Do experience and luck affect the behavior of institutional investors in IPO markets?

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Abstract

We use a unique set of bookbuilding data to examine the impact of personal experience and luck on the behavior of institutional investors in an IPO market. We find that, when deciding to participate in future IPOs, institutions take into account initial returns of the IPOs they participated in the past, regardless of the fact that they received a share allocation or not. While this type of behavior is consistent with Bayesian learning, we also find that institutions participate more often in future if they personally experienced a large gain from the past IPOs and if they were lucky with the share allocations in the past.

Finance literature has been showing an increasing interest toward the investor learning processes and the impact of these processes on investment decisions. Rational Bayesian belief updating and naive reinforcement learning are the two leading theories on an agent's learning behavior.[1] Naïve reinforcement learning refers to a strengthening of the behavior through experience (Skinner, 1980). Investors who are naïve reinforcement learners pay attention only to their past payoffs, and not necessarily to the model that generates those payoffs. On the other hand, Bayesian belief learning theory premises that investors keep track

[1] The original idea of naïve reinforcement learning, the law of effect, is due to Thorndike (1911). Through a famous experience named the "puzzle box", he investigates the learning process of animals and suggests that behaviors that generate good outcomes are likely to be repeated in the future. Build on the law of effect, Skinner (1938) and Zeiler (1968) formally establish the model of naïve reinforcement learning in the psychological realm. Cross (1973), Arthur (1991) and Roth and Erev (1995) introduce this psychological theory to the economics literature. Their experiments show that naïve reinforcement learning theory is more powerful in describing human behavior than predictions based on rational human beings. Researchers not only pay attention to naïve reinforcement learning but also construct theoretical models to investigate Bayesian learning process (Crawford (1995), Cheung and Friedman (1997), Crawford and Broseta (1998)). However, naïve reinforcement learning and rational Bayesian belief learning are mostly treated as fundamentally different in these researches. To integrate these two learning theories, Camerer and Ho (1999) build a hybrid learning model named experience-weighted attraction (EWA). They introduce a parameter to measure the payoffs that would have yielded relative to the payoffs that are actually received, by which EWA model shows better explanatory power than pure naïve reinforcement model and rational Bayesian learning model in most of game experiments.

of forgone outcomes as well as personally experienced ones, and then form their beliefs based on the updated information. Their future decisions are tend to be based on rationally formed beliefs (Camerer and Ho,1999). Therefore, the first distinction between these two theories is that naïve reinforcement learners weigh the outcomes that are personally experienced more than the outcomes that are merely observed, whereas Bayesian belief-learners weigh these two different types of outcome equally. Put differently, directly experienced outcomes have more impact on future decision under naïve reinforcement, but for rational Bayesian belief learning, directly experienced versus observed outcomes are equally influential. A second difference between the theories is that Bayesian belief-learners rationally learn from their past experiences, whereas naïve reinforcement learners do not.

In this research, we use a unique set of bookbuilding data to explore the impact of experience and luck on institutional investors' investment behavior in a new IPO market. The data includes 19,151 bids by 353 institutions that participated in 214 IPOs which took place on ChiNext, a new board of Shenzhen Stock Exchange launched in late 2009. The fact that shares are allocated via balloting in oversubscribed issues generates actual and forgone returns/payoffs and gives us an ideal setting to test Bayesian and naïve reinforcement learning theories. We investigate whether institutions take into account the initial returns of IPOs they participated but were not allocated shares when deciding to participate in future IPOs. On the other hand, the allocation mechanism generates lucky versus unlucky institutions. Lucky institutions win the lottery in hot IPOs (those with high initial returns) and lose the lottery in cold ones (those with negative initial returns), and vice versa. Consequently, we also examine whether luck in share allocations has an impact on the investment behavior of institutions.

Our first main finding is that institutions take into account initial returns of the IPOs they participated in the past, regardless of the fact that they received a share allocation or not. They do not weight the initial returns they experienced more. This is consistent with rational Bayesian learning. Interestingly, we also find that institutions participate more often in future IPOs if they personally experienced a large gain from the past IPOs, which hints that naïve reinforcement learning has an impact on institutions' investment decisions as well. Surprisingly, luck also plays a role when institutions decide to participate in future IPOs. After controlling for past returns and payoffs, institutions that were lucky with share allocations in the past seek shares in more IPOs in the future.

This study contributes to our understanding of the learning behavior of institutional investors in several ways. First, we provide evidence that both rational Bayesian learning and naïve reinforcement learning contribute to the learning process of institutional investors. This suggests that these two theories are not necessarily strict substitutes, but can complement each other. Second, we document that luck has some impact on investment decisions of institutional investors, who are often assumed to be more sophisticated investors than retail ones.

Our research is closely related to two other papers that study learning behavior of investors in new IPO markets. Kaustia and Knüpfer (2008) study the bids submitted by individual investors in Finnish IPOs and find that their learning behavior is consistent with naïve reinforcement learning. They do not examine the learning behavior of institutional investors. Following Kaustia and Knüpfer (2008), Chiang et al. (2011) study winning bids in Taiwanese IPO auctions. Beside the positive relationship between past returns and the likelihood of participating in future IPOs, they find individual investors' auction selection ability deteriorates as they become more experienced. According to this finding, they conclude that an individual investor's learning process is consistent with the naïve reinforcement learning theory rather than the rational Bayesian learning theory. They investigate the behavior of institutional investors as well and find that unlike individuals their auction selection ability does not deteriorate with experience.

