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Context-specific experience and institutional investors' performance

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A B S T R A C T

We examine how context-specific experience is correlated with the performance of institutional investors. Specifically, we explore how previous initial public offering (IPO) trading experience affects foreign institutional investors' selection, bidding, and the profitability of their future IPO investments. We find that investors who participate more frequently (i.e., those with more context-specific experience) exhibit different behaviors from those who participate less frequently. After controlling for *investor fixed effects* and time-varying heterogeneity, we find that only high-frequency investors improve their profitability over time by appropriately varying their subscriptions across IPOs. The effect of context-specific experience also appears to dominate other forms of general investment experience.

1. Introduction

Existing studies note that foreign institutional investors (FIIs) play an increasingly important role in the proper functioning of emerging markets. They contribute much-needed capital (Errunza, 2001), promote better governance through monitoring (Aggarwal et al., 2011), and encourage innovation (Luong et al., 2017). Although prior research examines the relative investment performance of FIIs, there is little work on how the previous experience of these investors in foreign markets affects their future performance. Using data from the Indian market, we address this question by examining whether prior context-specific investment experience allows FIIs to improve their investment performance in the context of initial public offerings (IPOs).

Scholars have been attempting to understand how previous experiences, whether encountered or observed, affect investors' future investment behavior. For instance, Malmendier and Nagel (2011) show that individuals who experience low stock and bond returns in their lifetime are less likely to invest in such securities. Others examine whether previous experience in the stock market leads to rational or naïve learning.[1] Consistent with the rational learning hypothesis, Seru et al. (2009) find that individual investors not only become better with experience but also are likely to stop trading upon realizing their poor investment abilities. Conversely, Kaustia and Knüpfer (2008), Chiang et al. (2011), Bailey et al. (2011), and Campbell et al. (2014) find support for naïve reinforcement learning. For instance, Kaustia and Knüpfer (2008) and Chiang et al. (2011) show that individual investors overweigh their past returns when subscribing to future initial public offerings (IPOs), with returns decreasing over time for frequent investors.

To date, much of the literature focuses on retail investors. However, more recently, research on institutional investors has begun to emerge. Prior experience should matter and have a first order effect on investment performance even among sophisticated institutional investors as it allows investors to overcome uncertainties and obtain informational advantages (Kempf et al., 2017; Cici et al., 2018). Using age as a measure of experience, Greenwood and Nagel (2009) find that mutual funds run by younger managers were more heavily invested in technology stocks during the peak of the technology bubble. Similarly, Pástor et al. (2015) find evidence of mutual fund managers' skills rising with fund age.

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[1] In rational learning, investors improve their decision-making abilities over time through experience, while in naïve learning they overweigh their personal success or failure and expect the same outcome in the future.

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As stated before, we extend this emerging area of research by examining how FIIs' previous context-specific investment experience is correlated with their future performance. Specifically, using a unique dataset that allows us to capture the time-varying learning that emerges from previous trading experience, we analyze the experience and learning of FIIs in the context of their IPO investments. Some recent work in this area highlights the importance of context-specific experience. Notably, Kempf et al. (2017) find that mutual fund managers exposed to industry shocks select better stocks with experience, and Cici et al. (2018) show that muovtual fund managers' investment performance is significantly better in industries in which they have prior work experience. Anagol et al. (2021) document that prior context-specific experience also appears to help retail investors. Using retail investors' subscription data in Indian IPOs, they show that investors with more prior domain-specific knowledge exhibit smaller behavioral biases than those without such experience.

Our main measure of experience captures the specific experience of IPO investments. We measure experience as the number of previous IPOs subscribed by an investor (Chiang et al., 2011).[2] For example, an investor with 10 previous IPO subscriptions is deemed to have more context-specific experience than an investor with only 2 subscriptions. To understand the effects of varying degrees of context-specific experience, we group investors into three categories according to their IPO investment frequency: high, moderate, and low-frequency investors.[3] We anticipate that while all investors should improve their investment performance over time, those with the highest level of context-specific experience are expected to perform significantly better than others. This argument is also consistent with the *learning-by-doing* view of experience, which posits that investors improve their investment skills by trading (Arrow, 1962; Grossman et al., 1977; Seru et al., 2009; Kempf et al., 2017).

To assess the effects of experience, we explore three aspects of IPO investment: selection, bidding, and profitability. Given the significant variation in the quality of IPO offerings, investors with more primary market experience should improve their ability to select better quality IPOs over time. Profitable IPO investments depend not only on selection but also on appropriate bidding, which is even more important in our setting involving auction IPOs, where both over- and under-bidding are common.[4] Given that a high degree of sophistication is required to avoid the winners' curse in auction IPOs (Jagannathan et al., 2015), we anticipate that experience would be positively associated with bid shaving. Finally, if previous experience improves investors' selection and bidding skills, then their profitability should increase over time.

We perform our analyses in the distinct setting of the Indian IPO market. The Indian setting is particularly interesting because of a publicly available FII transaction database with complete FII trade-level data from 2003 onwards.[5] Unlike previous studies that use either small proprietary or quarterly holdings data, we utilize granular trade-level data to examine the investment behavior of FIIs in a large sample over a long period. Our overall sample consists of 327 IPOs issued during the period 2004–2015. Our initial trade-level dataset comprises approximately 8500 primary trades (IPO subscriptions) involving more than 1100 FIIs. Following previous studies, we split the sample into two halves. We first classify investors according to their investment frequency over the 2004–2006 period. We then conduct all our tests over the 2007–2015 period only for those investors present in the first period. Therefore, our main sample consists of 2420 primary trades in the second half, and it forms the basis of our main empirical tests.

We perform our tests at the aggregate level and separately for the three investor categories. Importantly, owing to the long time series nature of our FII investment data, we include *investor fixed effects* to address the time-invariant unobserved investor heterogeneity. We begin by examining IPO selection and bidding. We begin by examining IPO selection and bidding. While FIIs across the three investor categories improve their IPO selection ability over time, we find that only high-frequency investors' bids are positively associated with IPO quality over time. In our next set of tests using first-day and realized profits[6], we find that experience is positively related with profits only among high-frequency investors, indicating the relative importance of bidding over selection. Consistent with our conjecture and the *learning-by-doing* view of experience, we thus observe that investors with the highest level of context-specific experience perform significantly better than their less experienced counterparts.

We conduct several other tests to ascertain the robustness of our results. First, we classify investors and run all tests over the entire sample period (2004–2015). Furthermore, we classify investors and perform our analysis using only auction IPOs. We also use alternative measures of IPO quality, bid shaving, realized profits, time-varying proxies for investor size, and investor demand. In addition, we use alternative classifications of the three investor categories with different approaches and cut-offs. Our results remain consistent in all robustness tests. We also find consistent results when including investor-underwriter fixed effects to address the concern that our results are driven by the long-term relationship between underwriters and FIIs.

Our measure of experience thus far captures FIIs' context-specific experience from their involvement in the primary market. In additional tests, we also consider their participation in the secondary market. We find that primary market (context-specific) experience remains significant even after the inclusion of secondary market and time based measures of experience. While secondary market experience is positively associated with bid shaving and profitability among high-frequency investors, the economic significance of this association is much weaker relative to that of the primary market experience. Interestingly, we find no evidence of improvement in bidding or profitability in tests that use time in the market as a measure of experience.

Although our extensive empirical analyses provide strong evidence of learning by FIIs, particularly those with a high-degree of context-specific experience, we must acknowledge the limitations of our research design to address potential endogeneity concerns. In our work, we employ *investor fixed effects* to address the effect of time-invariant investor heterogeneity and include the size of the institutional investor as a time-varying factor. However, it is still possible for an omitted institutional level variable to drive our results given that the identities of FIIs are masked in our dataset. Thus, a caveat, as in any research design, is that we cannot rule out the existence of an unobserved institutional level variable that may drive the investor-performance relationship.

[2] Although our approach is similar to that of Chiang et al. (2011), our measure is not as precise and strong. Unlike Chiang et al. (2011), our sample period does not begin from the very first IPO offered to FIIs. Nevertheless, we perform several tests such as splitting the sample into two halves, to address this concern.

[3] High, moderate and low-frequency investors are those in the top decile of frequency, deciles 7–9, and deciles 1–6, respectively. This is further discussed in Section 4.2.

[4] Further details on the Indian IPO market are provided in Section 2.2.

[5] To the best of our knowledge, this is the only large-scale institutional trade-level data that is publicly available. See Section 3 for further details.

[6] First-day profits are based on the stock's closing price on the first day of listing. As we are able to track the trading of IPO allocations in the secondary market, we calculate realized profits by using secondary trades data made during the first six months of the post-listing period. The calculation of realized profits is discussed in Section 4.

Our paper contributes to the existing literature on how investors perform in overseas markets (Grinblatt and Keloharju, 2000; Choe et al., 2005; Dvořák, 2005; Huang and Shiu, 2009). While prior studies focus on the investment performance of foreign investors primarily in the secondary market, we examine investments in the primary market showing that experience may allow FIIs to mitigate distance, cultural, and linguistic barriers and improve their investment performance. Interestingly, experience appears to be a valuable commodity even in a setting where the informational disadvantage for (foreign) investors is significantly weaker.

Importantly, our study is related to the growing literature on how experience influences investors' behavior (Kaustia and Knüpfer, 2008; Malmendier and Nagel, 2011; Chiang et al., 2011; Kempf et al., 2017). Given the depth and scale of our trading dataset, the evidence in this paper significantly improves our understanding of how institutional investors learn over time (Greenwood and Nagel, 2009; Pástor et al., 2015). While Kaustia and Knüpfer (2008) and Chiang et al. (2011) primarily focus on retail investors, we present comprehensive evidence of learning among institutional investors and show that, unlike retail investors, institutional investors' prior context-specific experience allows them to significantly improve their investment performance over time.

Specifically, our paper contributes to the literature on the role of domain-specific experience on investment performance. While our results are consistent with those of Kempf et al. (2017) and Cici et al. (2018), we further extend the literature by showing the dominating link of context-specific experience over other forms of general experience on investment performance. Finally, as we demonstrate diverse learning patterns by different investor subgroups, our evidence highlights the issue of analyzing data at the aggregate level, which masks important variation within subsets of the overall sample. We find that the relationship between experience and learning is nuanced and heterogeneous.

The rest of the paper is organized as follows. Section 2 discusses the relevant features of the Indian market. Sections 3 and 4 present the data and descriptive statistics, respectively. We present all our empirical results in Sections 5 and 6. Section 7 concludes.

2. Institutional background

2.1. FIIs in India

The structural economic reforms in India in the early 1990s led to significant growth in capital market investments by DIIs and FIIs. In 1992, the Indian government allowed qualified FIIs to buy equities in Indian listed companies directly. Figure 1 shows the net investments by FIIs in Indian equities during the 1994-95 to 2014-15 period. As a result of several corporate governance initiatives (Dharmapala and Khanna, 2013) and the rebound of confidence in global markets, FIIs' investments sharply increased starting in the 2003-04 period (which is also the beginning of our sample period). Over our sample period, FII investments grew at a compounded annual rate of almost 10%. The net FII investments stood at INR 1113 billion (approximately US$ 25 billion) for the 2014-15 financial year.[7] On average, FIIs hold about 20% of the BSE 500 index which accounts for nearly 90% of India's market capitalization. Thus, FIIs are integral to and play a significant role in the Indian capital market.

