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Predictable behavior, profits, and attention ☆

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Abstract

Stocks in the Shanghai market that hit upper price limits typically exhibit three characteristics: high returns, high volumes, and news coverage. We show that these price limit events attract investors' attention. Attention-grabbing events lead active individual investors to buy stocks they have not previously owned. Consistent with lowering investor search costs, events that affect a few (many) stocks lead to increased (decreased) buying. Upper price limit events coincide with initial price increases followed by statistically significant price mean reversion over the following week. Rational traders (statistical arbitrageurs) profit in response to attention-based buying. Smart traders accumulate shares on date t, sell shares on date $t+1$, and earn a daily average profit of 1.16%. We show the amount they invest predicts the degree of attention-based buying by individual investors. We end by decomposing individual investor trades in order to estimate losses attributable to behavioral biases.

JEL classification: G14; G15
Keywords: Attention; Statistical arbitrage; Behavioral finance

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1. Introduction

Recent work in financial economics suggests that individual investors have limited attention and processing capabilities.[2] Such traits become particularly apparent when studying the investment choices of active individual investors. When deciding which stock to purchase, individuals face a daunting search problem that is exacerbated by the thousands of stocks to choose from. Behavioral theories predict that attention-grabbing events help to narrow the universe of stocks an individual might research. This narrowed universe of stocks is called the "consideration set". In a world with limited short selling, newly considered stocks (even those stocks with poor prospects) do not induce investors to initiate short positions.[3] Most individual investors hold only three or four stocks in their portfolios, so they have narrow consideration sets when it comes to deciding which stock to sell next. Thus, attention-grabbing events lead to predictable behavior—individual investors become net buyers of stocks that catch their attention.

Barber and Odean (2005) are the first to comprehensively study individual trading behavior in the presence of attention-grabbing events. They argue that abnormal trading volume, extreme returns, and news can all be thought of as attention-grabbing events. Their empirical analysis shows that each of these three types of events is indeed linked to aggregate net buying by individual investors.[4]

In this paper we study trading behavior and stocks that catch individual investors' attention. First, we examine whether attention-grabbing events lead to predictable buying behavior by individual investors. We test whether attention-grabbing events (on date t) are linked with net individual trade imbalances the following trading day (on date $t+1$) by computing a net buy–sell imbalance measure on date $t+1$ for each event. This measure is the same one as that used in Barber and Odean (2005) and our results provide an out-of-sample confirmation of their results.

Second, the link between attention and investor behavior is predicated on substantial search costs faced by individual investors. If few events happen simultaneously, search costs are reduced, and the consideration set is considerably narrowed. We test this hypothesis by measuring individual imbalances on date $t+1$ as a function of the number of contemporaneous events on date t. We expect more positive (less positive) buy–sell imbalances on days following few (many) contemporaneous events.

Third, attention-grabbing events help individual investors narrow the set of stocks under consideration. After an event, an investor's consideration set may contain stocks the investor has not previously owned. If upper price limit events catch the attention of individual investors, there should be more first-time buys of a particular stock the day following an attention-grabbing event compared to other days. Therefore, we test whether price limit events cause investors to consider, and ultimately purchase, stocks they have not previously owned.

[2] For example, Hirshleifer and Teoh (2003) study firm disclosures in a world with limited attention. Peng (2005) and Peng and Xiong (2006) derive implications for stock prices when investors are constrained in their ability to process information. See also Lynch (1996), Mankiw and Reis (2002), Sims (2003), Gabaix et al. (2003), and Corwin and Coughenour (2005).

[3] In the Shanghai market we consider, short selling is prohibited by regulation.

[4] There are a number of papers that do not focus on investor attention per se but document interesting anecdotal evidence: Lee (1992) concludes that "small investor buy decisions are associated with news events which bring the security to small investors' attention." Graham and Kumar (2004) show that certain investors tend to purchase stocks after specific, attention-grabbing events such as dividend initiations. See also Gervais et al. (2001), Huberman and Regev (2001), Grinblatt and Keloharju (2001) and Choe et al. (1999).

Fourth, behavioral biases do not exist in a vacuum—especially when biases coincide with asset price movements. We hypothesize that there exist traders who rationally try to profit by trading against individuals who exhibit traits such as attention-based buying. Throughout the paper we refer to this group as “smart traders” or “statistical arbitrageurs”. Showing that smart traders profit by exploiting a group such as individuals is difficult. It requires data that are not available in many situations and also requires making a direct link between the trading behaviors of the two groups of investors. We outline a profitable strategy based on publicly available information that takes advantage of individual investor trading around upper price limit events. Smart traders accumulate shares during upper price events by buying from individuals who are (presumably) willing to sell for a gain (consistent with the disposition effect.) The smart traders then sell the following day to another group of individuals who are eager to buy (consistent with attention-grabbing events.) We identify accounts that execute such a strategy and describe the trading behavior in a level of detail previously not possible.

Rather than studying a number of different types of attention-grabbing events, we choose to study a single type of event that combines several important features: upper price limit events on the Shanghai Stock Exchange.[5] The exchange is an electronic limit order book system that allows us to know when a trade is placed, when a trade is executed, which account placed the trade, which account was on the other side of the trade, and where these accounts are located. Like many markets in the world, the Shanghai Stock Exchange imposes daily price movement limits. Studying stocks that hit their upper price limits has a number of benefits. First, an upper price limit event incorporates three characteristics previously associated with attention-grabbing events as in Barber and Odean (2005): i) return is high, ii) volume is high, and iii) the event generates news. Therefore our analysis can be viewed as an extension of the Barber and Odean (2005) study. After the Shanghai market closes for the day, a stock that has hit its daily limit is featured and discussed on investment-related television programs such as “China Business News”. Investors often watch television programs at the end of the trading day in order to get information before the next trading day. Second, using upper price limit events provides a fairly clean separation of event days and post-event days. The separation is possible because news and investment programs that report upper price limit events are typically aired after the close of the market.

Our choice of market and event type also has some costs associated with the benefits mentioned in the previous paragraph. Once a stock hits its upper price limit, the Shanghai Stock Exchange allows trading to continue, but transaction prices may not exceed the limit. Thus, the time series of transaction prices are probably censored. The censoring is not a problem when measuring individual investor net buy–sell imbalances; however it does become an issue when estimating economic losses borne by individual investors. We address censored prices by decomposing losses into two portions. The first portion is attributed to the disposition effect (i.e., investors who sell a stock once it hits its limit even though the price is likely to rise the next day). The second portion comes from attention-based buying (i.e., buying a stock only to see its price mean-revert downward over the next five days).

Our empirical analyses produce several important findings. We confirm existing results by showing that individuals have positive net buy–sell imbalances following attention-grabbing events. Further, individual investor net buy–sell imbalances are more positive (less positive) when a few (many) stocks hit their upper price limits on the same day. We find that attention-grabbing events induce individual investors to buy stocks they have not previously owned. In

[5] We are not able to study lower price limit events due to a lack of data. After granting access to transaction data on upper price limit events, the exchange declined a request for similar data on lower price limit events.

other words, the number of first-time buys for a given stock is significantly higher following an attention-grabbing event than during a typical trading day.

We confirm that attention-grabbing events coincide with statistically significant mean reversion in prices. The day after an attention-grabbing event, individual investors are net buyers and prices appear to be “pushed” upward. Between dates $t+1$ and $t+6$ prices mean-revert back to pre-event levels. Our study has interesting findings regarding the so-called “smart traders” who accumulate shares during date t in anticipation of individual buying demand on date $t+1$. The smart traders sell out these accumulated shares on date $t+1$ and earn an average daily profit of 1.16% (0.71% net of transaction costs). The smart traders build large positions during times when there are a limited number of attention-grabbing events and during events with high trading volumes. The size of the smart traders' positions in a given stock on date t predict the level of individual investor net buying on date $t+1$, suggesting that they are able to anticipate buying by individual investors.

