Retail Bubble Riders

Prachi Deuskar, Shubham Upadhyay, and Darya Yuferova*

August 23, 2022

Abstract

We investigate the behavior of retail traders during repeated bubble episodes in the stocks using detailed data provided by the Bombay Stock Exchange. We show that, after controlling for attrition, retail traders are more likely to participate in bubble stocks if they have prior bubble experience. In addition, retail traders making extreme profits in the previous bubble episodes are less prone to engaging in future bubble riding. Moving from extreme profits to extreme losses in the previous bubble episodes monotonically increases the likelihood of future bubble participation. This pattern is consistent with risk-seeking following losses, implied by the prospect theory.

JEL classification: G12; G14

*Deuskar is with the Indian School of Business; Upadhyay is an independent researcher; and Yuferova is with the Norwegian School of Economics (NHH).

1 Introduction

"Perceptions are important when people act on them... It's all supply and demand. If the demand goes crazy, the price can go crazy — temporarily."

Eugene Fama in "No-Nonsense Investing" MarketWatch by Howard Gold

The history of financial markets features many prominent bubble examples: from tulip mania and South Sea bubble in 17th and 18th centuries, respectively, to more recent episodes of DotCom bubble in 2001 and housing market bubble in 2007 leading to a severe financial crisis in 2008 – 2009. Independently of the reason of bubble emergence,[1] bubbles tend to grasp the attention of different types of traders promising easy and fast road to prosperity. Retail traders tend to be overconfident, like lottery-type payoffs, and purchase attention grabbing stocks (Barber and Odean (2013)). Thus, they would find bubble stocks attractive. But does this tendency change with a previous bubble encounter? Multiple channels make such an effect likely. Seru, Shumway, and Stoffman (2009) find that traders learn about their ability as well as learn to trade based on their experience. A number of recent papers document the effects of past personal experiences on subsequent financial market participation and risk-taking (for example, see Malmendier and Nagel (2011), Malmendier and Nagel (2016), Bernile, Bhagwat, and Rau (2017), among others). Previous bubble experience may make traders overconfident (Odean (1998)) as they consider themselves more competent to profit from bubbles (Graham, Harvey, and Huang (2009)). In this paper, we aim to shed light on how an retail trader's experience in one bubble episode impacts her participation in the next such episode.

[1] Recent theories provide, among others, the following explanations for bubble existence: trading synchronization issues (Abreu and Brunnermeier (2002) and Abreu and Brunnermeier (2003)); overconfidence of investors (Scheinkman and Xiong (2003)); and non-rational expectations: e.g., extrapolative expectations (Barberis, Greenwood, Jin, and Shleifer (2018)) or diagnostic expectations (Bordalo, Gennaioli, Kwon, and Shleifer (2021)).

We use a unique intraday trading data provided by the BSE (formerly, the Bombay Stock Exchange). The BSE and the National Stock Exchange (NSE) are the two major stock exchanges in India. The BSE is the older of the two (established in 1875) and has more companies listed, while the NSE is bigger by traded volume.[2] Both the Indian exchanges are in the top 10 exchanges globally by market capitalization.[3] The data have anonymized broker-trader identification and go from 2005 till 2011. We focus on 65 of the largest stocks, either having average annual market capitalization in the top 1 percentile or the being part of the S&P BSE SENSEX index during the period under consideration. Anonymous broker-trader identification combined with the legal classification of different accounts allows us to trace actions of the retail traders from one bubble episode to the next.[4]

We follow Greenwood, Shleifer, and You (2019) for ex-post bubble identification. Specifically, if stock experiences price increase of more than 100% within two years followed by a price drop of more than 40% in the subsequent two years, we classify that episode as a bubble (see Section 3.2 for details). In our data we identify 66 stock-specific bubble episodes. On average a bubble lasts for 3.5 years with the price increase from the start of the bubble to the peak of the bubble of 480%, with only 50% price increase remaining from the start till the end of the bubble. We combine bubble episodes into two regimes: bubbles with a peak during 2005 – 2008 (42 bubbles) and bubbles with a peak during 2009 – 2011 (24 bubbles). These two distinct regimes allow us to analyze the effect of retail trader's experience and performance during the first regime on her behavior in the second regime.

First, we document general behavior of retail trader's in bubble and non-bubble stocks across regimes. We observe that there is a high turnover of retail traders in the stock market: only 28% of retail traders are present in both regimes. In addition, retail traders get captivated by the bubble episodes, since 88% of retail traders are active during at least

[2]Handbook of Statistics 2020, Securities and Exchange Board of India.

[3]Statistics Guide by the World Federation of Exchanges, 2018.

[4]We can track unique broker-client combinations via anonymized ids, hence if retail traders have multiple accounts with different brokers they would appear as different traders in our data.

one bubble episode.

Second, we examine whether past bubble experience matter for the retail trader's decision to participate in the subsequent bubble episodes. We compare the likelihood of participation between bubble and non-bubble stocks to control for traders' attrition. We find that previous bubble experience increases the likelihood of retail traders' participation in bubble stocks as compared to non-bubble stocks by 2.96 to 3.38 percentage points.

Third, we analyze whether retail trader's performance matter for the decision to participate in the subsequent bubble episodes. In line with the prospect-theory, we find that making profits during the previous bubble episode is associated with a *lower* incremental (relative to non-bubble stocks) probability of participation in future bubble episodes by 2.27 to 2.86 percentage points. Moreover, the relation between profits/losses and likelihood of future bubble participation is highly non-linear with monotonically decreasing pattern while moving from extreme losses to extreme profits.

We contribute to three streams of literature. First, there is a large literature on how retail and institutional investors trade during bubble episodes. Brunnermeier and Nagel (2004) and Griffin, Harris, Shu, and Topaloglu (2011) document that, during the NASDAQ bubble of earning 2000s, hedge funds, institutional investors and other sophisticated investors bought during the run up. During the same episode, younger mutual fund managers exhibited trend-chasing behavior and were more heavily invested in technology stocks at the peak of the bubble compared to older managers (Greenwood and Nagel (2009)). Gong, Pan, and Shi (2017) provide evidence on the key role new investors play in initiation and sustenance of a bubble. In recent work, Pearson, Yang, and Zhang (2021) show that individual investors engaged in positive feedback trading in the Chinese warrant bubble. Li, Subrahmanyam, and Yang (2021) find that unskilled investors increase their holdings of overpriced asset while sophisticated investors do the opposite. Each of these studies looks at a single bubble episode. Our contribution to this literature is to document the relevance of experience during one bubble episode for the behavior of the next bubble episode.

Second, the literature on the behavior of retail traders in financial markets has uncovered many patterns. Barber and Odean (2013) present a comprehensive survey of studies on how traits and biases such as overconfidence, seeking sensation, reinforcement learning, and disposition effect influence investor behavior. Gao and Lin (2015) provide evidence consistent with the interpretation that retail investors treat trading and gambling as substitutes. Combining survey responses and actual turnover, Liu, Peng, Xiong, and Xiong (2022) find that perceived information advantage and gambling are two main motives for trading by retail investors. Other evidence points to rational motivation behind retail investor trading. Griffin, Harris, and Topaloglu (2003) find that retail investors are contratrian at intraday and daily frequency. Kaniel, Saar, and Titman (2008), Kaniel, Liu, Saar, and Titman (2012), Kelley and Tetlock (2013), and Boehmer, Jones, Zhang, and Zhang (2021) provide evidence that retail investor imbalances predict returns over short horizons, possibly consistent with liquidity provision as well as informed trading. Farrell, Green, Jame, and Markov (2021) point to technology-enabled information sharing making retail investors better informed. Seru, Shumway, and Stoffman (2009) document that retail investors learn as they trade. We contribute to this literature by showing that frequent bubble riders exist among retail investors. Their prior experience potentially makes them more overconfident and/or risk-seeking, increasing the likelihood that they take part in the next bubble episode. This evidence complements the recent findings of experimental studies that subjects' experience of bubbles does not necessarily eliminate future bubble formation (Hussam, Porter, and Smith (2008), Kopányi-Peuker and Weber (2021)).

Third, a recent but growing literature examines how history of personal experience influences future behavior. Malmendier and Nagel (2011) and Knüpfer, Rantapuska, and Sarvimäki (2017) find that people with experience of a great depression are less willing to take financial risk. Malmendier and Nagel (2016) provide evidence that prior experience with inflation significantly affects inflation expectations and household borrowing and lending behavior. Bernile, Bhagwat, and Rau (2017) show that intensity of exposure to natural disasters has a non-monotonic effect of CEOs' risk-taking behavior. Other papers in this area examine IPO participation (Kaustia and Knüpfer (2008), Chiang, Hirshleifer, Qian, and Sherman (2011)), margin lending (Koudijs and Voth (2016)), investment in securitized assets (Chernenko, Hanson, and Sunderam (2016)), aggregate expectations (Kuchler and Zafar (2019)), unexpectedly lucky disaster experiences (Gao, Liu, and Shi (2020)), and bankruptcies (Gopalan, Gormley, and Kalda (2021)). We add to this strand of research by documenting that retail traders with prior bubble experience, in particular extreme losses in previous bubbles, are more likely to participate in subsequent bubbles after controlling for attrition.

The rest of the paper is organized as follows. Section 2 develops testable hypotheses regarding retail bubble riders behavior in consecutive bubble episodes. Section 3 describes the data and methodology used to identify bubble episodes. Main results are presented in Section 4, followed by robustness checks in Section 5. Section 6 concludes.

2 Hypotheses

As discussed in the introduction, there could be different mechanisms that link experience in the previous bubble episode to the behavior in the next one. In this section, we formulate the hypotheses implied by the different channels.

