantity-weighted average bid price because each fund company can

[89] Detailed methodology and results will be provided upon request.

[90] In the sample, there are 155 selling cases (sell the allocated shares). The selling cases only occur in IPOs that took place after 15 Aug 2012. Before this date, there had enforced lock-up period that prevent institutions from selling their allocated shares within the three months after IPO. On the other hand, I cannot track the cases that institutions purchase shares from the secondary market but sell those shares immediately after purchase (i.e. the trading of buy and sell are completed between the first trading day and the first quarter-report day).

submit multiple bids with various prices and amounts. Hereafter, I denote the bid aggressiveness and quantity-weighted bid price as *Bid Agg* and P_b respectively. The initial price range is the price interval being disclosed to institutional investors by the lead underwriter in the roadshow. Therefore, it can be regarded as the underwriter's valuation of an ongoing IPO. Regarding the bid amount, it is one fund company's total subscribed amount from all of its funds in an IPO. However, the bid amount itself may not be an indication of interest since large funds are likely to subscribe more shares. Hence, I use the variable of *Adjusted Bid Amount* to control the impact of size. Specifically, *Adjusted Bid Amount* is defined as $\ln(\text{bid amounts}/\text{net asset of fund company})$.

With respect to the secondary market share performance, I use the *lowest* daily closing price between the first trading day and the first quarter-report day as the secondary market price benchmark[91] which is denoted as P_{min}. For instance, if one IPO starts trading on 1st January 2011, the following quarter-report date would be 31 March 2011[92], and the P_{min} of this IPO is the lowest daily closing price between 1st January 2011 and 31 March 2011. When making the investment decision, investors would compare their valuation (P_b) with the market price benchmark (P_{min}). Accordingly, I generate the variable of $\Delta Pice$ to measure the percentage difference between P_b and P_{min}. Specifically, $\Delta Price = (P_b - P_{min})/P_{min}$. If fund companies truthfully disclose their valuations, they should purchase more shares from the secondary market when $\Delta Price$ is high, and vice versa.

On the other hand, only a small number of participants can receive shares through IPO due to heavy oversubscription. To explore the impact of share allocation, I divide the fund companies into two groups based on the allocation outcome. The trading behaviors of fund companies from the two groups could be distinct. For

91 Alternatively, I use the *average* daily closing price between the first trading day and the following quarter-report day to measure the after-IPO share price in robustness test.

92 This period is not necessary to be three months since it depends on the first trading date. For example, one IPO may start trading on 5th Feb 2011. The first quarter-report date of this IPO would still be 31 Mar 2011. Therefore, this period ranges from one day to three months.

instance, fund companies that obtain an allocation may be satisfied with being allotted shares and therefore unwilling to purchase more shares immediately. But those who do not obtain any shares from the primary market could have a stronger willingness to purchase shares from the secondary market. Hence, I use the dummy variable of *Allocation* to control the impact of share allocation outcome. *Allocation* equals 1 if a fund company receives shares in an IPO and 0 otherwise.

Besides, institutions may have higher incentive to purchase shares from the secondary market if their demands are not fulfilled in the primary market. Therefore, I generate the variable of *Unfulfilled Proportion* to control the influence of unfulfilled demand. Herein, *Unfulfilled Proportion* is calculated as (subscribed amount - allocated amount)/ subscribed amount.

Moreover, IPO-specific characteristics could affect the institution's trading behavior as well. Institutions may be prone to invest in large/small IPOs or IPOs with high/low price-earnings ratio. Besides, factors such as an issuing firm's profitability, growth rate and industry need to be controlled as well. I use $\ln(\text{proceeds})$ to measure IPO size; net profit margin[93] as the proxy of profitability; sales growth[94] to gauge the growth rate; and Hi-tech dummy to indicate whether an issuing firm belongs to the Hi-tech industry or not. Hence, the regression equation is as follows:

$$\begin{aligned} Buy_{scale} = \alpha_0 &+ \beta_1 Bid\ Agg + \beta_2 Adjusted\ Bid\ Amount + \beta_3 \Delta Price \\ &+ \beta_4 Unfulfilled\ Proportion + \beta_5 Allocation + \beta_6 P/E + \beta_7 Size \\ &+ \beta_8 Profitability + \beta_9 Growth\ Rate + \beta_{10} Hitech + \varepsilon \end{aligned}$$

Herein, $Bid\ Agg$, $Adjusted\ Bid\ Amount$ and $\Delta Price$ are the variables of interest. If $Bid\ Agg$ and $Adjusted\ Bid\ Amount$ are positively significant, it insinuates that fund companies will purchase more shares from the secondary market when they showed a strong willingness to obtain shares in the quasi-bookbuilding process. If $\Delta Price$ is positively significant, it means fund companies will purchase more shares when their valuations are higher than the secondary market price

[93] Net profit margin is defined as net income/ net sales or revenues.

[94] It is calculated as the sales growth from the year before IPO to the IPO year.

benchmark. In other words, the positive significance of these three key variables suggests that fund companies truthfully reveal their information through bids, i.e. H1a is sustained. If the three variables are not positively significant or even negative, this implies that fund companies do not truthfully reveal their information, i.e. H1b is supported.

4.8. Empirical Result

4.8.1. Univariate Analysis

In this section, I test the relationship between fund companies' trading behaviors in the secondary market and the bidding information in the primary market to investigate whether fund companies truthfully reveal information. Regarding the trading behaviors, there are five possible behaviors based on two share allocation outcomes:

1. Allocated shares in IPO and make more purchases in the secondary market.
2. No allocation in IPO and make purchases in the secondary market.
3. Allocated in IPO and no further purchase in the secondary market.
4. No allocation in IPO and no purchase in the secondary market.
5. Allocated shares in IPO and sell those allocated shares[95].

In panel A of Table 4.5, I divide all of the 7,133 fund company-IPO observations into three groups on the basis of bid aggressiveness. As a result, there are 2,379, 2,377 and 2,377 observations for the low, mid and high bid aggressiveness groups respectively. Within each group, I calculate the proportion of the five aforementioned behaviors. It can be seen that the purchasing proportion increases from 3.03% (0.34%+2.69%) of the low-aggressive group to 4.96% (1.09%+3.87%) of the mid-aggressive group, and grows further to 7.83% (2.02%+5.81) for the high-aggressive group, although the purchasing proportions are low in all of the three groups. Accordingly, the positive relationship between the bid aggressiveness and the

[95] The selling cases can only happen in IPOs without lock-up requirement. In my research sample, 65 IPOs do not have lock-up requirement.

Table 4.5 Fund companies' trading behaviors based on different bid aggressiveness and bid amount

This table presents the fund companies' trading behaviors in the secondary market for different bid aggressive groups and bid amount groups. In panel A, the fund companies are classified into low/mid/high aggressive groups according to their bid aggressiveness, where bid aggressiveness is defined as the quantity-weighted bid price / midpoint of the initial price range. In panel B, fund companies are assigned as low/mid/high bid amount groups based on their bid amount. For either classification (aggressiveness/amount), there are five possible outcomes: 1. Allocated shares in IPO and make more purchases in the secondary market. 2. No allocation in IPO and make purchases in the secondary market. 3. Allocated in IPO and no further purchase in the secondary market. 4. No allocation in IPO and no purchase in the secondary market. 5. Allocated shares in IPO and sell those allocated shares.

Total cases	7,133					
Panel A: Behavior in different bid aggressiveness groups						
	Low bid aggressive group		Mid bid aggressive group		High bid aggressive group	
Total cases in different bid aggressive groups	2,379		2,377		2,377	
Allocated and purchase	8	**0.34%**	26	**1.09%**	48	**2.02%**
No allocation and purchase	64	**2.69%**	92	**3.87%**	138	**5.81%**
Allocated and no purchase	139	5.84%	265	11.15%	369	15.52%
No allocation and no purchase	2,155	90.58%	1,941	81.66%	1,733	72.91%
Sell allocated shares (only IPOs without lock-up requirement)	13	0.55%	53	2.23%	89	3.74%

Panel B: Behavior in different bid amount groups

	Low bid amount group		Mid bid amount group		High bid amount group	
Total cases in different bid amount groups	2,444		2,330		2,359	
Allocated and purchase	10	**0.41%**	22	**0.94%**	50	**2.12%**
No allocation and purchase	102	**4.17%**	98	**4.21%**	94	**3.98%**
Allocated and no purchase	145	5.93%	251	10.77%	377	15.98%

Table 4.5 – Continued

No allocation and no purchase	2,184	89.36%	1,935	83.05%	1,710	72.49%
Sell allocated shares (only IPOs without lock-up requirement)	3	0.12%	24	1.03%	128	5.43%

purchasing proportion shows that fund companies truthfully reveal their willingness to acquire IPO shares through bids. In panel B of Table 4.5, I group the fund company-IPO observations according to the bid amount [96] instead of bid aggressiveness. Comparing the purchasing proportions in the three bid amount groups, a positive relationship between bid amount and the number of purchasing cases is observed as well. It also demonstrates that fund companies truthfully disclose their interests in obtaining the IPO shares. The univariate analysis of bid aggressiveness and bid amount supports the hypothesis of H1a.

As discussed previously, the investor's trading behavior could be influenced by the market conditions as well. Hence, I observe fund companies' behaviors under two market conditions. The first condition is $P_{min} \geq P_b$ and the second one is $P_{min} < P_b$, where P_{min} is the lowest daily closing price between the first trading day and the first quarter-report day and P_b is the quantity-weighted bid price. The results are illustrated in panel A of Table 4.6. Firstly, it can be seen that P_b is normally lower than P_{in} with a mean and median difference of -9.79% and -11.11% respectively. This could be the reason why fund companies do not purchase shares from the secondary market in most of the cases. Most importantly, I find that the proportion of purchasing shares in the secondary market is 7.34% (2.45%+4.89%) when $P_{min} < P_b$, which is almost double compared with that of 4.36% (0.58%+3.78%) when $P_{min} \geq P_b$. This result implies that fund companies truthfully reveal their information through bids as they make the investment decisions based on the revealed valuation, i.e. H1a is sustained. To check the robustness, I replace P_{min} by

[96] In the univariate test, I do not adjust the bid amount using the size of fund company.

Table 4.6 Fund companies' trading behaviors under two different market conditions

This table presents the fund companies' trading behaviors in the secondary market when the secondary market price benchmark $\geq$ or $<$ the quantity-weighted average bid price P_b. In Panel A, I use the lowest daily closing price between the first trading day and the following quarter-report day P_{min} as a benchmark. In Panel B, I use the average daily closing price between the first trading day and the following quarter-report day $\overline{P_c}$ as a benchmark. In each market condition, there are five possible outcomes: 1. Allocated shares in IPO and make more purchases in the secondary market. 2. No allocation in IPO and make purchases in the secondary market. 3. Allocated in IPO and no further purchase in the secondary market. 4. No allocation in IPO and no purchase in the secondary market. 5. Allocated shares in IPO and sell those allocated shares.

Total cases	7,133			
Panel A: P_{min} is used as benchmark				
Mean of $(P_b - P_{min})/P_{min}$	-9.79%			
Median of $(P_b - P_{min})/P_{min}$	-11.11%			
	$P_{min} \geq P_b$ (should not purchase)		$P_{min} < P_b$ (should purchase)	
Total cases in different market conditions	4967		2166	
Allocated and purchase	29	**0.58%**	53	**2.45%**
No allocation and purchase	188	**3.78%**	106	**4.89%**
Allocated and no purchase	318	6.40%	455	21.01%
No allocation and no purchase	4,366	87.90%	1,463	67.54%
Sell allocated shares (only IPOs without lock-up requirement)	66	1.33%	89	4.11%

Panel B: $\overline{P_c}$ is used as benchmark				
Mean of $(P_b - \overline{P_c})/\overline{P_c}$	-19.61%			
Median of $(P_b - \overline{P_c})/\overline{P_c}$	-20.40%			
	$\overline{P_c} \geq P_b$ (should not purchase)		$\overline{P_c} < P_b$ (Should purchase)	
Total cases in different market conditions	5906		1227	
Allocated and purchase	49	**0.83%**	33	**2.69%**
No allocation and purchase	234	**3.96%**	60	**4.89%**
Allocated and no purchase	478	8.09%	295	24.04%

Table 4.6 – Continued

No allocation and no purchase	5,046	85.44%	783	63.81%
Sell allocated shares (only IPOs without lock-up requirement)	99	1.68%	56	4.56%

$\overline{P_c}$, which is the *average* daily closing price between the first trading day and the first quarter-report day. The result of the robustness test is presented in Panel B of Table 4.6 and is consistent with that of Panel A.

It is noteworthy that I do not deny the possibility that fund companies bid a low price but realize their valuation was low and still decide to participate in the secondary market. Actually, this is a plausible explanation for the finding of Table 4.6 that some fund companies still purchase shares from the secondary market when $P_{min} < P_b$ or $\overline{P_c} < P_b$. In other words, our results underestimate the truthfulness of bidders. If we could have been identified such particular cases, we should obtain a more clear and strong evidence for truthfulness. Despite of this underestimation, my results still support hypothesis H1a that institutional investors truthfully reveal their information through bids.

Based on Table 4.5 and Table 4.6, we can also see that most of the purchasing cases take place when fund companies do not get any allocation from an IPO. In the whole sample, there are 376 fund company-IPO cases of purchasing shares from the secondary market immediately after the IPO. However, only 82 cases happen when fund companies have already got shares from IPO. All of the remaining 294 cases occur when fund companies are not allocated shares in IPOs. This result suggests that fund companies that get an allocation may be satisfied with being allotted shares and are therefore not eager to purchase any more shares immediately thereafter. However, those who do not receive shares in IPOs have a stronger willingness to purchase shares from the secondary market to make up for what they missed out on in the primary market.

4.8.2. Multivariate Analysis

I now conduct the regression tests developed in the methodology section and present the results in Table 4.7. For all of the five models in Table 4.7, the dependent variable is Buy_{scale} which is defined as $\ln(1 + \text{purchase amount})$, where purchase amount is calculated as the difference between the holding amount on the first report day and the IPO allocation amount. In terms of how the data is structured, there is a panel dataset with 63 fund companies that submit bids across 410 IPOs. Since a fund company does not submit bids in every IPO, the panel data is unbalanced with 7,133 fund company-IPO observations in total. Therefore, I run the panel regression with fixed-effects for fund companies. Fixed-effect is used to control the fund company's time-invariant factors such as reputation.[97]

In model 1 and model 2, I regress Buy_{scale} on $Bid\,Agg$ and $Adjusted\,Bid\,Amount$ individually to test the correlation between the fund company's purchasing willingness and subsequent trading behavior. I observe that the explanatory variables are positively significant in both of the models, indicating that the purchase amount in the secondary market is positively associated with the purchase willingness as revealed in the quasi-bookbuilding process.

To control the impact of post-IPO market condition, $\Delta Price$ is used as the independent variable in model 3 to explore whether fund companies make investment decisions based on the valuations disclosed by their bids. The variable of $\Delta Price$ also has a positively significant impact on the dependent variable. Put another way, the higher the bid price is relative to the after-market share price, the more issued shares fund companies will purchase from the secondary market, i.e. fund companies' investment decisions are based on the valuation revealed in the bidding process. In model 4, I use the three key variables as independent variables simultaneously with all of them showing positive significance.

[97] I admit that fund companies' characteristics vary over time, but the sample period is less than two years which is too short for a fund company's characteristics change substantially.

