Predictable Behavior, Profits, and Attention

Mark S. Seasholes
U.C. Berkeley

Guojun Wu
University of Michigan

This version: 05-Jan-2005

Abstract*

This paper studies the set of links between a behavioral bias, transitory price movements, and the rational response to the bias. We show that attention-grabbing events lead active individual investors to consider and ultimately buy stocks they have not previously owned. Not all attention-grabbing events lead to predictable behavior. Only those events that lower search costs (i.e., events that narrow the set of stocks under consideration) lead to attention-based buying. We show that attention-based buying is linked to transitory price shocks with a magnitude of 1.29% and duration of 10 days. We also hypothesize and show that behavioral biases do not exist in a vacuum—especially biases that are linked to asset price movements. Rational arbitrageurs (smart traders) profit in response to attention-based buying. The smart traders earn one day profits of 0.76% net of transaction costs. We are able to decompose the smart traders' profits into a portion related to liquidity provision (58%) and a portion related to taking advantage of attention-based buying (42%). Our data and profit decomposition allow us to calculate the substantial economic cost of a behavioral bias borne by individual investors.

Keywords: Attention, statistical arbitrage, behavioral finance

JEL number: G14, G15

* We thank Terry Hendershott, David Hirshleifer, Terry Odean, Gideon Saar, Nejat Seyhun, Tyler Shumway, Anjan Thakor, and Ning Zhu for helpful comments. We also thank seminar participants at the Shanghai Stock Exchange, 2004 Behavioral Finance Conference at Notre Dame University, University of California Berkeley, and University of Michigan for their input. Jun Cui and Fred P. Wessells provided excellent research assistance. Wu gratefully acknowledges financial support from Center for International Business Education. This paper is made possible with help from the Market Surveillance Department of the Shanghai Stock Exchange.

Contact information: Mark S. Seasholes, University of California, Haas School of Business, 545 Student Services Building, Berkeley, CA 94720-1900, U.S.A. Phone: (510) 642-3421; Fax: (510) 642-4700; Email: mss@haas.berkeley.edu. Guojun Wu, Ross School of Business, University of Michigan, 701 Tappan Street, Ann Arbor, MI 48109, U.S.A. Phone: (734) 936-3248; Fax: (734) 936-0274; Email: gjwu@umich.edu.

1. Introduction

Recent work in financial economics suggests that individual investors have limited attention and exhibit limited processing capabilities. Such traits become particularly apparent when studying the investment decisions (stock portfolios) of active individual investors. When deciding which stock to buy next, individuals face a daunting search problem. Behavioral theories predict that attention-grabbing events help narrow the universe of stocks a given individual might research. This narrowed universe of stocks is called the "consideration set." In a world where short selling is rare or prohibited, attention-grabbing events lead to predictable behavior—individual investors become net buyers of certain stocks in aggregate. Interestingly, the decision of which stock to sell is not subject to the same search costs since most individual investors hold only three or four stocks in their portfolios. Again, in a world where short selling is rare or prohibited, the selling consideration set is narrowed to these three or four stocks.

This paper makes five new contributions. The first two contributions relate to our understanding of individual investor behavior and biases. We show that attention-grabbing events lead to predictable buying behavior by individual investors. However, imbalance measures do not sufficiently link attention and behavior because imbalance measures may be co-determined by liquidity shocks, portfolio re-balancing, and/or other unobserved factors. Therefore, this is the first paper to show that attention-grabbing events lead active individual investors to consider and ultimately buy stocks they have not previously owned. This paper makes a second contribution to our understanding of attention by showing that not all attention-grabbing events lead to predictable behavior. If many events happen simultaneously, search costs are not reduced, and the universe of stocks under consideration is not narrowed. If search costs are not reduced, there is no net buying by active individual investors.

The third contribution of this paper extends beyond simply understanding investor behavior. We link predictable behavior (attention-based buying) to large, transitory price movements. Attention-based buying causes stock prices to rise 1.29% on average. We show the shock and subsequent mean reversion in prices continues for ten days on average. We devote much of the paper to checking alternative explanations for our results. However, tests consistently support our conclusions.