2.1 Previous bubble exposure

As Seru, Shumway, and Stoffman (2009) show retail traders improve as they gain more trading experience. Thus, retail traders who have participated in the bubble previously may become better "bubble-riders" and hence, are more likely to participate in the next bubble episode. Even if the retail traders do not become better, they may *think* that they are more competent following an experience of participating in a bubble. This is likely to make them overconfident (Graham, Harvey, and Huang (2009)) and hence more willing to participate in the next bubble. Both these channels imply the following hypothesis:

Hypothesis 1. *Controlling for attrition, retail traders who have participated in a previous bubble episode are more likely to participate in the next bubble episode.*

2.2 Previous bubble performance

The first hypothesis relates prior participation to subsequent participation. However, whether the trader made profit or loss in the previous bubble is likely to play a crucial role. Malmendier and Nagel (2011) find that investors who experienced lower stock (bond) returns are less likely to own stocks (bonds). Other studies (discussed in the introduction) linking previous experience to future behavior also typically find similar effects – more positive previous experience results in greater likelihood of engaging in the same behavior in future. Thus we hypothesize:

Hypothesis 2. *Controlling for attrition, retail traders who have made profit in a previous bubble episode are more likely to participate in the next bubble episode than those who made a loss.*

However, if retail traders display preferences described by the prospect theory (Kahneman and Tversky (1979), Tversky and Kahneman (1992)), they are risk-seeking over losses. Participating in a bubble is a risky activity. Those experiencing a loss in a previous bubble episode may become risk-seeking and thus more likely to participate in future bubbles. Hence, as an alternative to Hypothesis 2, we get the following opposite prediction:

Hypothesis 3. *Controlling for attrition, retail traders who have made profit in a previous bubble episode are less likely to participate in the next bubble episode than those who made a loss.*

Intensity of the previous experience may not always have a monotonic effect on future behavior. Bernile, Bhagwat, and Rau (2017) find that CEOs who experienced natural disasters without extremely negative consequences take on more corporate risk than those without any natural disaster exposure. On the other hand, the tendency to seek risk within the prospect theory framework may increase with more extreme losses. Based on these mechanisms, we have the following hypothesis:

Hypothesis 4. *Controlling for attrition, retail traders' likelihood of participation in future bubbles is different based on whether made extreme or moderate profit/loss in the previous bubble.*

Next we describe the data used for testing these hypotheses and method for bubble identification.

3 Data and method

3.1 Sample selection

We use unique intraday trading data at broker-trader level provided by the BSE (formerly, the Bombay Stock Exchange) for the period from 2005 to 2011. In addition to unique broker-trader identifier, data include legal classification for each broker-trader which allows us to identify retail traders. We select largest 65 stocks active during 2005 – 2011 on the following basis. The stock should either have average annual market capitalization in the top 1 percentile or the stock should be part of the S&P BSE SENSEX index during the period under consideration. In addition, we include only those stocks that have price and trading volume data available for at least 17 trading days in each month.[5] We also exclude those stocks that were merged or delisted during our sample period. Finally, we exclude

[5]In the spirit of Amihud (2002) eligibility criteria of 200 trading days in a year.

stocks that were listed after the second quarter of 2009 to ensure stocks have trading data from 2007 onward (required for bubble detection). We combine trading data with data on closing prices, market capitalization, the book value of equity and returns from Prowess and accounting data from S&P Capital IQ.

3.2 Bubble identification

In order to identify bubble episodes, we follow Greenwood, Shleifer, and You (2019) (see Figure 1 for the timeline of bubble identification). For each date, t_1, we check if the price of a stock has increased by more than 100% within the past two years. If yes, we mark $t_0 = t_1 - 24\ months$ as a starting date of the potential bubble. Then we check whether in the two years after t_1 the stock price has experienced a decrease by more than 40% of the price observed on t_1. If so, we conclude that a stock has experienced a bubble with the ending date of the bubble, t_4, being the first date when the drawdown of 40% was observed. Naturally, if 100% threshold is reached today, it is most likely will be reached tomorrow. This gives us a set of t_1 and t_4 dates for each bubble episode. We use the earliest of all t_1 dates and the latest of all t_4 dates as bubble start and bubble end dates, respectively. Figure 2 shows the graphical representation of the idea using the example of bubble episodes in one stock – ACC Limited. The peak of the bubble, t_3, is defined as the date with a maximum price between starting and ending dates. The run-up start, t_2, is defined as 12 months before the peak.

INSERT FIGURES 1 – 2 HERE

We group bubble episodes identified using methodology described in this section into two regimes: 2005 – 2008 (Regime 1), and 2009 – 2011 (Regime 2). This division is based on the clustering of peaks of the bubbles in individual stocks around January 2008 and November 2010. Our sample includes 49 and 54 stocks for Regime 1 and Regime 2, respectively. See Table 1 for the summary of the number of bubbles.

INSERT TABLE 1 HERE

During the first regime we have 42 bubble stocks and 7 non-bubble stocks, while during the second regime we have 24 bubble stocks and 30 non-bubble stocks. Overall, there are 66 bubbles in 54 stocks, out of which 9 stocks do not experience any bubble, 24 stocks have experienced bubble in one regime, and 21 stocks have experienced bubbles in both regimes.

INSERT TABLE 2 HERE

Table 2 shows summary statistics for the percentage price change and time elapsed between the start of the bubble, start of the run-up, the peak, and the end of the bubble. We observe an average (median) price increase of 480% (200%) within 2.2 (2.3) years from the bubble start. The average (median) price change from the run-up start (one year before the peak) to the peak of the bubble is 170% (100%). This increase is followed by an average (median) price drop of -60% (-60%) within 1.3 (1.1) years from the peak of the bubble to bubble end. On average, from the start of the bubble till bubble end the price increase by only 50% as compared to 480% from the start of the bubble till the peak of the bubble.

INSERT TABLE 3 HERE

Table 3 provides mean and standard deviation of the characteristics of the bubble and non-bubble stocks, measured at the first fiscal year-end of the two regimes on 31 March 2005 and 31 March 2009, respectively. Average cumulative return is -0.19% (-0.25%) for bubble (non-bubble) stocks, daily stock price volatility of around 3% and share of retail trading volume is around 45% for both bubble and non-bubble stocks. Bubble stocks tend to be a bit smaller (244 vs 343 INR bln) and trade slightly more actively (295 vs 258 INR mln per day) than non-bubble stocks. From the accounting perspective, bubble stocks tend to have on average larger revenue growth (79.43% vs 38.97%) and smaller ROE (23.48% vs 30.62%) than non-bubble stocks.

In addition to reporting summary statistics, we also perform a univariate t-test for the mean difference between the two groups of stocks. Notably, there is no statistical difference between bubble and non-bubble stocks, in the beginning of the regime. However, as we show later, the trajectory of the bubble and non-bubble stocks diverges as the bubble progresses.

4 Empirical results

In this section, we start by documenting retail traders participation and profitability during the bubble episodes (see Section 4.1). Then, we move to analyzing how previous bubble exposure affects the decision of retail trader to participate in the next bubble (see Section 4.2). We finish with analyzing how performance in the previous bubble episodes affects traders' decision to participate in the next bubble (see Section 4.3).

4.1 Retail traders and bubbles

During our sample period for both bubble and non-bubble stocks, there are 5.67 million unique broker-trader combinations identified as retail trading accounts (referred to as retail traders going forward). Out of them only 1.58 million (27.8%) are present in both regimes. 2.25 million of retail traders are present only during the first regime (2005 – 2008) and 1.74 million of retail traders are present only during the second regime (2009 – 2011). Interestingly, the vast majority of the retail traders participate in bubble stocks: only 0.69 million (12.2%) of retail traders are active exclusively in non-bubble stocks. To sum up, (i) there is a high turnover of retail traders in the stock markets and (ii) bubble episodes seem to attract retail traders' attention.

INSERT FIGURE 3 HERE

Figure 3 shows the cumulative returns of the value-weighted portfolio of bubble stocks and non-bubble stocks in the event time (with the date when the maximum price is reached by the value-weighted portfolio of bubble stocks in each of the regimes being $Event\_Day = 0$). Although Table 3 shows that there is no difference in the key characteristics of bubble and non-bubble stocks before the bubble gets going, here we can clearly see that bubble stocks experience much greater price appreciation than non-bubble stocks once the bubble starts. The figure also plots the cumulative proportion of retail traders having entered the bubble (i.e., either buying/selling the stock for the first time during the bubble episode) till that point. This proportion steadily increases from the start of the bubble till the bubble end. Around 40% of the traders enter after the start of the run-up period (a year before price reaches its peak). Surprisingly, even after the peak retail traders continue to enter the bubble stocks. Roughly, 20% of retail traders buy/sell the bubble stocks after the peak.

INSERT TABLE 4 HERE

Table 4 provides further summary statistics about retail traders' behavior during two regimes under consideration. On average, retail trader participates in 3.8 (1.7) bubble (non-bubble) stocks. The median retail trader is active in 2 bubble stock and 1 non-bubble stock. There is a huge heterogeneity within retail traders: e.g., some of the traders are active across all stocks included in our sample as can be seen from the maximum statistic of 42 bubble and 30 non-bubble stocks. For the stocks retail trader is active in, we compute profits that she makes at the trader-stock-regime level from the start of the run-up till the end of the bubble (see Eq. (1)). We focus on the period from the start of the run-up till the end of the bubble, since the returns from the start of the bubble till the start of the run-up might induce the traders to trade differently in bubble vs non-bubble stocks.

$$Profit\_ratio\_runup_{k,i,t} = \frac{EndInvVal_{k,i,t} + SellVal_{k,i,t} - BuyVal_{k,i,t} - StartInvVal_{k,i,t}}{ScalingFactor_{k,i,t}} \tag{1}$$

where $EndInvVal_{k,i,t}$ is value in INR of trader k's end-of-day inventory at the end of the regime t in stock i; $SellVal_{k,i,t}$ ($BuyVal_{k,i,t}$) is value in INR of trader k's sell (buy) transactions from the run-up start till the end of the regime t in stock i; and $StartInvVal_{k,i,t}$ is value in INR of trader k's inventory right before the start of the run-up period in regime t in stock i. In order to obtain the $StartInvVal_{k,i,t}$, we use the fact that there are severe constraints to overnight short-selling by retail investors in India. Thus, we could obtain the starting inventory position of trader k at regime t in stock i as her most negative end-of-day cumulative inventory position in that stock and regime. $ScalingFactor_{k,i,t}$ is equal to $StartInvVal_{k,i,t}$ if the later one is positive. However, not all retail traders have strictly positive inventory in the beginning of the run-up period. These traders include those who reach positive end-of-day inventory in stock i later during regime t and intraday traders who always have zero end-of-day inventory. For these two groups of traders, we use the maximum of buy and sell trading volume in INR on their first trading day between the run-up start and the end of the regime t in stock i as $ScalingFactor_{k,i,t}$. As a robustness check, we also use the maximum of buy and sell trading volume in INR on their first trading day during regime t from the run-up start till the end of the regime t in stock i as a $ScalingFactor_{k,i,t}$ for *all* traders.