Table 4.7 Factors that affect fund companies' purchasing behaviors in the secondary market

This table presents the results of panel regression with fixed-effects for fund companies. The dependent variable of Buy_{scale} is defined as $\ln(1+\text{purchase amount})$, where purchase amount is measured by the difference between the holding amount on the first report day and the IPO allocation amount. *Bid Agg* is defined as the quantity-weighted bid price / midpoint of the initial price range. $\Delta Price$ is calculated as ($P_b - P_{min})/P_{min}$, where P_b is the quantity-weighted average bid price and P_{min} is the lowest daily closing price between the first trading day and the following quarter-report day. The dummy variable of *Allocation* equals 1 if a fund company receives shares from an IPO allocation and 0 otherwise. *Size* is measured by the natural logarithm of total IPO proceeds. *Profitability* is measured by the net profit margin. *Growth rate* is gauged by the sales growth rate. The dummy variable of *Hi-tech* equals 1 if the issuing firm belongs to the Hi-tech industry and 0 otherwise. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: Buy_{scale}					
Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5
Bid Agg	1.2362***			1.0155***	0.5827***
	(8.85)			(6.69)	(3.07)
Adjusted Bid Amount		0.1237***		0.1183***	0.1366***
		(3.98)		(3.77)	(4.00)
$\Delta Price$			1.0309***	0.8231***	0.6716***
			(6.84)	(5.09)	(3.79)
Unfulfilled Proportion					0.3726
					(0.94)
Allocation					0.2044
					(1.53)
P/E					0.0021
					(1.01)
Size					0.2804***
					(4.17)
Profitability					1.0773***
					(3.40)
Growth Rate					0.3457**
					(2.37)
Hi-tech					0.0445
					(0.40)
Constant	-0.4257***	1.1901***	0.7428***	0.3717*	-1.7462***
	(-3.41)	(8.63)	(20.79)	(1.77)	(-2.73)
Number of obs	7,133	6,969	7,133	6,969	6,969
Number of funds	63	61	63	61	61
R-squared within	1.10%	0.23%	0.66%	1.64%	2.40%
R-squared between	0.05%	4.75%	1.05%	6.06%	0.38%
R-squared overall	1.07%	0.04%	0.62%	1.30%	2.00%

As discussed in the methodology section, other factors may have an impact on fund companies' purchasing decisions as well. Accordingly, I incorporate the control variables of $Unfulfilled\ Proportion,\ Allocation$, P/E , $Size$, $Profitability$, $Growth\ Rate$ and $Hi\text{-}\ tech\ dummy$ in model 5 besides the key variables of $Bid\ Agg$, $Adjusted\ Bid\ Amount$ and $\Delta Price$. When including the control variables, all of the three key variables in model 5 are still statistically significant at 1% level and have a positive impact on Buy_{scale}. In terms of the economic significance, a one-unit increase in a fund company's bid aggressiveness makes the purchase amount increase by 58.27% when holding all other variables at a certain value. This indicates that the impact of bid aggressiveness is economically meaningful. Ceteris paribus, the purchase amount is expected to grow by 0.14% for a 1% increase in bid amounts/net asset of fund company, implying that the variable of $Adjusted\ Bid\ Amount$ is economically insignificant. However, $\Delta Price$ is also economically meaningful as a predictor of the purchase amount in the secondary market. Holding the other variables at a fixed value, the purchase amount will increase by 67.16% along with one-unit growth in $\Delta Price$. Based on the statistically and economically significant results of $Bid\ Agg$ and $\Delta Price$, and the weak evidence of $Adjusted\ Bid\ Amount$, I conclude that fund companies truthfully reveal their information through bids, i.e. H1a is supported.

Meanwhile, it is also worth studying the impact of control variables on fund companies' investment decisions. In Section 4.8.1, I have found that fund companies that do not receive shares in IPOs have a stronger willingness to purchase shares from the secondary market. However, the variable of *Allocation* does not show significance in the multivariate analysis. On the other hand, it is attested that fund companies will purchase more shares in large IPOs and in those with a high profitability and rapid growth rate, which is consistent with the conventional wisdom that investors prefer to invest in firms with better operating performances. Economically, as a one-unit increase for the variables of *Profitability* and *Growth Rate* occurs, the purchasing amount is estimated to be enhanced by 1.07 times and

34.57% respectively, when the other variables are kept as constant. The economical meaning of $Size$ is relatively low because a 1% increase for IPO proceeds only raises the purchase amount by 0.28%. Moreover, the variables of $P/E\ ratio$ and $Hi\text{-}tech\,dummy$ do not have an influential impact on the dependent variable, indicating that fund companies do not favor Hi-tech firms and IPOs with high P/E ratios.

4.8.3. Robustness Tests

In this section, I conduct several robustness tests. Firstly, I use an alternative measurement to control the post-IPO market condition. Specifically, I re-generate the variable of $\Delta Price$ using the *average* daily closing price between the first trading day and the following quarter-report day, $\overline{P_c}$, instead of the *lowest* daily closing price P_{min}. Hence, $\Delta Price$ is calculated as $(P_b - \overline{P_c})/\overline{P_c}$. The results based on $\overline{P_c}$ are presented in Table 4.8. In Table 4.8, we can see that the key variables of $Bid\ Agg$, $Adjusted\ Bid\ Amount$, and $\Delta Price$ are still positively significant in all of the models, which supports H1a. For the other control variables, they are qualitatively consistent with the results of Table 4.7 as well. Accordingly, this test shows that my results are not driven by the choice of the secondary market price benchmark.

Essentially, I would like to investigate whether the purchase willingness revealed in the quasi-bookbuilding mechanism has any influence on the number of shares purchased in the secondary market. Since the purchase amount is a count variable, when it is used as dependent variable I can apply negative binomial regression or Poisson regression. Negative binomial regression is typically used for over-dispersed count data, which is when the variance of a dependent variable is much higher than the mean. On the contrary, Poisson regression is more suitable when the data is not over-dispersed, i.e. the variance of the dependent variable does not exceed the mean. For my research sample, the variance of purchase amount is 17,611 million shares which is significantly higher than the mean value of 12,469 shares. Therefore, I apply negative binomial panel regression with fixed-effects as another robustness test. In this test, *purchase amount* is being directly used as the dependent variable without a logarithm transformation. In addition, I exclude the 155 selling cases since the dependent variable in negative binomial regression has to be non-negative. With regard to the independent variables, they are the same as in Table 4.7. The results of negative binomial panel regression are presented in Table 4.9.

In general, the results based on negative binomial panel regression are qualitatively similar to those shown in Table 4.7. The only difference is the variable of $Adjusted\ Bid\ Amount$ in Table 4.9 is not only economically insignificant but also statistically insignificant. This implies that $Adjusted\ Bid\ Amount$ is a relatively unreliable indicator of investor's demand. In addition, I also conduct negative binomial panel regression in the case that $\Delta Price$ is calculated using $\overline{P_c}$ instead of P_{min} and present the results in Table 4.10. Except the variable of adjusted Bid Amount turns to be insignificant, the results of Table 4.10 are qualitatively consistent with those of Table 4.8.

Table 4.8 Factors that affect fund companies' purchasing behaviors in the secondary market (Robustness tests: $\overline{P_c}$ is used as benchmark)

This table presents the results of panel regression with fixed-effects for fund companies. The dependent variable of Buy_{scale} is defined as $\ln(1 + \text{purchase amount})$, where purchase amount is measured by the difference between the holding amount on the first report day and the IPO allocation amount. *Bid Agg* is defined as the quantity-weighted bid price / midpoint of the initial price range. $\Delta Price$ is calculated as $(P_b - \overline{P_c})/\overline{P_c}$, where P_b is the quantity-weighted average bid price and $\overline{P_c}$ is the average daily closing price between the first trading day and the following quarter-report day. The dummy variable of *Allocation* equals 1 if a fund company receives shares from an IPO allocation and 0 otherwise. *Size* is measured by the natural logarithm of total IPO proceeds. *Profitability* is measured by the net profit margin. *Growth rate* is gauged by the sales growth rate. The dummy variable of *Hi-tech* equals 1 if the issuing firm belongs to the Hi-tech industry and 0 otherwise. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: Buy_{scale}					
Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5
Bid Agg	1.2362***			1.0209***	0.6149***
	(8.85)			(6.71)	(3.25)
Adjusted Bid Amount		0.1237***		0.1179***	0.1326***
		(3.98)		(3.75)	(3.89)
$\Delta Price$ (Using $\overline{P_c}$)			1.0597***	0.8377***	0.6339***
			(6.66)	(4.90)	(3.39)
Unfulfilled Proportion					0.3802
					(0.96)
Allocation					0.2220*
					(1.67)
P/E					0.0017
					(0.82)
Size					0.2845***
					(4.21)
Profitability					1.0536***
					(3.33)
Growth Rate					0.3526**
					(2.41)
Hi-tech					0.0408
					(0.37)
Constant	-0.4257***	1.1901***	0.8496***	0.4486**	-1.7474***
	(-3.41)	(8.63)	(18.85)	(2.06)	(-2.70)
Number of obs	7,133	6,969	7,133	6,969	6,969
Number of funds	63	61	63	61	61
R-squared within	1.10%	0.23%	0.62%	1.62%	2.35%
R-squared between	0.05%	4.75%	4.23%	7.94%	0.70%
R-squared overall	1.07%	0.04%	0.58%	1.27%	1.97%

Table 4.9 Factors that affect fund companies' purchasing behaviors in the secondary market (Robustness tests: negative binomial panel regression)

This table presents the results of negative binomial panel regression with fixed-effects for fund companies. The dependent variable is the purchase amount which is measured by the difference between the holding amount on the first report day and the IPO allocation amount. *Bid Agg* is defined as the quantity-weighted bid price / midpoint of the initial price range. $\Delta Price$ is calculated as $(P_b - P_{min})/P_{min}$, where P_b is the quantity-weighted average bid price and P_{min} is the lowest daily closing price between the first trading day and the following quarter-report day. The dummy variable of *Allocation* equals 1 if a fund company receives shares from an IPO allocation and 0 otherwise. *Size* is measured by the natural logarithm of total IPO proceeds. *Profitability* is measured by the net profit margin. *Growth rate* is gauged by the sales growth rate. The dummy variable of *Hi-tech* equals 1 if the issuing firm belongs to the Hi-tech industry and 0 otherwise. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: *Purchase amount*					
Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5
Bid Agg	1.4328***			1.2076***	0.8620***
	(9.77)			(7.71)	(4.15)
Adjusted Bid Amount		0.0752*		0.0785*	0.0665
		(1.86)		(1.92)	(1.54)
$\Delta Price$			1.5774***	1.3015***	0.9774***
			(7.17)	(5.59)	(3.79)
Unfulfilled Proportion					1.2315*
					(1.91)
Allocation					0.4987***
					(2.89)
P/E					0.00003
					(0.01)
Size					0.5147***
					(5.00)
Profitability					1.5763***
					(3.53)
Growth Rate					0.4467**
					(1.97)
Hi-tech					0.1309
					(0.76)
Constant	-6.9605***	-5.3431***	-5.5642***	-6.3367***	-11.1530***
	(-45.66)	(-29.63)	(-98.31)	(-25.26)	(-11.57)
Number of obs	6,597	6,597	6,597	6,597	6,597
Number of funds	49	49	49	49	49

Table 4.10 Factors that affect fund companies' purchasing behaviors in the secondary market (Robustness tests: negative binomial panel regression $\overline{P_c}$ is used as benchmark)

This table presents the results of negative binomial panel regression with fixed-effects for fund companies. The dependent variable is the purchase amount which is measured by the difference between the holding amount on the first report day and the IPO allocation amount. *Bid Agg* is defined as the quantity-weighted bid price / midpoint of the initial price range. $\Delta Price$ is calculated as $(P_b - \overline{P_c})/\overline{P_c}$, where P_b is the quantity-weighted average bid price and $\overline{P_c}$ is the average daily closing price between the first trading day and the following quarter-report day. The dummy variable of *Allocation* equals 1 if a fund company receives shares from an IPO allocation and 0 otherwise. *Size* is measured by the natural logarithm of total IPO proceeds. *Profitability* is measured by the net profit margin. *Growth rate* is gauged by the sales growth rate. The dummy variable of *Hi-tech* equals 1 if the issuing firm belongs to the Hi-tech industry and 0 otherwise. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: *Purchase amount*					
Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5
Bid Agg	1.4328***			1.2607***	0.9257***
	(9.77)			(7.83)	(4.40)
Adjusted Bid Amount		0.0752*		0.0803**	0.0657
		(1.86)		(1.97)	(1.53)
$\Delta Price$ (Using $\overline{P_c}$)			1.7445***	1.4776***	1.0853***
			(7.29)	(5.92)	(3.92)
Unfulfilled Proportion					1.2537*
					(1.95)
Allocation					0.5022***
					(2.92)
P/E					-0.0005
					(-0.19)
Size					0.5033***
					(4.87)
Profitability					1.5472***
					(3.48)
Growth Rate					0.4491**
					(1.99)
Hi-tech					0.1278
					(0.74)
Constant	-6.9605***	-5.3431***	-5.3815***	-6.2227***	-11.0163***
	(-45.66)	(-29.63)	(-84.47)	(-24.14)	(-11.35)
Number of obs	6,597	6,597	6,597	6,597	6,597
Number of funds	49	49	49	49	49

Notably, the number of groups in Table 4.9 and Table 4.10 are only 49 rather than the whole sample of 63. This is because these 14 fund companies never purchased the issued shares from the secondary market during the sample period. Consequently, these 14 fund companies are dropped from the analysis because of no variance within group, which accounts for 536 fund company-IPO observations. Therefore, the number of observations decreases from 7,133 to 6,597. I further checked the features of the 14 dropped fund companies and find that they are small in size and rarely submit bids in the IPO market with a mean participating frequency of 27.5 times which is much lower than the sample mean value of 113.22 times.

As mentioned in the data section, the holding data of fund companies are mostly accurate for quarter 1 and quarter 3 but fully accurate for quarter 2 and quarter 4. In previous tests, I used the entire four-quarter sample for the purpose of maximizing the sample size. To ensure that my conclusions are not affected by data biases, I replicate all of the preceding tests using only IPOs whose first quarter report day is in June or December. Consequently, the sub-sample consists of 52 fund companies and 194 IPOs. Among the 194 IPOs, 101 of them list in the SME board and the other 93 firms list in the ChiNext board. The results of the sub-sample are illustrated in Table 4.11 - Table 4.14 and are qualitatively consistent with all of the results when the full sample is applied. In conclusion, the robustness tests also imply that fund companies truthfully reveal their information through bids in this quasi-bookbuilding mechanism.

Table 4.11 Fund companies' trading behaviors based on different bid aggressiveness and bid amount (Quarter 2 and 4 samples only)

This table presents the fund companies' trading behaviors in the secondary market for different bid aggressive groups and bid amount groups. In panel A, the fund companies are classified into low/mid/high aggressive groups according to their bid aggressiveness, where bid aggressiveness is defined as the quantity-weighted bid price / midpoint of the initial price range. In panel B, the fund companies are assigned as low/mid/high bid amount groups based on their bid amount. For either classification (aggressiveness/amount), there are five possible outcomes: 1. Allocated shares in IPO and make more purchases in the secondary market. 2. No allocation in IPO and make purchases in the secondary market. 3. Allocated in IPO and no further purchase in the secondary market. 4. No allocation in IPO and no purchase in the secondary market. 5. Allocated shares in IPO and sell those allocated shares.

Total cases	3,395					
Panel A: Behavior in different bid aggressiveness groups						
	Low bid aggressive group		Mid bid aggressive group		High bid aggressive group	
Total cases in different bid aggressive groups	1,132		1,132		1,131	
Allocated and purchase	4	**0.35%**	16	**1.41%**	23	**2.03%**
No allocation and purchase	31	**2.74%**	59	**5.21%**	69	**6.10%**
Allocated and no purchase	82	7.24%	119	10.51%	158	13.97%
No allocation and no purchase	1,007	88.96%	908	80.21%	844	74.62%
Sell allocated shares (only IPOs without lock-up requirement)	8	0.71%	30	2.65%	37	3.27%

Panel B: Behavior in different bid amount groups

	Low bid amount group		Mid bid amount group		High bid amount group	
Total cases in different bid amount groups	1,132		1,137		1,126	
Allocated and purchase	4	**0.35%**	11	**0.97%**	28	**2.49%**
No allocation and purchase	54	**4.77%**	59	**5.19%**	46	**4.09%**
Allocated and no purchase	68	6.01%	112	9.85%	179	15.90%

Table 4.11 – Continued

No allocation and no purchase	1,005	88.78%	945	83.11%	809	71.85%
Sell allocated shares (only IPOs without lock-up requirement)	1	0.09%	10	0.88%	64	5.68%

Table 4.12 Fund companies' trading behaviors under two different market conditions (Quarter 2 and 4 samples only)

This table presents the fund companies' trading behaviors in the secondary market when the secondary market price benchmark $\geq$ or $<$ the quantity-weighted average bid price P_b. In Panel A, I use the lowest daily closing price between the first trading day and the following quarter-report day P_{min} as benchmark. In panel B, I use the average daily closing price between the first trading day and the following quarter-report day $\overline{P_c}$ as benchmark. In each market condition, there are five possible outcomes: 1. Allocated shares in IPO and make more purchases in the secondary market. 2. No allocation in IPO and make purchases in the secondary market. 3. Allocated in IPO and no further purchase in the secondary market 4. No allocation in IPO and no purchase in the secondary market. 5. Allocated shares in IPO and sell those allocated shares.