Our focus on FIIs is relevant as prior literature shows conflicting evidence on the investment abilities of these investors. On one hand, some studies show that FIIs outperform their local domestic counterparts presumably because of better access to resources as well as expertise and talent (e.g., Grinblatt and Keloharju, 2000; Seasholes, 2000, among others) On the other hand, there are studies that document inferior performance of FIIs, which is primarily due to their informational disadvantage (Dvořák, 2005; Huang and Shiu, 2009). FIIs should be better off with experience even when their investment abilities are superior. More importantly, the likely benefits of experience should assist FIIs to better process and understand information. This should reduce their informational disadvantage, which in turn should lead to improved investment performance for the more experienced investors.

2.2. The Indian IPO market

The Indian IPO market is unique in several respects (please refer to Bubna and Prabhala, 2011 and Neupane and Poshakwale, 2012 for a detailed discussion). Here, we briefly highlight some interesting aspects of the market relevant to our study. First, India is one of the few markets in which auctions are the predominant IPO selling mechanism.[8] After a few years of experimenting with the bookbuilding mechanism, regulators abandoned it in late 2005 and adopted the auction approach, which affords less discretion to underwriters. While some firms in our sample use the bookbuilding mechanism, most IPOs come from the auction regime. The type of auction used in India is the 'dirty Dutch auction', which allows the underwriter to set the offer price below the market clearing price but requires shares to be allocated on a pro-rata basis. Figure 2 shows the distribution of IPOs over the sample period. Although our sample period extends to 2015, most IPO activity is concentrated over the 2004–2011 period.

Second, an interesting aspect of the Indian market is that a predetermined quota of shares is allocated to different investor categories. The three primary categories are institutional investors, non-institutional (NIIs) investors, and retail individual (RIIs) investors, and they receive 50%, 15% and 35% of the shares in the offering, respectively.[9] Large investors registered with the SEBI are allowed to submit bids in the institutional investor category. FIIs, which are the focus of this study, bid for shares and receive allocations from this institutional investor category. Third, the market features enhanced transparency during the offer period (see Neupane and Poshakwale, 2012 for a detailed discussion). When an IPO is open for subscription, real-time information related to investor demand is available on the Bombay(BSE)/National(NSE) stock exchange websites. Hence, investors can gauge the overall subscription and the subscription of different investor categories (i.e. DIIs, FIIs, NIIs, and RIIs) before submitting their own bids. We control for this information in our empirical analyses.

Neupane and Poshakwale (2012) show that the transparency of the Indian IPO mechanism allows less informed investors to free-ride and improve their performance by simply following informed institutional investors. In this sense, the enhanced transparent mechanism sets up a high bar for empirically observing learning between more and less experienced investors. Less informed may simply mimic the subscription of other (informed) in-

[7] Further, according to the 2015 Bank of America Merrill Lynch Fund Manager Survey, India was the most preferred equity market for global investors at 43%, followed by China at 26%.

[8] While auction is the predominant mechanism, regulators have allowed firms that do not meet the auction criteria to go public with a fixed price mechanism. There are 65 fixed price issues during the 2004–2015 period.

[9] Investors who submit bids up to a sum of INR two hundred thousand are considered to be RIIs while those who submit in excess of INR two hundred thousand are considered to be NIIs.

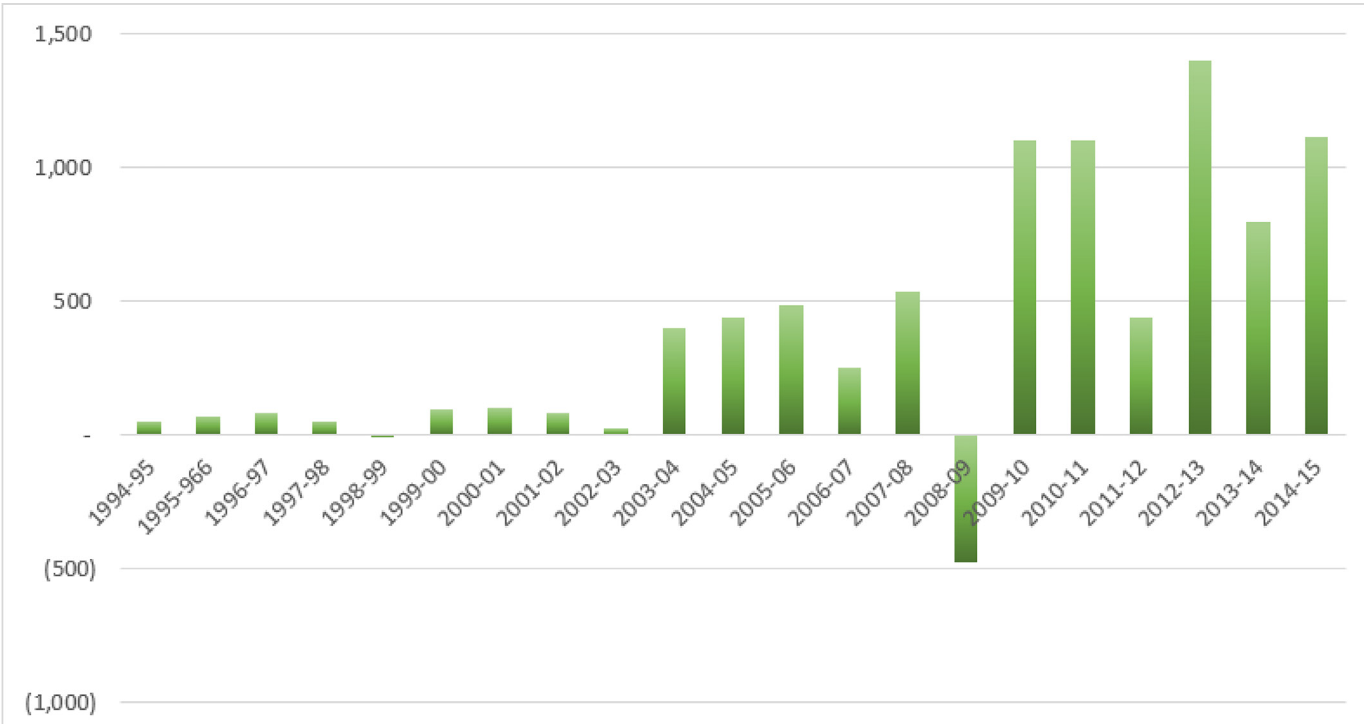

Fig. 1. Net Investments by FIIs in India. Figure 1 shows net investments by FIIs (in INR billions) in India over the 1994-95 to 2014-15 period. Source: NSDL FPI Monitor.

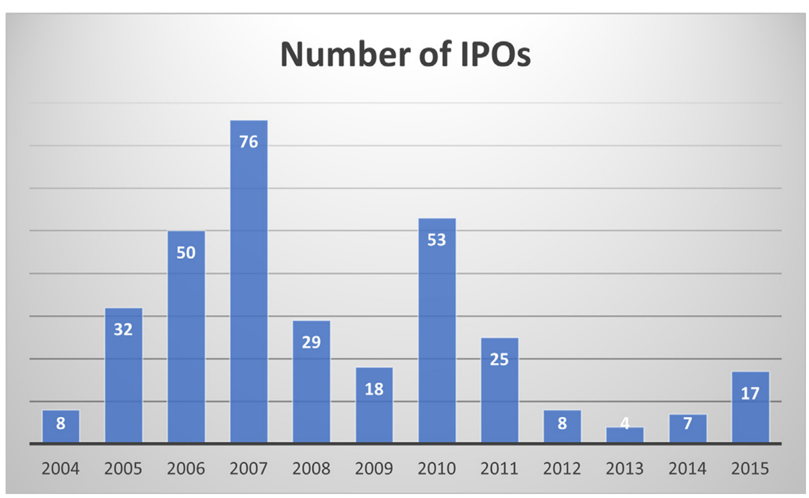

Fig. 2. Distribution of IPOs over the sample period. Figure 2 shows the distribution of IPOs over the sample period (2004–2015).

vestors, thereby rendering any advantage of the more experienced investors worthless. We address the mimicking concern by incorporating the demand of DIIs in our empirical analysis and by comparing the IPO subscriptions of DIIs and FIIs.

3. Data

This study uses a sample of Indian IPOs issued during the period January 2004 to December 2015. We begin our sample in 2004 as data on FIIs participating in Indian IPOs are only available from 2004 onwards. Furthermore, the year 2004 marks a resurgence in IPO activity following the market crash of 2000 and the dull period between 2001 and 2003.[10] In total, 463 IPOs were issued during the 2004–2015 period. We exclude 65 fixed price IPOs as there is negligible participation of FIIs in these offerings. We also exclude 14 large privatization IPOs due to their size and the nature of their deals. We do not find any FII transactions in 57 IPOs. Thus, our final sample consists of 327 IPOs, including 45 bookbuilding and 282 auction IPOs. We gather the data on firm and offer characteristics from the prospectus and those on in-

[10] A total of 24 IPOs were issued during the 2001–2003 period, whereas 20 and 55 IPOs were issued in 2004 and 2005, respectively.

Table 1
Summary statistics. This table reports the sample statistics of the key variables for IPOs listed on the BSE and/or NSE between 2004 and 2015. Appendix A provides definitions for all the variables.

Particulars	P25 (1)	Mean (2)	Median (3)	P75 (4)
Panel A: Firm Characteristics				
Assets (INR million)	804.00	7,765.64	2,004.00	6,883.00
Proceeds (INR million)	688.00	3,805.53	1,330.00	3,519.00
Age (Years)	8.00	15.19	12.00	17.00
Underwriter reputation	0.00	0.60	1.00	1.00
Initial return	(0.07)	0.19	0.10	0.40
Panel B: Investor Participation				
Institutional bids	13	84	38	116
Non-institutional bids	47	691	132	352
RII bids	13,552	125,409	48,634	156,157
FII bids	4	22	12	31
DII bids	7	60	24	85
Total demand	1.95	19.22	6.80	27.29
Institutional demand	1.33	22.16	6.60	28.90
NII demand	1.56	33.97	6.64	43.75
RII demand	1.54	9.98	4.05	10.79
% of shares allocated to FIIs	21%	31%	29%	40%

vestors' participation (subscription and number of bids) and stock prices from the BSE/NSE websites.

We obtain the FII trading data from the NSDL's FPI Monitor database, an entity affiliated with the SEBI. This publicly available online database provides data on all FII trades starting in January 2003. Appendix B provides a snapshot of the dataset related to primary allocation (Panel A) and secondary sells (Panel B).[11] The Transaction Type (TR_TYPE*) field is key to categorizing transactions as primary or secondary trades and as buy or sells. Transaction types 1 and 2 refer to secondary and primary buys (IPO allocations), respectively. Type 4 refers to secondary sells. We identify more than 8,100 primary allocations in our sample of 327 IPOs. Our final dataset consists of a slightly smaller sample of 6450 primary allocations after excluding the FIIs involved in fewer than four IPOs. The dataset also provides information on transaction date (TR_Date), transaction price (Rate), transaction volume (Quantity), and value of the trade (Value in Rs). Although the identity of an FII is masked, every trade is allotted a particular FII registration number (second column in the tables).[12] Using this unique code, we track the secondary trades relating to initial IPO allocations. Over the entire sample period (2004 – 2015), more than six hundred thousand buy and sell secondary trades were made by FIIs who were allocated primary market shares. We use this secondary data (primarily sell trades) to perform tests on realized profitability.