Individual investors' behavioral biases are costly. A portion of individual losses comes from selling stock on date t even though prices rise (on average) the following day. The desire to sell shares during a day with large price increases (therefore most likely at a gain) can be thought of as a form of the disposition effect or a simple misunderstanding of censored prices. The remaining portion of individual losses comes from buying stock on date $t+1$ because prices mean-revert (on average) over the following five days. This second source of individual loss is of particular interest to us since we can attribute these losses to attention-based buying. Using our transaction data, we estimate that individual lose 1.46% over one day due to selling too early (disposition) and 0.88% over five days due to attention-based buying. Losses are naturally related to the smart trader profits, but are not the result of adding-up constraints, as there are other participants operating in the market.

The rest of the paper is organized as follows. Section 2 describes our unique datasets. In Section 3 we study individual investor trading around upper price limit events documenting and testing for attention-based buying. In Section 4 we show that stock prices experience significant mean-reversion following attention-grabbing events. The focus of Section 5 is on the rational response to attention-based buying. In Section 6, we decompose individual investor losses into a portion attributable to selling and a portion attributable to attention-based buying, and Section 7 includes the conclusion.

2. Data

This paper considers a very specific and well-defined type of attention-grabbing event called an “upper price limit event”. An upper price limit event is defined as the date t on which a given stock k hits its upper price limit. Therefore, the unit of analysis is stock-days. The Shanghai Stock Exchange has a ±10% daily price limit for most stocks (“Normal” stocks). The price range is based on the previous day's closing price. A few stocks labeled “special treatment stocks” (or “ST” stocks) have a narrower daily price limit of ±5%. A stock is put on the “ST List” if accounting profits are negative for two consecutive years or if the net asset value per share is lower than the par value of the stock. For both “Normal” stocks and “ST” stocks, intra-day trading regularly takes place after a stock first hits its upper price limit, but never at a price that exceeds the limit. At the end of the trading day, unfilled orders are canceled. On a few days, such as immediately after an IPO or if the stock is emerging from trading suspension, price limits are lifted. During our sample period, which starts on January 2, 2001 and ends July 25, 2003, there are 2442 upper price limit events. On average, there are approximately 1000 upper price limit

Table 1
Overview of events

	Normal stocks	ST stocks	Total events
Upper price limit events	1842	600	2442
Number of unique stock tickers	635	76	657 [a]
Number of unique dates	287	305	416 [a]

This table reports the number of upper price limit events in our sample. An upper price limit event is defined as a day a stock hits its upper price limit. “Normal” stocks have a ±10% daily price limit, while “ST” stocks have a ±5% limit. A given stock may switch classification between Normal and ST over time. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

[a] Indicates number is not additive within the row because stocks may change classification over time.

events per year. Table 1 gives an overview of the events used in this study. In our sample period, there is at least one upper price limit event on 416 of the 610 trading days. These events involve 657 different stocks. Of the 2442 upper price limit events, 1842 involve “Normal” stock-dates and 600 involve “ST” stock-dates. Fig. 1 plots the monthly time series of upper price limit events for both “Normal” and “ST” stocks.

2.1. Transaction data (main dataset)

For each of the 2442 upper price limit events, we collect all transactions for each stock on the day the stock hits its upper price limit (date t). We also collect all transactions for the same stocks on the trading day immediately following the upper price limit event (date $t+1$). A single trading record includes: transaction date, transaction time, stock ticker, transaction price, size of trade in shares, time buy order was placed, time sell order was placed, trading account number of buyer,

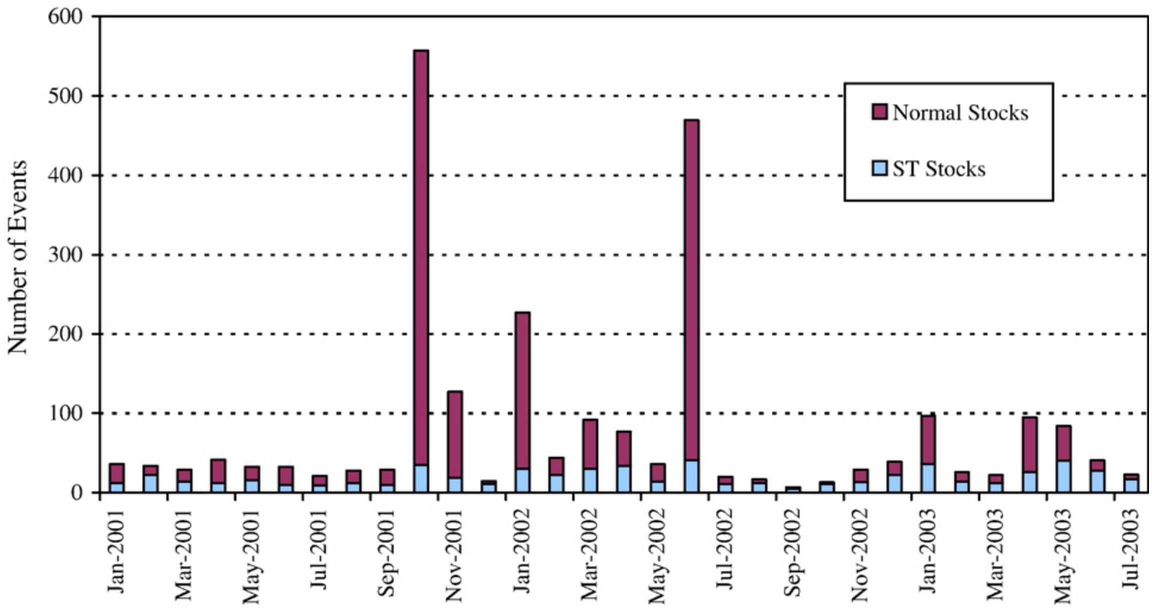

Fig. 1. Number of events per month. This figure graphs the monthly distribution of upper price limit events during our sample period. “Normal” stocks have a ±10% daily price limit, while “ST” stocks have a ±5% limit. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

and trading account number of seller. Account numbers allow us to identify individual accounts.[6] The complete dataset consists of 21,567,617 matched transactions from 6,459,723 different accounts. The number of matched transactions is about twice as large as the number of actual orders executed by investors since a single buy order (e.g., 1000 shares) may be matched with (executed against) two different sell orders (e.g., 300 and 700 shares). Likewise, a single sell order may be matched against multiple smaller buy orders. In total, there are 10,224,018 buy orders and 12,014,707 sell orders executed. For more background on market structure, please see Appendix A. Transaction prices allow us to calculate intra-day prices at the individual stock level. We do not, however, have order flow data from unexecuted (unmatched) transactions. Therefore, we cannot reconstruct a stock's order book throughout the day.

Individual investors sell during all 2442 upper price limit event days (date t), but buy during only 2439 event days. Individual investors execute an average of 3752 buy and 4239 sell transactions per event per stock on date t. On the day following an upper price limit event (date $t+1$), individuals execute an average of 4338 buy and 4105 sell transactions per event per stock. The fact that the number of buy transactions is greater than the number of sell transactions following upper price limit events (date $t+1$) is preliminary evidence of attention-based buying. We perform more formal tests in Section 3.

2.2. Auxiliary dataset

The size and completeness of our main dataset allow for a wide variety of tests. However, we only have complete transaction data for specific stocks during upper price limit events (date t) and the day following upper price limit events (date $t+1$). Thus, we are thus limited in our ability to measure quantities such as individual investor buy–sell imbalances at medium- and long-term horizons. For horizons longer than two days we rely on daily stock price data and an auxiliary dataset.