Total cases	3,395			
Panel A: P_{min} is used as benchmark				
Mean of $(P_b - P_{min})/P_{min}$	-7.84%			
Median of $(P_b - P_{min})/P_{min}$	-9.79%			
	$P_{min} \geq P_b$ (should not purchase)		$P_{min} < P_b$ (should purchase)	
Total cases in different market conditions	2,227		1,168	
Allocated and purchase	14	**0.63%**	29	**2.48%**
No allocation and purchase	96	**4.31%**	63	**5.39%**
Allocated and no purchase	145	6.51%	214	18.32%
No allocation and no purchase	1,945	87.34%	814	69.69%
Sell allocated shares (only IPOs without lock-up requirement)	27	1.21%	48	4.11%

Panel B: $\overline{P_c}$ is used as benchmark				
Mean of $(P_b - \overline{P_c})/\overline{P_c}$	-16.89%			
Median of $(P_b - \overline{P_c})/\overline{P_c}$	-18.12%			
	$\overline{P_c} \geq P_b$ (should not purchase)		$\overline{P_c} < P_b$ (should purchase)	
Total cases in different market conditions	2,668		727	
Allocated and purchase	21	**0.79%**	22	**3.03%**
No allocation and purchase	118	**4.42%**	41	**5.64%**
Allocated and no purchase	204	7.65%	155	21.32%

Table 4.12 – Continued

No allocation and no purchase	2,285	85.64%	474	65.20%
Sell allocated shares (only IPOs without lock-up requirement)	40	1.50%	35	4.81%

Table 4.13 Factors that affect fund companies' purchasing behaviors in the secondary market (Quarter 2 and 4 samples only & P_{min} is used as benchmark)

This table presents the results of panel regression with fixed-effects for fund companies. The dependent variable of Buy_{scale} is defined as $\ln(1 + \text{purchase amount})$, where purchase amount is measured by the difference between the holding amount on the first report day and the IPO allocation amount. *Bid Agg* is defined as the quantity-weighted bid price / midpoint of the initial price range. $\Delta Price$ is calculated as $(P_b - P_{min})/P_{min}$, where P_b is the quantity-weighted average bid price and P_{min} is the lowest daily closing price between the first trading day and the following quarter-report day. The dummy variable of *Allocation* equals 1 if a fund company receives shares from an IPO allocation and 0 otherwise. *Size* is measured by the natural logarithm of total IPO proceeds. *Profitability* is measured by the net profit margin. *Growth rate* is gauged by the sales growth rate. The dummy variable of *Hi-tech* equals 1 if the issuing firm belongs to the Hi-tech industry and 0 otherwise. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: Buy_{scale}					
Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5
Bid Agg	1.1499***			1.0244***	0.5656**
	(5.70)			(4.87)	(1.97)
Adjusted Bid Amount		0.0985**		0.1115**	0.1187**
		(2.20)		(2.45)	(2.38)
$\Delta Price$			1.0731***	1.0725***	0.7238***
			(5.20)	(5.00)	(3.07)
					0.5335
					(0.90)
Allocation					0.2782
					(1.38)
P/E					-0.0019
					(-0.54)
Size					0.5242***
					(5.30)
Profitability					1.2722***
					(2.64)
Growth Rate					0.3345
					(1.62)
Hi-tech					0.0566
					(0.33)
Constant	-0.2974*	1.1341***	0.7752***	0.3951	-3.3126***
	(-1.65)	(5.68)	(15.36)	(1.35)	(-3.57)
Number of obs	3,395	3,309	3,395	3,309	3,309
Number of funds	59	58	59	58	58
R-squared within	0.97%	0.15%	0.80%	1.83%	3.26%
R-squared between	0.02%	0.19%	6.39%	2.22%	1.27%
R-squared overall	0.94%	0.03%	0.68%	1.46%	2.85%

Table 4.14 Factors that affect fund companies' purchasing behaviors in the secondary market (Quarter 2 and 4 samples only & $\overline{P_c}$ is used as benchmark)

This table presents the results of panel regression with fixed-effects for fund companies. The dependent variable of Buy_{scale} is defined as $\ln(1 + \text{purchase amount})$, where purchase amount is measured by the difference between the holding amount on the first report day and the IPO allocation amount. *Bid Agg* is defined as the quantity-weighted bid price / midpoint of the initial price range. $\Delta Price$ is calculated as $(P_b - \overline{P_c})/\overline{P_c}$, where P_b is the quantity-weighted average bid price and $\overline{P_c}$ is the average daily closing price between the first trading day and the following quarter-report day. The dummy variable of *Allocation* equals 1 if a fund company receives shares from an IPO allocation and 0 otherwise. *Size* is measured by the natural logarithm of total IPO proceeds. *Profitability* is measured by the net profit margin. *Growth rate* is gauged by the sales growth rate. The dummy variable of *Hi-tech* equals 1 if the issuing firm belongs to the Hi-tech industry and 0 otherwise. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Dependent variable: Buy_{scale}					
Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5
Bid Agg	1.1499***			1.0102***	0.5581*
	(5.70)			(4.79)	(1.94)
Adjusted Bid Amount		0.0985**		0.1107**	0.1182**
		(2.20)		(2.43)	(2.36)
					0.7557***
					(2.90)
$\Delta Price$ (Using $\overline{P_c}$)			1.1515***	1.1339***	0.5380
			(5.04)	(4.75)	(0.91)
Allocation					0.2892
					(1.44)
P/E					-0.0022
					(-0.63)
Size					0.5325***
					(5.40)
Profitability					1.2677***
					(2.63)
Growth Rate					0.3580*
					(1.74)
Hi-tech					0.0375
					(0.22)
Constant	-0.2974*	1.1341***	0.8855***	0.5109*	-3.2853***
	(-1.65)	(5.68)	(14.42)	(1.70)	(-3.51)
Number of obs	3,395	3,309	3,395	3,309	3,309
Number of funds	59	58	59	58	58
R-squared within	0.97%	0.15%	0.76%	1.76%	3.23%
R-squared between	0.02%	0.19%	5.29%	1.61%	1.08%
R-squared overall	0.94%	0.03%	0.64%	1.39%	2.83%

4.9. Exaggerated Bid Amount

Taking into account the heavy oversubscription in Chinese IPOs, fund companies could exaggerate the bid amount so that they can attain a higher probability of obtaining shares. Therefore, it is also important to test whether the subscribed amounts properly reflect the bidder's demand. Specifically, I will test whether fund companies buy as many shares as they subscribed.

In this test, I only focus on the 376 cases where fund companies purchased shares from the secondary market. I firstly calculate the subscribed and allocated amount. Since one institution's purchase quantity is reasonably driven by a demand that is not fulfilled in the allocation, I calculate the unfulfilled amount which is the difference between the subscribed amount and the allocated amount. Moreover, I divide the unfulfilled amount by the subscribed amount to generate the variable of unfulfilled proportion. Finally, the purchase amount and the proportion of purchase amount to the unfulfilled amount are computed.

Table 4.15 presents the mean and median of the aforementioned variables. The mean subscribed amount for the 376 purchasing cases is 11.23 million shares. However, only 0.26 million shares are allocated in the average case due to the severe oversubscription. As a result, there is on average an unfulfilled demand of 10.97 million shares for one institution in an IPO, accounting for 96.59% of the initial subscription. Although the allocation barely meets fund companies' demands, institutions only purchase 0.77 million shares from the secondary market. The purchase amount barely takes up 20.63% of the unfulfilled demand, indicating that fund companies do not purchase as many shares as they subscribed in the primary market. Alternatively, it could be the case that the purchase proportion is positively correlated to the unfulfilled proportion despite the absolute value of purchase proportion is low. Hence, I calculate the correlation coefficient between the two variables. The insignificantly low coefficient of -0.0155 suggests that the two proportions are uncorrelated to each other. Based on the low purchase proportion and the insignificant coefficient, it shows that fund companies exaggerate their bid amounts in the primary market.

The results based on all of the 376 purchasing cases do not consider the market conditions. Fund companies may only fully purchase what they missed in an IPO when the secondary market price is lower than fund companies' valuations. As same as the method used in Table 4.6, therefore, I explore fund companies' purchasing behaviors under two market conditions. The first condition is $P_{min} \geq P_b$ and the second is $P_{min} < P_b$, where P_{min} is the lowest daily closing price between the first trading day and the first quarter-report day and P_b is the quantity-weighted bid price. The results are presented in Panel A of Table 4.15 In line with the full sample of 376 cases, tests on sub-samples also show a low purchase proportion and an insignificant correlation coefficient between the purchase proportion and the unfulfilled proportion. In addition, I conduct an equality test for the purchase proportion of the two sub-samples. The result of the t-test shows the difference is insignificant. In Panel B of Table 4.15, I present the results when $\overline{P_c}$, the average daily closing price between the first trading day and the first quarter-report day, is used as the after-market benchmark. The result based on $\overline{P_c}$ is qualitatively consistent with that of P_{min}.

The finding that fund companies exaggerate their amounts is consistent with the statistically significant but economically insignificant result of the *Adjusted Bid Amount* in the multivariate tests. I argue that the exaggeration does not mean that bid amount is an entirely unreliable indicator of interest. For example, there are two fund companies with a subscribed amount of 500 and 100 million shares respectively. My results indicate that the value of both could be inflated, but the willingness to obtain IPO shares is higher for a fund company that demands 500 million shares than a fund company that subscribes only 100 million shares. In other words, the bid amount reflects an institution's *relative* willingness while the absolute degree of demand is inflated.

Table 4.15 The exaggeration in bid amount

This table describes the share subscription, allocation and fund companies' purchase behaviors. Herein, the unfulfilled amount is the difference between the subscribed amount and the allocated amount. Besides, unfulfilled proportion is calculated as the subscribed amount divided by the unfulfilled amount. The purchase proportion is the proportion of purchase amount to the unfulfilled amount. Besides the full sample, I also conduct tests when the secondary market price benchmark ≥ or < the quantity-weighted average bid price P_b. In Panel A, I use the lowest daily closing price between the first trading day and the following quarter-report day P_{min} as benchmark. In panel B, I use the average daily closing price between the first trading day and the following quarter-report day $\overline{P_c}$ as benchmark.

Panel A: P_{min} is used as benchmark

	All purchasing cases		$P_{min} \geq P_b$ (should not purchase)		$P_{min} < P_b$ (should purchase)	
Number of cases	376		217		159	
	Mean	Median	Mean	Median	Mean	Median
Subscribed amount	11.23	5.48	11.04	5.52	11.49	5.00
Allocated amount	0.26	0.00	0.16	0.00	0.39	0.00
unfulfilled amount	10.97	5.14	10.88	5.50	11.10	4.80
unfulfilled proportion	96.59%	100%	98.24%	100%	94.34%	100%
Purchase amount	0.77	0.42	0.74	0.40	0.80	0.44
Purchase proportion	**20.63%**	**7.40%**	**19.70%**	**6.35%**	**21.92%**	**7.68%**
Correlation between the purchase proportion and the unfulfilled proportion	**-0.0155**		**-0.0123**		**-0.0105**	

Panel B: $\overline{P_c}$ is used as benchmark

	Full		$\overline{P_c} \geq P_b$ (should not purchase)		$\overline{P_c} < P_b$ (should purchase)	
Number of cases	376		283		93	
	Mean	Median	Mean	Median	Mean	Median
Subscribed amount	11.23	5.48	11.49	6.00	10.42	4.00
Allocated amount	0.26	0.00	0.22	0.00	0.38	0.00
unfulfilled amount	10.97	5.14	11.28	6.00	10.04	3.96

Table 4.15 – Continued

unfulfilled proportion	96.59%	100%	97.77%	100%	92.99%	100%
Purchase amount	0.77	0.42	0.80	0.43	0.68	0.37
Purchase proportion	**20.63%**	**7.40%**	**20.09%**	**6.67%**	**22.31%**	**7.89%**
Correlation between the purchase proportion and the unfulfilled proportion	**-0.0155**		**-0.0547**		**0.0653**	

There are two plausible reasons for fund companies overstating their demands. Firstly, a higher subscription can potentially increase the chance of receiving an allocation since more bids could be qualified for the lottery-based allocation. Secondly, Khurshed et al. (2014) state that institutions might inflate their demand in the early stage of bookbuidling in order to attract the attention of retail investors. As a Chinese IPO is a sequential hybrid offering in which individual investors start subscribing the IPO shares after the offering to institutions, institutions could exaggerate their demands to attract retail investors and make the offering "hot".

4.10. Conclusions

In this paper, I find that fund companies will purchase more shares from the secondary market if they have shown strong willingness to obtain shares in a quasi-bookbuilding IPO mechanism. Meanwhile, when the fund company's valuation is higher than the after-market share price, they also have a strong propensity to make purchases, and vice versa. In other words, their investment decisions are based on the valuation revealed in the quasi-bookbuilding process. Therefore, I conclude that fund companies truthfully disclose their private information (honest valuation) via bids.

My findings contribute to the literature by providing new empirical evidence on the information compensation theory. In common with Cornelli and Goldreich (2003), I find that investors truthfully reveal their information via bids although the mechanism being tested in my research does not have discretionary allocation. This finding also provides empirical evidence for the theoretical models developed by Biais et al. (2002) and Biais and Faugeron-Crouzet (2002) as they illustrated that both the bookbuilding and the *Offre a Prix Minimum* mechanisms, an auction-like IPO method, have information elicitation and price discovery functions although the latter is not embedded with a discretionary allocation.

On the other hand, my findings contrast with the conclusion of Benveniste and Wilhelm (1990) which stated that information gathering is impossible when allocation discretion is restricted. I argue that the compensation for revealing information can be replaced by the mechanism design, for example the qualification system and the lottery-based allocation mechanism. The model of Busaba and Chang (2010) suggests that informed investors could conceal their information in the primary market and profit from this private information via trading in the secondary market. Empirically, my findings show that investors truthfully reveal their information in the primary market rather than trading on their private information in the secondary market. This is consistent with the conclusion of Busaba and Chang (2010) that informed investors should reveal their information in the primary market in exchange for underpricing compensation, rather than strategically trade until the issued shares start trading in the secondary market because the former generates a higher profit.

My research also provides implications for IPO mechanism design. For the quasi-bookbuilding mechanism tested in this paper, its allocation rule is specified and publicly available in advance. It also offers institutional investors an equal chance to obtain IPO shares. In addition, this mechanism avoids the free-rider problem as the highest bids are not given priority in allocation. Moreover, detailed bid information is disclosed to the public, making the process more transparent. Although this mechanism raises a concern over the incentive behind revealing private information, my results suggest that institutions still play a price discovery role even if there is no guaranteed compensation such as favored allocation. The incentives to provide honest valuation could come from the mechanism design where institutions will not be qualified for the allocation process if an extremely low price is bid, and the chance to obtain shares will not increase significantly even if an excessively high price is submitted. Hence, my findings imply that this relatively fair and transparent quasi-bookbuilding mechanism is able to exert the same price discovery function as opaque alternatives.

Chapter 5

5. The Valuation Premium of Foreign IPOs in the United States

5.1. Introduction

As a consequence of global financial integration and China's high-speed economic development, a large number of Chinese firms have been listed in the international stock markets. On 26th July 1993, Sinopec Shanghai Petrochemical listed in the New York Stock Exchange (NYSE) and became the first Chinese firm to issue shares in a foreign country. As of May 2014, there were 1,226 Chinese firms listed on foreign stock exchanges. Among them, 786 firms were listed in Hong Kong,[98] 216 firms were listed in the US, 134 firms were listed in Singapore, and 26 and 20 firms listed on London Stock Exchanges (LSE) and Frankfurt Stock Exchange respectively[99]. It can be seen that the US market is the primary destination for foreign-listed Chinese firms in terms of the listing volume. Most of the US-listed Chinese firms are either state-owned enterprises (SOEs) that have an enormous impact on China's economy or the leading private firms in their industries. Taking into account the growing impact of the Chinese economy on global financial markets and the dominant position of these US-listed Chinese firms in China, it is meaningful to investigate why these Chinese firms bypass the domestic market and list in the US.