In addition, we also report benchmark profit for retail traders: return between the start of the run-up at regime t for stock i and the end of regime t. This parameter captures profits of retail trader if she had no trading activity throughout the period form the start of the run-up till the end of the bubble. For traders with $StartInvVal_{k,i,t}$ equal to zero, benchmark profits are set to zero. We call this $Benchmark\_ratio\_runup$.

Table 4 shows that on average across trader-stock-regime retail traders make 2.57% return in bubble stocks and 9.52% return in non-bubble stocks, with median return being 0% for both bubble and non-bubble stocks alike.[6] The majority of profits/losses are concentrated in the top/bottom 10% of the distribution: profits (losses) for bubble stock at the 90th (10th) percentile are 120.09% (-77.29%) for bubble stocks, while the maximum (minimum) is much

[6]Profit ratios are winsorized at 99.5%.

larger in absolute terms and is equal to 756.21% (-1,486.92%). We note that that the average benchmark ratio is -7.42% (-3.56%) for bubble (non-bubble) stocks. The difference in means between actual profits and benchmark profits is 9.99% and 13.07% for bubble and non-bubble stocks, respectively, however it is not statistically significant. The difference between profit ratios of bubble and non-bubble stocks is -6.95%, statistically significant at 1%.[7]

After documenting overall behavior of retail traders during the two regimes under consideration, we analyze how previous bubble experience shapes their behavior in the future bubbles in the next section.

4.2 Previous bubble exposure

In this section, we investigate whether the mere fact of experiencing a bubble episode affects the likelihood of participation of retail traders in the next bubble. We combine stocks into two groups during each regime t: bubble stocks ($g = B$) and non-bubble stocks ($g = NB$).[8] We focus our attention on the period from the start of the run-up till the end of the regime. For non-bubble stocks, we measure participation and profits between the run-up start date of the value-weighted portfolio of bubble stocks and the end of the regime.

We use a linear probability / logit models[9] to estimate the following specification:

$$\begin{aligned} Y_{g,t,k} = \beta_0 + \beta_1 BubbleStock_{g,t} + \beta_2 ActivityBubble_{t-1,k} + \\ + \beta_3 BubbleStock_{g,t} \times ActivityBubble_{t-1,k} + \epsilon_{g,t,k} \end{aligned} \tag{2}$$

[7]The results are qualitatively similar if we use maximum of buy and sell trading volume in INR on their first trading day for all traders as the scaling factor.

[8]We note that not all stocks are present throughout the two regimes and only 21 stocks have more than one bubble. Further, an individual trader is active only in 3.8 (1.7) bubble (non-bubble) stocks, on average. Therefore, vast majority of retail investors do not have a stock-specific previous bubble experience. The aggregation of stocks into bubble and non-bubble groups helps us to overcome this issue as it allows us to relate overall experience of bubble episodes to future bubble participation.

[9]According to Wooldridge (2002), the linear probability model is often a good approximation. The case for it is stronger when the explanatory variables are all indicator variables, as is situation here. See discussion in Chapters 15.2, 15.8.2, and 15.8.3 in Wooldridge (2002).

where dependent variable $Y_{g,t,k}$ takes value one if trader k trades in any stocks in group g in regime t from run-up start till the end of the regime and zero otherwise. $ActivityBubble_{t-1,k}$, takes value one if trader k was active in bubble stocks from run-up start till the end of the regime $t-1$ and zero otherwise. Indicator variable $BubbleStock_{g,t}$ is one if $g = B$ in regime t and zero otherwise. Under Hypothesis 1, β_3 should be positive and significant indicating that previous experience in the bubble episodes increases probability of participation in bubble stocks relative to non-bubble stocks. First two columns of Table 5 show estimation results of Eq. (2). Column (1) shows the coefficients from the linear probability model and Column (2) marginal effects from logit model.

INSERT TABLE 5 HERE

We find that retail traders who have experienced bubble episodes in the past are 2.96 (3.38) percentage points more likely to again participate in bubble stocks relative to non-bubble stocks for linear probability (logit) model, in line with Hypothesis 1.

We note that by comparing bubble and non-bubble stocks, we control for the attrition effect that we observe in our sample as discussed in Section 4.1 and also documented by previous literature (e.g., Seru, Shumway, and Stoffman (2009)). In other words, some retail traders, present in Regime 1, may trade neither in bubble stocks nor in non-bubble stocks in Regime 2. It is important to use the benchmark of non-bubble stocks, to correctly gauge the differential behavior of retail traders towards bubble stocks.

Next, we enhance the main specification by including the variables capturing previous experience in the non-bubble stocks (see last two columns of Table 5). We see that the main results remain unchanged for the enhanced specification as well. As per the linear probability model, retail traders who have experienced bubble episodes in the past are 3.14 percentage points more likely to again participate in bubble stocks relative to non-bubble stocks. In contrast, previous experience in non-bubble stocks decreases the likelihood of participation in bubble stocks in the current regime by 0.89 percentage points compared to the likelihood of participation in the non-bubble stocks. Logit model produces similar results. However, we note than in the first regime there were only 7 non-bubble stocks (14% of all stocks in the sample) and thus, results should be interpreted with caution.

Having documented that previous experience matters for the decision on bubble stock participation, we move towards examining the effect previous performance in the bubble episodes have on that decision.

4.3 Previous bubble performance

In this section, we enhance the analysis in the previous section by adding indicator variables capturing profitability of the retail trader in the prior bubble. As before, we combine stocks into two groups during each regime t: bubble stocks ($g = B$) and non-bubble stocks ($g = NB$). In particular, we estimate the following regression:

$$\begin{aligned} Y_{g,t,k} = \beta_0 &+ \beta_1 BubbleStock_{g,t} + \\ &+ \beta_2 ActivityBubble_{t-1,k} + \beta_3 ActivityBubble_{t-1,k} \times BubbleStock_{g,t} + \\ &+ \beta_4 ProfitBubble_{t-1,k} + \beta_5 ProfitBubble_{t-1,k} \times BubbleStock_{g,t} + \\ &+ \epsilon_{g,t,k} \end{aligned} \tag{3}$$

where $ProfitBubble_{t-1,k}$ is one if a trader k made on average a profit in bubble stocks in regime $t-1$ from run-up start till the end of the regime, and zero otherwise. Specifically, the indicator variable is defined based on the average of the profit ratios across bubble stocks (for profit ratio definition see Section 4.1).

Under Hypothesis 2 (3), we expect that β_5 is positive (negative) and significant. First two columns of Table 6 show estimation results of Eq. (3).

INSERT TABLE 6 HERE

We find that making losses in previous bubble episodes increases the likelihood of participating in bubble stocks as compared to non-bubble stocks by 4.81 and 4.84 percentage points for linear probability model and logit model, respectively, in line with Hypothesis 1. This is now captured by coefficient β_3 in the presence of the profit indicator. The incremental effect of making a profit turns out to be negative: -2.86 and -2.27 percentage points, respectively. Therefore, we can reject Hypothesis 2 that more positive previous experience in bubble episodes is related to greater likelihood of participation in the next bubble, after controlling for attrition. In contrast, this supports Hypothesis 3 that retail traders become more risk-seeking over losses in line with the prospect theory behavior. Overall, making profit in previous bubble episodes, still increases the likelihood of participation in bubble stocks relative to non-bubble stocks by 1.95 percentage points (4.81-2.86) and by 2.57 percentage points (4.84-2.27) according to linear probability and logit models.

We also estimate the enhanced version of the main specification that includes previous experience and profit indicators for non-bubble stocks (see the last two columns of Table 6). The main results remain unchanged, with previous performance in non-bubble stocks having opposite effect on the likelihood of participation in the next bubble episodes as compared to non-bubble stocks, similar to the results in the previous Section 4.2.

Given that more extreme profits/losses might have a stronger effect on the retail traders' behavior than moderate profits/losses. Thus, we enrich the analysis by including multiple indicator variables for trader k in regime $t-1$ from run-up start till the end of the regime to capture (i) extreme losses (bottom 20% of losses), (ii) moderate losses, and (iii) extreme profits (top 20% of profits) in bubble stocks (with moderate profits becoming a baseline category), and including respective interactions with an indicator variable, $BubbleStock_{g,t}$, which takes value one if $g = B$ in regime t and zero otherwise. Specifically, We use the following model:

$$
\begin{aligned}
Y_{g,t,k} = \beta_0 &+ \beta_1 BubbleStock_{g,t} + \\
&+ \beta_2 ActivityBubble_{t-1,k} + \beta_3 ActivityBubble_{t-1,k} \times BubbleStock_{g,t} + \\
&+ \beta_4 ExtrProfitBubble_{t-1,k} + \beta_5 ExtrProfitBubble_{t-1,k} \times BubbleStock_{g,t} + \\
&+ \beta_6 ModLossBubble_{t-1,k} + \beta_7 ModLossBubble_{t-1,k} \times BubbleStock_{g,t} + \\
&+ \beta_8 ExtrLossBubble_{t-1,k} + \beta_9 ExtrLossBubble_{t-1,k} \times BubbleStock_{g,t} + \\
&+ \epsilon_{g,t,k}
\end{aligned} \tag{4}
$$

The first two columns of Table 7 present the estimation results of Eq. (4) for linear probability model and logit model. We focus our discussion on linear probability model, with logit model results being quantitatively similar. Also, we discuss only coefficients for interaction with $BubbleStock_{g,t}$, i.e., incremental effects relative to participation in non-bubble stocks. We find that retail traders with moderate profits in bubble stocks are 2.70 percentage points more likely to participate again in bubble stocks. Those with extreme losses are 5.42 percentage points (2.70+2.72) more likely to engage again in trading in bubble stocks. For retail traders with moderate loss, the likelihood increases by 4.66 percentage points. In case of extreme prior bubble profits, they are by 1.08 percentage points less likely to participate again in bubble stocks.[10]

INSERT TABLE 7 HERE

As an alternative specification, we estimate the following equation:

[10]The formal tests for statistical significance for the sum of the coefficients in front of interaction terms $ActivityBubble_{t-1,k} \times BubbleStock_{g,t}$ and $ExtrProfitBubble_{t-1,k} \times BubbleStock_{g,t}$, $ModLossBubble_{t-1,k} \times BubbleStock_{g,t}$, and $ExtrLossBubble_{t-1,k} \times BubbleStock_{g,t}$ show that the respective sums are statistically significant at the 1% level.