The fourth contribution comes from hypothesizing that behavioral biases do not exist in a vacuum—especially when biases are linked to asset price movements. We outline, and test for, the rational response to attention-based buying. While tests based on the rational response to predictable behavior may strike some readers as obvious, we do not know of any other behavioral/empirical study that employs this methodology. To be fair, showing that a group of traders profits by exploiting another group is very difficult. It requires data that is not available in many situations and it requires making a direct link between the trading behavior of the two groups of investors. In the process of studying the rational response, we describe an actual, high-frequency stock trading strategy in a level of detail previously not possible. Detailing a specific trading strategy cannot be counted as a major contribution to our general understanding of finance. However, we believe our analysis of the trading strategy provides interesting insights into the workings of stock markets. We obtain a very detailed dataset with over 21 million matched transactions. Through the help of a market surveillance department, we are able to track the trades of a group of statistical arbitrageurs or "smart traders." Studying the rational response is not limited to only attention-grabbing events. Rather, the methodology is applicable to studying any behavioral theory which claims to impact asset prices beyond transaction cost boundaries. Unlike existing work on arbitrage strategies, we do not need to simulate possible strategies, nor do we need to estimate the price impact function of trading. We base all calculations on actual, executed transactions and find the smart traders earn one day profits of 0.76% net of transaction costs.

The fifth and final contribution of this paper comes from decomposing the profits of the smart traders. We find that 58% of their profits can be attributed to providing liquidity and 42% can be attributed to taking advantage of attention-based trading. By studying the profits earned by rational speculators we are able to measure the substantial economic costs borne by individual investors. The cost of attention-based buying (an indirect cost) is of the same magnitude as the round-trip direct cost associated with brokerage commissions and exchange fees.

1.1 Background on limited attention

Over the past decade, economists have become increasingly interested in studying attention as a scarce resource. Research spans a number of diverse areas. For example, Lynch (1996) studies the relationship of periodic decision making with consumption and the equity premium puzzle. Mankiw and Reis (2002) study price adjustment when information is disseminated slowly through the economy while Sims (2003) details an economy-wide dynamics when information processing constraints are present. Hirshleifer and Teoh (2003) study firm disclosures in a world with limited attention. Finally, Gabaix, et. al. (2003) provide a theoretical paper with experimental evidence. The paper gives a nice overview of existing literature.

In financial markets, Graham and Kumar (2004) show that certain investors tend to purchase stocks after specific, attention-grabbing events (dividend initiations.) In a comprehensive study, Barber and

Odean (2003) link behavior to three types of attention grabbing events. The authors claim that abnormal trading volume, extreme returns, and news can all be thought of as attention-grabbing events. The authors then show that each of these three types of events are, in turn, linked to aggregate net buying by individual investors. Gervais et. al. (2001) argue that high volume stocks increase in visibility. Grinblatt and Keloharju (2001) find households in Finland buy more stock than they sell if returns are positive over the past two days.[1] Chan (2003) finds post-news drift in stock prices (though he doesn't actually look at trading imbalances.) While both the Graham and Kumar (2004) and Barber and Odean (2003) papers are similar to our work in spirit, we believe our current paper contains significant and new contributions (discussed above.) The contributions come from a more extensive series of tests centered around a single type of attention-grabbing event (see Section 1.2 below.) We show a link between attention-based buying and reduced search costs. Finally, we introduce a new methodology and exploit a market structure in order to estimate the economic costs associated with behavioral biases.

1.2 Research design

Rather than studying a number of different types of events, we choose to study a single type of event from a single stock market. We study this type of event in detail. We choose to study the Shanghai Stock Exchange because it uses 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. In addition, we receive unique data from the Market Surveillance Department that helps us identify a group of traders engaged in high-frequency stock trading strategies.

Like many markets in the world, the Shanghai Stock Exchange imposes daily price movement limits. Choosing to study trading in stocks that hit their upper price limits has a number of benefits. First of all, an "upper price limit day" incorporates the three characteristics previously associated with an attention-grabbing event: i) returns are high; ii) volume is high; and iii) the event generates news. After the Shanghai market closes for the day, stocks that hit their daily limits are featured and discussed in investment-related television programs such as "Finance One." 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 as a way to identify attention-grabbing events has some nice properties. Since news and investment programs appear after the close of market, we can separate event days and post-event days.