Among the extensive literature on foreign listing, the vast majority focuses on foreign cross-listing, particularly among developed countries. Cross-listing, sometimes called dual-listing or inter-listing, refers to the behavior of firms that make their shares tradable on at least one foreign exchange following an IPO in their domestic markets. Several theories such as bonding theory, market segmentation theory and improvement of information environment theory are used to explain the

[98] The listing of mainland China firms in Hong Kong are normally perceived as foreign listing in the literature since Hong Kong and mainland China have very different economic and political systems.

[99] Source: Annual Foreign IPO Report for Chinese Firms (2014), published by the Shanghai Stock Exchange.

phenomenon of cross-listing. In contrast to the decline in cross-listing activity, there is a growing trend that firms bypass their domestic markets and directly undertake an IPO on a foreign stock exchange (Caglio et al., 2013), which is defined as a foreign IPO in the literature. However, studies on foreign IPOs are limited when comparing with the large amount of research on cross-listing. Therefore, it is not conclusive that whether the explanations for cross-listing phenomenon are applicable to foreign IPOs or not.

For instance, cross-listing is perceived as an effective way to mitigate the costs of market segmentation as cross-listing firms can expand their investor bases. For foreign IPOs, it also helps firms to expand their investor bases from board members or venture capitalists to public investors. Different from domestic IPOs, the public investors in foreign IPO cases are foreign investors who may have better evaluation abilities than domestic counterparts or need investment in foreign shares to diversify their portfolios. Moreover, as Chinese foreign IPO firms come from a developing market with lower regulatory standards, undertaking IPOs in a developed foreign market would force IPO firms to adhere to more rigorous regulations. One potential benefit of this behavior, known as "bonding" is to improve the information environment, which could motivate foreign investors to offer a higher valuation as a form of compensation for the voluntary compliance and information availability. Since foreign IPOs are firms that are financed abroad, raising capital plays a decisive role as suggested by the IPO literature (Chemmanur and Fulghieri, 1999; Pástor and Veronesi, 2005). Pagano et al. (2002) argue that firms with higher growth or investment are more likely to cross-list on a developed and deep market for the sake of raising capital, and are expected to obtain a higher P/E ratio than comparable domestic counterparts because of the promising potential expansion. Correspondingly, a similar question is raised in the context of a foreign IPO: whether foreign IPO firms can obtain higher valuations than their domestic counterparts? This is the question I will answer in this research.

Building upon the theories derived from the cross-listing research, I investigate the impact of foreign IPOs on the valuation of Chinese firms using a sample of 136 US-listed Chinese firms and their domestic-listed peers during the period of 1999-2012. Specifically, price multiples (price-to-book ratio and price-to-sales ratio) and underpricing are used as the proxies for valuation. After controlling for firm characteristics, I find that US-listed Chinese firms have higher price multiples and experience less underpricing than domestic-listed Chinese firms. The empirical results support the hypothesis that Chinese firms that conduct IPOs in the US can obtain a higher valuation. This finding is consistent with the conclusion of Sundaram and Logue (1996) and Doidge et al. (2004) who discovered that a valuation premium exists for foreign firms cross-listing in the US. Therefore, this paper contributes to the literature by providing evidence that theories derived from cross-listing research can also be used to aid explanations of the foreign IPO phenomenon. In addition, I find that high-tech firms with high growth speed but low profitability are more likely to list their shares in the US, particularly for firms that belong to semiconductors, software and online business services. Industry clustering implies that accessing foreign expertise is also an important incentive for Chinese firms to conduct IPOs in the US, and is consistent with the argument of Allen and Gale (1999) who claim that the US equity market has the ability to evaluate the prospects of innovative firms.

The remainder of this paper is structured as follows. Section 5.2 will review the literature pertaining to cross-listing and foreign IPOs. The hypothesis is developed in Section 5.3. Section 5.4 describes the data and Section 5.5 illustrates the descriptive statistics of the research sample. The methodology is discussed in Section 5.6. In Section 5.7, I present the results. Finally, Section 5.8 concludes.

5.2. Literature Review

5.2.1. Cross-Listing

As pointed out by Caglio et al. (2013), the determinants of foreign IPOs and cross-listing are different. Hence, I review the literature about these two types of the foreign-listing phenomenon separately. There are three prevalent theories put forward to explain cross-listing; namely market segmentation theory, bonding theory and the improvement of information environment theory. Based on these three major theories, scholars have summarized several cross-listing benefits/motives such as broadening the shareholder base (Mittoo, 1992; Foerster and Karolyi, 1999; Bancel and Mittoo, 2001), lowering the cost of capital (Foerster and Karolyi, 1993; Jayaraman et al., 1993; Sundaram and Logue, 1996; Foerster and Karolyi, 1999), increasing liquidity (Mittoo, 1992; Foerster and Karolyi, 1993; 1999), reducing trading cost (Foerster and Karolyi, 1998), improving reputation and visibility in foreign market (Saudagaran, 1988; Saudagaran and Biddle, 1995; Pagano et al., 2002; Bancel and Mittoo, 2001; Baker et al., 2002), accessing foreign capital (Saudagaran, 1988; Mittoo, 1992; Pagano et al., 2002), strengthening corporate governance and protecting shareholder rights (Coffee, 1999; Stulz, 1999; Coffee, 2002; Reese and Weisbach, 2002; Doidge et al., 2004), improving information environment (Baker et al., 2002; Lang et al., 2003; Bailey et al., 2006), obtaining foreign expertise (Pagano et al., 2002) and so forth. On the other hand, costly underwriting and listing fees, stringent reporting and compliance requirements are normally perceived as the main costs of foreign-listing (Mittoo, 1992; Saudagaran and Biddle, 1992; 1995).

I begin with the primary question of why firms cross-list in a foreign market. Saudagaran (1988) was the first paper that attempted to answer this question. Using a sample of 223 foreign-listed firms and 258 non-foreign listed firms, the author identified various factors that affect the decision of foreign-listing, such as the absolute size of the firm, nationality and industry. Consistent with market segmentation theory, he found that the relative firm size to its domestic capital market is positively correlated with the likelihood of undertaking foreign-listing. In addition, a large proportion of foreign sales also drives firms to issue shares in a foreign equity market. Pagano et al. (2002) studied the cross-listing phenomenon of European and US companies. By demonstrating the trends of foreign listings and analyzing a firm’s distinctive prelisting characteristics and post-listing performance, they found that US exchanges attract high-tech and export-oriented firms that expand rapidly without heavy leverage, which indicates the cross-listing incentives of obtaining foreign expertise, foreign sales expansion, and raising capital. However, it was also revealed that European firms that cross-list within Europe neither grow quickly, nor can they rely on foreign sales or increase their leverage after cross-listing. The result suggests that the cross-listing motives vary across companies from different regions.

Beyond the reasons of foreign cross-listing, a series of research focuses on the choice of foreign-listing location. Using a dataset of 302 foreign-listed firms in nine major stock exchanges by the end of 1987, Saudagaran and Biddle (1992) found that the choice of foreign-listing location is influenced by the financial disclosure level of the listing venues. More importantly, they created a financial disclosure index for the nine stock exchanges through the survey on 142 experts who are heavily involved in foreign-listing activities. Taking this idea one step further, Saudagaran and Biddle (1995) documented that firms are more likely to list on foreign stock exchanges with lower financial disclosure levels than their domestic exchanges[100] or account for larger marketing shares for the firms' products. By comparing the European and US capital markets, Pagano et al. (2002) showed that the US exchanges are attractive for high-tech firms with fast growth and seeking capital while the European exchange caters for mature companies with large size and little need for capital. Moreover, Sarkissian and Schill (2004) found the geographic, economic, cultural, and industrial proximity of foreign stock exchanges between two countries plays a decisive role in the choice of cross-listing location. Furthermore, they identified that firms tend to list

[100] This finding is in contrast with the results of latter research, for example Reese and Weisbach (2002), Doidge et al. (2004). However, Saudagaran and Biddle state that "changes in financial markets could affect motivations and choices of foreign listings". As the sample period covered by Saudagaran and Biddle (1995) is prior to the end of 1992, the inconsistent results could due to the change of market condition. In addition, most of the sample used in Saudagaran and Biddle (1995) are from developed countries, so the disclosure level is not significantly different across countries. In latter research, more firms from emerging market are included as research sample when they start listing overseas. Therefore, the various features of research sample potentially cause the inconsistent results.

in large and highly capitalized markets with low tax environments. Henderson et al. (2006) also found that geographic closeness has an impact on the issuing of securities overseas. In addition, they revealed that advanced markets, especially the US and UK, are ideal listing locations for firms from countries with illiquid equity markets.

Moreover, the literature studies the impact of foreign cross-listing on firms' share prices and operating performance. Foerster and Karolyi (1993) studied 49 cases of Canadian firms cross-listing on US exchanges from 1981 to 1990 and documented that the share prices of cross-listing Canadian firms increased by more than 9.4% during the 100 days before the cross-listing, and rose a further 2% around the day of cross-listing, but dropped 9.7% in the 100 days after cross-listing. The authors interpreted this finding as evidence of market segmentation between Canada and the US. Using a sample of 95 non-US firms that issued ADR from 1983 to 1988, Jayaraman et al. (1993) found that shares traded on cross-listing firms' home markets experienced a positive abnormal return of 0.47% on the ADR listing day, which is consistent with Foerster and Karolyi (1993). Regarding the impact on risk, they revealed that the issuance of ADR was accompanied by an increase in volatility of 56% for the underlying shares, indicating that cross-listing facilitates informed investors to take use of information asymmetry between the two markets. Analogously, Foerster and Karolyi (1999) documented a 19% cumulative abnormal return during the year before ADR listing and 20.2% during the listing week, but a significant decline of 14% in the year after cross-listing. These findings not only support market segmentation theory (Foerster and Karolyi, 1993; Jayaraman et al., 1993), but are also linked with an increase of shareholder base and can be interpreted as evidence in support of the investor recognition theory (Merton, 1987).

Scholars have also studied the cross-listing phenomenon from alternative angles. Instead of investigating cross-listing on the US market, Lau et al. (1994) studied 346 US firms that cross-listed on 10 non-US stock exchanges with the resulting having showed positive abnormal return around the acceptance of application by foreign exchanges, negative abnormal return on the first trading day and negative abnormal return after cross-listing for firms issuing shares on the Tokyo and Basel exchanges. These findings are different from the conclusions drawn from research on non-US firms listing in the US, for example Jayaraman et al. (1993). Typically, event study on share price performance is used as a way to explore the impact of cross-listing. However, Sundaram and Logue (1996) used the valuation measures of price-to-book, price-to-cash-earnings, and price-to-earning to directly investigate the impact of cross-listing on firms' share prices. By doing so, Sundaram and Logue found the share valuations of cross-listing firms increased by up to 10% relative to the home country and world industry benchmarks. These findings are in line with those based on event study. On the other hand, Foerster and Karolyi (1998) examined the impact of cross-listing for Canadian firms in the US on trading cost and used bid-ask spread as the proxy for trading cost and found that the domestic bid-ask spread decreased after Canadian firms cross-listed. More importantly, the decline in trading costs is only documented for firms whose trading volumes shift from the domestic market (Canada) to the foreign exchanges (US), rather than for those without trading volume movement.

In summary, the aforementioned literature (Foerster and Karolyi, 1993; Jayaraman et al., 1993; Sundaram and Logue, 1996; Foerster and Karolyi, 1998; 1999) shows that cross-listing, mainly non-US firms listing in the US, increases the equity values and the liquidity of the listing firms, thereby reducing the cost of capital by alleviating the international market segmentation.

Building upon Jensen and Meckling (1976), Coffee (1999) and Stulz (1999) proposed the bonding hypothesis for the cross-listing phenomenon. The bonding hypothesis states that firms commit to stringent regulations and monitoring by listing their shares in a more sophisticated market relative to their domestic markets. By doing so, these firms can improve corporate governance and provide better protection to minority shareholders so that they can raise capital on better terms, for example a low cost of capital. Stulz (1999) analyzed different mechanisms through which a firm could improve its management and discussed how foreign-listing reduces the cost of capital by improving corporate governance instead of necessarily mitigating the market segmentation. Coffee (2002) referred to empirical findings in the literature to illustrate the effect of the bonding mechanism. For instance, Coffee interpreted the findings of Miller (1999), namely that exchange listing programs such as level II and level III ADRs experience higher abnormal returns than those listing in the over-the-counter (OTC)[101] market or PORTAL[102], as evidence for the bonding theory. In support of bonding theory, Reese and Weisbach (2002) found both the number and value of equity issues increase after cross-listing. More importantly, this increase is much stronger for cross-listed firms whose home countries have weaker shareholder protection than those from countries with strong shareholder protection, with the former subsequently more likely to issue equity outside the US. Doidge et al. (2004) also provided evidence in support of bonding theory and documented a significant valuation premium for foreign firms that cross-list on the US exchanges by revealing that Tobin's q ratio of cross-listed firms in the US is 16.5% higher than that of non-cross-listed firms from the same country, particularly those from countries with weak levels of investor protection.

Moreover, the literature investigates cross-listing from the perspective of a firm's information environment and proposes the theory of information environment improvement, which suggests that cross-listing enhances a firm's value by improving its information environment. Notably, the theory of information environment improvement is associated with the bonding hypothesis to some extent since firms have to disclose more information as a result of compliance with stringent regulations. With respect to the empirical evidence, Baker et al. (2002) documented that the volume of analysts' coverage and the frequency of appearances in leading financial journals increases the likelihood of cross-listing in the NYSE and the LSE, and that enhanced visibility is also associated with a lower cost of capital. This is

[101] It is also widely known as Pink Sheets.

[102] PORTAL is an abbreviation for private offerings, resale, and trading through automated linkages. It is the market for issues under SEC Rule 144a.

also consistent with the investor recognition hypothesis (Merton, 1987). In addition, Lang et al. (2003) found that non-US firms benefit from an increase in analysts' coverage and the improvement of forecast accuracy once they list shares on US exchanges; and that firms with higher levels of analyst coverage and forecast accuracy enjoy higher valuations. These findings provide empirical evidence supporting the theoretical models built by Diamond and Verrecchia (1991) and Baiman and Verrecchia (1996). On the other hand, Bailey et al. (2006) revealed that the reactions of both absolute return and trading volume to earnings announcements increase after a firm's cross-listing in the US, which implies an emerging change of the information environment with regards to cross-listing.

Moreover, researchers have also directly interviewed managers regarding the issues of cross-listing. Mittoo (1992) illustrated the costs, benefits and net benefits (benefits less costs) of cross-listing based on 78 questionnaires from Canadian managers whose firms cross-listed in the US. Accessing foreign capital markets, broadening investor base and increased marketability of a firm's securities were perceived as the major benefits of cross-listing by these Canadian managers. However, the reporting requirements of the Securities and Exchange Commission (SEC) are regarded as a major cost. Comparing the benefits and costs, the net benefits for these Canadian firms were positive although not very significant. In this case, it is plausible that these managers would decide to cross-list in US markets because they would like to capture these net benefits. Unlike the Canadian managers, Bancel and Mittoo (2001) found that the mangers of European firms do not regard the improvement of stock liquidity as a major benefit, and cite public relations costs as the major foreign-listing cost ahead of stringent disclosure regulations. This difference could be attributable to the cultural diversity between firms from different countries (Sarkissian and Schill, 2004). However, there are also common perceptions for Canadian and European managers. For example, managers from both countries regard increasing visibility and expanding shareholder base as benefits, and most think that the benefits exceed the costs of foreign-listing.

5.2.2. Foreign IPO

As shown above, the literature extensively focuses on the phenomenon of cross-listing. During the 1990s, there was a new trend where firms bypassed their domestic markets and undertook an IPO on a foreign stock exchange. Blass and Yafeh (2001) was the first that shed light on the area of foreign IPO. Using 163 domestic-listed and 56 US-listed Israeli firms from 1990 to 1996, they discovered that Israeli IPOs in the US were young, high-tech firms and in need of certification for their values. In addition, the US-listed firms raised more funds through their IPOs despite severe underpricing, exhibited lower profit margins but higher growth rates and had a higher ratio of exports to sales than the Israeli domestic issuers. Besides, Israeli companies listed in the US displayed superior performance both in terms of stock returns and revenue growth rate after undertaking foreign IPOs; however domestic-listed firms underperformed after undertaking IPOs in Israel. According to these findings, Blass and Yafeh concluded that foreign IPOs in the US serve as a signal of a high firm quality. Using the sample of European firms between 1991 and 2001, Hursti and Maula (2007) studied the foreign IPO decision primarily from the perspective of pre-IPO ownership structure and revealed that foreign venture capitalists, foreign shareholders and foreign experience of management teams have a positive impact on the propensity of foreign IPOs. In addition, they also found that high-tech firms and large firms are inclined to conduct foreign IPOs.