$$
\begin{aligned}
Y_{g,t,k} = \beta_0 &+ \beta_1 BubbleStock_{g,t} + \\
&+ \beta_2 ActivityBubble_{t-1,k} + \beta_3 ActivityBubble_{t-1,k} \times BubbleStock_{g,t} + \\
&+ \beta_4 ProfitQuintileBubble_{t-1,k} + \beta_5 ProfitQuintileBubble_{t-1,k} \times BubbleStock_{g,t} + \\
&+ \beta_6 LossQuintileBubble_{t-1,k} + \beta_7 LossQuintileBubble_{t-1,k} \times BubbleStock_{g,t} + \\
&+ \epsilon_{g,t,k}
\end{aligned} \tag{5}
$$

where $ProfitQuintileBubble_{t-1,k}$ and $LossQuintileBubble_{t-1,k}$ are variables ranging from one to five with one corresponding to small profit/loss and five corresponding to large profit/loss in bubble stocks during regime $t-1$ from run-up start till the end of the bubble. The last two columns of Table 7 present the estimation results of Eq. (5) for linear probability model and logit model respectively. The coefficient for $ProfitQuintileBubble_{t-1,k} \times BubbleStock_{g,t}$ is negative and statistically significant and is equal to -1.01% (-1.06%) according to linear probability (logit) model. Thus, consistent with the previous analysis, more extreme profits reduces the likelihood of bubble participation. The coefficient for $LossQuintileBubble_{t-1,k} \times BubbleStock_{g,t}$ is insignificant in linear probability model specification, while negative and statistically significant in logit model specification, however the magnitude of the coefficient is smaller by a factor of 5 in absolute sense as compared to the respective coefficient of interaction between profit quintile and bubble stock indicator.

To sum up, our results suggest that the relation between previous performance in bubble episodes and the decision of retail trader to participate in the bubble stocks is highly non-linear in line with Hypothesis 4.

We visualize the results of Eq. (4) and (5) by plotting the likelihood of participating in bubble stocks as compared to non-bubble stocks conditional on the loss/profit made in the previous bubble episodes, after controlling for attrition (see Figure 4).

INSERT FIGURE 4 HERE

Figure 4 shows that retail traders' behavior is in line with the prospect theory: more losses make trader more risk-seeking and vice versa. Put differently, larger the losses, more likely are the retail traders to participate in future bubble episodes. The likelihood of participation decreases slightly or remains unchanged in the loss region at around 5% and decreases sharply in the profit region entering negative domain for the top profit quintile.

5 Robustness checks

In this section, we discuss additional results performed to ensure the robustness of our analysis. First, instead of focusing on the period from the run-up start till the end of the regime, we zoom out and use the whole regime for the analysis. Second, we use profit ratio that has the same scaling factor for all traders to ensure that our results regarding non-linear relation between profit/loss made in the previous bubble episodes are not driven by the difference in the scaling factor.

5.1 Whole regime analysis

We repeat our main analysis using participation and profits measured over the whole regime rather than the period from the run-up start till the end of the regime (see Eq. (3) – (5)).

INSERT TABLES 8 – 9 HERE

Table 8 shows the relation between past profit/loss during whole regime and participation in the future bubble episodes. We find that making losses in the previous regime in bubble stocks increases the likelihood of participating in bubble stocks as compared to non-bubble stocks by 1.35 and 1.53 percentage points for linear probability model and logit model, respectively. Making profit in previous bubble episodes, increases the likelihood of participation in bubble stocks relative to non-bubble stocks by 0.62 percentage points (1.35-0.73) and by 0.87 percentage points (1.53-0.66) according to linear probability and logit models, respectively.

Table 9 reports the results for the non-linearity of the relation between past profit/loss during whole regime and participation in the future bubble episodes. In particular (focusing on liner probability model), making extreme loss increases participation in bubble stocks by 2.08 percentage points (0.55+1.53), making moderate loss increases participation in bubble stocks by 1.18 percentage points (0.55+0.62), making moderate profit increases participation in bubble stocks 0.55 percentage points, and making extreme profit increases participation in bubble stocks by 0.91 percentage points (0.55+0.36) relative to non-bubble stocks.[11] Specification that includes profit/loss quintiles shows similar effect with coefficient of $LossQuintileBubble_{t-1,k} \times BubbleStock_{g,t}$ being significantly positive and equal to 0.23 percentage points, with coefficient of $ProfitQuintileBubble_{t-1,k} \times BubbleStock_{g,t}$ being insignificantly different from zero.

To sum up, though the effects from the whole regime analysis are of a smaller magnitude than the ones focusing on the period from the run-up start till the end of the regime, the overall effect is in line with the main findings. The relatively smaller magnitudes might be explained by the fact that it is harder to distinguish bubble and non-bubble stocks in the beginning of the regime rather than at the start of the run-up period.

5.2 Robust profit ratio analysis

We repeat our main analysis using profit ratios that use the same scaling factor for *all* traders independently on whether they have positive inventory at the start of the run-up period or not. Namely, we use the maximum of buy and sell trading volume in INR on the first trading day during the period from the run-up start till the end of the regime.

[11] The formal tests for statistical significance for the sum of the coefficients in front of interaction terms $ActivityBubble_{t-1,k} \times BubbleStock_{g,t}$ and $ExtrProfitBubble_{t-1,k} \times BubbleStock_{g,t}$, $ModLossBubble_{t-1,k} \times BubbleStock_{g,t}$, and $ExtrLossBubble_{t-1,k} \times BubbleStock_{g,t}$ show that the respective sums are statistically significant at the 1% level.

INSERT TABLES 10– 11 HERE

Table 10 shows that using robust profit ratio leads to only minor differences regarding the effect of past performance on the decision to participate in the future bubble episodes: for instance, using the specification in Column (1), making profits decrease a likelihood of participation in future bubble episodes by 3.10 percentage points relative to non-bubble stocks in comparison to the baseline results of 2.86 percentage points.[12] Table 11 shows that using robust profit ratios results into similar non-linear patterns between future bubble participation and profits/losses made in the previous bubble episodes.

To sum up, we document that our results of non-linear relationship between past performance and participation in future bubble episodes are not driven by the differences in scaling factor used for profit computation.

6 Conclusion

The landscape of the modern equity markets facilitates the engagement of individuals in equity trading. According to Financial Times, in the U.S. retail trading activity accounts for as much as joint activity of mutual funds and hedge funds.[13] Therefore, understanding on how trading experience affects the behavior of retail traders becomes of utmost importance.

In this paper, we use detailed trading data provided by the BSE (formerly, the Bombay Stock Exchange) that allows us to trace retail traders' activity through time to shed light on i) whether they tend to repeatedly participate in the bubble episodes and if so, ii) how their past performance influences their decision to participate in the future bubbles.

Using 66 bubble episodes in 54 stocks during 2005 till 2011, we document that retail traders are very active on the BSE accounting for around 45% of total trading volume. In

[12] As described in the discussion of Eq. (3), the indicator variable for profits $ProfitBubble_{t-1,k}$ ($ProfitNonBubble_{t-1,k}$) is based on the average of the profit ratios in bubble (non-bubble) stocks.

[13] See Financial Times "Rise of the retail army: the amateur traders transforming markets".

addition, we show that there is a high turnover of retail traders: roughly, 27.8% of traders are present during the whole period under consideration. We also note that bubble episodes are attracting retail traders' attention: only 12.2% of traders choose not to be active in any of the bubble episodes.

We show that, after controlling for attrition, retail traders are more likely to engage in bubble episodes if they have bubble riding history. Moreover, the relation between past performance and decision to participate in the future bubbles is highly non-linear and is in accordance with prospect theory. Traders making extreme profits in the previous bubble episodes are less likely to engage in future bubbles. On the other hand, those with extreme losses have a greater likelihood of future bubble participation, consistent with risk-seeking behavior following losses.

The paper contributes to the literature on the trading patterns of individuals and institutions during bubble episodes, to the studies about individual trader behavior, and to the research linking past experience to the future behavior by documenting the relevance of experience during one bubble episode for the behavior during the next bubble episode. The findings has implications for understanding financial market patterns in today's times of increased retail participation.

References

Abreu, D. and M. K. Brunnermeier (2002). Synchronization risk and delayed arbitrage. *Journal of Financial Economics 66*(2), 341–360.

Abreu, D. and M. K. Brunnermeier (2003). Bubbles and crashes. *Econometrica 71*(1), 173–204.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Barber, B. M. and T. Odean (2013). The behavior of individual investors. In *Handbook of the Economics of Finance*, Volume 2, pp. 1533–1570. Elsevier.

Barberis, N., R. Greenwood, L. Jin, and A. Shleifer (2018). Extrapolation and bubbles. *Journal of Financial Economics 129*(2), 203–227.

Bernile, G., V. Bhagwat, and P. R. Rau (2017). What doesn't kill you will only make you more risk-loving: Early-life disasters and CEO behavior. *Journal of Finance 72*(1), 167–206.

Boehmer, E., C. M. Jones, X. Zhang, and X. Zhang (2021). Tracking retail investor activity. *Journal of Finance 76*(5), 2249–2305.

Bordalo, P., N. Gennaioli, S. Y. Kwon, and A. Shleifer (2021). Diagnostic bubbles. *Journal of Financial Economics 141*(3), 1060–1077.

Brunnermeier, M. K. and S. Nagel (2004). Hedge funds and the technology bubble. *Journal of Finance 59*(5), 2013–2040.

Chernenko, S., S. G. Hanson, and A. Sunderam (2016). Who neglects risk? Investor experience and the credit boom. *Journal of Financial Economics 122*(2), 248–269.

Chiang, Y.-M., D. Hirshleifer, Y. Qian, and A. E. Sherman (2011). Do investors learn from experience? Evidence from frequent IPO investors. *Review of Financial Studies 24*(5), 1560–1589.

Farrell, M., T. C. Green, R. Jame, and S. Markov (2021). The democratization of investment research and the informativeness of retail investor trading. *Journal of Financial Economics*.

Gao, M., Y.-J. Liu, and Y. Shi (2020). Do people feel less at risk? Evidence from disaster experience. *Journal of Financial Economics 138*(3), 866–888.

Gao, X. and T.-C. Lin (2015). Do individual investors treat trading as a fun and exciting gambling activity? Evidence from repeated natural experiments. *Review of Financial Studies 28*(7), 2128–2166.