This paper differs from Kaustia and Knüpfer (2008) and Chiang et al. (2011) in a number of ways. We test the rational Bayesian and naïve reinforcement theories in a novel way by decomposing initial returns into two parts: experienced versus forgone returns. Since the fundamental difference between Bayesian learning and naïve reinforcement learning is the various weights apportioned to experienced payoffs and forgone payoffs, our setting is ideal for testing whether the behavior of institutional investors is consistent with these theories. On the contrary, Kaustia and Knüpfer (2008) and Chiang et al. (2011) conclude investor's learning pattern as naïve reinforcement learning merely based on the result they got without explicitly identifying experienced and forgone returns. Secondly, the lottery-based allocation mechanism allows us to investigate the impact of luck on the investment decisions of institutional investors. Thirdly, the analysis in Kaustia and Knüpfer (2008) is exclusively based on individual investors and the one in Chiang et al. (2011) is only partially based on institutional investors. Furthermore, the share allocation mechanism in our setting differs from the one in Chiang et al. (2011). Therefore, our analysis adds to the literature by providing new evidence on the learning behavior of institutional investors, who are considered to be better informed and sophisticated investors (Cohen et al. (2002), Nagel (2005), Chiang et al. (2010)), under a different share allocation mechanism.

The remainder of this paper is organized as follows. In section 1, we briefly discuss the institutional features of ChiNext. Section 2 describes the data. Hypotheses are developed in Section 3 and Section 4 presents our methodology and results. Finally, Section 5 concludes.

1. Institutional Background

Aiming to promote the innovative small and mid-sized enterprises (SMEs) and perfect the structure of China's capital market, ChiNext, a new exchange board affiliated with Shenzhen Stock Exchange, was launched in 2009.[2] The first batch of 28 SMEs started trading on ChiNext on 30 October 2009. As of this writing, there are 355 firms from across industries 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 issuers could sell in the institutional offering was 20%. A new rule that became effective in May 2012 requires 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.[3]

The essential function of institutional offering is to set offer price. In our sample, bookbuilding is used as the primary pricing mechanism. The lead underwriter conducts a roadshow to promote the issue and collect data about institutional demand. In particular, institutional investors submit limit bids that specify prices and quantities. For each investment account[4], an institution is allowed to bid for up to 3 different prices with a tick size of 0.01 yuan[5]. 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 China Securities Regulatory Commission (CSRC), only the bids that are at or above the offer price qualify for the lottery-based allocation that follows bookbuilding.[6]

Our sample starts from November 2010 when balloting is initially introduced as allocation method in ChiNext. Since this unique allocation mechanism is never used in other capital markets, we assume that institutions do not have any knowledge about this new

[2] ChiNext can be regarded as the equivalent of Nasdaq or AIM in China.
[3] The decree No.78 became effective on May 18, 2012. The majority of IPOs in our sample take place before this date.
[4] An investment account refers to investment products under the management of an institution. Institutions can submit bids through several investment accounts in a single IPO.
[5] Yuan is the base unit of Chinese currency.
[6] 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 lottery, but with lower qualified amount compared to its total bid amount.

mechanism and have to learn it as novice.[7] The process of allocation is best explained by an example. One of the issuers in our sample offered 8 million shares to institutions at an offer price of 21.09 yuan.[8] In this IPO, 42 institutions submitted orders during bookbuilding with the total demand of 232 million shares. 23 out of the 42 institutions were eligible for the allocation as their bid prices were not less than 21.09 yuan and the total qualified amount was 103.2 million shares.[9] Since the minimum bid amount for institutions in this IPO was 0.8 million shares, 10 tickets (80 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 lottery. The numbers of tickets hold by each institution are determined by their qualified amounts. For instance, one institution in this IPO has qualified amount of 4 million shares, but only 0.8 million subscribed shares are qualified for another institution. As a consequence, they got 5 tickets and 1 ticket respectively for the following balloting. It is worth noticing that the more qualified bids institutions have the higher probability they can get allocation, 0.0388 versus 0.0078 in this example. At the end of the balloting, two institutions had two winning tickets and got 1.6 million shares, 6 institutions had only one winning ticket and obtained 0.8 million shares. However, the other 15 qualified institutions did not get any shares due to their bad luck in the balloting.

2. Data

To investigate the learning behavior of institutions, we study the IPOs that took place on ChiNext between November 2010 and September 2012. The reason we choose November 2010 as the starting date of our sample is because balloting is introduced as a share allocation mechanism during this month. Balloting not only creates forgone returns/payoffs, which is essential to test Bayesian and reinforcement learning theories, but also introduces an element of luck to the process, such that we can investigate whether institutional investors' actions are affected by it.[10] In total, 353 unique institutions submitted 19,151 bids in 214 IPOs that took place during our sample period.

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[7] Although the lottery-based allocation mechanism is used in retail offering for individual investors before, institutions still need to learn from the beginning as they have very different characteristics comparing with individuals.

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

[9] When one institution submit 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≥ P> P2, the amount being qualified for allocation is Q1; if P2≥ P>P3, the amount being qualified for allocation is Q1+Q2; if P3≥ P, the amount being qualified for allocation is Q1+Q2+Q3.