As shown above, the research generally focuses on the differences between foreign-listed firms and their domestic counterparts with regards either cross-listing or foreign IPOs. Bruner et al. (2004) and Ejara and Ghosh (2004), rather, compared the differences between foreign IPO firms and the domestic firms from the listing country rather than the originating country. Bruner et al. (2004) demonstrated that foreign IPO firms on US exchanges and local US firms experience similar issuing costs which are measured according to underwriting fees and underpricing scale. Secondly, a lack of information and country-specific risks are perceived as a risk of foreign IPOs. Thirdly, they explored that foreign US IPO issuers are typically large firms with tangible assets, listed on the NYSE and originating from countries that share a common border or language with the US. However, Ejara and Ghosh (2004) afforded a different finding in that ADR-backed IPOs[103] experienced less underpricing than the matched US local IPOs of around 15% even if the ADR-backed IPOs were significantly underpriced at a level of 12%. This could be attributed to the characteristics of ADR-backed firms in that they are large, lead their respective industry in their domestic markets, and enjoy strong reputations internationally. In order to list on US exchanges, these ADR-backed firms have to disclose large amounts of information in order to comply with SEC rules and the US Generally Accepted Accounting Principles (GAAP), which mitigate information asymmetry. Furthermore, it has also been documented that the more developed the home country is, the more severe the underpricing level will be; and that underpricing of privatization IPOs is lower than that of non-privatizations. Overall, Ejara and Ghosh concluded that foreign IPOs can enhance investor bases, increase liquidity, signal superior quality and therefore increase shareholders' wealth.

More comprehensively, Hasan and Waisman (2010) compared the performance of Israeli IPOs in the US with those from other countries and local US IPOs, and demonstrated that US-bound Israeli IPOs are less underpriced than their foreign and US local counterparts. The relatively moderate underpricing of Israeli IPOs may be due to the fact that Israeli IPOs are normally larger than their foreign peers; have products, licensing or franchising in the US market or US venture capitalists; and are highly involved with US institutional investors. These characteristics compensate the uncertainty and information asymmetry about the Israeli IPOs. Meanwhile, the

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[103] American Depositary Receipt (ADR) is a negotiable certificate representing the shares of a foreign company that traded in the US capital market. In the beginning, only cross-listing firms take use of ADR to make their shares tradable in the US. At present, non-US firms also use ADR to facilitate their IPOs in the US market. Instead of ADR program, non-US firms can directly list on US exchanges as well, but the process is much more complicated. Therefore, most of the non-US firms conduct IPOs in the US via ADRs, i.e. ADR-backed IPOs. Detailed description about ADR will be provided in Section 5.4.

Israeli issuers outperform those foreign and US local counterparts in terms of the long-run operating and share price performance. For the underpricing comparison, their findings are in line with Ejara and Ghosh (2004). In addition, this research also confirms that foreign firms conducting IPOs on US exchanges typically show a better quality (Blass and Yafeh, 2001; Bruner et al., 2004).

As analogous to foreign IPOs, another type of foreign IPO is the global IPO in which a certain proportion of primary shares are exclusively offered to foreign investors while the remaining shares are issued in the domestic market. Wu and Kwok (2003) and Wu and Kwok (2007) studied global IPOs by US firms from the perspectives of short-run and long-run performances. Wu and Kwok (2003) found that the underpricing of global IPOs were 4% less than those domestic-only IPOs , and that the more the shares were offered globally, the less underpricing occurred. This finding can demonstrate that foreign investors are optimistic and have an incentive to pay a high price in exchange for the benefits of international portfolio diversification. However, Wu and Kwok (2007) documented that the share price of global IPOs significantly underperformed domestic-only ones in the three years after the IPO, especially regarding those with a large offering proportion for foreign investors. However, global issuers outperformed domestic-only issuers in terms of operating performance. Both studies provide empirical evidence of the window of opportunity hypothesis whereby investors overestimate the prospects of global IPO firms.

Using ample data of 17,808 IPOs worldwide, Caglio et al. (2013) comprehensively reviewed the phenomenon of foreign-listing and disentangled the characteristics of foreign IPOs, cross-listing and global IPOs. Firstly, it was highlighted that the cases of cross-listing presents a declining trend globally whereas an increasing tendency for foreign IPO and global IPO. This could be the reason why the focus of research in this field has moved from cross-listing to foreign/global IPOs. In comparison with cross-listed firms, foreign IPO firms are smaller, have better growth prospects and are more likely to be innovative. More importantly, the motives of the cross-listing and foreign IPOs are different. Cases of foreign IPOs are more likely to be observed for firms from countries with an information disadvantage and inferior market quality since issuing firms expect that more capital can be raised in a foreign market with more proficient analysts and investors (Chemmanur and Fulghieri, 2006) and better information efficiency (Subrahmanyam and Titman, 1999). Besides the information environment consideration, Caglio et al. (2013) showed that bonding theory (Coffee, 1999; Stulz, 1999) is another explanation for foreign IPOs as issuing firms can increase the IPO proceeds if they commit to stringent regulations. However, the incentives of accessing a better information environment and "bonding" to rigorous laws on securities are not significant for those cross-listing firms. The authors also found that cross-listing firms choose to cross-list after conducting an IPO in their home countries rather than directly launching an IPO in a foreign country because the global market returns are low and the domestic IPO market is hot when they decide to go public. Regarding the choice of foreign listing venue, Caglio et al. (2013) found developed markets such as those of the US, the UK and Singapore are key listing locations, with the US a particularly attractive venue for foreign and global IPOs. In terms of IPO proceeds, issuing firms can raise more proceeds in a market with: high market returns one year before the ongoing IPO; a large number of IPO peers from the same industry; and a better bond market elaboration.

5.2.3. Foreign Listing of Chinese Firms

The literature also pays attention to the foreign-listing phenomenon of Chinese firms as China's rapid economic growth prompts more and more firms to become involved in international capital markets. In the past, research mainly focused on the phenomenon that mainland China's firms list on the Hong Kong stock exchange, especially after Hong Kong was returned to China in 1997. The cases where mainland China's firms list in Hong Kong are normally perceived as foreign listing in the literature since Hong Kong and mainland China have very different economic and political systems. In terms of the capital market, Hong Kong is far more developed than mainland China. For example, Allen et al. (2005) view Hong Kong as having a market with one of the best systems of investor protection, while those in mainland China are weak.

Chi and Zhang (2010) studied mainland China's firms that cross-list in the Hong Kong market from the view of executive compensation, and found that executive compensation is linked to operating performance such as sale growth for those cross-listing firms. In terms of the share performance, however, this does not seem to affect executive payment. Therefore, their study provides weak evidence for bonding theory as cross-listing in Hong Kong improves the rewarding system to some extent.

From the perspective of entrepreneurs, Ding et al. (2010) explored the question of why mainland China's firms undertake IPOs on the Hong Kong exchange, and found that the decision of undertaking an IPO in Hong Kong is driven by the entrepreneurial choice between a long-term prospect and a short-term financial benefit. In comparison with China's mainland-listed firms, Chinese firms that conduct IPOs in Hong Kong normally belong to high-growth industries, have a larger proportion of entrepreneur shareholdings before the IPO, issue less shares to the public, and apply better corporate governance mechanisms. Their findings provide supportive evidence for the hypothesis that foreign-listing is used as a signal of long-term entrepreneurial commitment.

On the other hand, Sun et al. (2013) studied 92 Chinese state-owned enterprises (SOEs) listed in Hong Kong to explore the reasons why Hong Kong is a better venue for privatization than the domestic market. Firstly, they argued that the domestic market is not yet well-developed enough to facilitate large-scale privatizations as the scale of Hong Kong-based IPOs is much larger than that of domestic alternatives. Secondly, listing in Hong Kong can help SOEs improve upon their corporate governance as they have to comply with stringent regulations. As a result, a valuation premium is awarded to firms listed in both Hong Kong and mainland markets.

Instead of the listing choice between mainland China and Hong Kong, Yang and

Lau (2006) investigated why Chinese firms prefer to list in Hong Kong rather than in the US. Using a sample of 136 Chinese firms, they revealed that Chinese firms listed in Hong Kong had a better information environment, measured by the level of analysts' coverage, than those listed only in the US. This finding suggests that the information environment is an important determinant for the choice of foreign-listing location beside obvious explanations such as geographical, language and cultural proximity, which is consistent with the conclusions of Baker et al. (2002) and Lang et al. (2003). In addition, Yang and Lau (2006) identified that the Hong Kong listed firms were less financially constrained, which was measured by the investment sensitivity to cash flows.

Besides listing in Hong Kong, a new trend of US listing has emerged in the past decade. Zhang and King (2010) studied Chinese firms' foreign-listing decisions by comparing the characteristics of foreign-listed Chinese firms with their those of their domestic counterparts. For the foreign-listing sample, the authors divided them into cross-listing in the US and foreign IPOs. Consistent with Pagano et al. (2002), they documented that the motivations that trigger Chinese firms to list in foreign markets are: adopting closer regulatory monitoring, significant demands for capital, broadening the shareholder base, foreign expertise and the ability of affording listing costs. However, their results are only significant for Chinese firms that cross-listed in the US rather than for those foreign IPO firms. Zhang and King also examined the operating and share performance of foreign-listed Chinese firms and found that operating performance deteriorates after foreign-listing while the share returns are negative after foreign-listing for both the short- and long-term.

Luo et al. (2012) focused on the post-IPO share performance of US-listed Chinese firms. Rather than comparing US-listed Chinese firms with their domestic counterparts, they documented that the US-listed Chinese firms generally underperformed their US-listing industry peers within the first three years after the IPO. Furthermore, the Chinese firms that cross-listed in the US performed better than those that directly undertook IPOs on US exchanges, which can be interpreted as being consistent with the bonding hypothesis.

On the other hand, Güçbilmez (2014) investigated the tendency of Chinese technology firms to bypass the domestic market and undertake an IPO in the US. Instead of the explanations regarding foreign sales and issuing cost, he found foreign venture capital to be a decisive driver that prompts Chinese technology firms to list in the US. In addition, US-listed firms are documented to be large and less profitable relative to their domestic peers, which is in line with the characteristics of US-listed Israeli firms as revealed by Blass and Yafeh (2001) and Hursti and Maula (2007).

There is also a stream of literature focusing on the accounting quality and litigations of US-listed Chinese firms, especially after Muddy Water revealed several fraud cases of Chinese firms, for example Orient Paper, RINO International Corporation, and Sino-Forest. Chen et al. (2016) examine the accounting quality of Chinese reverse merge firms. They find that Chinese reverse merge firms show lower financial reporting quality than Chinese ADR firms due to the weak bonding incentive and poor corporate governance. Similar conclusion was also drawn by Givoly et al. (2014). One of the causes of poor reporting quality is that US-listed Chinese firms are more likely to avoid hiring high quality US audit firms and US regulators are unable to have effective oversight of Chinese auditors (Carcello et al., 2014). Despite the negative publicity of reverse merge firms, Lee et al. (2015) document that reverse merge firms outperformed their matched counterparties even when most of the firms accused of accounting fraud are included in their sample. According to the literature, the majority of litigations are reverse merger cases by which private Chinese firms are acquired by a US-listed public shell company and merger into it. Comparing with ADR, the method of reverse merger is cheaper and quicker than listing through ADR. In addition, reverse merger firms typically trade over-the-counter. Jindra et al. (2015) conclude that the method of listing is the only statistically significant predictor of lawsuit risk. They find Chinese reverse merger firms are more likely to face litigation compared to US-listed Chinese firms by ADR. Therefore, the fraud cases have very little impact on my research because the sample used in my analysis is Chinese ADRs rather than reverse mergers. Although these litigations could harm the reputation of all US-listed Chinese firms due to spillover effect, the impact is limited because the scandals were disclosed after late 2010 that overlap slightly with my sample period.

5.2.4. Research Gap

The literature review suggests that more attention is paid to the cross-listing phenomenon than foreign IPO cases. Among the few papers that study foreign IPOs, many use US-based Israeli IPOs as a research sample because they were numerous during the 1990s. Since 2004, Chinese firms have presented a growing tendency to foreign-list in the US. As of 2012, there has been 149 Chinese firms listed on US exchanges. Therefore, it is worth investigating the new trend of Chinese firms listing in the US as the motivations for such listing of Chinese and Israeli firms can be distinct. For example, it has been documented that one of the decisive factors for Israeli firms in this regard concerns the scarcity of domestic funds (Blass and Yafeh, 2001). For the Chinese market, however, its domestic equity market had become the second largest market by 2012 in terms of market capitalization[104], suggesting that there are enough funds to meet the demand of growing firms. Hence, the listing motivations of Israeli firms cannot simply be attached to US-listed Chinese firms. Besides, an investigation into the impact of foreign IPOs on firms' valuations has not yet been conducted. As raising capital is crucial for IPO firms, my research complements the literature by exploring the foreign IPO phenomenon from the perspective of share valuation.

5.3. Hypothesis Development

In this research, I investigate why Chinese firms choose to undertake IPOs in the US. As discussed in the literature review, the theory of market segmentation proposes that foreign-listed firms issue shares abroad to conquer market segmentation. By doing so,

[104] Source: World Federation of Exchanges.

one of the benefits is that they can broaden their shareholder bases (Mittoo, 1992; Foerster and Karolyi, 1999; Bancel and Mittoo, 2001). For US-listed Chinese firms, they not only expand their shareholder bases via IPOs, but also intentionally issue shares in a foreign market that has more sophisticated investors than their domestic market. One advantage is that sophisticated investors possess a more adequate ability to evaluate the shares that are being newly issued. For example, there is a large amount of high-tech firms listed in US markets, while the businesses of some Chinese firms are similar to those already-listed US firms. Therefore, US investors are more knowledgeable in evaluating those Chinese high-tech firms since they have sufficient experience on the evaluation of such firms. Alternatively, if the high-tech firms choose to list domestically, they may suffer from downward bias in their valuation if domestic investors are unsophisticated or do not have the expertise required to appraise adequately the shares being issued. On the other hand, US investors may have the incentive to diversify their portfolios internationally by investing in firms from emerging markets. As a result, this could prompt US investors to offer a favorable evaluation of US-listed Chinese firms.

On the other hand, it has been found that expensive underwriting and listing fees, stringent reporting and compliance requirements are the major costs of listing in the US (Mittoo, 1992; Saudagaran and Biddle, 1992; 1995). Apparently, listing in US markets is more costly than doing so in China. Therefore, the high listing cost must be compensated by concrete benefits, otherwise very few Chinese firms would choose to issue shares in the US. As suggested by the literature on IPOs (Chemmanur and Fulghieri, 1999; Pástor and Veronesi, 2005), raising capital is the primary purpose for IPO firms since they need external funding to support further development. In such cases, foreign IPO firms become extremely concerned about the valuation of their shares as they wish to raise as much capital as they can. Therefore, a higher valuation for the IPO shares could compensate for the high costs of listing in the US.

In the context of cross-listing, Pagano et al. (2002) argued that firms with higher expected growth or investment are more likely to cross-list in a developed market, and that they are expected to obtain a higher P/E ratio more so than comparable domestic counterparts since the former have more promising prospects. Empirically, Sundaram and Logue (1996) and Doidge et al. (2004) showed a valuation premium for firms cross-listing in the US as they had higher price multiples than domestic peers, particularly for firms from countries with weaker investor protection. US-listed Chinese firms come from a developing market with a lower regulatory standard. Nevertheless, they voluntarily choose to issue shares in a foreign market that has much more stringent regulations. Therefore, the bonding theory, proposed by Coffee (1999) and Stulz (1999), may also carry explanatory weight on the phenomenon of US-based foreign IPOs although this theory is derived from cross-listing research. The behavior of “bonding” to higher criteria could be a way to signal the firms’ high qualities since US-listed firms must comply with stringent regulations and disclosure requirements. Accordingly, such commitment would improve a firm’s corporate governance and information environment, and therefore prompts investors to give a higher valuation. From a long-term perspective, firms with better governance are promising to operate in an efficient way and generate more profits in the future. As a result, the US-listed Chinese firms could receive a higher valuation from investors than their domestic-listed peers. Hence, I propose that Chinese firms choose a US exchange as their listing venue because they seek a higher valuation.