Gong, B., D. Pan, and D. Shi (2017). New investors and bubbles: An analysis of the baosteel call warrant bubble. *Management Science 63*(8), 2493–2508.

Gopalan, R., T. A. Gormley, and A. Kalda (2021). It's not so bad: Director bankruptcy experience and corporate risk-taking. *Journal of Financial Economics 142*(1), 261–292.

Graham, J. R., C. R. Harvey, and H. Huang (2009). Investor competence, trading frequency, and home bias. *Management Science 55*(7), 1094–1106.

Greenwood, R. and S. Nagel (2009). Inexperienced investors and bubbles. *Journal of Financial Economics 93*(2), 239–258.

Greenwood, R., A. Shleifer, and Y. You (2019). Bubbles for Fama. *Journal of Financial Economics 131*(1), 20–43.

Griffin, J. M., J. H. Harris, T. Shu, and S. Topaloglu (2011). Who drove and burst the tech bubble? *Journal of Finance 66*(4), 1251–1290.

Griffin, J. M., J. H. Harris, and S. Topaloglu (2003). The dynamics of institutional and individual trading. *Journal of Finance 58*(6), 2285–2320.

Hussam, R. N., D. Porter, and V. L. Smith (2008). Thar she blows: Can bubbles be rekindled with experienced subjects? *American Economic Review 98*(3), 924–37.

Kahneman, D. and A. Tversky (1979). Prospect theory: An analysis of decision under risk. *Econometrica 47*(2), 263–91.

Kaniel, R., S. Liu, G. Saar, and S. Titman (2012). Individual investor trading and return patterns around earnings announcements. *Journal of Finance 67*(2), 639–680.

Kaniel, R., G. Saar, and S. Titman (2008). Individual investor trading and stock returns. *Journal of Finance 63*(1), 273–310.

Kaustia, M. and S. Knüpfer (2008). Do investors overweight personal experience? Evidence from IPO subscriptions. *Journal of Finance 63*(6), 2679–2702.

Kelley, E. K. and P. C. Tetlock (2013). How wise are crowds? Insights from retail orders and stock returns. *Journal of Finance 68*(3), 1229–1265.

Knüpfer, S., E. Rantapuska, and M. Sarvimäki (2017). Formative experiences and portfolio choice: Evidence from the finnish great depression. *Journal of Finance 72*(1), 133–166.

Kopányi-Peuker, A. and M. Weber (2021). Experience does not eliminate bubbles: Experimental evidence. *The Review of Financial Studies 34*(9), 4450–4485.

Koudijs, P. and H.-J. Voth (2016). Leverage and beliefs: Personal experience and risk-taking in margin lending. *American Economic Review 106*(11), 3367–3400.

Kuchler, T. and B. Zafar (2019). Personal experiences and expectations about aggregate outcomes. *Journal of Finance 74*(5), 2491–2542.

Li, X., A. Subrahmanyam, and X. Yang (2021). Winners, losers, and regulators in a derivatives market bubble. *Review of Financial Studies 34*(1), 313–350.

Liu, H., C. Peng, W. A. Xiong, and W. Xiong (2022). Taming the bias zoo. *Journal of Financial Economics 143*(2), 716–741.

Malmendier, U. and S. Nagel (2011). Depression babies: Do macroeconomic experiences affect risk taking? *Quarterly Journal of Economics 126*(1), 373–416.

Malmendier, U. and S. Nagel (2016). Learning from inflation experiences. *Quarterly Journal of Economics 131*(1), 53–87.

Odean, T. (1998). Volume, volatility, price, and profit when all traders are above average. *Journal of Finance 53*(6), 1887–1934.

Pearson, N. D., Z. Yang, and Q. Zhang (2021). The chinese warrants bubble: Evidence from brokerage account records. *Review of Financial Studies 34*(1), 264–312.

Scheinkman, J. A. and W. Xiong (2003). Overconfidence and speculative bubbles. *Journal of Political Economy 111*(6), 1183–1220.

Seru, A., T. Shumway, and N. Stoffman (2009). Learning by trading. *Review of Financial Studies 23*(2), 705–739.

Tversky, A. and D. Kahneman (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty 5*(4), 297–323.

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. Number 2. Cambridge, Massachusetts: The MIT Press.

Figure 1. Bubble timeline

This figure shows the timeline of the events used to identify bubbles in the spirit of Greenwood, Shleifer, and You (2019).

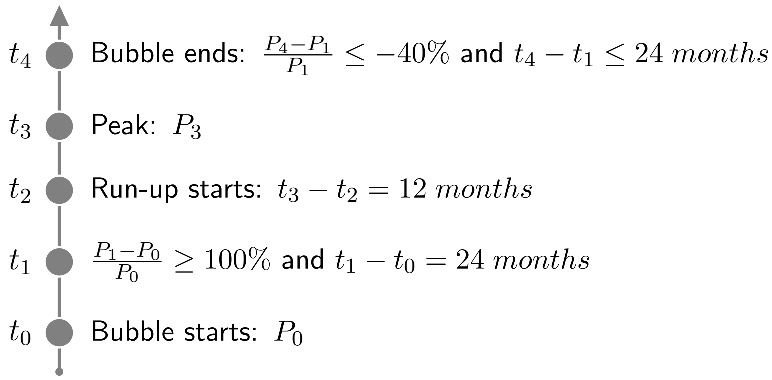


Figure 2. Nested bubbles

This figure shows bubbles in ACC Limited, as an example of multiple, overlapping bubbles in one stock identified by the procedure discussed in Section 3.2.

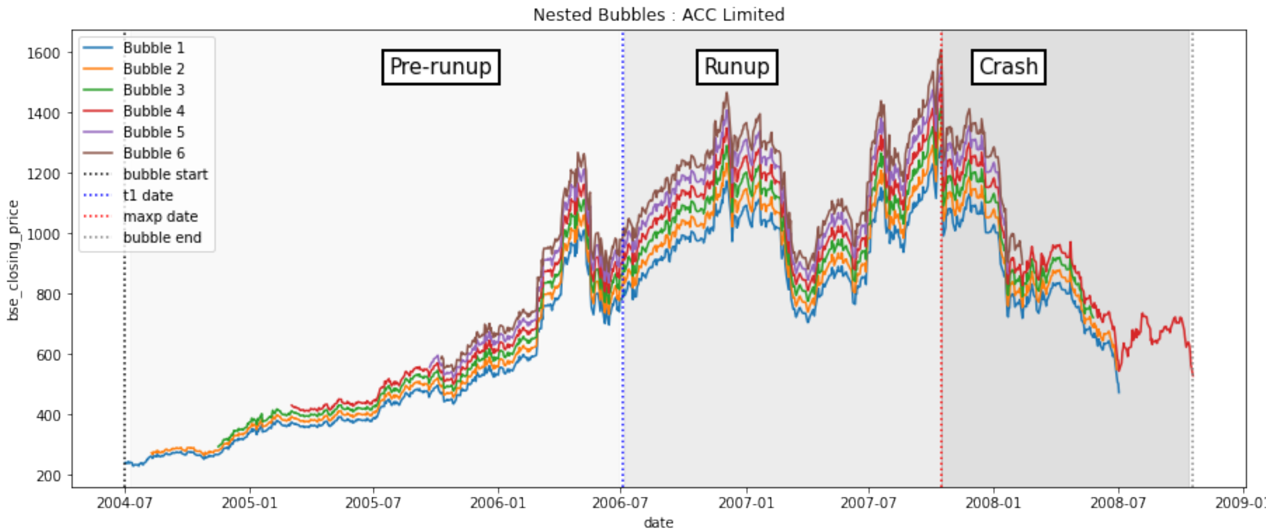


Figure 3. Bubble period returns and investor participation

This figure plots returns on the portfolios of bubble and non-bubble stocks and cumulative participation rate of retail investors in bubbles in event time (with the date when the maximum price is reached by the value-weighted portfolio of bubble stocks in each of the two regimes being $Event\_Day = 0$).

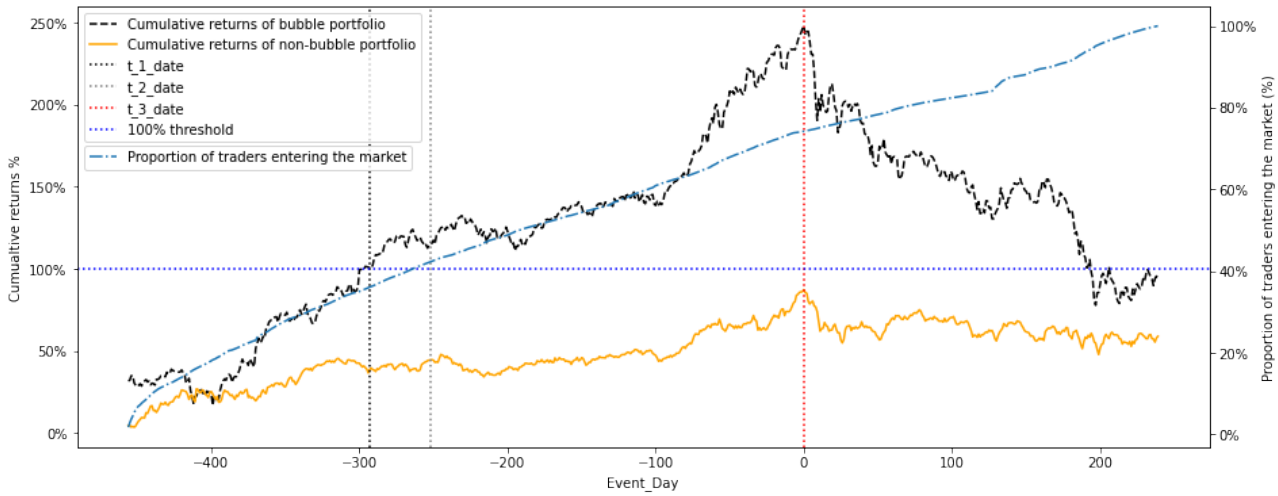
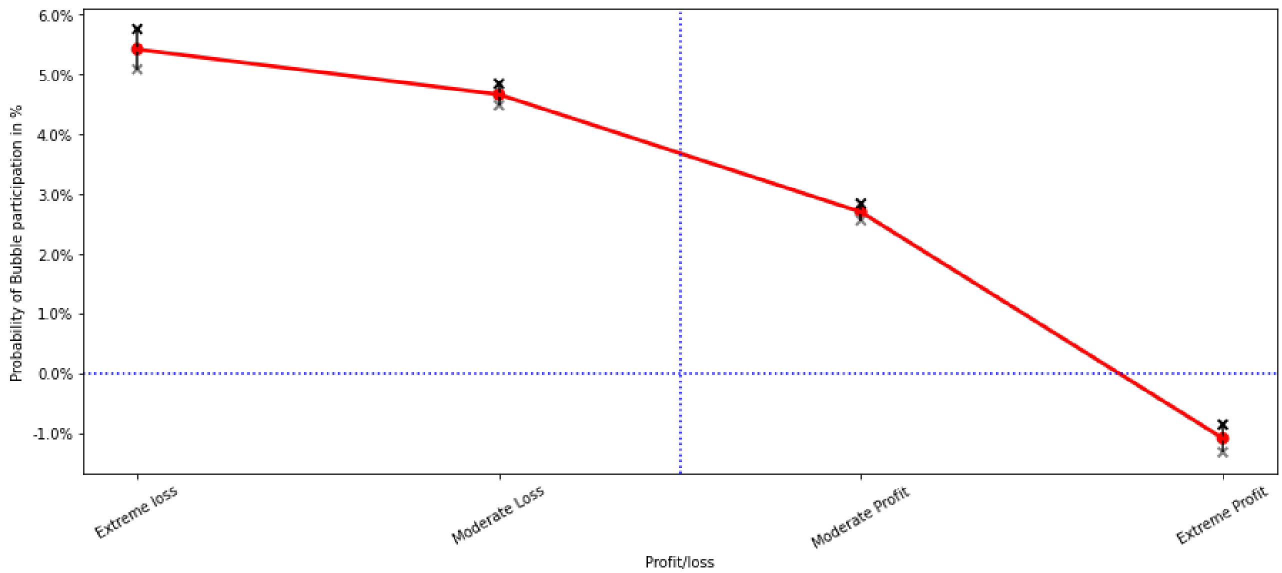