[1] Choe, Kho, and Stulz (1999) provide contrary evidence. The authors find little evidence of increased buying by individuals after a price rise.

Such separation is not possible in a market that trades continuously and/or without price limits. For example, separation is difficult when only using events such as high-volume days because we are forced to ask: when do individual investors first realize that trading volume is high? This difficulty is apparent in Barber and Odean (2003) who study attention-based buying after sorting by previous day stock returns. Interestingly, they also sort by current day, as opposed to previous day, stock volume. Third, the ability to separate event days and post-event days allows us to decompose trading strategy profits into a liquidity provision part and a part associated with attention-based buying.[2]

Our choice of market and event type also has some costs associated with the benefits already mentioned. Once a stock hits its upper price limit, trading can continue, but transaction prices may not exceed the limit. Thus, the time-series of transaction prices may (and probably does) consist of censored prices. Statistical tests must deal with such eventualities.[3] One way we deal with the censoring issue is to classify events. It turns out that the events in which censoring is likely to be the most severe, represent a very small fraction of our smart traders' profits (only 3.28% of all events and 6.28% of positions.) We further address censored prices by decomposing profits into two portions. The first portion is attributed to liquidity provision (i.e., buying from investors who want to sell after price increases and/or in the face of censored prices.) The second portion comes from selling to meet attention-based buying demand. Only the second portion factors into our estimates of the cost of the behavioral bias.

1.3 Generality of research design and results

Using non-United States data may worry some readers. However, individual trading behavior on the Shanghai Stock Exchange is very similar to individual trading behavior in the United States. Individual accounts typically hold between three and four stocks, have high turnover, exhibit the disposition effect, buy stocks headquartered close to where the investor lives, etc. Readers can also think of our paper as one of the first empirical tests of De Long et. at. (1990a), although the setting is slightly different. In De Long et. at. (1990a), price increases catch the attention of unsophisticated traders, who in turn place orders. Rational speculators profit by initially buying shares, which can cause a price increase, which then induces the unsophisticated traders to buy, and then pushes prices even higher. The rational

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2 Of course, some investors may actually engage in attention-based buying (after certain events) at an intra-day frequency. We argue our research design provides a clean day-by-bay separation of events. Identifying the exact time a stock catches an individual investor's attention would undoubtedly strengthen our results. Since such identification is near impossible with real market data, we use a daily frequency and remain confident of our results.

3 Section 1.3 discusses markets around the world with price limits. The imposition of limits is more common than many readers may believe.

speculators sell at these higher prices for a profit. In our paper, hitting the limit catches the attention of individual investors. The smart traders buy a stock after it hits its limit.[4] In fact, it is in the smart traders' best interests to have the price close near the limit, which increases the chances of the stock catching the attention of individual investors, which induces individual investors to buy the next day, and then pushes prices even higher. The major difference between our paper and De Long et. al. (1990a) is that there is no evidence of smart traders buying in an effort to initially "push" a stock price up to its limit. The smart traders in our study simply react to an attention-grabbing event (see the previous footnote.)

A skeptical reader may wonder how we are able to isolate events with unobservable (and hard-to-measure) quantities such as investor attention. To this end, we devote Section 6 to checking any plausible explanation that might explain our results. We show that the smart traders are not profiting from a simple momentum strategy, nor does it seem reasonable that profits compensate for risk. We remain confident with our interpretations.

Finally, some readers may worry that price limits are a unique feature of the market we study. Actually, regulators have adopted limits in a number of emerging equity markets such as China, Malaysia, the Philippines, Taiwan, and Thailand. More established stock markets such as Austria, Finland, Japan, Portugal, and South Korea also have price limits. Daily price limits are used extensively by futures markets around the world such as Hong Kong, Japan, Singapore, Turkey, and the United Kingdom. In the United States, Chicago Board of Trade (CBOT) and Chicago Mercantile Exchange (CME) both impose daily price limits on many commodities and financial contracts, including Treasury futures and stock index futures.