[10] 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. Therefore, unlike the current balloting mechanism, the previous equal pro-ration mechanism featured neither forgone returns/payoffs, nor an element of luck.

The data on bids is hand collected from official documents that issuing firms have to share with the public. From these documents, we obtain institution name, investment account name, bid price, bid quantity, quantity qualified for balloting (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 balloting), and quantity allocated. We use the institution name as an identifier and track each institution's bidding history.[11]

The descriptive statistics of institutions' activities are presented in Panel A of Table 1. On average, an institution participated in 30 (median: 8) out of the 214 IPOs during the sample period, the large difference between the mean and the median, or the skewness, hints that there are institutions that participate in most of the IPOs. The high-frequency participators in the sample are mostly security or fund companies who are the dominators in capital market and active for adjusting their portfolios through diverse investments. In average IPO, an institution submits 1.34 bids and demands 3.21 million shares that are worth of 73.49 million yuans.

With respect to the IPO data, issue date, 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 Shenzhen Stock Exchange. In addition, we collect data from the SDC to double check the accuracy of data for IPOs. Panel B of Table 1 presents descriptive statistics for the 124 IPOs in our 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 22.6%. Having considered the market condition between the issuing and listing day, we use the change of Shenzhen A-Share Stock Price Index during the waiting period, 13.84 days on average, to control it and generate the adjusted initial return. The mean and median of adjusted initial returns are 23.17% and 16.22% respectively. In the following tests, we use the adjusted initial returns of the IPOs institutions participated in the past to measure their experiences about payoffs. Panel B of Table 1 also shows that, on average, 50 institutions participate in an IPO, the order book contains 90 bids, and the amount of shares demanded by institutions (mean: 246.80 million) far exceeds the amount of shares offered (mean: 5.13 million). If we use the proportion of issued shares relative to qualified shares to measure the chance of getting a share allocation, the probability is as low as 9.27% on average. This

[11] We can identify 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 via across 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 Shenzhen Stock Exchange); The official website of China Securities Regulatory Commission (http://www.csrc.gov.cn/pub/newsite/);Baidu.com, the largest Chinese language-search engine (http://www.baidu.com/).

implies that the IPOs in our sample are heavily oversubscribed. Consequently, institutions often cannot obtain shares when they participate in the balloting. This generates foregone returns/payoffs and some institutions end up being luckier than others, when they win the lottery in hot IPOs and lose it in cold IPOs.

3. Hypotheses

In terms of naïve reinforcement learning theory, decision makers would like to repeat actions that generated favorable experience in the past. This theory implies that institutions are keen on participating IPOs once they experienced high returns. Attentively, the returns herein refer to those actually realized by institutions. Because of the lottery-based allocation mechanism, IPO returns can be realized on the condition that institutions are able to get shares via balloting. Therefore, the impact of actual return on institution's future decision can reflect the extent to which naïve reinforcement learning explains institution's learning behavior.

With respect to Bayesian belief learning, investors update their beliefs about IPOs through observing past experience and then make future investment decision based on the updated beliefs. Particularly, Bayesian learners do not only review the personally experienced outcomes but also those that would have been occurred. While Bayesian learning theory also suggests that favorable past return will make institutions to participate in more IPOs, the behavior is equally motivated by actual and missed return[12] rather than actual return itself.

Since the fundamental difference between rational Bayesian learning and naïve reinforcement learning is the weights allocated to experienced payoffs and missed payoffs. Thus, the extent to which actual return and missed return affect future decision can be used to explicitly identify which learning theory(ies) is(are) followed by institutional investors.

Hypothesis 1: If both high actual and missed returns in the past motivate institutions to participate in more IPOs and the effect of these two returns are equal, institution's learning behavior is subject to Bayesian learning. Alternatively, if the impact of actual return is more significant than missed return, institution's learning behavior is consistent with naive reinforcement learning.

In China, IPO shares are heavily oversubscribed such that the chance of obtaining shares is extremely low. For the 214 IPOs in our sample, the average allocation rate to institutional investors, which is measured as the number of shares offered to institutions divided by the

[12] Missed return results from bids that do not get share allocation in lottery.

number of shares subscribed by institutions, equals to 3.13%[13]. This low allocation rate raises a question that whether luckiness sway institution's future investment decision. For instance, one institution took part into ten IPOs in the past and only got shares from two of them due to the lottery-based allocation. If the two winning IPOs are hot (high initial returns) and the other eight are cold IPOs (relatively low or even negative initial returns), this institution is considered lucky. Therefore, we use the difference between experienced return and missed return to measure institution's luckiness and test if luck matters. If so, we will further examine whether institutions overweight their luckiness when deciding to participate in future.

Hypothesis 2a: If the high difference between experienced return and missed return makes institutions to participate in more IPOs, it shows luck has impact on their future investment decisions.

Hypothesis 2b: If the weight allocated to luckiness more than to other factors, it implies institutions overweight their luckiness when they make future decisions.

Apart from the experience about returns rate, monetary gain realized from previous IPOs could also affect institution's future investment behavior. For instance, one institution can earn enormous money from IPOs even if the return rate is relatively low. In this case, institution may concern absolute gain more than return rate when making future investment decision. Therefore, we propose that high monetary gain obtained in the past will prompt institutions to participate in more IPOs.