4. Descriptive statistics

4.1. Overall sample

Table 1 highlights several summary measures of firm characteristics and investor participation. Appendix A presents the variable descriptions. Panel A provides summary statistics for the characteristics of the IPO firms. The average (median) IPO in our overall sample has assets of INR 7,765 (2004) million, raises INR 3,805 (1330) million, and is 15.19 (12.0) years old.[13] Summary statistics also indicate that high reputation underwriters manage a large number of IPOs. The average (median) market-adjusted first-day return (initial return) for our sample of IPO firms is 19% (10%).

Panel B presents statistics on investment by investor category. The average (median) IPO attracts 125,409 (48,634) RII bids, 691 (132) NII bids, and 84 (38) institutional bids. Of these institutional bids, FIIs submit 22 (12) while DIIs submit 60 (24) bids. The average (median) IPO oversubscription is 19.22 (6.80) times, and the average (median) oversubscription for the institutional category is 22.16 (6.60) times. The mean (median) oversubscriptions for NII and RII categories are 9.98 (4.05) and 33.97 (6.64) times, respectively. Finally, the average (median) allocation to FIIs is approximately 31% (29%) of the shares on offer. Since institutional investors are allocated 50% of the shares, FIIs on average receive more shares than DIIs.

Table 2
Frequency of FIIs' IPO investments. This table reports the univariate statistics related to the frequency of FIIs' participation in Indian IPOs listed on the BSE and/or NSE between 2004 and 2015.

FII participation in IPOs	Number of FIIs	Percentage of FIIs
1 IPO	441	40.24%
2 - 3 IPOs	269	24.54%
4 - 5 IPOs	116	10.58%
6 - 10 IPOs	109	9.95%
11 - 25 IPOs	92	8.39%
26 - 50 IPOs	31	2.83%
51 - 74 IPOs	21	1.92%
75 or more IPOs	17	1.55%
Total	1109	100.00%

4.2. FIIs' investment frequency

In this section, we document FIIs' involvement in IPOs. Table 2 summarizes the FII investment data, which forms the basis of all our subsequent empirical analyses. As discussed earlier, although the database masks the identities of FII, we can observe and track trade data for FIIs across IPOs because of the unique code assigned to each investor. During our sample period, 1,109 FIIs invested in the primary market. As we are interested in experience and learning, we begin by analyzing the investment frequency of these investors. As Table 2 shows, a large number of FIIs are infrequent investors; specifically, about 40% (441) of investors bid in one IPO while 25% (269) bid in only two or three IPOs. In total, almost 85% (948) of FIIs bid in 10 or fewer IPOs.

However, we find that some FIIs are frequent and others extremely frequent participants in the primary market. More specifically, 52 investors (about 5%) participate in 26–74 IPOs, and a further 17 (2%) FIIs submit bids in 75 or more IPOs. The preliminary analysis shows that FII involvement in India is considerably heterogeneous. This assures us that the setting is appropriate for examining the role of regular participation and experience over time. Seru et al. (2009) show that investor attrition significantly affects learning estimates and is particularly relevant among low-frequency investors. Hence, to address attrition bias, we follow Kaustia and Knüpfer (2008) and limit our analyses to FIIs who participate in four or more IPOs. This reduces the number of FIIs in our sample from 1,109 to 386.

[11] The data which is available in CSV files can be found at www.fpi.nsdl.co.in. Some of the columns in the dataset that are not relevant are not shown here. Prior studies using this data include Neupane et al. (2017) and Neupane et al. (2021) and Marshall et al. (2022).

[12] The registration number is a 17 character alpha-numeric term (for instance the registration number of the first FII in Panel A of Appendix B is F5944222243200706). The last 6 digits consists of the year and month of transaction (200706 i.e. year: 2007 & month: June). The three digits prior to that (243) are a running number). Both these digits change over time. We use the remaining characters (the first eight alpha-numeric term that remains constant throughout the sample period) to uniquely identify each FII

[13] The average exchange rate during the period of our study was US$ 1 = INR 50.

Table 3
Univariate analysis of FIIs' involvement in IPOs by investor type. This Table reports the mean(median) statistics (# denotes the number) of the key variables by investor categories relating to their investments over the 2007–2015 period (second half). FIIs with investment frequency in the top decile, deciles 7–9, and lower deciles as categorized as high, moderate, and low-frequency investors, respectively. Appendix A provides definitions for all the variables.

	Investment Frequency		
	High (1)	Moderate (2)	Low (3)
# of IPOs subscribed	64 (57)	31 (28)	19 (17)
Allocation value (INR million)	46 (10)	55 (11)	38 (7)
% of shares allocated	0.018(0.020)	0.016 (0.015)	0.008 (0.001)
Initial return	0.35 (0.25)	0.37(0.27)	0.31 (0.24)
First-day profit (INR million)	5.02 (2.08)	5.94 (2.10)	4.87 (1.27)
Holding period (days)	64 (2)	70 (11)	127 (19)
Outstanding position – 1 month	0.18 (0.15)	0.25 (0.26)	0.70 (0.87)
Realized profit – 1 month (INR million)	5.93 (3.33)	5.27 (3.08)	5.81 (1.34)
Outstanding position – 6 months	0.09 (0.07)	0.11 (0.11)	0.56 (0.63)
Realized profit – 6 months (INR million)	7.45 (3.91)	7.88 (2.87)	6.19 (1.40)
Outstanding position – 12 months	0.07 (0.05)	0.10 (0.06)	0.52 (0.50)
Realized profit – 12 months (INR million)	8.08 (4.12)	8.11 (3.38)	6.18 (1.71)
FII size (INR million)	13,382 (5,680)	23,232 (15,945)	8,704 (1,887)

Given the varied participation and consequently different degrees of exposure to context-specific experience, we analyze separate FII categories on the basis of the frequency of their investments. In our empirical analysis, we follow Kaustia and Knüpfer (2008) and split the sample into two halves. We categorize investors in the first half and perform empirical analyses using data from the second half. This allows us to address endogeneity concerns stemming from investor activity and performance as well as alleviate any *ex post* bias when analyzing the full sample. Specifically, we first classify investors using their investment frequency over the 2004–2006 period. We then conduct all our tests over the 2007–2015 period only for the investors involved in the first period. This split allows us to have similar numbers of observations in the first and second halves. In the first half, 228 FIIs have at least four IPO subscriptions. We consider FIIs in the top decile, deciles 7–9, and lower deciles as high, moderate, and low-frequency investors, respectively. This classification yields 14 high, 34 moderate and 180 low-frequency investors.[14] The 228 FIIs from the first period make 2,420 IPO bids in the second period. These 2,420 bids form the sample for all our main tests.[15]

Table 3 reports the summary statistics (at the investor level) for the three different investor categories relating to their investments in the second period.[16] We find that the average (median) high, moderate and low-frequency FII bids are 64 (57), 31 (28) and 19 (17) IPOs, respectively. This results indicate a continuation of the strong differentiation between investors in terms of their investment frequencies. It also shows that the most frequent investors in the first half continue to invest more frequently in the second half. The statistics also reveal that the high and moderate-frequency investors receive, on average, about 2% of the allocation, which represents an allocation value of approximately INR 12 million.[17] The average initial return for IPOs in which high and moderate-frequency investors participate is quite similar at 36%. The average return is 31% for IPOs with low-frequency investors. Based on first-day closing price, the average (median) profits are approximately INR 5.02 (2.08) million for the high, INR 5.94 (2.10) million for the moderate and INR 4.87 (1.37) million for the low-frequency investor.

As we can track the trading of IPO shares in the secondary market, we calculate FIIs' realized Rupee profits. We calculate realized profits as the difference between the realized value and IPO allocation value (offer price multiplied by the number of shares allocated). To estimate the realized value (for each time window), we sum the value of all secondary sell transactions associated with IPO allocation and the value of the outstanding position. For instance, to estimate one month's realized value, we sum the value of IPO related secondary sell transactions in the first month of listing and the outstanding value obtained by multiplying the month-end closing price with the remaining shares from IPO allocation.[18]

Consistent with Neupane et al. (2017), we find substantial flipping among FIIs. Specifically, the median high-frequency (moderate-frequency) investor holds only about 18% (25%) of the initial allocation at the end of the first month of listing. This declines to 9% (11%) at the end of the six-month period. Meanwhile, low-frequency investors appear to hold on to their allocations much longer. The average (median) realized profits at the end of the six-month period are INR 7.45 (3.91) million, INR 7.88 (2.87) million, and INR 6.19 (1.40) million for high, moderate, and low-frequency investors, respectively. As profits and holdings do not change much after this, we use six months' realized profits in our empirical analysis.

Although the identities of FIIs are masked in our database, we use FII codes and their trading in the secondary market to construct proxies for investor size. Since FIIs trade and hold assets in other markets, it should be noted that our proxy of investor size is partial and therefore represents holdings in India only, and not an absolute size. While there is mixed evidence on the relationship between investor size and performance (Indro et al., 1999; Phillips and Rau, 2018), we still consider investor size as a time-varying characteristic in our empirical analyses. Using over 8.7 million individual FII transactions over the 2003 – 2015 period, we proxy for

[14] In the robustness tests (Section 5.4), we use alternative classification and cut-offs to create the three investor categories. Our results remain qualitatively similar.

[15] Although the second half is longer than the first, we have similar number of observations for the investors' categories in the two periods. This is because IPO activity is relatively muted in the post 2011 period (see Fig. 2). Moreover, FII activity in the post-2011 period dropped sharply due to global and macro-economic factors (such as GDP contraction, high inflation and declining Indian rupee). However, our results remain consistent if we split the sample in 2007.

[16] These statistics are broadly similar for the three investor categories for the overall sample (2004–2015).

[17] In total, the high-frequency FIIs obtain about 9% of the total offering, whereas moderate and low-frequency FIIs obtain 13% and 8%, respectively.

[18] As our focus is on IPO performance, we exclude secondary buy and associated sell trades from our tests. Further, in the few cases in which the sell volume in the period of consideration exceeds the number of shares allocated in the IPO, we exclude the additional sell volume in determining realized profitability.

yearly FII size by calculating the value of their aggregate holdings at the end of the year. The value of yearly aggregate holdings for an FII is equal to the value of aggregate holdings at the beginning of the year plus the value of buys during the year and minus the value of sells during the year. The value of aggregate holdings at the beginning of the year is equal to the value of cumulative holdings from the beginning of the dataset to the end of the previous year. As shown in Table 3, the mean (median) values of aggregate holdings for high, moderate, and low-frequency investors are INR 13,382 (5680), INR 23,232 (15,945), and INR 8,704 (1887) million, respectively. Thus, moderate-frequency investors appear to be the largest of the three investor categories.[19]

5. Experience and learning: Empirical results

In this section, we conduct several tests to explore the link of previous experience on FIIs' future investment decisions. Specifically, we examine whether prior experience allows FIIs to improve their investment performance. To this end, we first examine whether investors exhibit improvement in the two keys skills required to be successful in the IPO market: the ability to select high-quality IPOs and exhibit discretion in bidding (i.e., shave bids in weak IPOs and bid aggressively in good IPOs) (Sherman, 2005; Chiang et al., 2011). We supplement these tests with a profitability analysis using first-day and realized profits. As mentioned above, we perform all our tests using observations over the 2007–2015 period by classifying investors over the 2004–2006 period.