Figure 4. Response to profit / loss

This figure shows how the probability of the bubble participation in the next period depends on the profit / loss made by the investor in the previous bubble. Panel A plots the incremental probability (relative to participation in non-bubble stocks) for different levels of profitability using coefficients from Column (1) of Table 7. Panel B does the same for different quintiles of profit/loss using coefficients from Column (2) of Table 7.

Panel A: Extreme Profit / Loss



Panel B: Profit / Loss Quintiles

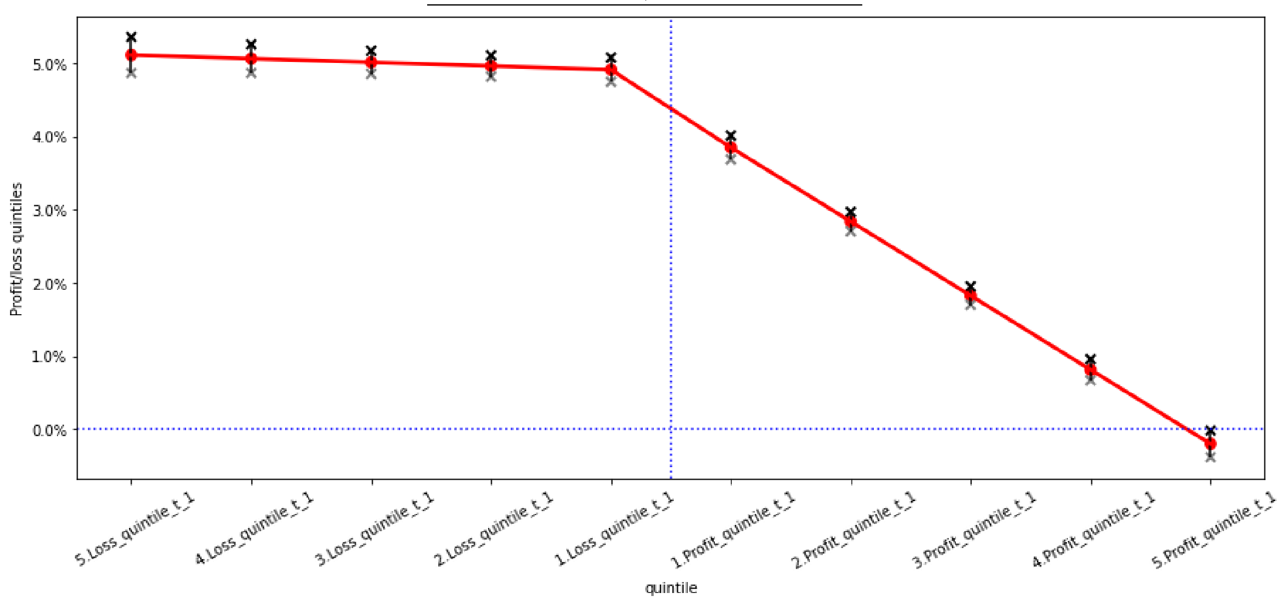


Table 1. Count of Bubble and Non-bubble Stocks

This table contains the information on the number of bubble and non-bubble stocks for the whole sample period (2005 – 2011) and separately for each of the two regimes: 2005 – 2008 (Regime 1) and 2009 – 2011 (Regime 2). Bubbles are identified as described in Section 3.2.

Period	Stock type	# of stocks
2005 - 2008	Bubble	42
	Non-bubble	7
2009 - 2011	Bubble	24
	Non-bubble	30
2005 - 2011	No bubbles	9
	One bubble	24
	Two Bubbles	21

Table 2. Key Characteristics of Bubbles

This table presents the descriptive statistics of the three key parameters of bubbles. Bubbles are identified as described in Section 3.2. *Start to peak of the bubble* shows the price change and duration in years between t_0 and t_3 dates. *Peak to end of the bubble* shows the price change and duration in years between t_3 and t_4 dates. *Start to end of the bubble* shows the price change and duration in years between t_0 and t_4 dates. *Run-up start to peak of the bubble* shows the price change and duration in years between t_2 and t_3 dates.

	Start to Peak of the bubble		Peak to end of the bubble		Start to end of the bubble		Run-up start to peak of the bubble	
	% price change	# of years	% price change	# of years	% price change	# of years	% price change	# of years
Mean	480%	2.2	-60%	1.3	50%	3.5	170%	1.0
Std. Dev.	1330%	0.6	10%	0.5	90%	0.6	320%	0.1
Min	100%	0.2	-90%	0.4	-10%	2.3	10%	0.2
10%	100%	0.5	-90%	0.4	-10%	2.3	10%	0.5
50%	200%	2.3	-60%	1.1	20%	3.4	100%	1.0
90%	5050%	3.3	-40%	2.5	390%	4.6	1310%	1.0
Max	10700%	3.3	-40%	2.6	620%	4.7	2540%	1.0
# of bubbles	66	66	66	66	66	66	66	66

Table 3. Bubble vs Non-Bubble stocks

This table presents the characteristics of bubble and non-bubble stocks averaged across stocks. All variables based on market data are computed over the first quarter of each of the two regimes, i.e., from 1 January till 31 March 2005 and 2009, respectively. All variables based on accounting data are computed at the end of the first fiscal year of each of the two regimes, i.e., on 31 March 2005 and 2009, respectively. *Cumulative returns (%)* are average cumulative returns over the first quarter. *Share of retail traders (%)* is the average share of retail traders in the daily trading rupee volume over the first quarter. *Market cap in INR billion* is the average market capitalization over the first quarter. *Trading volume in INR million* is the average daily rupee trading volume over the first quarter. *Volatility* is the standard deviation of daily returns over the first quarter.*Revenue Growth (%)* is revenue growth measured at the end of the first fiscal year. *ROE (%)* is revenue growth measured at the end of the first fiscal year. In addition, we report a t-test for the difference-in-means between bubble and non-bubble stocks. ***, **, * indicate statistical significance at 1%, 5%, 10%, respectively.

	Mean		Std. Dev.		Mean
	Non_Bubble	Bubble	Non_Bubble	Bubble	Difference
Cumulative returns (%)	-0.25	-0.19	0.31	0.26	0.06
Share of retail traders (%)	45.31	44.43	10.52	11.07	-0.87
Market cap in INR billion	343.43	243.93	427.45	275.61	-99.5
Trading volume in INR million	258.30	295.29	453.93	359.13	36.99
Volatility	0.03	0.03	0.01	0.01	-0.0
Revenue Growth (%)	38.97	79.43	86.55	475.20	40.46
ROE (%)	30.62	23.48	26.51	15.88	-7.14

Table 4. Stock Participation and Profit Ratios of Retail Traders

This table presents the descriptive statistics of participation and profitability of retail traders in bubble and non-bubble stocks. The columns for "Participation" show the statistics for number of stocks an investor participates in different regimes. The other columns show the statistics for various profit ratios as defined in Section 4.1: profit ratios from the run-up start till the end of the regime (*Profit_ratio_runup*), benchmark profit ratios from the run-up start till the end of the regime (*Benchmark_ratio_runup*), profit ratios from the run-up start till the end of the regime robust to alternative scaling factor (*Profit_ratio_robust*). For participation summary statistics observations are at trader-regime level, while for the profit ratios summary statistics observations are at stock-trader-regime level.