We obtain all trades for all stocks when either the buy-side or sell-side originates in the city of Ningbo. Trade location can be determined by checking the location of the brokerage office from which an order is placed.[7] The auxiliary dataset contains 2,989,462 matched transactions. While the auxiliary dataset seems large, it is a noisy sub-sample of the overall market. Investors in the auxiliary dataset trade during 64.46% of the available stock-date combinations. We measure the total value traded each day in our auxiliary dataset and the total value traded each day in the entire market. The correlation coefficient between these two time series is 0.7192, indicating that the auxiliary data is representative of the overall level of trading in the market. Conditional on investors from Ningbo trading, the auxiliary database contains an average of 16.35 matched transactions per date per stock.

2.3. Stock price data

We collect daily price data for all stocks traded on the Shanghai Stock Exchange, and consider all trading days from January 2, 2001 to July 25, 2003. Data include date, stock ticker, opening price, closing price, maximum price, minimum price, trading volume in shares, trading value in RMB (the

[6] This paper focuses only on the trading behavior of individual investors and smart traders. Other market participants include brokers and corporations. An earlier version of the paper contains results from all four categories (individuals, smart traders, brokers, and corporations). We discuss the trading imbalances of the latter two categories briefly at the end of Section 5. Results available upon request.

[7] We do not have access to the complete dataset of all trades from all stocks. The city of Ningbo was chosen based on the location of the original ten smart traders (statistical arbitrageurs) discussed in Section 5.

Table 2
Individual investor net buy–sell imbalances

Panel A: Upper price limit events (date t)

	Number of contemporaneous upper price limit events	(1) Average individual imbalances	(2) Standard error of mean	(3) t-statistics	(4) Average amount bought (RMB)	(5) Average amount sold (RMB)	(6) Relative turnover	(7) Number of observations
i.	All events	−0.0863	0.0104	−8.31	43,060,904	48,808,400	4.16	2442
ii.	[1, 5]	−0.0949	0.0063	−14.95	52,412,128	59,003,828	4.92	719
iii.	[6, 10]	−0.0910	0.0141	−8.74	55,819,140	60,244,436	4.79	334
iv.	[11, 20]	−0.0618	0.0207	−2.98	59,065,712	63,577,644	4.36	131
v.	[21, 100]	−0.0346	0.0118	−2.93	33,636,380	36,558,940	3.43	313
vi.	>100	−0.0987	0.0277	−3.56	32,339,706	39,019,156	3.59	945

Panel B: Days following upper price limit events (date $t+1$)

	Number of contemporaneous upper price limit events	(1) Average individual imbalances	(2) Standard error of mean	(3) t-statistics	(4) Average amount bought (RMB)	(5) Average amount sold (RMB)	(6) Relative turnover	(7) Number of observations
i.	All events	0.0254	0.0104	2.43	46,758,304	42,789,784	3.83	2402
ii.	[1, 5]	0.0616	0.0044	14.06	55,034,824	48,356,476	4.53	706
iii.	[6, 10]	0.0461	0.0081	5.69	57,009,548	51,040,444	4.59	329
iv.	[11, 20]	0.0388	0.0121	3.21	73,697,944	69,728,880	4.54	128
v.	[21, 100]	0.0161	0.0070	2.30	35,050,776	29,432,004	2.63	311
vi.	>100	−0.0083	0.0178	−0.46	37,035,116	36,390,556	3.34	928

This table reports net buy–sell imbalances of individual investors during upper price limit events (date t) and days following upper price limit events (date $t+1$). The imbalance measure is defined as the amount of stock k purchased on date t (or date $t+1$) minus the amount sold on the same date divided by the sum of the amounts bought and sold. All amounts are measured in RMB. Turnover is the ratio of value of stock k traded in RMB on date t (or date $t+1$) to the market capitalization of stock k (free float). Relative turnover is the ratio of the turnover of stock k on date t (or date $t+1$) to the average turnover of stock k during our sample period. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003. T-statistics are based on robust standard errors that take into account clustering of contemporaneous events.
Note that individuals neither buy nor sell on date $t+1$ following 40 events.

local currency), number of tradable shares outstanding (free float), and total number of shares outstanding. There are 743 listed stocks in the full sample. As noted above, upper price limit events affect 657 (88.4%) of these stocks. We also collect corresponding information for the major market composite index.

3. Individual investor trading behavior around upper price limit events

We begin by documenting individual investor trading behavior around upper price limit events. We compute a buy–sell imbalance measure on both date t and date $t+1$ for each upper price limit event. Eq. (1) is based on the amounts (in RMB) bought and sold by individual investors.

$$\text{Imbalance}_{k,t}^{\text{Indiv}} = \frac{\text{Buys}_{k,t}^{\text{Indiv}} - \text{Sells}_{k,t}^{\text{Indiv}}}{\text{Buys}_{k,t}^{\text{Indiv}} + \text{Sells}_{k,t}^{\text{Indiv}}}. \quad (1)$$

Table 2, Panel A shows that individual investors are net sellers of stock k on days the stock hits its upper price limit (date t). The average net buy–sell imbalance is −0.0863 with a −8.31 t-statistic when considering all 2442 events. All t-statistics in this paper are based on robust standard errors that control for clustering of contemporaneous events (Roger's standard errors). For an average event, individual investors buy RMB 43,060,904 and sell RMB 48,808,400 of the stock.[8] Individuals are both buying and selling stocks during upper price limit events (date t).

We test whether the events are associated with high or low trading volume by measuring each stock's relative turnover during the upper price limit event. Traditional finance theory predicts low turnover during upper price limit events. Investors realize prices are likely to be censored and sellers are willing to wait one day before transacting at a higher (expected) price. Behavioral finance theory predicts some investors may be willing to sell during upper price limit events due to the disposition effect. Stock k's turnover on date t is defined as the amount traded in RMB divided by the market capitalization of the free float.

$$\mathrm{Turn}_{k,t} = \frac{\mathrm{Volume(RMB)}_{k,t}}{\mathrm{MktCap(FreeFloat)}_{k,t}} \qquad \mathrm{RelTurn}_{k,t} = \frac{\mathrm{Turn}_{k,t}}{\mathrm{Avg}(\mathrm{Turn}_{k,t})}. \tag{2}$$

Relative turnover is defined as the ratio of the turnover of stock k on date t to the average turnover of stock k during our sample period. Table 2, Panel A shows that upper price limit events are high turnover events. The relative turnover is 4.16 when averaged across all 2442 events. The high turnover associated with upper price limit events play a key role in our analysis of smart trader activity (Section 5).

More than one stock may hit its upper price limit on the same day, so we divide our sample of 2442 events into groups based on the number of contemporaneous events. When one to five stocks hit their respective upper price limit on the same day, the average net buy–sell imbalance is −0.0949 with a −14.95 t-statistic. When between 21 and 100 stocks hit their upper price limit on the same day, the average net buy–sell imbalance is −0.0346 with a −2.93 t-statistic.

Although not reported in Table 2, we use order placement times to measure the average value (in RMB) sold *after* a stock initially hits its upper price limit. We find that RMB 32 million out of RMB 48 million sold per event come after a stock initially hits its upper price limit. The average net buy–sell imbalance is −0.1112 with a −9.82 t-statistic if we only consider transactions taking place after a stock initially hits its limit. These results provide evidence of individual investors' desire to realize gains—a form of the disposition effect.

We test whether attention-grabbing events (on date t) are linked with net individual trade imbalances on date $t+1$. To do so, we compute the imbalance measure on date $t+1$ for each upper price limit event. The measure shown in Eq. (1) and applied to date $t+1$ trading is the same as that used in Barber and Odean (2005). Therefore, our results relating to imbalances on date $t+1$ provide an out-of-sample confirmation of their results.

$\mathbf{H_A}$. If an upper price limit event for stock k on date t catches the attention of individual investors, then the net buy–sell imbalance on date $t+1$ is positive.

Table 2, Panel B provides strong evidence that attention-grabbing events are linked to net buying by individual investors. On average, the net buy–sell imbalance on date $t+1$ is 0.0254

[8] The average imbalance reported in Table 2 is the average across each event's imbalance measure. Differences between equal weighting and value weighting imply that the average amount bought and sold in RMB (across all events) cannot be used to calculate the average imbalance shown in the table.