5.1. Selection

We start with an analysis to shed light on whether experience allows investors to improve their ability to select quality IPOs. Given that our focus is on experience and performance, we use IPO initial returns as a proxy for IPO performance. Although Zheng and Stangeland (2007) show that initial returns are a strong indicator of IPO quality, we use additional proxies for IPO quality in robustness tests (Section 5.4). Thus, if selection ability improves over time, we should observe a positive relationship between IPO return and experience. To formally test this conjecture, we follow Chiang et al. (2011) and run the regression model shown in equation (1):

$$\begin{aligned} Initial\ return_{i,j} = \alpha &+ \beta_1 Ln(IPO\ order_{i,j}) + S_i \\ &+ \sum Y_i\ Control\ variables \\ &+ Time\ trend + Industry\ fixed\ effects \\ &+ Year\ fixed\ effects + \epsilon_{i,j} \end{aligned} \tag{1}$$

The dependent variable, initial return, is the market adjusted first-day return (for investor *i* in IPO *j*). We use IPO order (natural logarithm) to measure investors' past IPO specific experience, which is one plus the cumulative number of previous IPO subscriptions of the investor. We consider the number of IPOs invested in the first half (2004–2006) to calculate IPO order. Thus, the IPO order is three plus the number of IPOs subscribed in the first half for an investor who has invested in two previous IPOs in the second half.[20] We use the first trading day to identify the sequence of IPOs; if an FII participates in two or more IPOs listed on the same trading day, we use the offer subscription period to construct the IPO order.

Owing to the availability of each FII investor's long-term series data on investment in the primary market, we include investor fixed effects (S_i) in our regression analyses. This allows us to control for unobserved time-invariant characteristics at the institutional level (such as investment philosophy and culture) and individual manager level (such as sophistication, ability, gender, age, education, occupation and birth cohort) (Campbell et al., 2014). As we are interested in the effects of experience over time, we include a time trend variable to control for any trend in IPO returns. Other control variables include several firm and market characteristics that may affect IPO returns. We include market return and market volatility in the three months prior to the listing, underwriter reputation, firm size (natural logarithm of proceeds) and age (natural logarithm of age) of the firm.

We also include investors' unexpected entry to control for private information and investor sentiment in the offering (Chiang et al., 2011).We control for unexpected entry for RIIs, NIIs and DIIs separately.[21] This is important in the Indian IPO setting as during the bookbuilding period investors are able to observe demand from different investor categories in real-time (Neupane and Poshakwale, 2012). As discussed previously, although the identities of FIIs are masked, we use trading data from the secondary market to construct a proxy for investor size and use the natural logarithm of their lagged values as a control variable. Including investor size in our regressions allows us to control an important time-varying characteristic associated with institutional investors (Indro et al., 1999; Phillips and Rau, 2018). All variables are defined in Appendix A. In Table 4, we present our results after controlling for industry and year fixed effects and adjusting the standard errors for clustering and heterogeneity. Furthermore, we winsorize our variables at the 5% and 95% levels to attenuate the influence of outliers. As indicated earlier, the analysis only includes FIIs who participate in four or more IPOs.

Specification (1) shows that, for the overall sample, investors' IPO returns are positively related to IPO order, which is statistically significant at less than 5% level. In specifications (2), (3) and (4), we re-estimate the model separately for high, moderate and low-frequency investors, respectively. The coefficient of IPO order is positive and statistically significant for all investor categories. The interpretation is that experience allows all institutional investors to improve their selection ability over time. In addition to Model (1), we perform a logit regression in which the dependent variable takes the value of 1 if the first-day return is positive and 0 otherwise (not reported). We retain all aspects from Eq. (1) including the fixed effects and other control variables. Results are consistent with those in Table 4.

Among the control variables, a number of them are consistent with prior literature. As for firm and offer characteristics, we find that initial return is positively related to recent market return but negatively related to proceeds and volatility. Consistent with Chiang et al. (2011), we find that the unexpected entry of DIIs and NIIs/RIIs is positively related to the initial return. The time trend is significantly negative, suggesting that IPOs have a much lower initial return in the later period than in the earlier period.

[19] As our dataset begins from 2003, the value of aggregate holdings is understated for the early years. However, the differences in the values of aggregate holdings among the three investor categories are similar even when we exclude the values for the 2003–2005 period. Importantly, as our analysis of experience only begins from 2007, our estimate of underlying holdings should provide a reasonable measure of institution size. In addition to aggregate holdings, we construct an additional proxy of size using annual trading values, which we briefly discuss in the robustness tests section (Section 5.4). With trading values as a proxy for investor size, the moderate-frequency investors remain the largest investor category.

[20] For instance, if an investor has subscribed to 20 IPOs in the first half, the IPO order will take the value of 23 for an investor participating in the third IPO of the second half. We thank the anonymous reviewer for this suggestion.

[21] To avoid multicollinearity, we exclude the unexpected entry of FIIs in our model specifications. However, we find that our results are robust even with the inclusion of FIIs' unexpected entry.

Table 4

The effects of experience on selection. This Table reports the OLS regression estimates of experience on selection. The dependent variable in all the specifications is the initial return. FIIs with investment frequency in the top decile, deciles 7–9, and lower deciles as categorized as high, moderate, and low-frequency investors, respectively. Appendix A provides definitions for all the variables. All tests use White heteroscedasticity robust standard errors and standard errors are clustered at the firm level. The t-values are in brackets. ***, ** and * indicate statistically significance at 1%, 5% and 10% respectively.

		Investment Frequency		
	Total (1)	High (2)	Moderate (3)	Low (4)
Ln (IPO order)	0.161**	1.125***	0.448**	0.101**
	(2.48)	(2.87)	(2.30)	(2.01)
Recent market return	0.002	-0.009	0.002	0.006
	(0.15)	(-0.93)	(0.14)	(0.53)
Market volatility	-0.133*	-0.168**	-0.186**	-0.092
	(-1.92)	(-2.45)	(-2.58)	(-1.33)
Underwriter reputation	-0.081	-0.059	-0.116	-0.150
	(-0.66)	(-0.56)	(-0.82)	(-1.10)
Ln(Proceeds)	-0.106	-0.109*	-0.140*	-0.089
	(-1.56)	(-1.81)	(-1.84)	(-1.26)
Ln (Age)	0.021	0.063	0.060	0.003
	(0.30)	(0.95)	(0.75)	(0.03)
Unexpected entry - RII	0.035	0.070	0.023	-0.023
	(0.50)	(1.09)	(0.26)	(-0.33)
Unexpected entry - NII	0.241***	0.200**	0.301***	0.275***
	(2.98)	(2.61)	(2.78)	(3.39)
Unexpected entry - DII	0.092*	0.108***	0.045	0.097*
	(1.96)	(2.87)	(0.65)	(1.70)
Ln (FII size)	-0.010	0.031	-0.032	-0.013
	(-0.85)	(1.61)	(-1.01)	(-0.80)
Time trend	-0.082*	-0.087*	-0.046*	-0.093
	(1.98)	(-1.90)	(1.88)	(1.37)
Investor, industry and time FE	Yes	Yes	Yes	Yes
Constant	0.061	-3.268**	-0.280	0.083
	(0.08)	(-2.46)	(-0.32)	(0.10)
Observations	2,420	661	668	1,091
Adjusted R^2	0.556	0.562	0.583	0.565

5.2. Bid shaving

Next, we explore whether investors' prior experience affects their ability to bid for IPO shares in the primary market. Specifically, we investigate whether FIIs bid aggressively in better performing IPOs and shave their bids sufficiently in poor quality IPOs as they gain experience. For this analysis, we use the regression model shown in Eq. (2).

$$\begin{aligned} Ln(Abnormal\ bid)_{i,j} = {} & \alpha + \beta_1 Ln(IPO\ order_{i,j}) + \beta_2 Initial\ return_{i,j} \\ & + \beta_3 [Ln(IPO\ order_{i,j}) \times Initial\ return_{i,j}] \\ & + S_i + \sum Y_i\ Control\ variables + Time\ trend \\ & + Industry\ fixed\ effects \\ & + Year\ fixed\ effects + \epsilon_{i,j} \end{aligned} \quad (2)$$

The dependent variable is the natural logarithm of abnormal bids (for investor i in IPO j) and we use two different approaches to estimate this value. In the first approach, we consider the historical bidding preference and estimate FII's abnormal bid for each IPO by adjusting the bid amount with its median bid value for all IPOs in which an investment was made within the previous 12-month period (scaled by their respective IPO proceeds). In the second approach, we estimate the abnormal bid value using residuals from a linear regression model to predict the bidding value. Guided by previous research (Derrien, 2005; Rocholl, 2009; Neupane and Poshakwale, 2012), we use the following independent variables in our first stage regression: IPO proceeds, age of the IPO firm, recent IPO return, market volatility, and underwriter reputation. We also control for time and industry fixed effects. We exclude the unexpected entry variables in the first stage as they also proxy for abnormal participation, but we include them in the main regressions.

As before, we use IPO order (natural logarithm) to measure experience and initial return as an *ex ante* proxy of a good quality IPO. For this analysis, the key variable of interest is the interaction between the IPO order and initial return. If FIIs do indeed learn over time, this should be reflected in higher (lower) bidding in IPOs with better (lower) first-day returns. As with the selection regressions, we include investor fixed effects and other control variables that are likely to be related to investor subscription (recent IPO returns, market volatility, high reputation underwriter dummy, natural logarithm of proceeds, natural logarithm of age, mechanism dummy, unexpected entry of DIIs, NIIs and RIIs, natural logarithm of FII size, and industry and year fixed effects). All variables are defined in Appendix A. The standard errors are adjusted for clustering and heterogeneity. We winsorize each variable at the 5% and 95% levels to attenuate the influence of outliers.

Table 5 shows the results for abnormal bidding using the first approach. In specification (1), we first report the results of the base model without the interaction term. The coefficient of returns and IPO order are positive and significant. Thus, FIIs appear to bid significantly more in IPOs with better returns. Furthermore, FIIs tend to bid more with experience. In specification (2), we include the interaction term ($Ln(IPO\ order_{i,j}) \times Initial\ return_{i,j}$). The interaction term is positive and statistically significant, which implies that FIIs bid significantly more in better quality IPOs as they increase their participation in the primary market. In other words, in overall terms, our results show that FIIs appear to improve their bidding skills over time as they gain experience.

In specifications (3)–(5), we run the analysis separately for high, moderate, and low-frequency investors. Interestingly, the interaction term is positive and significant only for high-frequency investors. Thus, the positive and statistically significant coefficient in specification (2) appears to be primarily related to high-frequency investors. The positive coefficient of the interaction term in specification (3) suggests that experienced high-frequency investors bid more (less) in IPOs that are more likely to provide better (lower) returns. In other words, high-frequency investors demonstrate an ability to fine-tune their bidding behavior as they gain more experience. Although positive, the interaction term is insignificant for moderate and low-frequency investors. Among the control variables, the abnormal bid value is positively related to the unexpected entry of DIIs, underwriter reputation, and fund size and negatively related to market volatility. We re-run the analysis using the second measure for abnormal bidding and find that the results (unreported) using this alternative proxy are consistent with those presented in Table 5. Specifically, we find that only high-frequency investors demonstrate learning over time in relation to bidding behavior.