	Participation		Profit_ratio_runup		Benchmark_ratio_runup		Profit_ratio_robust	
	Non_Bubble	Bubble	Non_Bubble	Bubble	Non_Bubble	Bubble	Non_Bubble	Bubble
Mean	1.7	3.8	9.52%	2.57%	-3.56%	-7.42%	5.91%	-1.28%
Std. Dev.	2.9	5.0	133.97%	178.28%	17.74%	19.63%	103.24%	105.34%
Min	0.0	0.0	-1486.92%	-1486.92%	-81.38%	-97.12%	-835.35%	-835.35%
10%	0.0	0.0	-38.94%	-77.29%	-15.11%	-41.52%	-34.60%	-52.14%
50%	1.0	2.0	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
90%	5.0	10.0	115.38%	120.09%	0.00%	0.00%	100.00%	100.00%
Max	30.0	42.0	756.21%	756.21%	126.02%	139.49%	353.78%	353.78%
Observations	7,243,129	7,243,129	12,218,851	27,853,108	12,218,851	27,853,108	12,218,851	27,853,108

Table 5. Persistent Bubble Participation

This table presents the analysis of the effect trader's experience in the past bubble episode has on trader's decision to participate in the next bubble episode (see Eq. (2)). We focus on the two groups of stocks: bubble stocks ($g = B$) and non-bubble stocks ($g = NB$). The dependent variable $Y_{g,t,k}$ takes value one if trader k trades in any stock in group g in regime t from run-up start till the end of the regime and zero otherwise. Independent variables are $ActivityBubble_{t-1,k}$ ($ActivityNonBubble_{t-1,k}$) that takes value one if trader k was active in bubble (non-bubble) stocks in regime $t-1$ from run-up start till the end of the regime and zero otherwise; indicator variable $BubbleStock_{g,t}$ is one if $g = B$ in regime t and zero otherwise; and their interactions. Columns (1) and (3) show the coefficient from a linear probability model (LPM), and Columns (2) and (4) show the marginal effects from a logit model. The observations are at the group-trader level. t-statistics are in the parentheses. Heteroskedasticity-robust standard errors are used for linear probability model. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1) LPM	(2) Logit	(3) LPM	(4) Logit
$\text{BubbleStock}_{g,t}$	3.56***	3.43***	3.58***	3.46***
	(90.17)	(90.22)	(90.33)	(91.09)
$\text{AcitivityBubble}_{t-1,k}$	-12.01***	-12.24***	-14.36***	-14.77***
	(-294.85)	(-293.60)	(-339.32)	(-332.96)
$\text{AcitivityNonBubble}_{t-1,k}$			11.21***	11.60***
			(164.00)	(171.89)
$\text{BubbleStock}_{g,t}$ x $\text{AcitivityBubble}_{t-1,k}$	2.96***	3.38***	3.14***	3.76***
	(50.68)	(57.34)	(51.60)	(59.88)
$\text{BubbleStock}_{g,t}$ x $\text{AcitivityNonBubble}_{t-1,k}$			-0.89***	-1.47***
			(-9.07)	(-15.43)
Intercept	44.47***		44.17***	
	(1,598.44)		(1,580.41)	
Observations	11,329,374	11,329,374	11,329,374	11,329,374
Adj. R^2/Pseudo R^2	0.0100	0.0100	0.0200	0.0100

Table 6. Profit/Loss and Future Bubble Participation

This table presents the analysis of the effect trader's experience and performance in the past bubble episode has on trader's decision to participate in the next bubble episode (see Eq. (3)). We focus on the two groups of stocks: bubble stocks ($g = B$) and non-bubble stocks ($g = NB$). The dependent variable $Y_{g,t,k}$ takes value one if trader k trades in any stock in group g in regime t from run-up start till the end of the regime and zero otherwise. Independent variables are $ActivityBubble_{t-1,k}$ ($ActivityNonBubble_{t-1,k}$) that takes value one if trader k was active in bubble (non-bubble) stocks in regime $t-1$ from run-up start till the end of the regime, and zero otherwise; $ProfitBubble_{t-1,k}$ ($ProfitNonBubble_{t-1,k}$) is one if a trader k on average made profit in bubble (non-bubble) stocks in regime $t-1$ from run-up start till the end of the regime, and zero otherwise; indicator variable $BubbleStock_{g,t}$ is one if $g = B$ in regime t and zero otherwise; and their interactions. Columns (1) and (3) show the coefficient from a linear probability model (LPM), and Columns (2) and (4) show the marginal effects from a logit model. The observations are at the group-trader level. t-statistics are in the parentheses. Heteroskedasticity-robust standard errors are used for linear probability model. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1) LPM	(2) Logit	(3) LPM	(4) Logit
$BubbleStock_{g,t}$	3.56***	3.42***	3.60***	3.46***
	(90.17)	(90.22)	(90.75)	(91.44)
$ActivityBubble_{t-1,k}$	-7.30***	-7.23***	-10.11***	-10.22***
	(-124.48)	(-122.36)	(-167.88)	(-165.06)
$ActivityNonBubble_{t-1,k}$			13.55***	13.84***
			(111.49)	(117.81)
$ProfitBubble_{t-1,k}$	-7.30***	-7.85***	-6.48***	-7.01***
	(-115.75)	(-117.32)	(-103.33)	(-104.20)
$ProfitNonBubble_{t-1,k}$			-3.84***	-3.74***
			(-27.80)	(-28.26)
$BubbleStock_{g,t}$ x $ActivityBubble_{t-1,k}$	4.81***	4.84***	4.98***	5.23***
	(57.24)	(58.50)	(57.45)	(60.33)
$BubbleStock_{g,t}$ x $ActivityNonBubble_{t-1,k}$			1.38***	0.73***
			(8.00)	(4.37)
$BubbleStock_{g,t}$ x $ProfitBubble_{t-1,k}$	-2.86***	-2.27***	-2.82***	-2.29***
	(-31.56)	(-24.39)	(-31.24)	(-24.46)
$BubbleStock_{g,t}$ x $ProfitNonBubble_{t-1,k}$			-3.38***	-3.18***
			(-17.29)	(-17.02)
Intercept	44.47***		44.20***	
	(1,598.44)		(1,581.43)	
Observations	11,329,374	11,329,374	11,329,374	11,329,374
Adj. R^2/Pseudo R^2	0.0200	0.0100	0.0200	0.0200

Table 7. Extreme Profit/Loss and Future Bubble Participation

This table presents the analysis of the effect trader's experience and extreme performance in the past bubble episode has on trader's decision to participate in the next bubble episode (see Eq. (4) – (5)). We focus on the two groups of stocks: bubble stocks ($g = B$) and non-bubble stocks ($g = NB$). The dependent variable $Y_{g,t,k}$ takes value one if trader k trades in any stock in group g in regime t from run-up start till the end of the regime and zero otherwise. Independent variables are $ActivityBubble_{t-1,k}$ that takes value one if trader k was active in bubble stocks in regime $t-1$ from run-up start till the end of the regime and zero otherwise; multiple indicator variables for trader k in regime $t-1$ from run-up start till the end of the regime to capture (i) extreme losses, $ExtrLossBubble_{t-1,k}$ (bottom 20% of losses), (ii) moderate losses, $ModLossBubble_{t-1,k}$, and (iii) extreme profits, $ExtrProfitBubble_{t-1,k}$ (top 20% of profits) in bubble stocks for Columns (1) and (2); quintile variables, $ProfitQuintileBubble_{t-1,k}$ / $LossQuintileBubble_{t-1,k}$, ranging from one to five with one corresponding to small profit/loss and five corresponding to large profit/loss in bubble stocks for trader k during regime $t-1$ from run-up start till the end of the regime for Columns (3) and (4); indicator variable $BubbleStock_{g,t}$ is one if $g = B$ in regime t and zero otherwise; and their interactions. For brevity, we report the coefficients of the relevant interactions only. Columns (1) and (3) show the coefficient from a linear probability model (LPM), and Columns (2) and (4) show the marginal effects from a logit model. The observations are at the group-trader level. t-statistics are in the parentheses. Heteroskedasticity-robust standard errors are used for linear probability model. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1) LPM	(2) Logit	(3) LPM	(4) Logit
$BubbleStock_{g,t}$ x $ActivityBubble_{t-1,k}$	2.70***	3.24***	4.86***	5.64***
	(37.93)	(44.01)	(46.36)	(49.97)
$BubbleStock_{g,t}$ x $ExtrProfitBubble_{t-1,k}$	-3.78***	-3.64***		
	(-30.14)	(-24.42)		
$BubbleStock_{g,t}$ x $ModLossBubble_{t-1,k}$	1.97***	1.48***		
	(19.32)	(14.27)		
$BubbleStock_{g,t}$ x $ExtrLossBubble_{t-1,k}$	2.72***	2.08***		
	(15.38)	(11.90)		
$BubbleStock_{g,t}$ x $ProfitQuintileBubble_{t-1,k}$			-1.01***	-1.06***
			(-33.34)	(-31.41)
$BubbleStock_{g,t}$ x $LossQuintileBubble_{t-1,k}$			0.05	-0.18***
			(1.43)	(-4.95)
Observations	11,329,374	11,329,374	11,329,374	11,329,374
Adj. R^2/Pseudo R^2	0.0200	0.0100	0.0200	0.0100

Table 8. Profit/Loss and Future Bubble Participation: Whole Regime

This table presents the analysis of the effect trader's experience and performance in the past bubble episode has on trader's decision to participate in the next bubble episode (see Eq. (3)). We focus on the two groups of stocks: bubble stocks ($g = B$) and non-bubble stocks ($g = NB$). The dependent variable $Y_{g,t,k}$ takes value one if trader k trades in any stock in group g during the whole regime t. Independent variables are $ActivityBubble_{t-1,k}$ ($ActivityNonBubble_{t-1,k}$) that takes value one if trader k was active in bubble (non-bubble) stocks during the whole regime $t-1$ and zero otherwise; $ProfitBubble_{t-1,k}$ ($ProfitNonBubble_{t-1,k}$) is one if a trader k on average made profit in bubble (non-bubble) stocks during the whole regime $t-1$, and zero otherwise; indicator variable $BubbleStock_{g,t}$ is one if $g = B$ in regime t and zero otherwise; and their interactions. Columns (1) and (3) show the coefficient from a linear probability model (LPM), and Columns (2) and (4) show the marginal effects from a logit model. The observations are at the group-trader level. t-statistics are in the parentheses. Heteroskedasticity-robust standard errors are used for linear probability model. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1) LPM	(2) Logit	(3) LPM	(4) Logit
$\text{BubbleStock}_{g,t}$	-1.45***	-1.62***	-1.37***	-1.55***
	(-35.79)	(-35.79)	(-33.93)	(-34.28)
$\text{ActivityBubble}_{t-1,k}$	-37.33***	-35.44***	-38.41***	-36.46***
	(-422.60)	(-416.50)	(-430.40)	(-424.13)
$\text{ActivityNonBubble}_{t-1,k}$			2.90***	2.77***
			(25.62)	(27.90)
$\text{ProfitBubble}_{t-1,k}$	6.33***	5.96***	6.15***	5.80***
	(71.47)	(69.67)	(69.74)	(67.70)
$\text{ProfitNonBubble}_{t-1,k}$			2.67***	2.47***
			(21.55)	(22.84)
$\text{BubbleStock}_{g,t}$ x $\text{ActivityBubble}_{t-1,k}$	1.35***	1.53***	1.79***	1.96***
	(10.82)	(12.36)	(14.20)	(15.69)
$\text{BubbleStock}_{g,t}$ x $\text{ActivityNonBubble}_{t-1,k}$			-2.76***	-2.62***
			(-17.30)	(-18.65)
$\text{BubbleStock}_{g,t}$ x $\text{ProfitBubble}_{t-1,k}$	-0.73***	-0.66***	-0.74***	-0.68***
	(-5.81)	(-5.48)	(-5.89)	(-5.59)
$\text{BubbleStock}_{g,t}$ x $\text{ProfitNonBubble}_{t-1,k}$			1.31***	1.25***
			(7.48)	(8.16)
Intercept	73.14***		72.94***	
	(2,581.39)		(2,570.17)	
Observations	11,329,374	11,329,374	11,329,374	11,329,374
Adj. R^2/Pseudo R^2	0.100	0.0700	0.100	0.0700