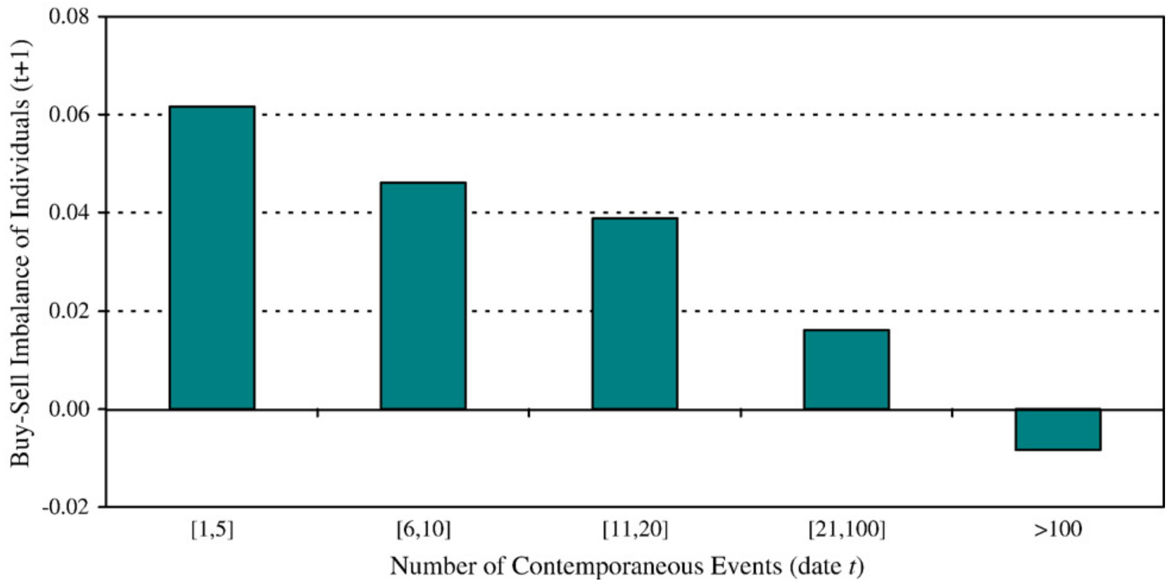

Fig. 2. Attention-based buying and search costs. This figure reports the average net buy–sell imbalances of individual investors on date $t+1$ as a function of number of contemporaneous upper price limit events on date t. Imbalances are reported on a per stock, per event basis. The imbalance measure (shown on the Y-axis) is defined as the amount of stock k purchased on date $t+1$ minus the amount sold divided by the sum of the amounts bought and sold. All amounts are measured in RMB. The X-axis is the number of stocks that hit their upper price limit on the same day (date t). For example, the X-axis value of "[1, 5]" includes the 719 events when between one and five stocks hit their limit on the same day. These 719 events take place on 354 different calendar days. The sample period is from January 2001 to July 2003.

with a 2.43 t-statistic. Our results are consistent with those of Barber and Odean (2005). To check the robustness of the results, we exclude events for the same stock on consecutive days. There are 171 such events. The remaining events produce a net buy–sell imbalance on date $t+1$ of 0.0256 with a 2.27 t-statistic—a result that is virtually identical to the result shown in Table 2, Panel B, Row *i*.

3.1. Reduction of search costs (narrowing the consideration set)

The link between attention and investor behavior is predicated on substantial search costs faced by individual investors. Sorting by large price movements, high volumes, and/or news stories may not necessarily identify attention-grabbing events. A limited number of simultaneous events help to reduce search costs by focusing investors' attention on the affected stocks. Many simultaneous events do not help focus investor attention on any one stock, the consideration set is not narrowed, and search costs are not reduced. We propose and test the following hypothesis:

H_B. The net buy–sell imbalance associated with an attention-grabbing event is decreasing in the size of investors' consideration set.

We test H_B by studying individual investor net buy–sell imbalances on date $t+1$ as a function of the number of contemporaneous events on date t. Table 2, Panel B, Row *ii* shows that when there are between one and five contemporaneous events (on a given day), the average imbalance for the following day is 0.0616 with a 14.06 t-statistic. Row *iii* shows that when there are between six and ten contemporaneous upper price limit events on date t, the mean buy–sell imbalance on date $t+1$ is 0.0461 with a 5.69 t-statistic. The average individual imbalance decreases as the

Table 3
First-time buys for individual accounts

Baseline		Fraction of account-stock-dates with first-time buys	Difference from baseline	Total number of account-stock-dates combinations
All account-stock-date combinations		47.84%	–	549,419
	Number of contemporaneous upper price limit events	Fraction of account-stock-dates with first-time buys	Difference from baseline	Total number of account-stock-dates combinations
i.	All Events	66.49%	18.65%***	7930
ii.	[1, 5]	73.35%	25.51%***	2697
iii.	[6, 10]	67.85%	20.01%***	1359
iv.	[11, 20]	65.48%	17.64%***	588
v.	[21, 100]	62.18%	14.34%***	702
vi.	>100	61.23%	13.39%***	2584

This table reports the fraction of first-time buys following attention-grabbing events. We examine all trades originating from brokerage offices in the city of Ningbo. For each account-stock-date combination, we code first-time buys, second-time buys, third-time buys, and so on. We calculate the fraction of account-stock-dates that exhibit first-time buying. This is our baseline measure. We calculate the fraction of account-stock-dates that exhibit first-time buying following upper price limit events. A Kolmogorov–Smirnof test for differences in distributions produces P-values <0.01 indicated by *** (at the number of first buys). Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

number of contemporaneous events goes up. Row *vi* shows that when there are more than 100 contemporaneous events, the average imbalance is -0.0083 with a -0.46 t-statistic. The difference between the average imbalance measures of Panel B, Row *ii* and Panel B, Row *vi* is statistically significant at all conventional levels. Fig. 2 depicts the monotonically decreasing relationship between the number of contemporaneous upper price limit events on date t and the buy–sell imbalance of individual investors on date $t+1$. Attention-based buying occurs when there are few contemporaneous events. Our results provide new evidence of a link between attention-grabbing events, search costs, and investor behavior.

3.2. First-time buys of individual investors

Attention-grabbing events help individual investors narrow the set of stocks under consideration. After an event, an investor's consideration set may contain stocks the investor has not previously owned. We hypothesize that attention-grabbing events induce investors who have never owned a particular stock before to purchase that stock for the first-time. More formally, we test:

H_C. If an upper price limit event for stock k on date t catches the attention of individual investors, there are more first-time buys of the stock on date $t+1$ than on other days.

In other words, H_C tests whether price limit events induce investors to consider stocks they have not considered previously. To carry out this test, we use the auxiliary dataset and aggregate buy transactions into account-stock-date combinations. The auxiliary dataset contains a total of 549,419 account-stock-date combinations. For each combination, we note whether it is the first-time an account has bought a particular stock (or the second-time, third-time, and so on). We then compare the distribution of first-time buys for account-stock-date combinations following upper price limit events to the distribution of first-time buys for all stock-day combinations. Table 3 shows that 47.84% of all buys are first-time buys for a typical account-stock-purchase. Following a price limit event, this number jumps to 66.49%, indicating a large surge in new buyers. The difference between the number of first-time buyers following an upper price limit event and the baseline is statistically significant at all conventional levels. Our test is based on a Kolmogorov–Smirnof test for differences between discrete distributions. The largest difference occurs at the number of first-time buys. For days associated with between one and five contemporaneous events, the fraction of first-time buys jumps further to 73.35%. Table 3, Rows *iii, iv, v*, and *vi* show the fraction of account-stock-dates with first-time buys goes down as the number of contemporaneous events goes up. Interestingly, even with large numbers of contemporaneous events, the fraction does not fall to the baseline value of 47.84%. The result comes from new investors entering the market for the first-time.[9] We find our test of first-time buying to be extremely strong evidence of attention-based trading. Active individual investors who have not previously owned a particular stock buy in large numbers following attention-grabbing events.