5.3. Profits

The above two sub-sections provide evidence of different types of learning among different investor categories; however, we do not know whether such learning improves profitability. To address this question, we examine the relationship between experience and investment performance. To estimate the effect of learning on profits, we use regressions of the following form:

$$\begin{aligned} Ln(Profits_{i,j}) = {} & \alpha + \beta_1 Ln(IPO\ order_{i,j}) \\ & + S_i + \sum Y_i\ Control\ variables \\ & + Time\ trend + Industry\ fixed\ effects \\ & + Year\ fixed\ effects + \epsilon_{i,j} \end{aligned} \quad (3)$$

The dependent variable is profits (for investor i in IPO j). As profits are highly skewed, we transform raw profits into natural logarithmic values and use median regression, which is less sensi-

Table 5

The effects of experience on bid shaving. This Table reports the OLS regression estimates of experience on bid shaving. The dependent variable in all the specifications is the natural logarithm of abnormal bid value. FIIs with investment frequency in the top decile, deciles 7–9, and lower deciles as categorized as high, moderate, and low-frequency investors, respectively. Appendix A provides definitions for all the variables. All tests use White heteroscedasticity robust standard errors and standard errors are clustered at the firm level. The t-values are in brackets. ***, ** and * indicate statistically significance at 1%, 5% and 10% respectively.

	Total		Investment Frequency		
			High	Moderate	Low
	(1)	(2)	(3)	(4)	(5)
Initial return	0.255**	-0.944***	-4.507**	0.148	-0.843
	(2.15)	(-5.55)	(-2.57)	(0.19)	(-1.21)
Ln(IPO order)	-0.003	-0.062	0.162	-0.480	-0.102
	(-0.04)	(-0.87)	(0.21)	(-1.65)	(-1.33)
Ln(IPO order) × Initial return		0.347***	1.171***	0.034	0.354
		(5.01)	(2.76)	(0.17)	(1.29)
Recent market return	0.011	0.011	0.021	0.019*	0.004
	(1.37)	(1.55)	(1.64)	(1.68)	(0.93)
Market Volatility	-0.185***	-0.193***	-0.240***	-0.216***	-0.112***
	(-3.81)	(-3.92)	(-2.63)	(-2.97)	(-3.03)
Underwriter reputation	0.283***	0.282***	0.275**	0.409***	0.169*
	(3.67)	(3.61)	(2.32)	(3.93)	(1.95)
Ln(Proceeds)	0.020	0.040	-0.001	0.075	-0.010
	(0.51)	(1.00)	(-0.03)	(1.33)	(-0.21)
Ln(Age)	0.068	0.043	0.013	0.021	0.050
	(1.35)	(0.79)	(0.16)	(0.24)	(0.92)
Unexpected entry - RII	-0.038	-0.032	0.074	-0.142	-0.058
	(-0.58)	(-0.47)	(0.67)	(-1.60)	(-1.21)
Unexpected entry - NII	-0.024	-0.015	-0.062	0.033	0.092
	(-0.37)	(-0.21)	(-0.58)	(0.33)	(1.16)
Unexpected entry - DII	0.143***	0.120**	0.139*	0.131	0.064
	(3.01)	(2.35)	(1.87)	(1.40)	(1.23)
Ln(FII size)	0.088***	0.083***	0.211***	0.035	0.008
	(3.06)	(2.98)	(2.87)	(0.50)	(0.26)
Time trend	-0.053	-0.067	-0.293**	0.104	-0.002
	(-0.70)	(-0.87)	(-2.17)	(0.90)	(-0.02)
Investor, industry and time FE	Yes	Yes	Yes	Yes	Yes
Constant	-1.449**	-1.013	1.262	-0.496	-0.299
	(-2.17)	(-1.54)	(0.46)	(-0.51)	(-0.56)
Observations	2420	2420	661	668	1091
Adjusted R^2	0.356	0.384	0.446	0.405	0.271

tive to non-normality than OLS regressions (Chiang et al., 2011).[22] We estimate profits using two approaches. First, following the literature, we estimate profits as the product of initial profit (the difference between the first-day closing price and the offer price) and the number of shares allocated. We refer to this estimate as first-day profits (Kaustia and Knüpfer, 2008; Chiang et al., 2011). In the second approach, we calculate profits using secondary trade data, as discussed in Section 4. As there is relatively little change in profits thereafter, we use the realized profits calculated at the end of the first six months after listing (see Table 3).

As before, the main independent variable is the IPO order (natural logarithm), which measures investors' prior IPO experience. As in the previous sections, we include investor fixed effects and other control variables that are likely to be related to IPO profits (recent IPO returns, market volatility, high reputation underwriter dummy, natural logarithm of proceeds, natural logarithm of age, mechanism dummy, unexpected entry of DIIs, NIIs and RIIs, natural logarithm of FII size, and industry and year fixed effects). As profits are larger for higher allocations, we control for this by including the value of the initial allocation (IPO allocation) in our model. We also control for any time trends. All variables are defined in Appendix A. The standard errors are clustered at the firm level. We winsorize each variable at the 5% and 95% levels to attenuate the influence of outliers. Following Kaustia and Knüpfer (2008), we only include FIIs that participate in four or more IPOs. The results of this analysis are presented in the two panels of Table 6.

Panel A of Table 6 shows the results using first-day profits. As shown in specification (1), IPO order is positively related to profits (although not statistically significant). In specifications (2)–(4), we re-run the analysis separately for high, moderate and low-frequency investors. The coefficients of IPO order are positive across all three categories; however, they are economically and statistically significant only for high-frequency investors. In Panel B, we repeat our test using realized profits (as defined previously) based on fully closed positions for almost 90% of the IPO allocations (see Table 3). Overall, the results are similar to those in Panel A. Furthermore, we find a stronger relationship between experience and profits among high-frequency investors.

Economically, the realized return specification suggests that, on average, a 30% increase (corresponding to a one standard deviation increase) in experience leads to INR 181 thousand increase in profits for high-frequency investors.[23] Our results are consistent when using OLS regression where, as expected, the size of the co-

[22] Since there are positive and negative profit numbers, we construct log values by adding 100 to the raw profit figures. We also use OLS regression and raw profit figures for robustness purposes and find consistent results.

[23] We use the median realized profit of INR 3.91 million to estimate the economic significance [(0.155 × 30%)× 3.91].

Table 6
The effects of experience on profits.

Panel A: Using first day profits. This Table reports the estimates of the median regression analysis of profits using first day profits. The dependent variable is log (100 + first day profits). FIIs with investment frequency in the top decile, deciles 7–9, and lower deciles as categorized as high, moderate, and low-frequency investors, respectively. Appendix A provides definitions for all the variables. All tests use robust standard errors clustered at the firm level. The t-values are in brackets. ***, ** and * indicate statistically significance at 1%, 5% and 10% respectively.

		Investment Frequency		
	Total (1)	High (2)	Moderate (3)	Low (4)
Ln(IPO order)	0.004	0.093**	0.026	0.002
	(1.55)	(2.21)	(0.64)	(0.36)
IPO Allocation	0.0001***	0.0001***	0.0001***	0.000***
	(5.91)	(5.03)	(3.03)	(7.88)
Recent market return	-0.000	-0.001	-0.001	0.000
	(-0.02)	(-1.05)	(-0.21)	(0.57)
Market Volatility	-0.003	0.002	-0.002	-0.003
	(-0.25)	(0.13)	(-0.08)	(-0.62)
Underwriter reputation	-0.001	-0.007	0.007	-0.009
	(-0.05)	(-0.54)	(0.32)	(-0.85)
Ln(Proceeds)	0.006*	0.007	0.022**	0.001
	(1.91)	(1.46)	(2.20)	(0.29)
Ln(Age)	0.007	0.010	0.017	0.003
	(0.83)	(0.78)	(0.79)	(0.61)
Unexpected entry - RII	-0.012	-0.003	-0.016	-0.009*
	(-1.31)	(-0.18)	(-0.66)	(-1.92)
Unexpected entry - NII	0.018**	0.016	0.027	0.012**
	(2.00)	(1.16)	(1.27)	(1.99)
Unexpected entry - DII	0.006	0.007	0.013	0.006
	(1.06)	(1.01)	(1.19)	(1.12)
Ln(FII size)	0.004	0.006*	0.005	0.002
	(1.40)	(1.88)	(0.39)	(1.03)
Time trend	0.007	-0.018	0.012	0.005
	(0.86)	(-1.10)	(0.48)	(0.96)
Investor, industry and time FE	Yes	Yes	Yes	Yes
Constant	4.430***	4.268***	4.195***	4.528***
	(40.48)	(26.20)	(19.04)	(71.96)
Observations	2420	661	668	1091
R^2	0.260	0.175	0.410	0.336

Panel B: Using realized returns

This Table reports the estimates of the median regression analysis of profits using realized profits. The dependent variable is log (100 + realized profits). FIIs with investment frequency in the top decile, deciles 7–9, and lower deciles as categorized as high, moderate, and low-frequency investors, respectively. Appendix A provides definitions for all the variables. All tests use robust standard errors clustered at the firm level. The t-values are in brackets. ***, ** and * indicate statistically significance at 1%, 5% and 10% respectively.

		Investment Frequency		
	Total (1)	High (2)	Moderate (3)	Low (4)
Ln(IPO order)	0.008	0.155**	0.029	0.008
	(1.11)	(2.24)	(0.46)	(0.78)
IPO allocation	0.0001***	0.0001**	0.0001**	0.0001***
	(3.85)	(2.57)	(2.12)	(5.09)
Recent market return	-0.000	-0.000	-0.000	-0.001
	(-0.11)	(-0.12)	(-0.02)	(-0.68)
Market Volatility	-0.006	0.002	-0.011	-0.004
	(-0.38)	(0.11)	(-0.34)	(-0.33)
Underwriter reputation	-0.013*	-0.029	-0.008	-0.021*
	(-1.93)	(-1.63)	(-0.18)	(-1.99)
Ln(Proceeds)	0.021**	0.026*	0.050**	0.010
	(2.22)	(1.95)	(2.18)	(1.44)
Ln(Age)	0.021	0.012	0.046*	0.023
	(1.37)	(0.56)	(1.75)	(1.53)
Unexpected entry - RII	-0.021	-0.006	-0.042	-0.026*
	(-1.12)	(-0.24)	(-0.76)	(-1.74)
Unexpected entry - NII	0.045**	0.042	0.087	0.039**
	(2.23)	(1.25)	(1.34)	(2.44)
Unexpected entry - DII	-0.002	-0.000	0.001	0.001
	(-0.24)	(-0.02)	(0.07)	(0.08)
Ln(FII size)	0.005	0.009	0.016	0.006
	(1.03)	(0.66)	(0.52)	(1.49)
Time trend	0.005	-0.034	0.008	0.003

(*continued on next page*)

Table 6 (*continued*)

		Investment Frequency		
	Total (1)	High (2)	Moderate (3)	Low (4)
	(0.50)	(-1.39)	(0.28)	(0.24)
Investor, industry and time FE	Yes	Yes	Yes	Yes
Constant	4.285***	3.987***	3.891***	4.394***
	(29.97)	(11.69)	(10.17)	(36.20)
Observations	2420	661	668	1091
R^2	0.293	0.228	0.475	0.320

efficients are larger. As for the control variables, we find that profitability is positively related to IPO allocation, firm age, size of the offering, and unexpected entry of the NIIs. Conversely, profitability is negatively related to underwriter reputation, and unexpected entry of RIIs.