We believe the research made possible by studying trading on the Shanghai Stock Exchange far outweighs any drawbacks. A key contribution of the paper is the analysis of rational response to predictable behavior. The analysis requires complete transactions data for stocks that identify the buyer and seller account numbers for each and every trade. Such data is simply not available in the United States, though it is available from markets such as Finland, Taiwan, and the PRC. The rest of the paper proceeds as follows. Section 2 describes the data used in this paper. Section 3 tests for a link between attention-grabbing events and individual investor behavior. Section 4 shows the impact on asset prices. Section 5 presents the rational response to predictable behavior. It is in this section that we decompose trading profits and calculate the economic costs of behavioral biases. As mentioned above, Section 6 is entirely devoted to alternative explanations of our results. Section 7 concludes.

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[4] Over 95% of transacted orders are placed <u>after</u> a stock initially hits its limit.

2. Data

2.1 Event data

As mentioned in Section 1.3, this paper considers a very specific and well-defined type of attention-grabbing event called an "upper price limit event." We define an upper price limit event as a day in which a given stock 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. 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 January 2, 2001 and ends July 25, 2003, there are 2,442 upper price limit events. There is at least one upper price limit event on 416 of the 610 trading days in our sample period. These events involve 657 different stocks. Of the 2,442 upper price limit events, 1,842 involve "Normal" stock-days and 600 involve "ST" stock-days. Table 1, Panel A gives an overview of the events used in this study. Figure 1 plots the monthly time series of upper price limit events for both "Normal" stocks and "ST" stocks.

2.2 Transaction data (main dataset)

For each of the 2,442 upper price limit events, we collect all transactions for each stock on the day the stock hits its upper price limit. We also collect all transactions for these stocks on the trading day immediately following the upper price limit event. 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, and trading account number of seller. Account numbers allow us to separate buyers and sellers into three groups: individuals, corporations, and brokers. 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 actual orders placed by investors since a single buy order (e.g., 1,000 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. 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. We are also not able to reconstruct the bid-ask spread throughout the day.

2.3 Auxiliary dataset

Note that the size and completeness of our main dataset allow for a wide variety of tests. However, the Shanghai Stock Exchange has only provided compete transaction data for stocks on their upper price limit days and the day following an upper price limit event. We are thus limited in our ability to measure quantities such individual investor buy imbalances at medium-term horizons and long-term horizons. At horizons of longer than two days, we rely on daily stock price data and an auxiliary dataset.

We collect 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 the order is placed.[5] The auxiliary dataset contains 2,989,462 matched transactions. While the auxiliary dataset seems large, it is a noisy sample of the overall market. Investors from Ningbo trade approximately 17.39% of available stock-day combinations. Conditional on investors from Ningbo trading, the auxiliary database contains an average of 16.35 matched transactions per day per stock.[6]

2.4 Stock price data

We collect daily price data for all stocks traded on the Shanghai Stock Exchange. We consider all trading days starting January 2, 2001 and ending July 25, 2003. Data include date, stock ticker, opening price, closing price, maximum price, minimum price, trading volume in shares, trading value in RMB, 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, or 88.4%, of these stocks. We also collect corresponding information for the major market composite index.

2.5 Event types

As a first step in addressing issues involved with price limit events, we devise a classification scheme. The goal of the scheme is to separate events into those with market-wide implications, those that are

5 Appendix A provides additional details about market structure in the PRC and determining location of trade.
6 Comparing this number with a similar measure from the main dataset does not make sense. The main dataset only contains transactions for stocks during upper price limit days and the following day.

likely to involve censored stock prices, and those in which a volatile stock may have bumped up against a price limit. The classification will also help us focus on events most likely associated with attention-based trading. We define five types of events as follows:[7]