Hypothesis 3: If both high actual and missed monetary gain in the past motivate institutions to participate in more IPOs and the impact of these two returns are equal, institution's learning behavior is subject to Bayesian learning. Alternatively, if the impact of actual monetary gain is more influential than the missed ones, institution's learning behavior is consistent with naive reinforcement learning

4. Methodology and Results

4.1. Univariate Tests

First of all, we divide our sample into sub-period A and B that have the same number of IPOs. The sub-period A includes 107 IPOs with 9584 bids and the sub-period B involves 107 offers with 9567 bids. For each institution, we calculate participating frequency in sub-period A N_A

[13] This probability is still as low as 9.27% even if we calculate it using qualified shares amount instead of gross demand.

and sub-period B N_B, the times of getting share allocation in sub-period A N_e , and the nominal average IPO returns in sub-period A $\bar{R}_n$. Because of the balloting allocation, $\bar{R}_n$ can be decomposed into the actually experienced average return $\bar{R}_e$ [14] and the missed average return $\bar{R}_m$ [15], where $\bar{R}_e$ and $\bar{R}_m$ are weighted by the scaled times of winning lottery $\frac{N_e}{N_A}$ and losing lottery $1-\frac{N_e}{N_A}$. Therefore, the following equation is deduced:

$$\bar{R}_n = \frac{N_e}{N_A}\bar{R}_e + \left(1-\frac{N_e}{N_A}\right)\bar{R}_m$$ [16]

In this test, we investigate whether the returns earned in sub-period A $\bar{R}_n$ influence institution's investment propensity in sub-period B which is measured by N_B. Beside the past experience, inherent investment appetence could affect institution's behavior as well. We have already found some institutions are exceedingly active in IPO market. Therefore, we group institutions into tertiles according to N_A. Within each group, institutions are further split into two sub-groups based on $\bar{R}_n$. In addition, we exclude 80 institutions that did not take part in IPOs in sub-period A, i.e. $N_A = 0$, because they do not have any experiences in the past.

Figure 1 illustrates the relationship between the nominal return in sub-period A and the times of participating in IPOs in sub-period B with controlling of natural investment propensity. For the middle[17] and high[18] participation group, we find clearly positive pattern between $\bar{R}_n$ and N_B for both mean and median. The median participating time increases from 4 to 12 when middle-frequency participators experienced an additional 4.36% return. However, the mean of N_B marginally increases by 0.12 from the low return group to the high return group for low-frequency participators, which could result from these institutions participate in IPOs occasionally[19] so that past experience does not matter so much for them.

From the univariate test, we discover that past nominal return has positive impact on the frequency of participating in IPOs in the future, which indicates that institutions' behaviors are driven by their past experiences about initial return. However, how the decomposed returns $\frac{N_e}{N_A}\bar{R}_e$ and $(1-\frac{N_e}{N_A})\bar{R}_m$ affect institution's investment decision respectively is not

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[14] $\bar{R}_e = \frac{\sum_{i=1}^{N_e} r_i}{N_e}$, where r_i is the adjusted initial return for IPO_i in which institution obtained shares.

[15] $\bar{R}_m = \frac{\sum_{i=1}^{N_A-N_e} r_i}{N_A-N_e}$, where r_i is the adjusted initial return for IPO_i in which institution did not obtain shares.

[16] Lichtenberg (1900) and Lach (1933) suggest that, the OLS model suffers from omitted variable bias when the aggregate variable is used as explanatory variable but the true model is constructed by decomposed variables. Therefore, $\bar{R}_n$ should be decomposed.

[17] The mean and median of N_A for middle participation group are 9.92 and 8 respectively.

[18] The mean and median of N_A for high participation group are 50.43 and 41 respectively.

[19] The mean and median of N_A for low participation group are 1.64 and 1 respectively.

clear yet.

4.2. Multivariate Test

4.2.1 Past return rate and future behavior

For testing to what extent $\frac{N_e}{N_A}\bar{R}_e$ and $(1-\frac{N_e}{N_A})\bar{R}_m$ influence institution's future behavior, we conduct the following regression:

$$\text{Log}\,(1+N_B) = a + \beta_1 \text{Log}\,(1+N_A) + \beta_2 r_e + \beta_3 r_m + e$$

$$\text{where } r_e \text{ is } \frac{N_e}{N_A}\bar{R}_e \text{ and } r_m \text{ is } (1-\frac{N_e}{N_A})\bar{R}_m$$

The dependent variable $\text{Log}\,(1+N_B)$ is the proxy for future participating propensity; $\text{Log}\,(1+N_A)$ is used to control inherent investment tendency. Since N_A and N_B are ordinal variables, $\text{Log}\,(1+N_B)$ and $\text{Log}\,(1+N_A)$ are used in this regression. The coefficients of β_2 and β_3 are the key measurements that detect how institutions weight experienced return r_e and missed return r_m. Recall hypothesis1, if institutional investors weight the returns they have experienced and those they have not equally ($\beta_2 = \beta_3$), their learning behaviors are consistent with rational Bayesian belief learning. Alternatively, if institutional investors care more about the returns they have experienced than those missed ($\beta_2 > \beta_3$), institutions are subject to naïve reinforcement learning.