4. Stock price movements around upper price limit events

This section confirms that upper price limit events coincide with temporary but significant price pressure. Studying a market with price limits requires care when analyzing asset price movements. Consider a stock with a 10% price limit. What happens if the company receives news that increases its equity value by 12%? Traditional asset pricing has a simple and straightforward answer to this question. If all information is public and there are no limits to arbitrage, the price shoots up 10% today on low volume. The price then opens tomorrow up another 2%. After tomorrow's open, prices level off if there is no additional news.

In a market with limited risk-bearing capacity, demand shocks may be associated with temporary price pressure. Attention-grabbing events induce net buying demand from individual investors. If individuals do not have value-relevant information, these demand shocks can cause temporary price pressure (an upward spike followed by mean reversion in prices). Therefore, a company that receives the same 12% good news may see its price shoot up 10% today and hit the limit. The return, the news, and hitting the limit may catch individual investors' attention and cause them to place net buy orders. Thus, prices tomorrow may open more than 2% up (i.e., more than 12% up in total) and later mean-revert back a level representing a total change o 12%.

We use calendar-time portfolios to study price movements around upper price limit events. Our portfolios mimic the returns of an investor who invests $1 on a specific date and holds the shares for h days. We consider purchasing the $1 of shares at the close of market on a number of different days surrounding upper price limit events, and also consider holding periods of one to five days.[10] A calendar-time portfolio produces a single time series of returns that controls for cross-sectional correlation. The resulting time series of returns can easily be regressed on a constant and market returns to produce an average risk-adjusted return (alpha.).

[9] A study of individual investors opening accounts and trading for the first-time is beyond the scope of this paper (though it will be the focus of future research). When an individual opens an account, the first stocks purchased are, by definition, first-time buys. Large market movements are associated with a number of stocks hitting their upper price limits. Large market movements are also associated with individuals opening accounts. This association explains the high fraction of first-time buys in Table 3, Row *vi*.

[10] In this section we are implicitly measuring returns assuming that transactions take place at closing prices. In Sections 5 and 6 we refine our analysis in order to measure profits and losses. In these latter sections, we use transaction data to determine the prices at which investors actually buy and sell shares, and also use the actual number of shares bought or sold in our calendar-time portfolio. For more information on calendar-time portfolios, see Barber and Lyon (1997) and Lyon and Barber (1999).

Table 4
Price reactions around upper price limit events

Panel A: Transactions from date $t-1$ to date t

Group	From	To	Holding period in days	Daily price reaction	Return over holding period	Daily alpha	t-statistics
Market	Buy on $t-1$	Sell on t	1	6.0252%	6.0252%	5.8890%	51.00

Panel B: Transactions from date t to date $t+1$

Group	From	To	Holding period in days	Daily price reaction	Return over holding period	Daily alpha	t-statistics
Market	Buy on t	Sell on $t+1$	1	0.6324%	0.6324%	0.6085%	5.47

Panel C: Transactions from date $t+1$ to date $t+6$

Group	From	To	Holding period in days	Daily price reaction	Return over holding period	Daily alpha	t-statistics
Market	Buy on $t+1$	Sell on $t+6$	5	−0.1777%	−0.8853%	−0.1312%	−2.41

This table reports price reactions and profits/losses surrounding upper price limit events. We use calendar-time portfolios to calculate average daily returns. The table also reports market adjusted returns or "Alpha". This table considers transacting at closing prices referred to as "market" returns. The sample period is from January 2001 to July 2003. *T*-statistics are based on standard errors that control for heteroscedasticity.

Table 4 reports price reactions associated with attention-grabbing events. Panel A shows the average daily calendar-time portfolio return associated with buying at the close on date $t-1$ and selling at the close on date t is 6.0252%. After adjusting for systematic risk, the average daily return (alpha) is 5.8890% with a 51.00 t-statistic. This large positive return is expected since stock prices must increase by 10% for normal stocks (5% for ST stocks) at some point during the day in order for the event to be defined as an upper price limit event.

Table 4, Panel B shows that the average daily return between date t and date $t+1$ is 0.6324% with a 5.47 t-statistic. Panel C shows that the average five-day holding period return from our calendar-time portfolios based on buying at the close on date $t+1$ and selling at the close on date $t+6$ is −0.8853%. The daily alpha over the five days is −0.1312% with a −2.41 t-statistic.

The price reactions documented in Table 4 are consistent with the hypothesis that individual investors' attention drives purchases on date $t+1$ and these purchases have temporary positive price pressure, which disappears within a week. While our data allow us to link upper price limit events to statistically significant mean reversion in prices, we are limited in our ability to make this link more formal. Future research might try to show that a significant degree of attention-based buying leads to a significant degree of mean reversion in prices.[11]

5. Rational response to attention-based buying

Sections 3 and 4 show that the upper price limit events on date t coincide with a significant price spike on date $t+1$, significant net buy–sell imbalances on date $t+1$, and significant mean

[11] Our data simply do not have enough power to run a regression of mean-reversion on imbalance. To understand why, note that we have only three days (observations) with 100 or more simultaneous events. As Table 2 shows, it is these events that are associated with essentially zero net buy–sell imbalances.

reversion in prices from date $t+1$ to date $t+6$. Given these findings, it is not difficult to imagine potentially profitable trading strategies. This section of the paper includes a discussion of such strategies.

We consider trading strategies that: i) involve upper price limit events, ii) do not involve short selling, and iii) do not require private information about a particular stock. A natural strategy is based on: a) accumulating shares on date t after a stock hits its upper price limit, b) selling shares on date $t+1$. Such a strategy has two sources of profit. The first source is from buying shares on date t, and the second source is from selling shares on date $t+1$.[12]

Studying the rational response to attention-based buying is motivated by an article in a Chinese periodical called *21st Century Economic Report* (15-May-2003), which describes the actions of a group of traders from the city of Ningbo. We identify ten accounts that follow a strict trading rule of accumulating shares during upper price limit events (date t) and selling out on date $t+1$. A previous version of the paper studied only these ten accounts and described the typical order placing strategy. The smart traders wait until a stock first hits its upper price limit before placing a large number of orders. In fact, 58% of their buy orders during upper price limit events are placed in the five minute interval immediately following the time a stock first hits its limit. Less than 5% of the day's orders are placed before the stock hits the limit, while 85% of the day's orders are placed in the hour immediately following the time a stock first hits its limit. The success of this strategy clearly depends on being able to purchase shares on date t (which explains the strategy of placing a large number of buy orders immediately following the time a stock first hits its limit). Table 2, Panel A shows that the average turnover during upper price limit events is 4.16 times the normal turnover level. While many of the Ningbo traders' orders may go unfilled, high volume and the quick placement of buy orders is key to making profits. The fact that individuals have negative net buy–sell imbalances on date t (likely due to the disposition effect) also helps the traders from Ningbo to profit. Smart traders are net buyers, while individual investors are net sellers. In this version of the paper, we use an expanded definition of smart traders (described in the paragraph below). Regardless of whether we use the original ten accounts from Ningbo or the expanded definition, the results in this section remain qualitatively unchanged.

We identify smart traders by recording the account number of any trader who: i) on at least five different occasions, buys shares during upper price limit events (date t) and sells the same number of shares the following day (date $t+1$), and ii) commits at least RMB 100,000 to an overnight trading strategy during an upper price limit event. We identify 7878 smart trader accounts using this methodology. To the extent that we misclassify traders, noise is added to our results and our reported results can be considered conservative. The 173 most active traders comprise 50% of the volume traded by all 7878 accounts. We choose the cutoff value of RMB 100,000 in order to identify traders who commit a significant amount of money to short-term trading strategies. Using a larger cutoff value (such as RMB 500,000) reduces the number of accounts identified but does not significantly alter our results. The ten original Ningbo accounts are included in the 7878 empirically chosen accounts.