Type I	**Market-wide events:** At least 200 stocks hit their upper price limits during a single day. We consider these events as reflecting market-wide good news. There are two market-wide events during our sample period. These events do not reduce search cost for individual investors so we do not expect any attention-based trading.
Type II	**Focused informational events:** At most 50 stocks hit their upper price limits during a single day. Price jumps to the limit must be ≥ 4%. Price must close within RMB 0.05 of limit. We consider these events as ones where price is most likely to be censored. We expect volume to be low since any current shareholder who wants to sell can profit (almost surely) by waiting one extra day. We should see further price increases on the following day. We expect attention-based trading for this type of events.
Type III	**Quasi-informational events:** At most 50 stocks hit their upper price limits during a single day. Price slowly reaches limit during the day. Price must close within RMB 0.05 of limit. We think of these events as possibly having censored prices. We expect attention-based trading for this type of events.
Type IV	**Noisy events:** At most 50 stocks hit their upper price limits during a single day. Prices hit limit at some point during the day, but close significantly below their limits (1% or more.) These are volatile stocks where prices are not censored by the end of the day. We expect limited attention-based trading for this type of events.
Type V	**Other events:** Everything that does not fall into an above category. We have no priors on these types of events.

We present some overview statistics for the five different event types in Table 1, Panel B. The minimum tick size is RMB 0.01 and Table 1, Panel B shows returns >10.0% (and >5.0% for "ST" stocks) are possible due to rounding. Most price limit events are associated with high trading volume and we calculate relative turnover. Turnover for stock "k" on date "t" is simply total shares traded divided by shares outstanding. Relative turnover is the ratio of turnover to the sample average turnover for stock "k" minus one. A value of zero indicates turnover on that day is at normal levels. For quasi-informational events (Type III) involving "Normal" stocks, we see the relative turnover is 554% above normal. As we hypothesize, volume during focused informational events (Type II) shows some of the lowest turnover values. However, these events are still associated with higher than normal turnover which presents a bit of a puzzle. We return to this puzzle later in the paper (in Section 6.3).

[7] We choose these classifications to aid in our understanding of attention-based trading. Readers who are uncomfortable with the classification scheme can focus on results for all events grouped together—our conclusions remain unchanged. The cutoff values of 200 and 50 are chosen to differentiate between many stocks and a manageable number of stocks. We choose one set of values and do not search for cutoff values that give the strongest set of results.

3. Attention-Based Buying

3.1 Confirmation of existing results

We test if attention-grabbing events (on date t) are linked with net individual trade imbalances (on date $t+1$). To do this, we simply compute an imbalance measure on day for each event (an event is indexed by stock "k" hitting its upper price limit on date "t"). We focus on shares bought and sold by individual investors, but using value traded gives quantitatively very similar results:

$$imbalance_{k,t+1}^{indiv} = \frac{buy_{k,t+1}^{indiv} - sell_{k,t+1}^{indiv}}{buy_{k,t+1}^{indiv} + sell_{k,t+1}^{indiv}} \tag{1}$$

The measure in Equation (1) is the same one used in Barber and Odean (2003) and therefore our results provide an out-of-sample confirmation of their results. Our results, presented in Table 2, provide strong evidence that attention grabbing events are linked to net buying by individual investors. Consistent with the attention story, for events where a limited number of stocks hit their upper price limits in a given day (Types II, III, and IV), the net imbalance number is significantly positive. The table shows only 2,402 events instead of 2,442 due to suspended trading for forty (1.64%) of the stock-days following the associated events.

3.2 Reduction of search costs (narrowing of the consideration set)

The link between attention and investor behavior is predicated on substantial search costs faced by individual investors. We refine this notion by proposing and testing the following hypothesis:

> H_A Simply sorting by large price movements, high volume, or news stories is not sufficient to identify an attention-grabbing event. If many events happen simultaneously, search costs are not reduced, and the consideration set is not narrowed.

We test H_A by measuring individual imbalances on days following market-wide upper price limit events. More than 200 stocks hit their upper price limit twice during our sample period (there were 439 events on 23-Oct-2001 and 398 events on 24-Jun-2002.) These market-wide events feature prominently in Figure 1. As Table 2 clearly shows, individual imbalances are not positive during these events (Type I). In fact, our imbalance measure is not significantly different from zero. Our results provide a new link between attention grabbing events, reduced search costs, and investors behavior.