5.4. Robustness tests

5.4.1. The transparency of Indian IPO mechanism

As discussed previously, the Indian IPO mechanism is characterized by a high degree of transparency, with information on aggregate investor demand available on a real-time basis during the offer period. One concern with regards to our results is whether the experience-performance evidence that we show is driven by FIIs mimicking local DIIs. While the possibility of mimicking, which is more likely to be done by new or less-experienced investors, sets a high bar for us to observe learning among different FII categories, we nevertheless perform additional analyses to alleviate this concern. To a certain extent, the mimicking concern is addressed by the inclusion of DIIs' IPO subscription variable (unexpected entry - DII). If FIIs' participation (as in the abnormal bids reported in Table 5) is purely driven by DIIs' demand, then this should be absorbed by the unexpected entry variable. As is evident from our results, this is certainly not the case, as the effect of experience remains significant even after controlling for DIIs' demand. We carry out additional robustness tests to address this concern.

First, we perform a univariate analysis of the overall subscription by DIIs and FIIs and find that FIIs submit significantly more bids than DIIs. Furthermore, because there is DII and FII demand in most IPOs, we specifically look at IPOs that these investors ignore. For the overall sample of 327 IPOs (2004–2015), DIIs and FIIs avoid subscriptions in 54 and 27 IPOs, respectively. Interestingly, FIIs avoid only 11 of the 54 IPOs that DIIs shun. Thus, if FIIs simply follow DIIs, they should have avoided all the 54 IPOs ignored by DIIs. Additionally, there are 38 other IPOs in which DIIs' demand multiple is less than 0.5; FIIs' subscriptions in some of these IPOs are significantly higher than 1. Second, to complement the results reported in Table 5, we perform an additional test by including institutional investors' penultimate day's demand on FIIs' abnormal bids. If FIIs simply follow DIIs, their abnormal bids should be captured by the early institutional investor demand.[24] The result of this analysis (not reported) shows that our overall evidence holds even after accounting for the penultimate day's demand.

5.4.2. Anchor investors

In July 2009, Indian regulators allowed investment banks to allocate (on a discretionary basis) up to 30% of the institutional investors' quota to anchor investors. Furthermore, the anchor investors are required to hold their allocation for a period of least 30 days. As we are unable to determine whether an allocation to FII relates to the regular or anchor investor category, we re-run our analyses by excluding all observations from IPOs with allocations to anchors investors. Our results (not reported) remain qualitatively similar.

5.4.3. Risk-taking

One concern with the inference of our results is that different investors have different risk-return appetites and that the observed relationship between experience and performance is simply a reflection of risk preferences. Although our empirical specifications include investor fixed effects to address unobserved investor level heterogeneity, we perform additional tests to rule out the risk-taking explanation of our results. We rerun all our analyses by excluding smaller and riskier IPOs below the 25th percentile in terms of size, IPO proceeds, and underwriter reputation (separate tests for each measure). We obtain similar results as before in all these additional tests.[25]

5.4.4. Investor-underwriter relationship

Another concern with our results is that the investor-underwriter relationship is driving the association that we observe between experience and learning. In other words, investors, particularly those who are more frequent, forge long-term relationships with local underwriters, thereby gaining access to better-performing IPOs. We address this concern by using investor-underwriter pair fixed effects. If our evidence is due to such connections, then the investor-underwriter pair fixed-effect should absorb our results, rendering the experience proxy insignificant. We create investor-underwriter pairs by grouping each investor with lead managers responsible for the IPO. To remain consistent with our approach, we create this pair in the first period (2004–2006) and perform our tests in the second period. We find that our results remain qualitatively similar even with the inclusion of the investor-underwriter pair fixed effect.[26]

5.4.5. Using the full sample

As an additional robustness test, we run all our analyses using the entire sample. We first use the overall sample to group investors into the three categories and then run the selection, bidding, and profitability analyses using all observations over the 2004–2015 period. Our results, particularly those related to bidding and profitability, remain qualitatively similar.

[24] A limitation of this analysis is that we do not have information on bids separately for DIIs and FIIs for the penultimate day. Hence, we conduct this analysis using overall institutional investor demand at the end of the penultimate day of the offer based on the assumption that informed DIIs submit their bids early than other investor categories.

[25] For the sake of brevity, we do not report the results herein. These results can be made available by the authors upon request.

[26] We do not report the results herein, but they can be made available by the authors upon request. Furthermore, our results remain similar when creating the investor-underwriter pair and analyzing it using the full sample (2004–2015).

5.4.6. Bookbuilding IPOs

Our sample in the main tests includes bookbuilding and auction IPOs. To alleviate the concern that investors behave differently in different IPO regimes, we re-run all our analyses using only the auction sample (2006–2015). As IPO activity is relatively muted in the post-2011 period, we categorize FIIs on the basis of their participation in auction IPOs in 2006 and perform our tests over the 2007–2015 period. We use the same classification as before to classify these investors into high (top decile), moderate (7–9 deciles), and low-frequency investors. Despite using one-year to classify investors, 2006 was a very active year in terms of IPO issuance, and as a result, the FIIs in the three categories based on this classification are similar to those from earlier classifications. Although the number of observations is smaller when using this classification (as we use only those investors who were present in 2006), all our results remain consistent.

5.4.7. Alternative measures

To ascertain the robustness of our results, we employ alternative measures for some of the important variables used in the study. First, we use three alternative measures of IPO quality (for Models (1) and (2)): (i) one-week instead of first-day returns, (ii) average sales growth in the three years prior to the IPO year (Zheng and Stangeland, 2007), and (iii) grey market premium (as in Neupane et al., 2014). Sales growth and grey market premium are less likely to have issues such as reverse causality (higher bidding by FIIs may have caused higher first-day returns) as both occur prior to bidding and are therefore unlikely to be influenced by institutional investors. Consistent with prior studies, we find a strong correlation between IPO initial returns and sales growth/grey market premium. Importantly, the selection and bidding results (not reported) remain consistent with these alternative performance measures.

Second, instead of using abnormal bids in our bid shaving analysis, we use ranks based on how big or small an FII's bid is relative to the other bids in the same IPO. We group the bids into quintiles (deciles) with bids in the top quintile (decile) denoting larger bids and those in the lower quintiles (deciles) denoting smaller bids. Third, we use raw measures of investor demand (RIIs, NIIs and DIIs) in place of the unexpected entry measure. Fourth, we run profitability tests using several alternative windows including 1, 3, and 12 month periods. Fifth, instead of using aggregate holdings, we use the value of total trades (purchases plus sales) during a particular year as an alternative proxy for institution's size. Our results continue to hold across all these additional tests.

Finally, we use alternative approaches and cut-offs to categorize investors to ensure that our results are not driven by investor classification. In additional tests, we consider investors in the top two deciles as high-frequency, those in deciles 5–8 as moderate-frequency investors, and the rest as low-frequency investors. Furthermore, to address the concern that perhaps one or two of the frequent investors are causing the results, we rerun all our tests by removing the trades for the top 2 frequent investors (we lose 124 observations for the high-frequent investor category).[27] Overall, the same conclusions continue to hold across all these additional tests.

6. Other tests

6.1. Secondary market experience

In addition to participating in the primary market, FIIs are also active in the main or the secondary market. One could plausibly argue that experience in the secondary market could also be equal to, or more, important than experience in the primary market. It could also be that the secondary market experience is driving our results. Although the skills required to succeed in the primary market are likely to be different from those required in the secondary market, we nevertheless re-run all of our analyses by also considering the effects of secondary market experience.

To measure this market experience, we follow our approach of measuring IPO experience and consider the number of trades conducted by FIIs in the secondary market. As investors are likely to learn more from buying and selling different companies rather than trading the companies they already hold, we consider the number of different companies traded (referred to as market order) by an investor during the first period (2003–2006). To construct the measure, we sum the number of unique buys and sells for which we do not have a previous buy transaction in our database.[28] We find a strong correlation between the frequency of trades in the primary and secondary markets. In other words, frequent FIIs in the primary market also appear to trade significantly more frequently in the secondary market. For instance, the median (mean) number of unique trades by high-frequency investors in the first period (2004–2006) is 77 (78); the corresponding numbers for moderate and low-frequency investors are 32 (34) and 16 (19), respectively. The correlation between IPO order and market order is 0.66 (significant at the less than 1% level). To estimate the effect of secondary market experience and compare it with primary market experience, we run all our earlier tests for the second period by also including market order in our specifications. All our regressions include investor fixed effects and all the control variables discussed previously (Section 4). The results of these analyses are shown in the three Panels of Table 7.

Panel A presents the results for the selection model in which the dependent variable is initial return. Results in all the specifications show that the coefficients of IPO order remain positive and statistically significant even with the inclusion of market order. Although positive in most specifications, the coefficient of market order is statistically insignificant. The results concerning bidding are shown in Panel B (the dependent variable is abnormal bids, as previously defined). The main variables of interest are the two interaction terms: IPO order and initial return and market order and initial return. We find that the interaction between IPO order and initial return remains positive and significant for the high-frequency investors (specification (3)) after the inclusion of market order and its interaction with initial return. The interaction between market order and initial return is insignificant in all the specifications. Finally, Panels C presents the results of the profitability analysis using the median regressions. In the interest of space, we only show the results using realized profits, although the results using first-day profits are similar. Consistent with our main results, we find that the IPO order remains positive and significant only among high-frequency investors even with the inclusion of market order.

As market order is correlated with IPO order, we further run all these test by including only the market order and dropping the IPO order from our specifications. In unreported results, we find that the market order is significant in explaining selection for all investor categories. Furthermore, the interaction between market order and initial return is significant for bidding among the high-frequency investors. Moreover, we find that market order is significant in explaining profitability only among high-frequency investors. Thus, it appears that even a high degree of secondary market experience, which is prevalent among high-frequency investors,

[27] We also use classification based on quartiles and quintiles and obtain similar results. Again, for brevity, we do not present the results in the manuscript but they are available from the authors on request.

[28] As our database begins in 2003, we include all trades from this year onwards. In addition to the number of unique trades, we also run our tests using the total number of trades as well as the total buys and total sells separately. Results are qualitatively similar.

Table 7
Secondary market experience. This Table reports the estimates of the OLS regression analysis of experience by including secondary market experience. Panels A and B use OLS regressions where the dependent variables are initial return and the natural logarithm of abnormal bid value, respectively. FIIs with investment frequency in the top decile, deciles 7–9, and lower deciles as categorized as high, moderate, and low-frequency investors, respectively. Tests in Panel A and B use White heteroscedasticity robust standard errors clustered at the firm level. Panel C uses median regression where the dependent variable is log (100 + realized profits). Tests in Panel C use robust standard errors clustered at the firm level. Appendix A provides definitions for all the variables. The t-values are in brackets. ***, ** and * indicate statistically significance at 1%, 5% and 10% respectively.