Table 2 presents the result of the multivariate tests. In model 1, we only regress $\text{Log}\,(1+N_B)$ on the nominal return $\bar{R}_n$ and Log $(1+N_A)$. We find that $\bar{R}_n$ has significantly positive impact on the frequency of participating in future IPOs. This result is consistent with univarite tests and supports both rational Bayesian learning and naïve reinforcement learning. To distinguish these two learning theories, we decompose the nominal return $\bar{R}_n$ into experienced return r_e and missed return r_m and regress $\text{Log}\,(1+N_B)$ on these two returns in model 2 in which the effect of missed return is statistically significant but the experienced ones is not. This result could due to the fact that many institutions did not get any shares[20] in sub-period A so that the variance of r_e is too low. Furthermore, the last row reports the p-value of coefficient equality test where the null hypothesis is $\beta_2 = \beta_3$. In model 2, the p-value is 0.732, which implies the null hypothesis of $\beta_2 = \beta_3$ cannot be rejected. Referring to hypothesis 1, this result supports that institutions give equal weight to the experienced and missed return. In model 3, we exclude the 144 institutions with $r_e = 0$ from our sample and run the same regression as model 2. It is

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[20] In the data description section, we find that Chinese IPO market is heavily oversubscribed so that the chance of getting shares is extremely low. If one institution does not get any share, we make its $r_e = 0$. In model 2, there are 144 institutions with $r_e = 0$.

showed that a 10% additional missed return increases the times of participation by 25.07% in the future. The t-value of r_e increases from 0.67 to 1.07 although the impact of r_e is still insignificant. Meanwhile, the influence of r_m becomes stronger with t-value of 3.35. On the other hand, we find the coefficient of β_2 and β_3 become much closer to each other, 2.617 versus 2.507. Hence, the results of model 2 and model 3 sustain that institutional investors are subject to Bayesian learning.

In model 2 and model 3, we weight the experienced return and missed return based on the scaled times of getting shares $\frac{N_e}{N_A}$ and $(1-\frac{N_e}{N_A})$. The rare chance of obtaining shares leads to a quite low $\frac{N_e}{N_A}$ and high $1-\frac{N_e}{N_A}$ such that most of the nominal return is attributed to the missed part[21]. In practice, however, institutions may not assess these two returns as the way we did. They could just calculate the simple-averaged return for experienced payoffs and the missed ones without any weighting. In model 4, we use $\bar{R}_e$ and $\bar{R}_m$ instead of $\frac{N_e}{N_A}\bar{R}_e$ and $(1-\frac{N_e}{N_A})\bar{R}_m$ to measure institutions' past returns. Similarly, we get close estimations of β_2 and β_3 with 0.605 and 0.695 respectively and the t-test cannot reject the null that $\beta_2 = \beta_3$.

Based on the aforementioned results, we conclude that, when deciding to participate in future IPOs, institutions take into account initial returns of the IPOs they participated in the past, regardless of the fact that they received a share allocation or not. This type of behavior is consistent with Bayesian learning.

4.2.2 Luckiness and future behavior

In this section, we investigate whether luckiness matters when institution make future investment decision. To get a proxy for luck, we decompose $\bar{R}_n$ as follows and use r_l to measure the luckiness.

$$\bar{R}_n = \bar{R}_m + r_l \ , \qquad \text{where } r_l = \frac{N_e}{N_A}(\bar{R}_e - \bar{R}_m)$$

We run the following regression:

$$\text{Log}\,(1+N_B) = a + \beta_1 \text{Log}\,(1+N_A) + \beta_2 \bar{R}_m + \beta_3\, r_l + e$$

According to hypothesis 2, if r_l has impact on $\text{Log}\,(1+N_B)$ it suggests luckiness affects institution's future decision. Furthermore, if $\beta_3 > \beta_2$, it implies institutional investors even overweight their luck. Regression results are exhibited in model 5 of Table 2. We find that the

[21] In model 2, the mean and median of $\frac{r_m}{R_n}$ are 94% and 100%. In model 3, the mean and median of $\frac{r_m}{R_n}$ are 87% and 92%. In addition, we regress $\bar{R}_n$ on r_m . 98.55% variance of $\bar{R}_n$ are explained by r_m if we keep institutions with $N_e = 0$. After excluding those unlucky institutions, the explanatory power of r_m is still quite high with R-square of 91.2%.

luckiness term r_l positively affect institution's decision at 5% significant level, which is consistent with hypothesis 2a. On the other hand, the coefficient of luckiness term equals to 4.354 which is much higher than the coefficient of $\bar{R}_m$ with $\beta_2 = 0.812$. A 10% increasing of r_l makes the times of participation rise by 43.54%. For the equality test, the null hypothesis of $\beta_2 = \beta_3$ is rejected. This result sustains hypothesis 2b that institutions overweight their luckiness when they make future decisions. In model 6, we exclude institutions that did not get any shares in sub-period A and conduct the same test as model 5. The coefficient difference between β_2 and β_3 becomes wider comparing with model 5. Meanwhile, the equality test of $\beta_2 = \beta_2$ is rejected more strongly at 5% significant level relative to the one of 10% in model 5.

4.2.3 Monetary gain and future behavior

In respect of hypothesis 3, we explore whether monetary gain generated from previous IPOs also influences institution's future investment behavior. Firstly, we calculate the nominal monetary gain G_n in the sub-period A for each institution and decompose G_n into actually experienced gain G_e[22] and missed gain G_m[23] for measuring naïve reinforcement learning and Bayesian learning respectively.

$$G_n = G_e + G_m$$

Same as previous tests, we use Log $(1 + N_A)$ to control inherent investment propensity and Log $(1 + N_B)$ to measure the tendency of participating in future IPOs. Table 3 exhibits the seven models that test the impact of monetary gain on future investment tendency.