Hypothesis: Chinese firms that conduct IPOs in the US obtain higher valuation than their domestic-listed peers since US-listed firms issue shares to more sophisticated investors and comply with stricter regulations.

5.4. Data

Most US-listing Chinese firms facilitate their foreign-listing by issuing an American Depository Receipt (ADR), which is a negotiable certificate representing non-US stocks that are traded on the US market. The ADR can be generally classified into the following different types:

1. Unsponsored ADR: This is the lowest level of ADR trading in the OTC market without formal agreement between a foreign company and a depository bank. Unsponsored ADRs are usually initiated by the depository bank to meet US investors' demands for a non-US company's shares.
2. Level I ADR: This is the lowest level of sponsored ADR without the requirement of issuing annual reports and in compliance with GAAP. The only document which needs to be submitted to the US SEC by level I ADR firms is the registration form (Form F-6). Like unsponsored ADR, level I ADR can only be traded in the OTC market. Therefore, level I ADR is the most convenient vehicle for foreign firms to have their shares traded in the US.
3. Level II ADR: The major advantage for a firm upgrading from level I to level II ADR is that its shares can be traded on the NYSE, NASDAQ and the American Stock Exchange (AMEX). To obtain this advantage, the firm has to issue an annual report (Form 20-F) besides the registration form (Form F-6). In addition, the financial report should be produced under the US GAAP.
4. Level III ADR: This is the highest level of ADR. The most important difference between level III and level II ADR is that a firm can raise capital through the level III ADR program. Correspondingly, the regulation for level III ADR is the most stringent. Annual report and compliance with GAAP are required while level III ADR firms need a file prospectus (Form F-1) for issuing shares and disclosing material information through Form 6-K.
5. Private placement ADR (SEC Rule 144A): This is one of two restricted ADR programs. The shares of a company under Rule 144A can only be held or traded by a Qualified Institutional Buyer (QIB).
6. Offshore ADR (SEC Regulation S): This is another restricted ADR program. Shares can only be issued to or traded by non-US residents who are identified under Regulation S.

I firstly obtained a list of 225 US-listed Chinese firms between 1993 and 2012 from Thomson One Banker (T1B). The T1B database contains information of delisted firms, which helps to avoid survival bias. The sample period of 1993-2012 is determined because the first US-listing Chinese firm started trading on the NYSE in 1993. On the other hand, China's domestic IPO market was closed in 2013. Consequently, the foreign market is the only potential listing venue for Chinese IPO firms during this closing period. In other words, there is no choice between foreign and domestic listing in 2013.

After checking the list of the 225 US-listed Chinese firms, I excluded three firms that actually issued shares in the Hong Kong stock exchange and one US-based IPO case[105] that was eventually withdrawn, which took the sample size down to 221 firms. As the objective of this research is to investigate the share valuation of US-based foreign IPOs, I only study firms that raise capital in the US, i.e. level III ADRs and direct IPOs. With respect to the price of unsponsored, level I and level II ADRs, they are based on the original share price in the home market. In addition, private placement ADR and offshore ADR only issue to particular investors. Therefore, I excluded these ADR programs from the research sample. I cross-checked the list of T1B with the database of Bank of New York (BNY) Mellon Depositary Receipts in order to guarantee that only level III ADRs and direct IPOs are kept. Based on these two databases, a US-listing sample of 148 Chinese firms was obtained.

Sun et al. (2013) argued that the foreign listing of Chinese firms, particularly for those SOEs, are *imposed* by government policy rather than self-selection. In addition, the SOEs normally issue their shares in multiple markets simultaneously, i.e. global listing or cross-listing. Caglio et al. (2013) pointed out that the incentives of foreign IPOs, global IPOs and cross-listing are different. Therefore, I further exclude SOEs and firms that had conducted either global IPOs or cross-listings. As a result, 12

[105] The company name is Jintai Mining Group Inc.

firms are excluded from the sample. Finally, a research sample of 136 US-listing Chinese firms from 1999[106] to 2012 was eventually determined.

I also collected IPO data such as the filling date, trade date, offer price, share price of the first trading day, the number of shares offered, the number of shares outstanding after IPO and the total proceeds from T1b. The firms' characteristics, total assets, total sales, standard industrial classification (SIC) code and net margin were obtained from DataStream.

5.5. Descriptive Statistics

Table 5.1 illustrates a chronological list of the 136 firms, which are further classified into high-tech and non-high-tech groups. Herein, I follow the 4-digit SIC code classification criterion of Loughran and Ritter (2004). An IPO firm is defined as high-tech if it belongs to the following industries: computer hardware (3571, 3572, 3575, 3577, 3578), communications equipment (3661, 3663, 3669), electronics (3671, 3672, 3674, 3675, 3677, 3678, 3679), navigation equipment (3812), measuring and controlling devices (3823, 3825, 3826, 3827, 3829), medical instruments (3841, 3845), telephone equipment (4812, 4813), communications services (4899), and software (7371, 7372, 7373, 7374, 7375, 7378, 7379). In Table 5.1, we can see that the evolution of Chinese firms' US listing is similar for high-tech and non-high-tech firms, although the latter is in larger quantity. For both of the two groups, there were listing peaks in 2007 and 2010. A plausible explanation is that market conditions have a significant impact on the IPO volume (Ibbotson and Jaffe, 1975; Michelle, 2003). The year 2007 was the year before the financial crisis broke out while 2010 was the beginning of the recovery from the financial crisis. On the other hand, it needs to be clarified that the US listing of Chinese firms can be traced back to 1993 despite this list starting from 1999. In 1993, Sinopec Shanghai Petrochemical became

[106] The beginning of sample period changes from 1993 to 1999 because all of the Chinese firms that conducted IPOs in the US during 1993 and 1998 are excluded after the filter process.

the first US-listed Chinese firm when it listed on the NYSE. Thereafter, other Chinese firms started entering the US capital market in the late 1990s. During this period, however, these US-listed firms were SOEs and had generally conducted global IPOs in both Hong Kong and the US. As discussed before, these firms are excluded from my research sample due to the different listing motivations in comparison with foreign IPOs.

Table 5.1 The chronological list of US-listed Chinese firms

This table illustrates a chronological list of the 136 US-listed Chinese firms. The firms are classified into high-tech and non-high-tech groups. Herein, 4-digit SIC code classification criterion created by Loughran and Ritter is used to identify high-tech firm. A IPO firm is defined as high-tech if it belongs to the following industries: computer hardware (3571, 3572, 3575, 3577, 3578), communications equipment (3661, 3663, 3669), electronics (3671, 3672, 3674, 3675, 3677, 3678, 3679), navigation equipment (3812), measuring and controlling devices (3823, 3825, 3826, 3827, 3829), medical instruments (3841, 3845), telephone equipment (4812, 4813), communications services (4899), and software (7371, 7372, 7373, 7374, 7375, 7378, 7379).

Year	All	High-Tech	Non-high-tech
1999	1	1	0
2000	4	3	1
2001	0	0	0
2002	0	0	0
2003	1	0	1
2004	8	2	6
2005	8	6	2
2006	8	5	3
2007	30	11	19
2008	5	1	4
2009	13	2	11
2010	41	15	26
2011	15	7	8
2012	2	1	1
Total Number	136	54	82

Table 5.2 presents the descriptive statistics for the 136 US-listed Chinese firms in the research sample. Herein, total assets, total revenues, net margin and leverage are measured by the accounting data at the end of fiscal year before the IPO. On average, the size and revenues of these US-listed Chinese firms are US$ 119.32 million and US$ 78.38 million respectively. In terms of profitability, US-listed Chinese firms are not yet profitable when they launch IPOs as shown by the mean value of net margin at only 7.53%. Despite the low levels of profitability, these firms are in a high-speed developing stage during the IPO period, which is shown by the mean growth rate of 115.50%. Therefore, these numbers suggest that Chinese firms raise capital from the US market in order to facilitate their high-speed growth. With respect to the offering, Chinese firms typically offer 55.71 million ordinary shares in a US IPO[107]. Among the shares offered, 48.32 million of them are primary shares and 7.38 million are secondary shares. Moreover, Chinese firms raise US$ 127.85 million from the US market in an average IPO case while around 7% of the proceeds are paid to underwriters as an underwriting fee. The level of gross spread is consistent with the number documented in the cases of local US firms' domestic listings (Chen and Ritter, 2000). In addition, the mean value of underpricing is 20.51% which is calculated as the percentage difference between the offer price and the closing price of the first trading day. The underpricing level is in line with the findings of Loughran and Ritter (2004) and Ljungqvist (2007) that the average underpricing for the US market ranges from 15% to 20%. As documented by Bruner et al. (2004), the findings also demonstrate that foreign IPO firms on US exchanges and US local IPO firms are charged an equal underwriting fee and experience similar levels of underpricing.

[107] For those ADR cases, the number of ordinary shares is calculated by the number of ADRs times the ADR ratio, where ADR ratio is the number of ordinary shares represented by each ADR.

Table 5.2 Descriptive statistics of US-listed Chinese firms

This table presents the descriptive statistics for the 136 US-listed Chinese firms in the research sample. Total assets, total revenues, net margin and leverage are measured by the accounting data at the end of the fiscal year before the IPO. Specifically, net margin is defined as net income over total revenues; leverage is calculated by total debt divided by total capital. Growth rate is measured by the percentage change of total revenues from the year before IPO to the IPO year. The number of ordinary shares for ADR cases is calculated according to the number of ADRs multiplied by the ADR ratio, where the ADR ratio is the number of ordinary shares represented by each ADR. Underwriting fee is the underwriting discount per share divided by offer price. Underpricing is calculated as the percentage difference between the offer price and closing price of the first trading day.

	N	Mean	Median	SD
Total assets (in $ million)	135	119.32	67.54	132.245
Total revenues (in $ million)	135	78.58	55.43	84.45
Net margin	133	7.53%	14.67%	57.39%
Growth rate	132	115.50%	59.23%	270.62%
Leverage	120	20.58%	6.07%	38.91%
Underwriting fee	134	7.02%	7%	0.84%
Number of primary shares offered (millions)	136	48.32	23.42	88.65
Number of secondary shares offered (millions)	136	7.38	0	18.33
Number of total shares offered (millions)	136	55.71	24.50	97.25
Total proceeds (in $ million)	136	127.85	94.75	143.01
Underpricing	136	20.51%	5.13%	51.13%

5.6. Methodology

To explore the impact of US listing on share valuation, I examine the valuation difference between US-listed Chinese firms and their domestic counterparts. Besides, firm-specific factors also affect an investor's valuation on the issuing firms. First of all, the timing of the IPO is a critical determinant since market conditions have a significant impact on the share prices (Ibbotson and Jaffe, 1975; Michelle, 2003). For example, IT firms undertaking IPOs during the internet bubble period were generally being appraised higher than those who launched IPOs in other periods. Secondly, the industry would also influence the valuation because investors have different preferences across various industries. For example, technically-orientated investors are more likely to give a higher valuation to high-tech firms than those belonging to the traditional industries. Moreover, firm-specific characteristics such as firm size, growth rate and profitability would affect the issuing firm's valuation as well. For instance, the valuations of firms with high profitability and fast growth rates are normally high because of their excellent operating-performance. Therefore, these factors have to be controlled to assure that the US-listed Chinese firms are comparable with domestic-listed firms. In other words, it minimizes that valuation difference, if any, results from the choice of US listing rather than other firm-specific characteristics. Therefore, I first match the 136 US-listed Chinese firms in my research sample with comparable domestic-listed firms. All of the domestic IPOs before 2013 are used as potential matching firms[108]. The matching procedures are as follows:

1. The US-listed and domestic-listed Chinese firms are first classified into two groups based on whether or not they belong to the high-tech industry. The classification is based on the 4-digit SIC code classification criterion created by Loughran and Ritter.

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[108] The list of domestic IPO firms is obtained from T1B. The data of firm size, SIC code, growth rate and profitability are collected from Datastream.

2. For both high-tech and non-high-tech groups, domestic-listed firms that issued shares within ±1 year relative to US-listed firms' IPO year are chosen as potential matching firms. For instance, domestic IPO firms between 1999 and 2001 are used as matching candidates for US-listed firms that conducted an IPO in 2000. [109] Table 5.1 shows that the 136 US-based IPOs took place between 1999 and 2012 but there are no IPO cases in 2001 and 2002. Therefore, this step generates 24 industry-year groups.
3. For each industry-year group, I use propensity score matching (PSM) to find comparable domestic-listed firms for the 136 US-listed firms. In particular, the propensity score is estimated based on firm size (total asset), profitability (net income over total revenues) and growth rate (the percentage change of total revenues from one year before IPO to the IPO year). The variables of size and profitability are measured using data at the end of the fiscal year before the IPO year. Once each firm obtains a propensity score, I apply the nearest neighbor (NN) algorithm to look for an appropriate peer for each of the 136 US-listed firms within the industry-year group. Notably, one Chinese firm could be defined as a matching peer for multiple US-listed firms. In addition, if domestic-listed Chinese firms also issue shares overseas before domestic listing, they will not be chosen as matching firms.

After the matching process, I compare the valuation difference between the US-listed firms with their domestic-listed counterparts, which is a method used in the extant literature (Sundaram and Logue, 1996; Swaminathan and Purnanandam, 2004). In this research, the extent of IPO underpricing and firms' price multiples are used as proxies. Specifically, underpricing is calculated as the percentage difference between the offer price and the closing price of the first trading day. A higher underpricing

[109] The matching time range is between minus one and plus one year, so there exists some domestic firms that could be chosen as counterparts in different years. For example, a domestic listed firm conducted IPO in 2010 could be matched with three US-listed firms that fulfilled IPO in 2009, 2010 and 2011 respectively.

level indicates that the offering share is undervalued. In other words, a higher level of underpricing means the issuers "leave more money on the table" when they undertake IPOs. It is noteworthy that there is a waiting period between the IPO day[110] and the first trading day for IPOs in China. Derrien and Womack (2003) pointed out that the lag between the IPO day and the first trading day leads to greater underpricing. Therefore, I adjust the underpricing of domestic IPOs by subtracting the percentage change of market index during the waiting periods, so that the market impact is controlled. As the research sample contains IPOs in both of the Chinese stock exchanges, I use the Shanghai composite index and Shenzhen composite index as market index proxies for corresponding IPOs. Such adjustment is not necessary for the US-listed IPOs because their shares start trading immediately after the offer price is set.

For the price multiples, price to sales ratio (P/S ratio) and market-to-book ratio are computed. The price multiples are equal to the offer price divided by the sales per share or book value per share. Herein, sales value is the year-end sales one year before the offering, while book value is the common equity value after the offering. Meanwhile, the total number of outstanding ordinary shares[111] is used when calculating the price multiples. Finally, I compare the underpricing and price multiples between the US-listed firms and those matched peers.

5.7. Empirical Results

5.7.1. The Valuation Premium of US Listing

Table 5.3 presents the valuation comparison between the US-listed Chinese firms and their domestic-listed peers. Besides the NN matching method, I also apply Caliper matching, Kernel matching and Radius matching algorithms for the robustness

[110] IPO day is the day on which offer price is set.

[111] The number of shares includes over-allotment option. So the price multiples are fully diluted.

check.[112] For Caliper matching, one US-listed firm is matched with up to five domestic firms that have propensity scores within a caliper of 0.05. The Kernel method matches one US-listed firm with all of the domestic-listed firms in the same industry-year group and allocates a higher weight to the domestic peers that have a closer propensity score with this US-listed firm. In particular, Epanechnikov kernel is applied here. Radius matching assigns one US-listed firm with all of the domestic-listed firms in the same industry-year group that have a caliper no more than 0.05. Moreover, t-test and Wilcoxon signed-rank test are used to explore whether the price multiples and the magnitude of underpricing are statistically different for the two groups in terms of mean and median.

In Panel A of Table 5.3, it can be seen that the underpricing of domestic-listed Chinese firms is overwhelmingly higher than that of US-listed firms for all of the four matching methods.[113] Through NN matching[114], the mean underpricing level of the domestic group is as high as 107.14%, but the scale is only 16.15% for the US group. In addition, the median values also show that the underpricing of the domestic group is rather severe. Although the underpricing of the domestic group is relatively low for the other three matching mechanisms, it is still much higher than the US group. The difference in underpricing levels across the four matching algorithms is because of the fact that the matching criteria of Caliper, Kernel and Radius matching are stricter than NN matching, which decreases the number of observations as some US-listed firms do not have proper domestic-listed peers. In summary, compared

[112] For each of the matching method, I compare the characteristics (size, profitability and growth rate) between the treatment group and the matched firms. The insignificant difference of t-test indicates that PSM effectively makes firms in the two groups have similar size, profitability and growth rate which are determinants for firm's valuation.