Panel A: The effects of experience on selection

		Investment Frequency		
	Total	High	Moderate	Low
	(1)	(2)	(3)	(4)
Ln(IPO order)	0.131*	0.997**	0.458**	0.075*
	(1.86)	(2.50)	(2.22)	(1.70)
Ln(Market order)	0.041	0.212	0.018	0.088
	(0.72)	(1.56)	(1.27)	(0.91)
Controls	Yes	Yes	Yes	Yes
Investor, industry and time FE	Yes	Yes	Yes	Yes
Constant	-0.286	-4.092***	-0.688	0.254
	(-0.36)	(-2.78)	(-0.77)	(0.27)
Observations	2420	661	668	1091
Adjusted R^2	0.540	0.520	0.559	0.552

Panel B: The effects of experience on bid shaving

	Total		High	Moderate	Low
	(1)	(2)	(3)	(4)	(5)
Initial return	0.164*	-0.574***	-2.057*	0.073	-0.550
	(1.92)	(-5.58)	(-1.96)	(0.13)	(-1.61)
Ln(IPO order)	-0.043	-0.107	0.231	-0.397	-0.059
	(-0.43)	(-1.13)	(0.36)	(-1.55)	(-0.78)
Ln(IPO order)× Initial return		0.272***	0.931**	0.036	0.183
		(5.67)	(2.17)	(1.20)	(1.46)
Ln(Market order)	0.079	0.097	0.014	0.076	-0.030
	(1.35)	(1.61)	(0.06)	(0.51)	(-0.44)
Ln(Market order)× Initial return		0.033	0.072	0.047	0.045
		(0.96)	(1.01)	(0.61)	(1.35)
Controls	Yes	Yes	Yes	Yes	Yes
Investor, industry and time FE	Yes	Yes	Yes	Yes	Yes
Constant	-1.611**	-1.184*	0.723	-0.706	-0.254
	(-2.39)	(-1.84)	(0.29)	(-0.70)	(-0.35)
Observations	2420	2420	661	668	1091
Adjusted R^2	0.412	0.433	0.473	0.412	0.301

Panel C: The effects of experience on profits (using realized profits)

	Total	High	Moderate	Low
	(1)	(2)	(3)	(4)
Ln(IPO order)	0.001	0.136*	0.010	0.000
	(0.07)	(1.91)	(0.13)	(0.01)
Ln(Market order)	0.019	0.037	0.004	0.023
	(1.12)	(0.86)	(0.20)	(1.01)
Controls	Yes	Yes	Yes	Yes
Investor, industry & time FE	Yes	Yes	Yes	Yes
Constant	4.175***	3.685***	3.940***	4.272***
	(23.07)	(7.60)	(11.40)	(24.62)
Observations	2420	661	668	1091
R^2	0.301	0.225	0.472	0.328

assist investors in improving their performance over time. However, just as the results in Table 7 show that IPO experience dominates the secondary market experience, we find that the economic significance for secondary market experience is much lower relative to the primary market experience. For instance, results from the median regression (using only market order) suggest that, on average, a 30% increase in secondary market experience leads to an increase in realized profits of INR 72 thousand, whereas the same change in primary market experience results in an increase of INR 182 thousand in realized profits.[29] Overall, we observe that regardless of type of investment experience, frequent investors appear to learn more and improve their investment performance over time than those who invest less frequently.

[29] We use the median realized profit of INR 3.91 million to estimate the economic significance. The coefficient of market order is 0.61 [(0.061 × 30%)× 3.91]

Table 8
Learning by observing the market. This Table reports the estimates of the OLS regression analysis of experience by including the time investors have been in the market. Panels A and B use OLS regressions where the dependent variables are initial return and the natural logarithm of abnormal bid value, respectively. FIIs with investment frequency in the top decile, deciles 7–9, and lower deciles as categorized as high, moderate, and low-frequency investors, respectively. Tests in Panel A and B use White heteroscedasticity robust standard errors clustered at the firm level. Panel C uses median regression where the dependent variable is log (100 + realized profits). Tests in Panel C use robust standard errors clustered at the firm level. Appendix A provides definitions of all the variables. The t-values are in brackets. ***, ** and * indicate statistically significance at 1%, 5% and 10% respectively.

Panel A: The effects of experience on selection

		Investment Frequency		
	Total	High	Moderate	Low
	(1)	(2)	(3)	(4)
Ln(IPO order)	0.115	0.743**	0.085	-0.020
	(0.81)	(2.17)	(0.38)	(-0.16)
Ln(Days traded)	0.157*	0.882**	0.713***	0.195**
	(1.81)	(2.26)	(2.84)	(2.36)
Controls	Yes	Yes	Yes	Yes
Investor, industry and time FE	Yes	Yes	Yes	Yes
Constant	-0.815	-7.580***	-4.088***	-0.528
	(-0.95)	(-2.85)	(-3.13)	(-0.54)
Observations	2420	661	668	1091
Adjusted R^2	0.542	0.527	0.566	0.592

Panel B: The effects of experience on bid shaving

	Total		High	Moderate	Low
	(1)	(2)	(3)	(4)	(5)
Initial return	0.257**	-0.869	1.932	-1.080	-0.744
	(1.98)	(-1.51)	(0.70)	(-1.16)	(-1.46)
Ln(IPO order)	-0.146	-0.225	-0.587	-0.112	-0.066
	(-0.84)	(-1.45)	(-0.74)	(-0.31)	(-0.54)
Ln(IPO order) × Initial return		0.370***	1.136***	0.020	0.279
		(5.35)	(2.24)	(0.09)	(1.32)
Ln(Days traded)	0.120	0.133	0.994	-0.720*	-0.140
	(0.84)	(1.02)	(1.17)	(-1.76)	(-1.02)
Ln(Days traded) × Initial return		0.021	0.762	0.195	0.015
		(1.04)	(1.12)	(1.23)	(0.22)
Controls	Yes	Yes	Yes	Yes	Yes
Investor, industry and time FE	Yes	Yes	Yes	Yes	Yes
Constant	-2.322**	-1.717*	-2.477	2.796	0.489
	(-2.32)	(-1.74)	(-0.47)	(1.30)	(0.55)
Observations	2420	2420	661	668	1091
Adjusted R^2	0.361	0.388	0.447	0.409	0.281

Panel C: The effects of experience on profits (using realized profits)

	Total	High	Moderate	Low
	(1)	(2)	(3)	(4)
Ln(IPO order)	0.012	0.092**	0.002	0.008
	(0.87)	(2.01)	(0.03)	(0.33)
Ln(Days traded)	0.029	0.071	0.065	0.030
	(1.24)	(0.86)	(0.86)	(1.08)
Controls	Yes	Yes	Yes	Yes
Investor, industry & time FE	Yes	Yes	Yes	Yes
Constant	4.111***	3.351***	3.681***	4.183***
	(21.07)	(4.89)	(8.70)	(24.27)
Observations	2420	661	668	1091
R^2	0.304	0.227	0.464	0.311

6.2. Learning by observing the market

In addition to secondary market experience, we also consider an alternative source of learning. In the main analysis, we use IPO order as our learning proxy, i.e., learning-by-doing. The rationale behind this proxy selection is that most investors learn by actively trading in the market. However, sophisticated institutional investors may learn by passively observing market conditions. Thus, to test whether FIIs learn passively over time, we use the number of days an investor has been in the IPO market as an alternative proxy for experience (Seru et al., 2009).

We rerun all our analyses using the time proxy of experience along with the IPO experience (IPO order) and report our results in Table 8 (Panels A, B and C for selection, bid aggressiveness and profit analyses, respectively). Just as before, we measure experience in the first period (2004–2006) and perform all our tests in the second period (2007–2015). Specifically, for each investor, we count the number of days from their first IPO investment in the first period until the end of 2006. In Panel A of Table 8, we find that the time based measure of experience dominates IPO market experience in selection among the three investor categories. On the other hand, results from Panel B and Panel C show that context-specific experience (IPO order) dominates time based measure of experience in improving bidding and profitability over time, respectively. As before, we find improvements in bidding and profitability among only high-frequency investors. Furthermore, we re-run these tests by only including the time proxy of experience. While results for selection are significant among all the investor categories, we do not find any significant results for bidding and profitability. Thus, while simply observing and spending time in the market could lead to selecting better performing IPOs, it does not appear to improve bidding skills, and consequently, we do not observe any association between investors' time in the market and their profitability. Furthermore, we rerun these tests using the overall sample (2004–2015) and measure time in the market based on investors' first trades in the secondary market. Overall, the results remain qualitatively similar. Taken together with the evidence from the previous section (learning from the secondary market), our overall evidence is consistent with the *learning by doing* model (Arrow, 1962; Grossman et al., 1977; Seru et al., 2009; Kempf et al., 2017). Specifically, the results show that *learning by doing* effects are significant among institutional investors investing in a foreign market.

7. Conclusion

Using a large number of FII investors' trading data from the Indian IPO market, this paper contributes to our understanding of how learning effects the behavior of informed institutional investors. More specifically, we examine the effects of context-specific experience, IPO investments in our case, on FIIs' future investment performance. In our main tests, we examine the effects of learning on future investment performance by analyzing whether experience helps FIIs improve their IPO (i) selection (ii) bidding, and (iii) profitability. Owing to the unique nature of our dataset, which allows us to observe each FII over a long period, we include investor fixed effects in all our tests to control for unobserved investor heterogeneity. Furthermore, given the significant heterogeneity in investor participation in IPOs, we conduct separate tests for frequent and less frequent investors.

Overall, we find that frequent and less-frequent investor exhibit different learning patterns. We observe that the most frequent investors improve their profitability over time, primarily through an improved ability to shave their bids across IPOs. Conversely, among less frequent investors, who only improve their selection skills, we do not observe any improvements in their profitability as they gain more context-specific experience. Our results are robust to a battery of additional tests and are consistent with the *learning by doing* view (Arrow, 1962; Grossman et al., 1977; Seru et al., 2009; Kempf et al., 2017). Specifically, we find that the effects of experience from secondary market or from merely observing the market is not as powerful as the effects of experience from the primary market on future investment performance. Overall, we show that the relationship between institutional investors and learning is nuanced and heterogeneous.

Data availability

Data will be made available on request.

CRediT authorship contribution statement

Suman Neupane: Conceptualization, Data curation, Writing – original draft. **Chandra Thapa:** Visualization, Writing – review & editing. **Kulunu Vithanage:** Methodology, Data curation.