During an upper price limit event (date t), smart traders execute an average of 467 buy transactions and 103 sell transactions. During the day following an upper price limit event (date $t+1$), smart traders

[12] Note that smart traders need to be able to buy on date t and sell on date $t+1$ for the strategy to work. Therefore, the disposition effect exhibited by some investors is important to the smart traders. The ability of smart traders to buy on date t is a potential limit to arbitrage, which is evidenced by the fact that many of the smart traders' buy orders are not filled.

Table 5
Smart trader net buy–sell imbalances

Panel A: Upper price limit events (date t)

	Number of contemporaneous upper price limit events	(1) Average smart trader imbalances	(2) Standard error of mean	(3) t-statistics	(4) Average amount bought (RMB)	(5) Average amount sold (RMB)	(6) Relative turnover	(7) Number of observations
i.	All events	0.4772	0.0548	8.71	6,777,779	1,658,501	4.23	2378
ii.	[1, 5]	0.6405	0.0167	38.41	11,678,454	2,576,211	4.96	712
iii.	[6, 10]	0.6327	0.0269	23.53	11,996,056	2,701,179	4.85	330
iv.	[11, 20]	0.5373	0.0369	14.55	8,518,518	2,668,177	4.36	131
v.	[21, 100]	0.3649	0.0836	4.36	5,272,863	1,542,842	3.54	301
vi.	>100	0.3206	0.1089	2.94	1,261,888	447,276	3.64	905

Panel B: Days following upper price limit events (date $t+1$)

	Number of contemporaneous upper price limit events	(1) Average smart trader imbalances	(2) Standard error of mean	(3) t-statistics	(4) Average amount bought (RMB)	(5) Average amount sold (RMB)	(6) Relative turnover	(7) Number of observations
i.	All events	−0.3889	0.0219	−17.72	2,795,407	5,550,700	3.87	2346
ii.	[1, 5]	−0.4374	0.0184	−23.79	3,882,355	9,032,814	4.55	702
iii.	[6, 10]	−0.4313	0.0278	−15.51	4,213,524	9,511,183	4.62	327
iv.	[11, 20]	−0.4939	0.0471	−10.50	5,025,885	8,107,236	4.59	125
v.	[21, 100]	−0.3041	0.1280	−2.37	2,737,379	4,326,770	2.73	298
vi.	>100	−0.3489	0.0222	−15.70	1,130,660	1,418,309	3.39	894

This table reports net buy–sell imbalances of smart traders during upper price limit events (date t) and days following upper price limit events (date $t+1$). The imbalance measure is defined as the amount of stock k purchased on date t (or date $t+1$) minus the amount sold on the same date divided by the sum of the amounts bought and sold. All amounts are measured in RMB. Turnover is the ratio of value of stock k traded in RMB on date t (or date $t+1$) to the market capitalization of stock k (free float). Relative turnover is the ratio of the turnover of stock k on date t (or date $t+1$) to the average turnover of stock k during our sample period. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003. T-statistics are based on robust standard errors that take into account clustering of contemporaneous events.
Note that smart traders neither buy nor sell on date t during 64 events.
Note that smart traders neither buy nor sell on date $t+1$ following 96 events.

execute an average of 199 buy transactions and 363 sell transactions. Smart traders are active during 2378 upper price limit events (date t). They buy shares on date t and sell shares on date $t+1$ during 2235 events. These events take place on 407 separate calendar days during our sample period.

Table 5, Panel A reports the buy–sell imbalances for the smart traders during upper price limit events (date t) using a measure analogous to the one shown in Eq. (1). The mean imbalance is 0.4772 across all events with an 8.71 t-statistic. The smart traders buy an average of RMB 6,777,779 during each upper price limit event and commit an average net amount of RMB 5,119,278 (the difference between the amounts bought and sold in Row i). The net buy–sell imbalance increases to an average of 0.6405 when there are between one and five contemporaneous events (Row ii), and decreases to 0.3206 when there are over 100 contemporaneous events (Row vi).

Table 5, Panel B reports net buy–sell imbalances on date $t+1$. Smart traders are heavy net sellers. The average imbalance is −0.3889 with a 17.72 t-statistic. The imbalance measure is larger, at −0.4374, when there are between one and five contemporaneous events. The patterns of smart trader buying shown in Panel A and smart trader selling shown in Panel B are consistent with smart traders taking more aggressive positions during events that are more likely to grab the attention of individual investors.[13,14]

5.1. Determinants of smart trader investment

To better understand smart traders' investment decisions, we run a series of regressions and report the results in Table 6. The dependent variable is the smart traders' net investment (in RMB million) for each upper price limit event (on date t). Regression 1 shows that smart traders are net buyers on date t and the results match those shown earlier in Table 5. For example, when there are between one and five contemporaneous events, the average net investment is RMB 9.1022 million per event.[15] Investment falls to only RMB 0.8146 million per event when there are 100 or more contemporaneous events. Regression 2 shows that smart traders invest more, on average, in normal stocks and invest less in ST stocks. An indicator variable for events associated with ST stocks has a −11.1217 coefficient with a −9.78 t-statistic.

Regression 3 shows that smart traders tend to buy more during upper price limit events when the turnover (trading volume) is high. The regression coefficient on relative turnover (date t) is 1.1703 with a 4.10 t-statistic. We test whether the amount smart traders invest is limited by turnover or the net buy–sell imbalance of individual investors (in this case, selling). Regression 4 shows that the smart traders' net investment depends heavily on turnover (1.1071 coefficient with a 4.02 t-statistic), but only marginally on individual investor net buy–sell imbalances during upper price limit events (−0.1429 coefficient and −1.05 t-statistic). These results are not necessarily the product of an adding-up constraint, as there are other participants operating in the market. Finally, Table 6, Regression 5 shows that smart traders' buying during upper price limit events anticipates both high levels of turnover and individual investor net buy–sell imbalances on date $t+1$. The coefficient on date $t+1$ turnover is 1.0681 with a 5.81 t-statistic. The coefficient on individual investor net buy–sell imbalances on date $t+1$ is 0.3025 with a 4.10 t-statistic. The R-squared of Regression 5 is 0.4483, which is higher than the R-squared values using contemporaneous data (see Regressions 1–4). We interpret these results as smart traders having the ability to sort out exactly which types of upper price limit events they want to participate in. The smart traders invest more when they (correctly) anticipate high levels of future turnover and high levels of attention-based buying.

5.2. Smart trader profits

We form a calendar-time portfolio in order to calculate the average daily return experienced by smart traders around upper price limit events. Our portfolio buys stocks on date t at prices actually paid by smart traders. The number of shares of stock k bought on date t is equal to the number of

[13] Although not reported, we use order placement times to determine if smart traders initiate trades (demand liquidity) or have trades executed against outstanding limit orders (provide liquidity). During upper price limit events (date t), smart traders initiate 48.40% of their buy trades. Thus, we can say they provide liquidity for the other 51.60% of their trades. The following day, smart traders initiate 58.14% of their sell trades. Thus, we can say they provide liquidity for the other 41.86% of their trades.

[14] An earlier version of the paper calculated imbalances for individuals, smart traders, corporations, and brokers. During upper price limit events (date t), individual investors, corporations, and brokers all have negative net buy–sell imbalances. Only the smart traders have positive net buy–sell imbalances. Following upper price limit events (date $t+1$), smart traders and brokers are net sellers. Individuals and corporations are net buyers (though the net buy–sell imbalance for corporations is not significantly different from zero).

[15] The regression coefficient of 9.1022 indicates that the net buy–sell imbalance is RMB 9.1022 million—exactly the difference between Columns 4 and 5 in Table 5, Panel A, Row *ii* (11,678,454–2,576,211 = 9,102,243).