In model 1, we regress Log $(1 + N_B)$ on Log $(1 + N_A)$ and G_n only and find that favorable nominal monetary gain makes institution to participate IPOs more often in the future. In order to further distinguish Bayesian learning and naïve reinforcement learning, we use the decomposed terms G_e and G_m as explanatory variables in model 2. The outcome reveals that actual gain has significantly positive impact on future participating desire but missed gain doses not. In model 3, institutions without any allocation in sub-period A are excluded and the new results are consistent with model 2. Unlike the impact of return rate, we herein find only the actual component of gain influences institution's future decision. This finding suggests that institutions are naïve reinforcement learners in terms of monetary gain.

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[22] $G_e = \sum_{i=1}^{N_e} r_i * p_{oi} * q_{ei}$, where r_i is adjusted initial return for IPO_i; p_{oi} is the offer price for IPO_i; q_{ei} is the number of shares obtained in IPO_i. N_e is the times of getting shares in sub-period A.

[23] $G_m = \sum_{i=1}^{N_m} r_i * p_{oi} * q_{mi}$, where r_i is adjusted initial return forIPO_i; $p_{oi}$is the offer price for IPO_i; q_{mi} is the number of shares missed in IPO_i. N_m is the times of having missed shares in sub-period A.

In order to examine the influence of return rate and monetary gain simultaneously, G_e, G_m, r_e and r_m are included in model 4 and model 5 as explanatory variables. Same as previous outcomes, we find the actual gain G_e and missed return r_m positively affect future participating frequency. In addition, both of the two variables turn to be more significant after excluding those unlucky institutions. This result implies that both Bayesian learning and naïve reinforcement learning play roles in institution's decision making but from different aspects. In model 6 and model 7, we examine the effect of luck on future decision with the controlling of both monetary gain and return rate. The coefficient of r_l is significant in both of the models. When we exclude institutions with $r_e = 0$ in model 7, the coefficient of r_l is higher than the coefficient of $\bar{R}_m$ at 10% significant level. This result still shows that luckiness matters and being over weighted in institution's decision making process.

4.2. Robustness Tests

One could argue that our results are driven by the division point of the two sub-periods. Therefore, we split our sample in another way by which we track institution's experience in one year period. Based on the new division point, sub-period A covers 135 IPOs from November 2010 to November 2011 and sub-period B consist of 79 IPOs from December 2011 until now. We implement the same tests as before and the alternative results are quite similar to those found in Table 2 and Table 3. The results of robustness test are displayed in Panel A and Panel B of Table 4.

5. Conclusion

This research explores the impact of personal experience and luck on the behavior of institutional investors in an IPO market. First of all, we disclose that institutions take into account initial returns of the IPOs they participated in the past, regardless of the fact that they received a share allocation or not. This finding implies Bayesian learning plays role in institution's learning process. Secondly, we find that institutions participate more often in future if they personally experienced a large gain from the past IPOs, which hints that naïve reinforcement learning has impact on institution's future decision as well. Hence, we conclude that institutions are subject to both Bayesian and naïve reinforcement learning but in different aspects. Thirdly, we find that institutions are more likely to participate in future IPOs if they were lucky with the share allocation in the past.

References

ARTHUR, W. B. 1991. Designing Economic Agents that Act like Human Agents: A Behavioral Approach to Bounded Rationality. The American Economic Review, 81, 353-359.

CAMERER, C. & HO, T.-H. 1999. Experienced-Weighted Attraction Learning in Normal Form Games. Econometrica, 67, 827-874.

CHEUNG, Y.-W. & FRIEDMAN, D. 1997. Individual Learning in Normal Form Games: Some Laboratory Results. Games and Economic Behavior, 19, 46-76.

CHIANG, Y.-M., HIRSHLEIFER, D., QIAN, Y. & SHERMAN, A. E. 2011. Do Investors Learn from Experience? Evidence from Frequent IPO Investors. The Review of Financial Studies, 24, 1560-1589.

CHIANG, Y.-M., QIAN, Y. & SHERMAN, A. E. 2010. Endogenous Entry and Partial Adjustment in IPO Auctions: Are Institutional Investors Better Informed? The Review of Financial Studies, 23, 1200-1230.

COHEN, R. B., GOMPERS, P. A. & VUOLTEENAHO, T. 2002. Who underreacts to cash-flow news? evidence from trading between individuals and institutions. Journal of Financial Economics, 66, 409-462.

CRAWFORD, V. & BROSETA, B. 1998. What Price Coordination? The Efficiency-Enhancing Effect of Auctioning the Right to Play. The American Economic Review, 88, 198-225.

CRAWFORD, V. P. 1995. Adaptive Dynamics in Coordination Games. Econometrica, 63, 103-143.

CROSS, J. G. 1973. A Stochastic Learning Model of Economic Behavior. The Quarterly Journal of Economics, 87, 239-266.

DHAR, R. & ZHU, N. 2006. Up Close and Personal: Investor Sophistication and the Disposition Effect. Management Science, 52, 726-740.