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Appendix A. Variable Definition

Variable Name	Definition
Abnormal bid value	The value of total bid submitted by an investor (FII) less the median value of all bids made by the investor over the 12 months prior to the offer date of the current IPO.
Age	Difference (in years) between a firm's IPO year and the founding year.
Assets	The book value of total assets at the time of IPO (in INR millions).
Days traded	Number of days between an FII's first recorded IPO trade and the issue opening date of the current IPO.
FII size	The size of FII by year (in INR millions). We measure size as the value of FII's aggregate equity holdings by year. The value of aggregate holdings for year t= value of holdings at the beginning of the year t + value of buys during the year t - value of sells during the year t. The value of aggregate holdings at the beginning of the year is equal to the value of cumulative holdings from the beginning of the dataset (2003) until the end of the previous year. We use the lag of FII size in the regressions (e.g., the value of aggregate holding in 2006 for observations in 2007).
Initial return	The market adjusted first-day return. Market adjusted first-day return is the difference between raw first-day return and market return, where the market return is the return on the BSE Sensex index over the same period. Raw first-day return is based on the offer price and the closing price at the end of the first day of trading. We use initial return and first-day return interchangeably throughout the paper.
IPO allocation	The value of the initial allocation. This is calculated by multiplying the offer price with the number of shares allocated (in INR millions).
IPO order	One plus the cumulative number of primary market trades (subscriptions) made by an investor prior to the current IPO.
Market capitalization	Offer price times total shares outstanding immediately on the completion of the offering (in INR millions).
Market order	The cumulative number of unique companies traded by an investor prior to subscribing to the current IPO. The number of unique companies is equal to the sum of the number of unique buys and only those sells for which there is no buy transaction in the database.
Market volatility	The standard deviation of the market (BSE Index) returns during one month prior to the issue opening date.
Mechanism	Mechanism is a dummy variable that takes the value of 1 for bookbuilding and 0 for auction IPOs.
Outstanding position	The fraction of shares held at the end of the period relative to the number of shares allocated at IPO.
Past returns	The average of the allocation-weighted initial return earned by an investor from all IPOs invested in the first half.
Proceeds	Gross proceeds of the offer calculated by multiplying the offer price by the number of shares offered in the IPO (in INR millions).
First-day profits	The number of shares allocated at IPO multiplied by the difference between the first-day closing price and the offer price (in INR millions).
Realized profits	Realized profits in the difference between realized value and the allocation value (offer price times the number of shares offered). For each event window, we calculate realized value as the sum of the value of all the secondary sell transactions associated with IPO allocation and the value of the outstanding IPO position as of the end of the period. For instance, the six months' realized profit is the sum of the value of all sell transactions associated with IPO allocation in the first six months of listing and the value of the outstanding position at the end of the six-month period. The value of the outstanding position is calculated by multiplying the outstanding IPO position by the closing price at the end of the first six month of listing (in INR million).
Recent IPO return	The weighted average initial return of IPOs issued in the year prior to the issue opening date. The weights are based on (360 - N) [zero weight if 360 - N $<$ 0], where N is the number of days between a previous and current IPO's issue opening date.
Shares offered (Mill)	Total number of shares offered in the IPO offering (in millions).
Total, Institutional, NII & RII demand	Since investors subscribe and are allocated shares from their own pool/quota of shares, demand refers to the oversubscription for the respective investor category. Thus, demand is the ratio of total shares bid by total, institutional, non-institutional (NII) and retail (RII) investors to the total number of shares offered to the respective categories.
Total, Institutional, DII, FII, NII & RII bids	Total number of bids submitted by institutional, domestic institutional (DII), foreign institutional (FII), non-institutional (NII) and retail (RII) investors.
Underwriter reputation	A binary variable, which equals 1 for high reputation underwriters and 0 otherwise. IPOs managed by top seven underwriters (Enam Financials, ICICI Securities, DSP Merrill Lynch, Kotak Mahindra Capital, & SBI Capital Markets, IL&FS and JP Morgan Stanley) are considered as high reputation offerings.
Unexpected entry (RIIs, NIIs and DIIs)	The unexpected entry is estimated separately for RII, NII and DII, as the residual from the following regression model: $Ln(\#\ of\ bidders) = \alpha + \sum X_i\ Variables + Industry/Year\ FE + \epsilon_{i,j}$ (4) Variables included in the regressions are recent IPO return, market volatility, underwriter reputation, proceeds (log), age (log) and mechanism.

Appendix B. Snapshot of FII Trade-level Data

This appendix presents snapshot of FIIs trade level data related to IPO investments obtained from National Securities Depository Limited (NSDL). The data can be found at www.fpi.nsdl.co.in. Panel A shows IPO allocation data and Panel B shows data related to sell trades. FII denotes the unique FIIs registration number. SCRIP_NAME and ISIN denote the IPO firm's name and its corresponding ISIN number respectively. TR_DATE denotes transaction date. TR_TYPE(*) represents the type of transaction: 2 for primary buys and 4 for secondary sell trades. RATE and QUANTITY denote the price of the security and quantity of securities transacted. VALUE (in Rs) denotes the total value (RATE × QUANTITY) of the transaction. Some of the other columns in the dataset that are not relevant are not included in the snapshot.

No	FII	SCRIP_NAME	ISIN	TR_DATE	TR_TYPE(*)	RATE	QUANTITY	VALUE (in Rs)
242929	F5944222243200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	14,243	4,486,545
243022	F5749294909200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	28,486	8,973,090
243023	F9376090306200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	28,486	8,973,090
243024	F9376090306200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	28,486	8,973,090
243025	F2416570517200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	8,848	2,787,120
243026	F8220686857200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	28,486	8,973,090
243027	F1144449938200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	14,243	4,486,545
243028	F1144449938200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	28,486	8,973,090
243029	F9376090306200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	28,486	8,973,090
243030	F5567159012200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	28,486	8,973,090
243031	F8242938545200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	28,486	8,973,090
243049	F3074192340200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	2,105	663,075
243053	F7934501704200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	28,486	8,973,090
243075	F3074192340200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	3,508	1,105,020
243099	F4300281906200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	28,486	8,973,090
243308	F2513125271200706	Time Technoplast Ltd	INE508G01011	6/07/2007	2	315	3,403	1,071,945

No	FII	SCRIP_NAME	ISIN	TR_DATE	TR_TYPE(*)	RATE	QUANTITY	VALUE (in Rs)
251475	F9750606608200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	454.57	8,486	3,857,481
251483	F7432865793200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	465.84	14,239	6,633,096
251501	F7544786016200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	482.31	3,231	1,558,344
251520	F9750606608200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	457.26	20,000	9,145,200
251521	F3792221181200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	484.08	27,225	13,179,078
251586	F7869140708200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	490.64	4,836	2,372,735
251664	F2187704734200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	473.44	18,486	8,752,012
251665	F2187704734200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	471.54	10,000	4,715,400
251670	F8137812600200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	482.14	28,056	13,526,920
251702	F1144449938200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	485.3134	28,473	13,818,328
251733	F2187704734200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	478.665	28,486	13,635,251
251741	F3492903460200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	485.2	28,486	13,821,407
251742	F5567159012200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	450.7	2,179	982,075
251748	F5567159012200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	456	2,000	912,000
251873	F7137346073200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	450	2,161	972,450
251874	F7137346073200706	Time Technoplast Ltd	INE508G01011	6/13/2007	4	460.32	7,761	3,572,544

References

Aggarwal, R., Erel, I., Ferreira, M., Matos, P., 2011. Does governance travel around the world? Evidence from institutional investors. J. Financ. Econ. 100, 154–181.
Anagol, S., Balasubraman, V., Ramadorai, T., 2021. Learning from noise: evidence from India's IPO lotteries. J. Financ. Econ. 140 (3), 965–986.
Arrow, K.J., 1962. The economic implications of learning by doing. Rev. Econ. Stud. 29, 155–173.
Bailey, W., Kumar, A., Ng, D., 2011. Behavioral biases of mutual fund investors. J. Financ. Econ. 102, 1–27.
Bubna, A., Prabhala, N.R., 2011. Ipos with and without allocation discretion: empirical evidence. J. Financ. Intermed. 20, 530–561.
Campbell, J.Y., Ramadorai, T., Ranish, B., 2014. Getting Better or Feeling Better? How Equity Investors Respond to Investment Experience. Working paper. National Bureau of Economic Research.
Chiang, Y.M., Hirshleifer, D., Qian, Y., Sherman, A.E., 2011. Do investors learn from experience? Evidence from frequent IPO investors. Rev. Financ. Stud. 24, 1560–1589.
Choe, H., Kho, B.-C., Stulz, R.M., 2005. Do domestic investors have an edge? The trading experience of foreign investors in Korea. Rev. Financ. Stud. 18, 795–829.
Cici, G., Gehde-Trapp, M., Göricke, M.-A., Kempf, A., 2018. The investment value of fund managers' experience outside the financial sector. Rev. Financ. Stud. 31, 3821–3853.
Derrien, F., 2005. Ipo pricing in "hot" market conditions: who leaves money on the table? J. Finance 60, 487–521.
Dharmapala, D., Khanna, V., 2013. Corporate governance, enforcement, and firm value: evidence from india. J. Law Econ. Organ. 29, 1056–1084.
Dvořák, T.s., 2005. Do domestic investors have an information advantage? Evidence from indonesia. J. Finance 60, 817–839.
Errunza, V., 2001. Foreign portfolio equity investments, financial liberalization, and economic development. Rev. Int. Econ. 9, 703–726.
Greenwood, R., Nagel, S., 2009. Inexperienced investors and bubbles. J. Financ. Econ. 93, 239–258.
Grinblatt, M., Keloharju, M., 2000. The investment behavior and performance of various investor types: a study of Finland's unique data set. J. Financ. Econ. 55, 43–67.
Grossman, S.J., Kihlstrom, R.E., Mirman, L.J., 1977. A Bayesian approach to the production of information and learning by doing. Rev. Econ. Stud. 44, 533–547.
Huang, R.D., Shiu, C.-Y., 2009. Local effects of foreign ownership in an emerging financial market: evidence from qualified foreign institutional investors in Taiwan. Financ. Manage. 38, 567–602.
Indro, D.C., Jiang, C.X., Hu, M.Y., Lee, W.Y., 1999. Mutual fund performance: does fund size matter? Financ. Anal. J. 53, 74–87.
Jagannathan, R., Jirnyi, A., Sherman, A.G., 2015. Share auctions of initial public offerings: global evidence. J. Financ. Intermed. 24, 283–311.
Kaustia, M., Knüpfer, S., 2008. Do investors overweight personal experience? Evidence from IPO subscriptions. J. Finance 63, 2679–2702.
Kempf, E., Manconi, A., Spalt, O.G., 2017. Learning by Doing: The Value of Experience and the Origins of Skill for Mutual Fund Managers. Working paper.
Luong, H., Moshirian, F., Nguyen, L., Tian, X., Zhang, B., 2017. How do foreign institutional investors enhance firm innovation? J. Financ. Quant. Anal. 52, 1449–1490.
Malmendier, U., Nagel, S., 2011. Depression babies: do macroeconomic experiences affect risk taking? Q. J. Econ. 126, 373–416.
Marshall, A., Farag, H., Neupane, B., Neupane, S., Thapa, C., 2022. Tax threat and the disruptive market power of foreign portfolio investors. Br. J. Manage. 33, 1468–1498.
Neupane, B., Thapa, C., Marshall, A., Neupane, S., 2021. Mimicking insider trades. J. Corp. Finance 68, 1919–1940.
Neupane, S., Marshall, A., Paudyal, K., Thapa, C., 2017. Do investors flip less in bookbuilding than in auction IPOs? J. Corp. Finance 47, 253–268.
Neupane, S., Paudyal, K., Thapa, C., 2014. Firm quality or market sentiment: what matters more for IPO investors? J. Bank. Finance 44, 207–218.
Neupane, S., Poshakwale, S., 2012. Transparency in IPO mechanism: retail investors' participation, IPO pricing and returns. J. Bank. Finance 36, 2064–2076.
Phillips, B.P.K., Rau, P.R., 2018. Size does not matter: diseconomies of scale in the mutual fund industry revisited. J. Bank. Finance 88, 357–365.
Pástor, Stambaugh, R.F., Taylor, L.A., 2015. Scale and skill in active management. J. Financ. Econ. 116, 23–45.
Rocholl, J., 2009. A friend in need is a friend indeed: allocation and demand in IPO bookbuilding. J. Financ. Intermed. 18, 284–310.
Seasholes, M., 2000. Smart Foreign Traders in Emerging Markets. Working paper. Harvard Business School.
Seru, A., Shumway, T., Stoffman, N., 2009. Learning by trading. Rev. Financ. Stud. 23, 705–739.
Sherman, A.E., 2005. Global trends in IPO methods: book building versus auctions with endogenous entry. J. Financ. Econ. 78, 615–649.
Zheng, S.X., Stangeland, D.A., 2007. IPO underpricing, firm quality, and analyst forecasts. Financ. Manage. 36 (2), 46–64.