[113] To avoid the influence of outliers, I also exclude the cases that underpricing is higher than 200% in alternative test. Although this exclusion reduces the mean underpricing of domestic-listed IPOs to 54.37%, it is still significantly higher than the mean underpricing of US-listed Chinese firms of 16.09%.

[114] The number of observations drops from the full sample of 136 to 113 because either the variables for propensity matching are not available or some US-listed firms cannot be properly matched to a domestic-listed firm within the industry-year group.

with US-listed counterparts, Chinese firms are significantly undervalued if they choose to issue shares in the domestic market. In other words, domestic-listed Chinese firms do not make full use of the capital market. US-listed Chinese firms experience underpricing as well, but the degree is much more moderate.

Panel B of Table 5.3 presents the comparison of price to book ratio for the two groups. The mean values of price-book ratio for domestic-listed firms range from 3.26 to 3.22 across the four matching methods, which is much lower than the values of US-listed firms. In spite of the fact that the difference between the two groups is mitigated for median values, the price-book of US-listed firms is still significantly higher than the domestic-listed ones at a significant level of 1%. The high price-book ratio also suggests that US-listed Chinese firms receive more favorable valuation relative to their domestic counterparts.

The results for price to sales ratio are shown in Panel C of Table 5.3. Through NN matching, the mean P/S ratios are 8.14 and 14.51 for the China and US groups respectively, and the gap is statistically significant. However, the significant difference in price-sales ratio disappears when the Caliper, Kernel and Radius methods are used. Despite the inconsistency across the four matching mechanisms, the price-book ratios still provide weak evidence that US-listed firms have a higher valuation.

According to the comparison of valuation proxies between the US and domestic groups, US-listed Chinese firms are given a higher valuation than domestic-listed Chinese firms. Since the US-listed firms are matched with domestic peers based on industry, listing year, size, profitability and growth rate, such a high valuation is unlikely to be due to firm-specific characteristics. As heterogeneity is controlled, I attribute the high valuation to the nature of US-listed firms being compliant with stringent regulations and disclosing more information to the public. Making use of the information, US investors are also sophisticated enough to evaluate these newly-issued shares. Therefore, these results support the proposed hypothesis.

Table 5.3 Valuation comparison between US-listed firms and matched domestic peers

This table presents the valuation comparison between the US-listed Chinese firms and their domestic-listed peers. Underpricing is calculated as the percentage difference between the offer price and the closing price of the first trading day. Market-book ratio and price-sales ratio are equal to the offer price divided by the book value per share or sales per share one year before the IPO. Four different matching algorithms are applied. The Nearest neighbor (NN) method matches a US-listed firm with one domestic firm that has the closest propensity score in the same industry-year group. For Caliper matching, one US-listed firm is matched with up to five domestic firms that have propensity scores within a caliper of 0.05 in the same industry-year group. The Kernel method matches one US-listed firm with all of the domestic-listed firms in the same industry-year group and allocates a higher weight to domestic peers who have a closer propensity score with this US-listed firm. In particular, Epanechnikov kernel is applied here. Radius matching assigns one US-listed firm with all of the domestic-listed firms in the same industry-year group that have a caliper no more than 0.05. T-test and Wilcoxon signed-rank test are used for statistical tests.

	NN Matching	Caliper Matching	Kernel Matching	Radius Matching
Panel A: Underpricing				
Mean				
China	107.14%	68.20%	66.70%	66.47%
US	16.15%	16.07%	16.07%	16.07%
p-value	0.000	0.000	0.000	0.000
Median				
China	54.29%	42.12%	44.90%	43.97%
US	6.67%	6.67%	6.67%	6.67%
p-value	0.000	0.000	0.000	0.000
Observations	113	83	83	83
Panel B: Market-Book Ratio				
Mean				
China	3.26	3.23	3.24	3.22
US	19.00	16.83	16.83	16.83
p-value	0.000	0.003	0.004	0.004
Median				
China	2.92	3.05	3.23	3.19

Table 5.3 – Continued

US	6.70	6.99	6.99	6.99
p-value	0.000	0.000	0.000	0.000
Observations	104	72	72	72
Panel C: Price-Sales Ratio				
Mean				
China	8.14	8.48	8.07	8.09
US	14.51	9.52	9.52	9.52
p-value	0.007	0.433	0.255	0.263
Median				
China	6.47	7.82	7.45	7.45
US	7.48	5.84	5.84	5.84
p-value	0.067	0.831	0.856	0.842
Observations	113	83	83	83

In the valuation comparison, I do not use P/E ratio as a proxy for two reasons. Firstly, the accounting principles are different in the US and China. US-listed firms apply GAAP but China-listed firms use China's own accounting principles for financial reporting. As a result, the earning numbers are not comparable when distinct accounting rules are applied. Secondly, some US firms do not have a valid P/E ratio because their earnings are negative. In the US subsample, the earnings ratios of 21 US-listed firms are negative because the SEC has no requirement on the IPO firm's profitability. On the contrary, the CSRC requires that IPO firms must return profits during the past three consecutive years and that the accumulative profits must not be less than CNY 30 million. Therefore, firms with very little or no profit have to choose the US market as a listing venue and generate an extremely high or negative P/E ratio. For example, eLong and Baidu, two US-listed firms, only have net earnings of US$ 0.195 million and US$ 1.45 million at the end of the fiscal year before the IPO took place. As a result, their P/E ratios are as high as 991.8 and 612.2 respectively. The cases of negative P/E ratio and outliers actually support the finding that US-listed firms receive a higher valuation because these firms would not even qualify for be evaluated if they did not issue shares in the

US.

However, why do US investors still offer a higher valuation to currently unprofitable firms? One plausible explanation is that these firms comply with the stringent regulations when listing on the US market. It can be perceived as a commitment to better corporate governance through which firms show their potential for long-term development rather than short-term profitability (Ding et al., 2010). Hence, investors are willing to offer a high valuation although some of them are not yet very profitable at the IPO stage. Therefore, the negative earnings ratio also indicates that US-listed Chinese firms get a higher valuation than domestic listed firms as they obey the stricter regulations.

5.7.2. Benefits versus Listing Costs

Despite the valuation premium, the cost of US-listing is perceived as being much higher than in other markets. Chen and Ritter (2000) pointed out that the underwriter fee is the main component of direct costs and typically equals 7% of the total proceeds raised. Therefore, it is necessary to examine whether the valuation premium is still meaningful when the listing cost is considered. As with previous tests, I match the US-listed Chinese firms with domestic peers based on propensity score and then compare their listing costs.

Table 5.4 presents the comparison of IPO cost, where gross spread is used as a proxy. In line with Chen and Ritter (2000), the mean gross spread for the US listing sample approximately equals 7%. For the IPOs in China, the average underwriting fee is marginally higher than 5%. Statistically, the cost of US listing is significantly higher than China's domestic listing, but the difference is limited to 2% on average. Since both gross spread and underpricing are measured as the percentage of offer price, I compare these two variables to explore whether the superior valuation remains when listing cost is considered. Recalling the result in Panel A of Table 5.3, the minimum underpricing difference is 50.40% regarding the mean value. It suggests that US-listed firms are valuated at least 50.40% higher than their domestic peers even though an extra 2% underwriting fee is paid to the US underwriters. When the median is applied for comparison, the underpricing gap is more than 35.45% across the four matching mechanisms and the difference in listing fee is still less than 2%. In summary, the valuation of US-listed Chinese firms is higher than that of domestic-listed firms even if the listing cost is taken into account.

Table 5.4 Cost comparison between US-listed firms and matched domestic peers

This table presents a comparison of the underwriting fee between the US-listed Chinese firms and their domestic-listed peers. Gross spread is used to measure the underwriting fee and is defined as the underwriting discount per share divided by offer price. Four different matching algorithms are applied. The Nearest neighbor (NN) method matches a US-listed firm with one domestic firm with the closest propensity score. For Caliper matching, one US-listed firm is matched with up to five domestic firms with propensity scores within a caliper of 0.05. The Kernel method matches one US-listed firm with all of the domestic-listed firms in the same industry-year group and allocates a higher weight to domestic peers who have a closer propensity score with this US-listed firm. In particular, Epanechnikov kernel is applied here. Radius matching matches one US-listed firm with all of the domestic-listed firms in the same industry-year group having a caliper no greater than 0.05. T-test and Wilcoxon signed-rank test are used for statistical tests.

	NN Matching	Caliper Matching	Kernel Matching	Radius Matching
Panel A: Gross spread				
Mean				
China	5.34%	5.20%	5.14%	5.13%
US	6.97%	6.97%	6.97%	6.97%
p-value	0.000	0.000	0.000	0.000
Median				
China	5.00%	5.00%	5.27%	5.29%
US	7.00%	7.00%	7.00%	7.00%
p-value	0.000	0.000	0.000	0.000
Observations	64	55	55	55

5.7.3. High-Tech versus Non-High-Tech Firms

The US is the word leader in the high-tech industry. Therefore, high-tech firms have an advantage in obtaining investors' recognition in the US than in other countries. Pagano et al. (2002) found that US exchanges attract high-tech firms that expand rapidly without heavy leverage. Blass and Yafeh (2001) discovered that US-listed Israeli IPOs are generally high-tech firms and needs their values to be certified. Therefore, the higher valuation of US-listed Chinese firms may be due to the industry preference of US investors. In this section, I investigate whether the valuation premium only exists for high-tech firms.

I use the same matching methods and valuation measurements as before but conduct the analysis for non-high-tech and high-tech groups separately. Table 5.5 and Table 5.6 illustrate the results for non-high-tech and high-tech groups respectively. First of all, the result of the non-high-tech group is qualitatively consistent with the full sample, implying that US-listed Chinese firms belonging to non-high-tech industries also attain a higher valuation than domestic counterparts. For example, the underpricing level of the US group is significantly lower than that of the domestic group, and the market to book ratio is higher than that of their domestic peers. Moreover, the mean price to sales ratio of US-listed firms is also higher according to the NN matching method.

With respect to the high-tech group, the results of Table 5.6 still support the hypothesis but with relatively weak evidence. Beginning with underpricing, the significant level of mean difference becomes 10% except the NN matching. For market to book ratio, the mean difference lost significance in Caliper, Kernel and Radius matching. One plausible explanation for the weaker result is the fact that the sample size of the high-tech group is rather small due to some US-listed Chinese firms being unable to find properly matching peers when stricter matching criteria were applied. For instance, there are only 20 matched pairs when the Caliper, Kernel and Radius matching methods are employed. More formally, I re-conduct NN matching only for these 20 US-listed firms. Accordingly, the results are very similar to that of the other three matching algorithms. It shows that the relatively weak results are caused by the small number of observations rather than the matching methods. Most importantly, according to the results of Table 5.5 and Table 5.6, I can conclude that the higher regulation does not result from the industry preference of the US investors but rather the compliance with stringent regulations.

Table 5.5 Valuation comparison for non-high-tech firms

This table presents the valuation comparison between the *non-high-tech* US-listed Chinese firms and their domestic-listed peers. Underpricing is calculated as the percentage difference between the offer price and the closing price of the first trading day. Market-book ratio and price-sales ratio are equal to the offer price divided by the book value per share or sales per share one year before the IPO. Four different matching algorithms are applied. Nearest neighbor (NN) method matches a US-listed firm with one domestic firm with the closest propensity score in the same industry-year group. For Caliper matching, one US-listed firm is matched with up to five domestic firms that have propensity scores within a caliper of 0.05 in the same industry-year group. Kernel method matches one US-listed firm with all of the domestic-listed firms in the same industry-year group and allocates a higher weight to domestic peers who have a closer propensity score with this US-listed firm. In particular, Epanechnikov kernel is applied here. Radius matching matches one US-listed firm with all of the domestic-listed firms in the same industry-year group that have a caliper no greater than 0.05. T-test and Wilcoxon signed-rank test are used for statistical tests.

	NN Matching	Caliper Matching	Kernel Matching	Radius Matching
Panel A: Underpricing				
Mean				
China	87.18%	74.97%	72.23%	71.84%
US	12.73%	13.22%	13.22%	13.22%
p-value	0.000	0.000	0.000	0.000
Median				
China	54.29%	50.99%	54.29%	51.12%
US	4.75%	4.75%	4.75%	4.75%
p-value	0.000	0.000	0.000	0.000
Observations	73	63	63	63
Panel B: Market-Book Ratio				
Mean				
China	3.28	3.10	3.14	3.13
US	14.08	13.02	13.02	13.02
p-value	0.000	0.000	0.000	0.000
Median				
China	2.88	3.02	3.16	3.19
US	6.23	6.32	6.32	6.32

Table 5.5 – Continued

p-value	0.000	0.000	0.000	0.000
Observations	67	53	53	53
Panel C: Price-Sales Ratio				
Mean				
China	8.34	8.14	7.51	7.49
US	13.80	9.76	9.76	9.76
p-value	0.091	0.301	0.127	0.127
Median				
China	5.83	7.20	7.39	7.19
US	6.48	5.84	5.84	5.84
p-value	0.332	0.811	0.676	0.696
Observations	73	63	63	63

Table 5.6 Valuation comparison for high-tech firms

This table presents the valuation comparison between the *high-tech* US-listed Chinese firms and their domestic-listed peers. Underpricing is calculated as the percentage difference between the offer price and the closing price of the first trading day. Market-book ratio and price-sales ratio are equal to the offer price divided by the book value per share or sales per share one year before the IPO. Four different matching algorithms are applied. Nearest neighbor (NN) method matches a US-listed firm with one domestic firm with the closest propensity score in the same industry-year group. For Caliper matching, one US-listed firm is matched with up to five domestic firms having propensity scores within a caliper of 0.05 in the same industry-year group. Kernel method matches one US-listed firm with all of the domestic-listed firms in the same industry-year group and allocates a higher weight to domestic peers who have a closer propensity score with this US-listed firm. In particular, Epanechnikov kernel is applied here. Radius matching matches one US-listed firm with all of the domestic-listed firms in the same industry-year group that have a caliper no greater than 0.05. T-test and Wilcoxon signed-rank test are used for statistical tests.

	NN Matching	Caliper Matching	Kernel Matching	Radius Matching
Panel A: Underpricing				
Mean				
China	143.56%	46.91%	49.28%	49.55%
US	22.39%	25.06%	25.06%	25.06%
p-value	0.000	0.094	0.094	0.095
Median				
China	57.29%	35.42%	32.61%	34.16%
US	8.81%	12.33%	12.33%	12.33%
p-value	0.000	0.040	0.048	0.044
Observations	40	20	20	20
Panel B: Market-Book Ratio				
Mean				
China	3.22	3.60	3.51	3.47
US	27.91	27.48	27.48	27.48
p-value	0.022	0.142	0.140	0.140
Median				
China	3.05	3.08	3.44	3.41
US	8.70	8.70	8.70	8.70

Table 5.6 – Continued

p-value	0.000	0.005	0.005	0.005
Observations	37	19	19	19
Panel C: Price-Sales Ratio				
Mean				
China	7.77	9.53	9.85	9.96
US	15.80	8.78	8.78	8.78
p-value	0.011	0.774	0.680	0.653
Median				
China	6.47	8.81	8.55	8.81
US	8.45	5.67	5.67	5.67
p-value	0.060	0.433	0.279	0.296
Observations	40	20	20	20

5.7.4. Analysis for Unmatched Firms

During the matching process, a few US-listed firms do not have appropriate domestic peers when strict matching criteria are used. The characteristics of these unmatched US-listed firms must be absolutely distinct from domestic-listed peers so that their propensity scores are quite different. Therefore, I examine the features of unmatched firms to explore what kind of Chinese firms are hardly to be matched, i.e. more likely to bypass the domestic market and undertake an IPO in the US. Herein, I use the Caliper matching method with a caliper of 0.05 as the filter. A US-listed firm is defined as unmatchable if this firm cannot find any domestic peer in its industry-year group.