Table 6
Regression analysis of smart trader investments on date *t*

Dependent variable: Smart traders net investment on date *t* in RMB millions					
	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
# Events ∈ [1, 5]	9.1022	14.6318	6.9592	5.9145	5.1248
(*t*-statistics)	(10.36)	(11.35)	(4.15)	(3.46)	(3.86)
# Events ∈ [6, 10]	9.2949	13.7098	6.5835	5.9220	4.9013
(*t*-statistics)	(7.18)	(9.54)	(3.95)	(3.08)	(3.35)
# Events ∈ [11, 20]	5.8503	9.5859	3.2606	2.6136	1.4216
(*t*-statistics)	(5.81)	(11.80)	(2.00)	(1.82)	(1.15)
# Events ∈ [21, 100]	3.7300	4.9863	0.4658	0.1580	−0.2481
(*t*-statistics)	(2.49)	(3.15)	(0.27)	(0.10)	(−0.24)
# Events >100	0.8146	1.1222	−3.1616	−3.9364	−2.8535
(*t*-statistics)	(4.00)	(4.49)	(−2.12)	(−2.03)	(−4.37)
ST		−11.1217	−7.0545	−6.2512	−5.5460
(*t*-statistics)		(−9.78)	(−7.70)	(−5.43)	(−6.46)
Rel. Turn. (t)			1.1703	1.1071	
(*t*-statistics)			(4.10)	(4.02)	
Net Indiv. (*t*)				−0.1429	
(*t*-statistics)				(−1.05)	
Rel. Turn. (*t*+1)					1.0681
(*t*-statistics)					(5.81)
Net Indiv. (*t*+1)					0.3025
(*t*-statistics)					(4.10)
R-squared	0.1305	0.1874	0.2406	0.2928	0.4483
No. of observations	2378	2378	2378	2378	2378

Results from regressions where the dependent variable is the net amount invested by the smart traders during upper price limit events (date *t*) in RMB millions. We consider the 2378 of the 2442 events where smart traders trade on date *t*. The regression constant is suppressed and we use five indicator variables for the number of contemporaneous events. The variable "ST" is an indicator for stocks with a ±5% limit as opposed to normal stocks with a ±10% limit. "Rel. Turn." is a stock's turnover on the event date divided by its sample average turnover. "Net Indiv." is the net amount bought minus the amount sold by individual investors date *t* or date *t*+1 (in RMB millions.) Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003. *T*-statistics are based on standard errors that control for heteroscedasticity and clustering of contemporaneous events.

shares bought by the smart traders. We also consider the price of shares sold on date $t+1$ and calculate the one-day gross profit. The prices used are the volume-weighted average price (VWAP) of the net shares bought on date t and net shares sold on date $t+1$:

$$\text{Gross Profit}_{k,t+1}^{\text{Smart Traders}} = \frac{\text{VWAP}_{k,t+1}^{\text{Smart}}}{\text{VWAP}_{k,t}^{\text{Smart}}} - 1. \tag{3}$$

Table 7, Panel A shows that the average daily return of the calendar-time portfolio (i.e., smart trader gross profit) is 1.1621% with a 7.72 t-statistic. [16] The table also reports the "alpha" obtained

[16] As robustness checks, we calculate profits using a number of different methodologies. Eq. (3) ignores any mismatch between shares bought on date t and shares sold on date $t+1$. Therefore, we estimate the transaction prices of the mismatched shares while taking into account our data limitations. If the number of shares bought is greater than the number of shares sold, we use the opening price on the following day to compute the sale value for the extra shares purchased. This is conservative since we assume that smart traders sell at the opening price without applying their trading skills. If the cumulative number of shares purchased is lower than the cumulative sale, we use the limit price to compute the cost of those extra shares sold. The assumption is conservative since the smart traders are able to take up their positions at an average price several pennies below the limit price. Using different methodologies does not materially change our results.

Table 7
Profits and losses from trading around upper price limit events

Panel A: Transactions from date t to date $t+1$

Group	From	To	Holding period in days	Daily price reaction	Return over holding period	Daily alpha	t-statistics
Smart traders	Buy on t	Sell on $t+1$	1	1.1621%	1.1621%	1.1485%	7.72
Individuals	Sell on t	Buy on $t+1$	1	−1.4583%	−1.4583%	−1.4461%	−9.85

Panel B: Transactions from date $t+1$ to date $t+6$

Group	From	To	Holding period in days	Daily price reaction	Return over holding period	Daily alpha	t-statistics
Individuals	Buy on $t+1$	Sell on $t+6$	5	−0.1767%	−0.8804%	−0.1284%	−1.86

This table reports profits and losses surrounding upper price limit events. We use calendar-time portfolios to calculate average daily returns. The table also reports market adjusted returns or “Alpha”. Results for the “Individuals” and “Smart Traders” groups are based on the value-weighted average price obtained from the transactions of the respective group. The sample period is from January 2001 to July 2003. T-statistics are based on standard errors that control for heteroscedasticity.

from regressing the calendar-time portfolio returns on the market. The reported alpha of 1.1485% per day (t-statistic is 7.72) is not very different from the average unadjusted return of 1.1621% per day.

We use the gross profits calculated from Eq. (3) to calculate net profits. The price impact of any trade is already accounted for since we use actual transaction data. Direct transaction costs include a 0.200% transaction tax for each trade (based on value traded) and an exchange service fee of 0.010% (also based on value traded). These fees, combined with a brokerage fee of 0.015%, lead to a 0.450% round-trip cost for the smart traders.[17] There is no capital gains tax in the PRC. The average daily net profit earned by the smart traders is, therefore, estimated to be 0.71% per event.

Fig. 3 plots the distribution of daily gross profits from the calendar-time portfolio. Most financial studies of risky trading strategies are forced to simulate returns—see Mitchell and Pulvino (2001) and Baker and Savasoglu (2002). We are not subject to the same constraints. The profits we report are from actual trading strategies that have been implemented. The figure shows that trading around upper price limit events is risky. Approximately three quarters of all event days provide positive net profits, while approximately one quarter provide losses.[18]

6. Individual investor losses

Our final analysis consists of estimating individual investor losses due to the disposition effect and attention-based buying. These losses are suffered by two different groups of individual investors. The first group experiences losses due to selling shares on date t even though prices are likely to rise the following day. We can think of these losses as foregone profit from selling too early due to the disposition effect. The second group experiences losses due to buying shares on date $t+1$ and then watching prices fall over the next five days.

[17] Very large traders, such as those in our sample, typically negotiate a flat annual fee with the brokerage office. Such a fee gives the traders unlimited access to the broker's line to the exchange. Brokers in the PRC confirm that 0.015% is a reasonable amount to assume for large (high volume) clients. Small individual investors are assumed to pay 0.200%+0.010%+0.200% for a one-way cost of 0.410% and a round-trip cost of 0.820%.

[18] Analyses in an earlier version of the paper show that smart trader profits are not due to the momentum effect. Profits are also not risk premiums associated with higher volatility during the events. The Sharpe ratio of the smart traders' is too high to be explained by conventional asset pricing models. These analyses are available upon request.