DINSMOOR, J. A. 2004. The etymology of basic concepts in the experimental analysis of behavior. Journal of the Experimental Analysis of Behavior, 82, 311-316.

FENG, L. & SEASHOLES, M. S. 2005. Do Investor Sophistication and Trading Experience Eliminate Behavioral Biases in Financial Markets? Review of Finance, 9, 305-351.

KAUSTIA, M. & KN PFER, S. 2008. Do Investors Overweight Personal Experience? Evidence from IPO Subscriptions. The Journal of Finance, 63, 2679-2702.

LACH, S. 1993. Decomposition of Variables and Correlated Measurement Errors. International Economic Review, 34, 715-725.

LICHTENBERG, F. R. 1990. Aggregation of Variables in Least-Squares Regression. The American Statistician, 44, 169-171.

NAGEL, S. 2005. Short sales, institutional investors and the cross-section of stock returns. Journal of Financial Economics, 78, 277-309.

ROTH, A. E. & EREV, I. 1995. Learning in extensive-form games: Experimental data and simple dynamic models in the intermediate term. Games and Economic Behavior, 8, 164-212.

SERU, A., SHUMWAY, T. & STOFFMAN, N. 2010. Learning by Trading. Review of Financial Studies, 23, 705-739.

SKINNER, B. F. 1938. The behavior of organisms : an experimental analysis, New York : Appleton-Century-Crofts ; c1938.

THORNDIKE, E. 1911. Animal intelligence: Experimental studies., New York: Macmillian.

ZEILER, M. D. 1968. Fixed and variable schedules of response-independent reinforcement. Journal of the Experimental Analysis of Behavior, 11, 405-414.

Table 1

Panel A: Institutional investors' bid activities

Number of IPOs		214	
Number of institutions		353	
Number of bids		19,151	
	Mean	Median	SD
Number of IPOs participated	29.67	8	43.47
Number of bids submitted in an IPO	1.34	1	0.67
Number of shares (in millions) demanded in an IPO	3.21	2.25	3.30
The total bid value (in million yuans) in an IPO	73.49	54.05	67.21

Panel B: IPO characteristics

	N	Mean	Median	SD
Unadjusted initial return (%)	214	22.60	16.17	29.55
Number of days between the IPO and listing	214	13.84	13	2.75
Market return (%)	214	-0.57	-0.78	4.29
Adjusted initial return (%)	214	23.17	16.22	28.37
Number of institutions per IPO	214	48.93	45	18.64
Number of bids per IPO	214	89.49	76.50	49.12
Number of shares (in millions) demanded in bookbuilding	214	264.80	171.05	368.36
Number of shares (in millions) eligible for lottery	214	129.69	68.38	316.30
Number of shares (in millions) allocated in lottery	214	5.13	4.22	3.27
Probability of winning shares in lottery	214	9.27%	6.18%	9.78%

The sample includes 353 institutions who submitted 19,151 bids in 214 IPOs during the November 2010 and September 2012 period. Panel A reports the activities of institutional investors in bookbuilding. A bid is defined as an offer with specific price and quantity via an institution's investment account. The number of bid 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 times of participation will be counted as once no matter whether the bid (s) is (are) eligible for the following allocation. The bid value equals to bid quantity multiplies the corresponding bid price. Panel B describes the characteristics of the 214 IPOs. The probability of winning shares is estimated by the proportion of issued shares relative to shares eligible for lottery. Adjusted initial return is calculated as unadjusted initial return minus the corresponding market return.

Table 2
The effect of past returns on future decision

Dependent variable: Log $(1 + N_B)$

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log $(1 + N_A)$	0.975*** (25.28)	0.970*** (23.30)	1.088*** (14.37)	0.943*** (21.14)	0.981*** (25.48)	1.063*** (14.35)
$\bar{R}_n$	0.793*** (2.92)					
$r_e = \frac{N_e}{N_A}\bar{R}_e$		1.603 (0.67)	2.617 (1.07)			
$r_m = (1 - \frac{N_e}{N_A})\bar{R}_m$		0.784*** (2.88)	2.507*** (3.35)			
$\bar{R}_e$				0.605 (1.44)		
$\bar{R}_m$				0.695*** (2.65)	0.812*** (2.96)	2.725*** (3.64)
$r_l = \frac{N_e}{N_A}(\bar{R}_e - \bar{R}_m)$					4.354** (2.26)	6.894*** (3.13)
Constant	-0.569*** (-4.22)	-0.566*** (-4.18)	-1.356*** (-3.78)	-0.525*** (-3.89)	-0.569*** (-4.23)	-1.278*** (-3.77)
Obs.	273	273	129	273	273	129
R-sq	62.48%	62.49%	58.49%	62.61%	62.75%	59.42%
Comparison of β_2 and β_3		0.732	0.965	0.863	0.062*	0.034**

This table presents OLS regression results. The variable definitions are in Section 4.1. In model 1, 2, 4 and 5, all of the 273 institutions that took part in IPOs in sub-period A are included as observations. In model 3 and 6, we exclude the 144 institutions that did not get any share allocation in sup-period A from our sample. Robust t-values for eliminating heteroscedasticity are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 3