3.3 First time buys of individual investors

Simply measuring net buy imbalances may not confirm a strong link between attention-grabbing events and investor behavior. It is possible that large price movements are correlated with liquidity demands or other shocks. Large price movements might also be related to other unobservable factors. We therefore propose a stronger and more precise test of investor attention with the following hypothesis:

> H_B If upper price limit events truly catch the attention of individual investors, then we should see more first-time buyers of a particular stock the day following an attention-grabbing event than we see on other days.

In other words, H_B tests whether price limit events cause 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-day combinations. The auxiliary dataset contains a total of 563,488 account-stock-day combinations. For each combination, we note whether this is the first time the account has bought a particular stock (or the second time, third time, etc.). We then compare the distribution of first-time buys for account-stock-day combinations following price limit events to the distribution of first-time buys for all stock-day combinations. Our results are quite stunning. Table 3, Panel A shows that 47.94% of all buys are first-time buys for a typical account-stock-purchase. Following a price limit event, this number jumps to 65.76%, indicating a large surge in new buyers (see Table 3, Panel B.) For focused events (Type II and III) the percentage of first-time buys is 81.89% and 71.81% respectively. The differences in the distributions are statistically significant at all conventional levels. We find our test of first-time buying to be extremely strong evidence of attention-based trading. Active individual investors who had not previously owned a particular stock buy in large numbers following an attention-grabbing event.

3.4 First-time buys (revisited)

We do not have each account's trading history before 2001 and are forced to assume that the first buy we view is actually the first buy. This assumption may inflate our measure of first-time buys. One way to check our results is to only consider first time buys during 2003 only. We do this by effectively using 2001 and 2002 to more accurately estimate what is actually a first-time purchase. When considering 2003 dates only, a typical stock-day has 41.43% first-time buys. This estimate of normal first-time buying is lower than the 47.94% shown in Table 3, Panel A and makes perfect sense. We have used about 80% of our data to condition on what stocks investors have owned in the past. Days following price limit events have 63.50% first time buys (or 22.07% above the 2003 baseline.) For focused events of Type II and

Type III, the percent of first time buys is 72.80% (31.37% above 2003 baseline) and 67.35% (25.95% above) respectively.

3.5 First-time buyers

An astute reader might believe that results in Table 3, Panel B contradict earlier findings regarding reduced search costs (H_A). After all, we see that there are many first-time buys (61.56%) after market-wide events (Type I) and this number is well above the baseline (13.62% above, though this difference is smaller than the difference for Type II and Type III events.) Closer inspection reveals an interesting new finding. It turns out the 61.56% is driven by a very high number of first time *buyers*. In other words, investors who have never bought *any* stock before choose to enter the market immediately following a market-wide event.[8] Studying an individual's decision to first begin investing is a new research area and beyond the scope of this paper. We are pursuing it in a separate study. We end this section by simply saying that attention grabbing events at the individual stock level are linked to reduced search costs for active individual investors. Market-wide events appear to catch the attention of investors who have not previously invested in any stock. Such a result is consistent with reduced search costs when considering broad investment alternatives such as bank accounts, bonds, private loans, real estate, gold, direct investment in small businesses, etc.

4. Asset Pricing Implications

Studying a market with price limits demands careful thought when analyzing asset price movements. Consider a stock with a 10% price limit. What happens if the company receives news that increases its value by 12%? We first consider the traditional asset pricing answer to this question.

4.1 Traditional asset pricing without attention-based buying

If all information is public and there are no limits to arbitrage, we expect the price to shoot up 10% today on low volume. We then expect the price to open tomorrow up 2%. After tomorrow's open, prices should level off. The story is simple and straightforward.

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8 Results are available from authors upon request.