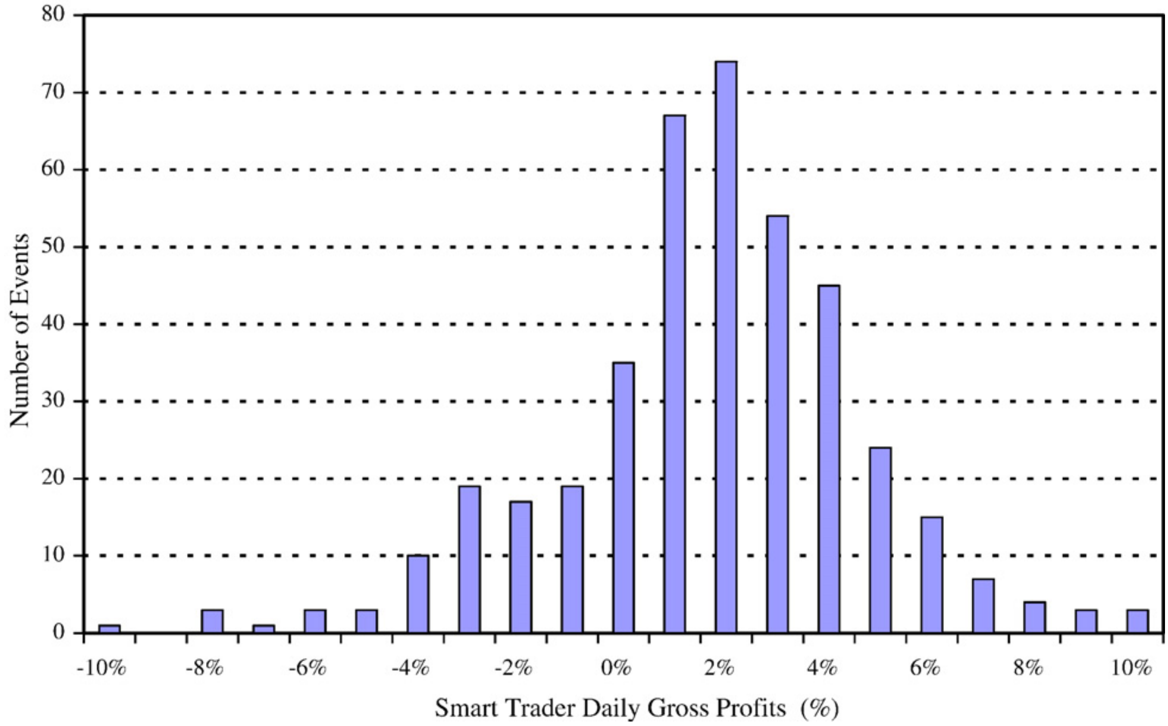

Fig. 3. Distribution of smart trader gross profits. This figure shows distribution of smart trader gross profits. Gross one-day returns are computed using the volume-weighted average sell price ($\mathrm{VWAP}^{\mathrm{sell}}$) on date $t+1$ and volume-weighted average buy price ($\mathrm{VWAP}^{\mathrm{buy}}$) on date t. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

Similar to our earlier analysis of smart trader profits, we use our transaction data to calculate VWAPs during upper price limit events (date t) and following these events (date $t+1$). This time, however, the VWAPs are based on individual investor transactions. We calculate the value-weighted average transaction price on date t and date $t+1$, much as we did in Eq. (3) for the smart traders. The number of shares held in the calendar-time portfolio is calculated using the number of shares sold by individuals on date t or bought by individuals on date $t+1$. Due to data limitations, we use the close of market price for each stock on date $t+6$ when calculating losses due to attention:

$$\mathrm{Loss}(\mathrm{Disposition})^{\mathrm{Indiv}}_{k,t\rightarrow t+1} = -1 \times \left(\frac{\mathrm{VWAP}^{\mathrm{Indiv}}_{k,t+1}}{\mathrm{VWAP}^{\mathrm{Indiv}}_{k,t}} - 1 \right) \tag{4}$$

$$\mathrm{Loss}(\mathrm{Attention})^{\mathrm{Indiv}}_{k,t+1\rightarrow t+6} = \frac{\mathrm{Close}_{k,t+6}}{\mathrm{VWAP}^{\mathrm{Indiv}}_{k,t+1}} - 1. \tag{5}$$

Table 7 shows losses borne by individual investors.[19] In Panel A, the average daily calendar-time portfolio return associated with individuals selling on date t and buying on date $t+1$ is -1.4583%. The number is larger than portfolio returns based on the market's closing prices

[19] As with our analysis of smart trader profits, using different methodologies to calculate individual investor losses does not materially change the results.

because individuals sell below the close on date t and buy above the close on date $t+1$. The risk-adjusted one day loss (alpha) is −1.4461% with a −9.85 t-statistic.

Panel B shows that the average daily calendar-time portfolio return associated with individuals buying on date $t+1$ and selling on date $t+6$ is −0.1767%. Over the five day holding period, this works out to a return (loss) of −0.8804%. Our results provide evidence of substantial losses borne by individual investors who trade around upper price limit events. A rough decomposition shows that individuals lose 1.4583% due to selling too early (disposition) and lose 0.8804% over five days due to buying at the wrong time (attention). Economically, the losses are significant as they occur during times of large trading volumes—Table 2 shows that turnover during upper price limit events (date t) and the following day (date $t+1$) are 4.16 and 3.83 times higher than normal, respectively.

7. Conclusions

This paper studies the set of links between attention-grabbing events, predictable behavior by individual investors, transitory price movements, and the rational response of statistical arbitrageurs. We show that attention-grabbing events lead active individual investors to be net buyers of stocks. Moreover, these events lead investors who have not previously owned a stock to consider and ultimately purchase the stock. We argue and present evidence that not all attention-grabbing events lead to predictable behavior. When many events happen simultaneously, search costs are not reduced, the consideration set is not narrowed, and we do not see attention-based buying.

Our paper shows that the buying coincides with transitory price movements. Stock prices temporarily rise following attention-grabbing events before mean-reverting to pre-event levels over the next five days. More importantly, we hypothesize that behavioral biases do not exist in a vacuum—especially when a bias is linked to asset price movements. To test our hypothesis, we study the high-frequency trading strategy of a group of statistical arbitrageurs or “smart traders” who are active around attention-grabbing events. The smart traders earn one-day profits of 1.16% by trading against individuals.

We end by estimating the losses suffered by individual investors. Individual investors who currently holds a company’s shares sell as prices increase during upper price limit events, but lose out on 1.46% of future price increases. Individuals who buy shares following attention-grabbing events lose 0.88% as prices mean-revert over the next five days.

Appendix A. Background on Stock Markets in the PRC

The PRC has two stock markets—one in Shanghai and one in the city of Shenzhen in Guangdong province. Stocks are listed on one exchange or the other, but are not cross-listed. This paper uses daily prices from Shanghai. The Shanghai Stock Exchange uses an electronic limit order book and offers continuous trading each day between 9:30 a.m. and 3:00 p.m. The opening price is determined by a single price auction, similar to the one used to determine the opening price on the New York Stock Exchange. Initial orders are entered between 9:15 a.m. and 9:25 a.m. and a single price which maximizes the transaction volume is used as the opening price. Unexecuted orders are automatically entered into the limit order book for the continuous auction beginning at 9:30 a.m. The continuous auctions continue until the market closes at 3:00 p.m., with a lunch break from 11:30 a.m. to 1:00 p.m. The official closing price of each stock is the volume-weighted average price during the last minute of trading, or the price of the last trade if there is no trading during the last minute. There is no short selling in the PRC.

In the PRC, shares owned by domestic investors are called "A-shares" and are denominated in RMB (the official exchange rate is essentially fixed at RMB 8.28 = USD 1.00 during our sample period). There are three classes of "A-shares": i) non-tradable government-owned shares called "state shares", ii) non-tradable institution-owned shares called "legal person shares", and iii) tradable shares that can be owned by any domestic investor. The division of shares into these three classes is a result of ongoing privatization efforts by the government to transform state-owned or collective enterprises into joint stock companies. The eventual goal of the reform is to make all shares tradable. The path from the current system to that eventual goal is a topic of heated discussion in academia, securities industry, government regulatory bodies, the financial media, and the investing public in the PRC.

Brokerage firms typically have multiple branch offices throughout the country, region, or city. Many brokerage firms are regionally focused. Investors open accounts at a specific branch office. Each investor applies for a unique stock trading account number, which allows the exchange–and financial economists–to identify accounts and orders. A given investor must place all of his or her trades through the branch office where he or she opened the account—see Feng and Seasholes (2004). The result of these rules is that the exchange–and financial economists–know exactly where orders are placed (which branch and the branch's address). The same type of information is known for both sides of any trade.

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