In total, 53 of 136 US-listed firms do not have comparable domestic peers and their features are shown in Table 5.7. In general, the total assets, total revenues and leverage of the unmatched firms are close to the scale of the full sample[115], while the net margin and growth rate are quite different. Specifically, the average net margin for unmatched firms is -7.38%. As mentioned before, all of the Chinese IPO firms

[115] See Table 5.2 for the values of full sample.

are required to have positive earnings, reaching a certain level before the IPO, but such a requirement does not exist for US listing. Therefore, those unprofitable firms are not qualified to issue shares in the Chinese market so that they do not have similar domestic peers in term of profitability. Meanwhile, the average growth rate of unmatched firms is as high as 209.80%, which is far beyond the value of 115.50% for the full sample and hereupon leads to difficulty in matching. For example, Solarfun Power Holdings Ltd and Trina Solar Ltd are two high-tech firms (SIC Code: 3674) that conducted an IPO on the US exchanges in 2006. Their growth rates are 290.31% and 319.80% in the IPO year. Nevertheless, the fastest-developing domestic firm within the industry-year group only has a growth rate of 98.83%. Consequently, the propensity score of these two US-listed firms are far different from those of domestic firms and violate the filter criterion of 0.05 caliper. Overall, it can be realized that the failure in matching is mainly caused by the low profitability and high growth rate. Furthermore, the deviation on net margin and growth rate means that temporarily unprofitable Chinese firms, with rapid growth rates, are more likely to bypass China’s domestic market and issue shares in the US.

In addition, I find that 34 out of the 53 unmatched firms belong to high-tech industries. Taking into account the total number of high-tech firms in the full sample, the large unmatched proportion indicates that Chinese high-tech firms are prone to undertake IPOs in the US market. For a more detailed depiction, I report the industry distribution of unmatched firms in Table 5.8, where industry clustering is apparent. Firstly, there are five industries that have more than two unmatched firms, accounting for more than half of the unmatched cases. More importantly, all of the top five unmatched industries are high-tech except the industry of business services. However, after browsing the prospectus of business service firms, I find that they do not provide traditional business services. They would be more accurately defined as falling with the e-commerce bracket since these firms offer online services. Therefore, the distribution of unmatched firms reveals that high-tech firms are more

Table 5.7 The features of unmatched US-listed Chinese fimrs

This table presents the descriptive statistics for the 53 unmatched US-listed firms. Total assets, total revenues, net margin and leverage are measured by the accounting data at the end of fiscal year before the IPO. Specifically, net margin is defined as net income over total revenues; leverage is calculated by total debt divided by total capital; and growth rate is measured by the percentage change of total revenues from the year before IPO to the IPO year.

	N	Mean	Median	SD
Total assets (in million $)	52	120.89	52.93	147.14
Total revenues (in million $)	52	58.47	42.77	66.97
Net margin	50	-7.38%	13.32%	88.72%
Growth rate	49	209.80%	115.88%	427.42%
Leverage	44	27.25%	6.34%	53.45%

likely to undertake foreign IPOs in the US. As documented by Pagano et al. (2002), obtaining foreign expertise is one of the motivations for foreign listing. Considering the leading position of US science and technology, accessing foreign expertise is an important incentive that prompts Chinese high-tech firms to choose US exchanges as listing venues.

In summary, the analysis on unmatched US-listed firms indicate that high-tech firms with high growth rate but low profitability are inclined to bypass domestic market and issue shares in the US. This finding is consistent with the conclusion of Yafeh and Blass (2000) and Zhang and King (2010). Specifically, this phenomenon is more apparent for particular industries, such as semiconductors, software and online business services. I interpret this industry clustering as a source of motivation for seeking foreign expertise.

Table 5.8 The industry distribution of unmatched US-listed Chinese firms

This table demonstrates the industry distribution of the 53 unmatched US-listed firms. Herein, 4-digit SIC code classification criterion created by Loughran and Ritter is used to identify high-tech industry. The following industries are defined as high-tech: computer hardware (3571, 3572, 3575, 3577, 3578), communications equipment (3661, 3663, 3669), electronics (3671, 3672, 3674, 3675, 3677, 3678, 3679), navigation equipment (3812), measuring and controlling devices (3823, 3825, 3826, 3827, 3829), medical instruments (3841, 3845), telephone equipment (4812, 4813), communications services (4899), and software (7371, 7372, 7373, 7374, 7375, 7378, 7379).

Industry	Four-Digit SIC Code	High Tech	Frequency	Percent	Cumulative Percent
Semiconductors and Related Devices	**3674**	**Y**	**10**	**18.87**	**18.87**
Prepackaged Software	**7372**	**Y**	**7**	**13.21**	**32.08**
Business Services, Not Elsewhere Classified	**7389**	**N**	**6**	**11.32**	**43.4**
Custom Computer Programming Services	**7371**	**Y**	**3**	**5.66**	**49.06**
Computer Processing and Data Preparation and Processing Services	**7374**	**Y**	**3**	**5.66**	**54.72**
Telephone and Telegraph Apparatus	3661	Y	2	3.77	58.49
Advertising Agencies	7311	N	2	3.77	62.26
Information Retrieval Services	7375	Y	2	3.77	66.04
Corn	115	N	1	1.89	67.92
Finfish	912	N	1	1.89	69.81
Drawing and Insulating of Nonferrous Wire	3357	N	1	1.89	71.7
Steam, Gas, and Hydraulic Turbines, and Turbine Generator Set Units	3511	N	1	1.89	73.58
Motors and Generators	3621	N	1	1.89	75.47
Electric Lamp Bulbs and Tubes	3641	N	1	1.89	77.36
Radio and Television Broadcasting and Communications Equipment	3663	Y	1	1.89	79.25
Electronic Components, Not Elsewhere Classified	3679	Y	1	1.89	81.13
Surgical and Medical Instruments and Apparatus	3841	Y	1	1.89	83.02

Table 5.8 – Continued

Radiotelephone Communications	4812	Y	1	1.89	84.91
Telephone Communications, Except Radiotelephone	4813	Y	1	1.89	86.79
Communication Services, not elsewhere classified	4899	Y	1	1.89	88.68
Catalog and Mail-Order Houses	5961	N	1	1.89	90.57
Functions Related to Depository Banking, not elsewhere classified	6099	N	1	1.89	92.45
Investment Advice	6282	N	1	1.89	94.34
Unit Investment Trusts, Face-Amount Certificate Offices, and Closed-End Management Investment Offices	6726	N	1	1.89	96.23
Radio, Television, and Publishers' Advertising Representatives	7313	N	1	1.89	98.11
Computer Integrated Systems Design	7373	Y	1	1.89	100

5.8. Conclusions

Using a sample of 136 US-listed Chinese firms and their domestic-listed peers, I find that US-listing generates higher price multiples and less underpricing than domestic listing in China. This valuation premium is sustained when a firm's characteristics and listing cost are being controlled. Moreover, the valuation advantage holds for both high-tech and non-high-tech firms, which excludes the alternative possibility that the high valuation comes from the investor's industry preference. This finding is consistent with the conclusion of Sundaram and Logue (1996) and Doidge et al. (2004) that cross-listed firms obtain higher valuation than non-cross-listed alternatives. I attribute the valuation premium to the voluntary compliance with stringent regulations that would improve a firm's corporate governance (Coffee, 1999; Stulz, 1999) and information environment (Baker et al., 2002; Lang et al., 2003) and the expansion of shareholder base (Mittoo, 1992; Foerster and Karolyi, 1999; Bancel and Mittoo, 2001) in a market that has more sophisticated investors who possess adequate abilities to evaluate the newly-issuing shares. Therefore, this research provides evidence that the theories derived from cross-listing are also applicable in the context of foreign IPOs. It can be concluded that valuation advantage is one of the motives that prompt Chinese firms to conduct IPOs in the US.

According to the analysis on unmatched firms, I also document that high-tech firms with a high growth rate but low profitability are more likely to issue shares in the US. This is consistent with the findings of Yafeh and Blass (2000) and Zhang and King (2010). In particular, this phenomenon is more apparent for particular industries, such as semiconductors, software and online business services. I interpret this industry clustering as a motivation to seek foreign expertise (Pagano et al., 2002). Taking into account the high valuation and the features of US-listed Chinese firms, the results also provide evidence to support the argument of Allen and Gale (1999) that US equity market have the ability to evaluate the prospects of innovative firms.

In summary, this paper contributes to the literature by specifically studying the foreign IPO phenomenon from the perspective of share valuation and providing new empirical evidence for the foreign listing theories.

Chapter 6

6. Conclusions

Using Chinese data, this thesis investigates the behavior of institutional investors in IPOs markets and the decision of going public abroad. In Chapter 3, I find that past experience affects the behavior of institutional investors in IPO markets. When deciding to participate in future IPOs, institutions take into serious account the past initial returns of the IPOs in which they were involved: experienced return (E) > observed return (O); return of qualified bid (Q) > return of unqualified bid (U). The distinct impact of different types of returns provide empirical support for the hybrid model of Camerer and Ho (1999) in which both actual and forgone payoff influence the decision-making process but with different weights. Therefore, I conclude that the learning behavior of institutional investors is consistent with reinforcement learning. This result is also in agreement with the finding of Seru et al. (2010) that individual investors gain experience by actively trading rather than observing hypothetical trades. Such a result is consistent with the conclusion in psychology literature stating that personally experienced outcomes have a greater impact on agents' decisions than those without personal involvement (Hertwig et al., 2004; Weber et al., 1993). In addition, I find that institutions equally take into account the returns that are derived from random events rather than their own investment decisions, which shows the rational aspect of institutions. Finally, this research identifies that institutions will bid more aggressively after experiencing a favorable outcome in the IPOs in which they were personally involved, which offers additional support to the learning behavior of reinforcement. Overall, this study contributes to the extant literature by providing new evidence on the learning behavior of institutional investors who are widely perceived as sophisticated investors.

In Chapter 4, I find that fund companies truthfully reveal private information in a quasi-bookbuilding IPO mechanism that is not embedded with guaranteed compensations for information revelation. In detail, fund companies will purchase more shares from the secondary market if they have shown strong willingness to obtain shares. This finding contributes to the literature by providing new empirical evidence on the information compensation theory. In common with Cornelli and Goldreich (2003), I find that investors truthfully reveal their information via bids although the mechanism being tested in my research does not have discretionary allocation. This finding also provides empirical evidence for the theoretical models developed by Biais et al. (2002) and Biais and Faugeron-Crouzet (2002) as they illustrate that both the bookbuilding and the *Offre a Prix Minimum* mechanisms, an auction-like IPO method, have information elicitation and price discovery functions although the latter is not embedded with a discretionary allocation.

On the other hand, my findings contrasts with the conclusion of Benveniste and Wilhelm (1990) which stated that information gathering is impossible when allocation discretion is restricted. I argue that the compensation for revealing information can be replaced by the mechanism design, for example the qualification system and the lottery-based allocation mechanism. The model of Busaba and Chang (2010) suggests that informed investors could conceal their information in the primary market and profit from this private information via trading in the secondary market. Empirically, my findings show that investors truthfully reveal their information in the primary market rather than trading on their private information in the secondary market.

This research also provides implications for IPO mechanism design. For the quasi-bookbuilding mechanism tested in this thesis, its allocation rule is specified and publicly available in advance. It also offers institutional investors an equal chance to obtain IPO shares. In addition, this mechanism avoids the free-rider problem as the highest bids are not given priority in allocation. Moreover, detailed bid information is disclosed to the public, making the process more transparent. Although this mechanism raises a concern over the incentive behind revealing private information, my results suggest that institutions still play a price discovery role even if there is no guaranteed compensation such as favored allocation. The incentives to provide honest valuation could come from the mechanism design where institutions will not be qualified for the allocation process if an extremely low price is bid, and the chance to obtain shares will not increase significantly even if an excessively high price is submitted. Hence, my findings imply that this relatively fair and transparent quasi-bookbuilding mechanism is able to exert the same price discovery function as opaque alternatives.

In Chapter 5, I find that US-listed Chinese firms obtain higher valuations than their domestic-listed counterparts in IPOs. This valuation premium is sustained when a firm's characteristics and listing cost are being controlled. This finding is consistent with the conclusion of Sundaram and Logue (1996) and Doidge et al. (2004) that cross-listed firms obtain higher valuation than non-cross-listed alternatives. I attribute the valuation premium to the voluntary compliance with stringent regulations that would improve a firm's corporate governance (Coffee, 1999; Stulz, 1999) and information environment (Baker et al., 2002; Lang et al., 2003) and the expansion of shareholder base (Mittoo, 1992; Foerster and Karolyi, 1999; Bancel and Mittoo, 2001) in a market that has more sophisticated investors who possess adequate abilities to evaluate the newly-issuing shares. Therefore, this paper provides evidence that the theories derived from cross-listing are also applicable in the context of foreign IPOs. It can be concluded that valuation advantage is one of the motives that prompt Chinese firms to conduct IPOs in the US.

According to the analysis on unmatched firms, I also document that high-tech firms with a high growth rate but low profitability are more likely to issue shares in the US. This is consistent with the findings of Yafeh and Blass (2000) and Zhang and King (2010). In particular, this phenomenon is more apparent for particular industries, such as semiconductors, software and online business services. I interpret this industry clustering as a motivation to seek foreign expertise (Pagano et al., 2002). Taking into account the high valuation and the features of US-listed Chinese firms, the results also provide evidence to support the argument of Allen and Gale (1999) that US equity market have the ability to evaluate the prospects of innovative firms.

Despite of the aforementioned findings, there are also some shortcomings in this thesis. In Chapter 3, I study institution's learning behavior using the sample of ChiNext IPOs between November 2010 and September 2012. There are no IPOs in 2013 because the market was shut down. As of this writing, there are 139 new IPOs took place in ChiNext Since the market re-opened in Jan 2014. Because the data used in this research is manually collected, I do not include theses new IPOs after 2014. Therefore, future research can study institution's behavior when participating in these new IPOs and investigate whether their behaviors have changed after a long-time market shut down.

In Chapter 4, we examine the bidding and trading behavior only using funds as research sample due to the inaccurate holding position data of other types of institutions. Therefore, the generalizability of the empirical results would be improved if researchers not only use fund companies but also include other institutions into analysis. In addition, we use the difference between the holding amount on the first report day and the IPO allocation amount to approximate the institution's purchasing behavior. However, this measurement ignores the special case that institutions purchase issued shares in the secondary market but sell these purchased shares before the first quarterly report day. Besides, we have to use the minimum and average daily closing price between the first trading day and the following quarter-report day to gauge the purchasing price in the secondary market. Ideally, future research can obtain more detailed data with the information of purchasing prices, purchasing amount and the time of purchase to have a more accurate analysis on the behaviors of institutions.

In Chapter 5, I exam the phenomenon that Chinese firms conduct IPOs in the U.S. In contrast to foreign IPO, some Chinese firms are planning go back to domestic market through privatization. Researchers can focus on these returned firms to investigate the reasons that make Chinese firms go back to domestics market and the impact of the going-back trend on China's capital market.

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Appendix A: Definition of Proper Nouns

Terms	Definition
Investment account	An investment account refers to the investment product under the management of an institution. Institutions can submit bids through several investment accounts in a single IPO
Qualified bid	The bid with bid price at or above the offer price
Qualified amount	Qualified amount refers to the number of shares that are qualified for the following lottery-based share allocation. When one institution submits several different bid prices, for example, 3 different prices P1, P2, P3 ($P1 > P2 > P3$) with bid amount of Q1, Q2, Q3 and the offer price is P, if $P > P1$, this institution cannot participate allocation; if $P1 \geq P > P2$, the amount being qualified for allocation is Q1; if $P2 \geq P > P3$, the amount being qualified for allocation is Q1+Q2; if $P3 \geq P$, the amount being qualified for allocation is Q1+Q2+Q3.
Unqualified bid	The bid with bid price lower than the offer price which is not eligible to participate in share allocation.
Experienced return (E)	The weighted-average adjusted initial return of IPOs in which institutions submitted bids.
Observed return (O)	The weighted-average adjusted initial return of IPOs in which institutions observed.
Return of unqualified bid (U)	The weighted-average adjusted initial return of IPOs in which institution submitted bids but its bids are unqualified for share allocation.
Return of qualified bid (Q)	The weighted-average adjusted initial return of IPOs in which institution submitted bids and its bids are qualified for share allocation.
Return of unallocated shares (L)	The weighted-average adjusted initial return of IPOs in which institutions were qualified for share allocation but did not receive shares.
Return of allocated shares (W)	The weighted-average adjusted initial return of IPOs in which institutions were qualified for share allocation and got allocation eventually.