Table 9. Extreme Profit/Loss and Future Bubble Participation: Whole Regime

This table presents the analysis of the effect trader's experience and extreme performance in the past bubble episode has on trader's decision to participate in the next bubble episode (see Eq. (4) – (5)). We focus on the two groups of stocks: bubble stocks ($g = B$) and non-bubble stocks ($g = NB$). The dependent variable $Y_{g,t,k}$ takes value one if trader k trades in any stock in group g during the whole regime t and zero otherwise. Independent variables are $ActivityBubble_{t-1,k}$ that takes value one if trader k was active in bubble stocks during the whole regime $t-1$ and zero otherwise; multiple indicator variables for trader k during the whole regime $t-1$ to capture (i) extreme losses, $ExtrLossBubble_{t-1,k}$ (bottom 20% of losses), (ii) moderate losses, $ModLossBubble_{t-1,k}$, and (iii) extreme profits, $ExtrProfitBubble_{t-1,k}$ (top 20% of profits) in bubble stocks for Columns (1) and (2); quintile variables, $ProfitQuintileBubble_{t-1,k}$ / $LossQuintileBubble_{t-1,k}$, ranging from one to five with one corresponding to small profit/loss and five corresponding to large profit/loss in bubble stocks for trader k during the whole regime $t-1$ for Columns (3) and (4); indicator variable $BubbleStock_{g,t}$ is one if $g = B$ in regime t and zero otherwise; and their interactions. For brevity, we report the coefficients of the relevant interactions only. Columns (1) and (3) show the coefficient from a linear probability model (LPM), and Columns (2) and (4) show the marginal effects from a logit model. The observations are at the group-trader level. t-statistics are in the parentheses. Heteroskedasticity-robust standard errors are used for linear probability model. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1) LPM	(2) Logit	(3) LPM	(4) Logit
$BubbleStock_{g,t}$ x $ActivityBubble_{t-1,k}$	0.55***	0.79***	0.63***	0.79***
	(9.07)	(12.82)	(6.51)	(8.21)
$BubbleStock_{g,t}$ x $ExtrProfitBubble_{t-1,k}$	0.36***	0.34***		
	(3.46)	(3.63)		
$BubbleStock_{g,t}$ x $ModLossBubble_{t-1,k}$	0.62***	0.55***		
	(4.56)	(3.93)		
$BubbleStock_{g,t}$ x $ExtrLossBubble_{t-1,k}$	1.53***	1.40***		
	(5.48)	(5.58)		
$BubbleStock_{g,t}$ x $ProfitQuintileBubble_{t-1,k}$			-0.00	0.02
			(-0.01)	(0.76)
$BubbleStock_{g,t}$ x $LossQuintileBubble_{t-1,k}$			0.23***	0.23***
			(5.17)	(5.58)
Observations	11,329,374	11,329,374	11,329,374	11,329,374
Adj. R^2/Pseudo R^2	0.100	0.0700	0.100	0.0800

Table 10. Profit/Loss and Future Bubble Participation: Robust Profit Ratio

This table presents the analysis of the effect trader's experience and performance in the past bubble episode has on trader's decision to participate in the next bubble episode (see Eq. (3)). We focus on the two groups of stocks: bubble stocks ($g = B$) and non-bubble stocks ($g = NB$). The dependent variable $Y_{g,t,k}$ takes value one if trader k trades in any stock in group g in regime t from run-up start till the end of the regime and zero otherwise. Independent variables are $ActivityBubble_{t-1,k}$ ($ActivityNonBubble_{t-1,k}$) that takes value one if trader k was active in bubble (non-bubble) stocks in regime $t-1$ from run-up start till the end of the regime, and zero otherwise; $ProfitBubble_{t-1,k}$ ($ProfitNonBubble_{t-1,k}$) is one if a trader k on average made profit in bubble (non-bubble) stocks in regime $t-1$ from run-up start till the end of the regime, and zero otherwise; indicator variable $BubbleStock_{g,t}$ is one if $g = B$ in regime t and zero otherwise; and their interactions. Profits are measured using alternative scaling factor: maximum of buy and sell trading volume in INR on their first trading day during regime t from the run-up start till the end of the regime t in stock i for *all* traders. Columns (1) and (3) show the coefficient from a linear probability model (LPM), and Columns (2) and (4) show the marginal effects from a logit model. The observations are at the group-trader level. t-statistics are in the parentheses. Heteroskedasticity-robust standard errors are used for linear probability model. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1) LPM	(2) Logit	(3) LPM	(4) Logit
$BubbleStock_{g,t}$	3.56***	3.42***	3.60***	3.46***
	(90.17)	(90.22)	(90.77)	(91.45)
$ActivityBubble_{t-1,k}$	-7.01***	-6.93***	-9.81***	-9.91***
	(-120.02)	(-118.12)	(-163.47)	(-161.08)
$ActivityNonBubble_{t-1,k}$			13.37***	13.65***
			(109.88)	(116.03)
$ProfitBubble_{t-1,k}$	-7.82***	-8.40***	-6.98***	-7.55***
	(-124.42)	(-126.13)	(-111.65)	(-112.63)
$ProfitNonBubble_{t-1,k}$			-3.65***	-3.55***
			(-26.46)	(-26.80)
$BubbleStock_{g,t}$ x $ActivityBubble_{t-1,k}$	4.94***	4.95***	5.11***	5.34***
	(59.13)	(60.27)	(59.26)	(62.01)
$BubbleStock_{g,t}$ x $ActivityNonBubble_{t-1,k}$			1.38***	0.74***
			(7.98)	(4.46)
$BubbleStock_{g,t}$ x $ProfitBubble_{t-1,k}$	-3.10***	-2.47***	-3.05***	-2.48***
	(-34.25)	(-26.56)	(-33.89)	(-26.58)
$BubbleStock_{g,t}$ x $ProfitNonBubble_{t-1,k}$			-3.41***	-3.22***
			(-17.44)	(-17.23)
Intercept	44.47***		44.20***	
	(1,598.44)		(1,581.47)	
Observations	11,329,374	11,329,374	11,329,374	11,329,374
Adj. R^2/Pseudo R^2	0.0200	0.0100	0.0200	0.0200

Table 11. Extreme Profit/Loss and Future Bubble Participation: Robust Profit Ratio

This table presents the analysis of the effect trader's experience and extreme performance in the past bubble episode has on trader's decision to participate in the next bubble episode (see Eq. (4) – (5)). We focus on the two groups of stocks: bubble stocks ($g = B$) and non-bubble stocks ($g = NB$). The dependent variable $Y_{g,t,k}$ takes value one if trader k trades in any stock in group g in regime t from run-up start till the end of the regime and zero otherwise. Independent variables are $ActivityBubble_{t-1,k}$ that takes value one if trader k was active in bubble stocks in regime $t-1$ from run-up start till the end of the regime and zero otherwise; multiple indicator variables for trader k in regime $t-1$ from run-up start till the end of the regime to capture (i) extreme losses, $ExtrLossBubble_{t-1,k}$ (bottom 20% of losses), (ii) moderate losses, $ModLossBubble_{t-1,k}$, and (iii) extreme profits, $ExtrProfitBubble_{t-1,k}$ (top 20% of profits) in bubble stocks for Columns (1) and (2); quintile variables, $ProfitQuintileBubble_{t-1,k}$ / $LossQuintileBubble_{t-1,k}$, ranging from one to five with one corresponding to small profit/loss and five corresponding to large profit/loss in bubble stocks for trader k during regime $t-1$ from run-up start till the end of the regime for Columns (3) and (4); indicator variable $BubbleStock_{g,t}$ is one if $g = B$ in regime t and zero otherwise; and their interactions. Profits are measured using alternative scaling factor: maximum of buy and sell trading volume in INR on their first trading day during regime t from the run-up start till the end of the regime t in stock i for *all* traders. For brevity, we report the coefficients of the relevant interactions only. Columns (1) and (3) show the coefficient from a linear probability model (LPM), and Columns (2) and (4) show the marginal effects from a logit model. The observations are at the group-trader level. t-statistics are in the parentheses. Heteroskedasticity-robust standard errors are used for linear probability model. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1) LPM	(2) Logit	(3) LPM	(4) Logit
$BubbleStock_{g,t}$ x $ActivityBubble_{t-1,k}$	2.52***	3.08***	4.54***	5.41***
	(35.42)	(41.63)	(43.46)	(47.83)
$BubbleStock_{g,t}$ x $ExtrProfitBubble_{t-1,k}$	-3.41***	-3.21***		
	(-27.13)	(-21.35)		
$BubbleStock_{g,t}$ x $ModLossBubble_{t-1,k}$	2.23***	1.73***		
	(22.04)	(16.71)		
$BubbleStock_{g,t}$ x $ExtrLossBubble_{t-1,k}$	3.19***	2.47***		
	(18.11)	(14.26)		
$BubbleStock_{g,t}$ x $ProfitQuintileBubble_{t-1,k}$			-0.94***	-1.01***
			(-30.86)	(-29.91)
$BubbleStock_{g,t}$ x $LossQuintileBubble_{t-1,k}$			0.20***	-0.06
			(5.82)	(-1.63)
Intercept	44.47***		44.47***	
	(1,598.44)		(1,598.44)	
Observations	11,329,374	11,329,374	11,329,374	11,329,374
Adj. R^2/Pseudo R^2	0.0200	0.0100	0.0200	0.0200