The effect of past monetary gain on future decision

Dependent variable: Log $(1+N_B)$

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
$\text{Log}\,(1+N_A)$	0.925***	0.905***	1.010***	0.915***	0.938***	0.915***	0.989***
	(18.23)	(17.77)	(11.54)	(17.94)	(9.85)	(17.97)	(10.91)
G_n	0.009*						
	(1.69)						
G_e		0.912**	0.884**	1.200**	1.302***	0.750**	0.553*
		(2.58)	(2.42)	(2.58)	(2.81)	(2.14)	(1.89)
G_m		-0.001	-0.003	-0.003	-0.004	0.002	0.002
		(-0.13)	(-0.71)	(-0.54)	(-0.92)	(0.34)	(0.37)
$r_e=\frac{N_e}{N_A}\bar{R}_e$				-2.088	-2.641		
				(-0.77)	(-0.92)		
$r_m=(1-\frac{N_e}{N_A})\bar{R}_m$				0.807***	2.877***		
				(2.9)	(3.82)		
$\bar{R}_m$						0.797***	2.631***
						(2.89)	(3.52)
$r_l=\frac{N_e}{N_A}(\bar{R}_e-\bar{R}_m)$						3.944*	6.536***
						(1.9)	(2.71)
Constant	-0.304**	-0.278**	-0.609**	-0.476***	-0.972***	-0.481***	-1.119***
	(-2.58)	(-2.35)	(-2.10)	(-3.39)	(-2.75)	(-3.43)	(-3.28)
Obs.	273	273	129	273	129	273	129
R-sq	61.71%	62.16%	56.46%	63.28%	60.25%	63.35%	60.27%
Comparison of β_2 and β_3						0. 123	0.070*

This table presents OLS regression results. The variable definitions are in Section 4.1, Section 4.2.2 and Section 4.2.3. In model 1, 2, 4 and 6, all of the 273 institutions that took part in IPOs in sub-period A are included as observations. In model 3, 5 and 7, we exclude the 144 institutions that did not get any share allocation in sup-period A from our sample. Robust t-values for eliminating heteroscedasticity are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Table 4 Panel A

The effect of past returns on future decision (Alternative sub-period division)

Dependent variable: Log $(1+N_B)$						
Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Log $(1+N_A)$	0.807*** (21.13)	0.797*** (18.28)	0.866*** (10.45)	0.772*** (15.77)	0.812*** (21.30)	0.832*** (9.79)
$\bar{R}_n$	0.703** (2.31)					
$r_e = \frac{N_e}{N_A}\bar{R}_e$		2.338 (0.90)	2.785 (0.97)			
$r_m = (1-\frac{N_e}{N_A})\bar{R}_m$		0.689** (2.26)	1.826* (1.91)			
$\bar{R}_e$				0.601 (1.25)		
$\bar{R}_m$				0.613** (2.08)	0.721** (2.34)	2.158** (2.20)
$r_l = \frac{N_e}{N_A}(\bar{R}_e - \bar{R}_m)$					4.241** (2.01)	6.486** (2.34)
Constant	-0.492*** (-4.32)	-0.485*** (-4.20)	-0.999*** (-2.84)	-0.444*** (-3.80)	-0.491*** (-4.31)	-0.896*** (-2.68)
Obs.	286	286	137	286	286	137
R-sq	57.38%	57.44%	45.67%	57.53%	57.64%	46.5%
Comparison of β_2 and β_3		0.526	0.739	0.984	0.089*	0.065*

Since the change in sub-period division, the number of institutions that participated in sub-period A IPOs increases to 286 and more institutions (137) got share allocation at least once in sub-period A. The definition of variables and models are same as Table 2.

Table 4 Panel B
The effect of past monetary gain on future decision (Alternative sub-period division)

Dependent variable: Log $(1+N_B)$							
Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Log $(1+N_A)$	0.764*** (15.95)	0.742*** (15.21)	0.790*** (8.10)	0.741*** (14.90)	0.671*** (5.87)	0.739*** (15.05)	0.732*** (6.92)
G_n	0.007** (2.06)						
G_e		0.804*** (2.91)	0.761*** (2.66)	1.019*** (2.97)	1.174*** (3.07)	0.722*** (2.62)	0.578** (2.27)
G_m		-0.002 (-0.64)	-0.003 (-0.93)	-0.004 (-1.00)	-0.004 (-1.15)	-0.001 (-0.24)	0.0002 (0.07)
$r_e=\frac{N_e}{N_A}\bar{R}_e$				-2.249 (-0.86)	-4.398 (-1.41)		
$r_m=(1-\frac{N_e}{N_A})\bar{R}_m$				0.719** (2.30)	2.340** (2.47)		
$\bar{R}_m$						0.712** (2.28)	2.037** (2.07)
$r_l=\frac{N_e}{N_A}(\bar{R}_e-\bar{R}_m)$						3.817* (1.78)	6.210** (2.14)
Constant	-0.257** (-2.37)	-0.226** (-2.07)	-0.370 (-1.16)	-0.385*** (-3.25)	-0.468 (-1.24)	-0.389*** (-3.28)	-0.660* (-1.90)
Obs.	286	286	137	286	137	286	137
R-sq	57.09%	57.76%	46.00%	58.57%	48.27%	58.63%	48.10%
Comparison of β_2 and β_3						0.140	0.090*

Since the change in sub-period division, the number of institutions that participated in sub-period A IPOs increases to 286 and more institutions (137) got share allocation at least once in sub-period A. The definition of variables and models are same as Table 3.

Figure 1
Past nominal returns and frequency of participating in following IPOs