4.2 Asset pricing with attention-based buying and limited risk bearing capacity

In a market with limited risk bearing capabilities, demand shocks are associated with temporary price pressure.[9] Attention-grabbing events induce net buying demand from individual investors. These demand shocks can cause temporary price pressure (a upward spike followed by mean reversion in prices.) Therefore a company that receives good news may see its price shoot up 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 above 2% and later mean-revert back to the 12% level. Figure 2 plots two possible price paths. The first path is relates to the traditional asset pricing view of the world when there is no attention-based buying. The second shows prices in a world with attention-based buying and limited risk-bearing capabilities. Please disregard the comments at the bottom of Figure 2 relating to profits. We will return to the issue of profitable trading in Section 5. The 1.29% of temporary price pressure shown in Figure 2 is not chosen randomly. We base the figure on actual stock price reactions—which we now turn to studying.

4.3 Actual stock price reactions and mean reversion

Figure 3 plots the average stock price reactions (cumulative returns in excess of market returns) for "Normal" stocks over the ten days immediately following an upper price limit event. In Panel A, we see basically no price reaction in excess of the market for market-wide events (Type I events.) Such a finding is not surprising since these events happen, by definition, on days when the entire market goes up. We can think of these days as times when either: i) economy-wide news is released; and/or ii) the aggregate discount rate falls. In other words, all prices go up together.

Figure 3, Panel B shows the price reaction to focused informational events (Type II events.) These are the events that we expect to involve censored prices on the upper price limit day. On the following day (date *t+1*), prices go up an additional 6% more than the market (16% higher than at the beginning of date *t*.) From Table 2, we know there is a strong individual buy imbalance on date *t+1*. Over dates *t+2* to *t+9* we see a continued increase in average price reaction and then mean reversion. By date *t+10* prices level-off at 6%. This panel highlights how additional imbalance data on dates *t+2* to *t+4* might be very useful. It is also clear that these events are very noisy. The mean reversion from dates *t+1* to *t+10* is not statistically significant.

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9 For examples, see: Campbell, Grossman, and Wang (1993), DeLong et. al. (1990b), Shleifer (1986), and Greenwood (2004).

Figure 3, Panel C shows the price reaction to quasi-informational events. We see that price reaction on date *t+1* (the day following the upper price limit event) is not permanent. Instead, prices mean revert by date *t+10*. From Table 2, we again know there are strong individual buy imbalances on date *t+1*.[10] The price reactions, especially the one shown in Figure 3, Panel C suggests profitable trading opportunities exist. We turn to examining exactly these opportunities in Section 5.[11]

5. The Rational Response to Predictable Behavior

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 firm. Figure 2 shows a profitable strategy based on: a) accumulating shares on date *t* after a stock has hit its upper price limit; b) selling shares on date *t+1*. Such a strategy has two sources of profit. The first source is from liquidity provision—buying shares on date *t* from those who no longer want to hold them. The second source is from taking advantage of attention-based buying.[12] We propose testing and evaluating the economic impact of attention-based buying by documenting the actions of smart traders who try to take advantage of this behavior. To our knowledge, ours is the first paper to test a specific behavioral theory by measuring the rational response to such behavior. Formally, we propose:

> H_C If some agents exhibit behavioral biases that cause them to act in a particular manner; and if their actions have asset pricing implications; then other agents try to profit.

5.1 Detecting smart traders

We test H_C using two screening methods. Our first screening method involves analyzing the trading behavior on price limit days. For each upper price limit event, we extract all the trades (buys) from any account that comprises more than 1% of total volume for that particular stock-day. We then rank these

[10] Barber and Odean (2003) document a pattern of underperformance following attention-grabbing events in the United States. Our results highlight the shape of transitory price impact. Our results also give insight into how long temporary price shocks survive.

[11] A Spearman correlation test shows the level of mean reversion and individual buy imbalances are positively correlated with p-values << 1%. Both the measure of mean reversion (over only ten days) and the imbalance measure are noisy. We hold-off linking these two quantities until Section 5.5.2 (where we link imbalances with a profitable trading strategy based, in-part, on mean-reversion.)

[12] Profits derived from providing liquidity can be further separated into providing liquidity to different types of investors (i.e., those with behavioral biases, those with specific needs, etc.). We discuss one such type liquidity demander in Section 6.3. We do not attempt to separate these different types since this paper focuses on measuring the profits and costs associated with attention-based buying.

accounts by the total value traded volume (in RMB) during all upper price limit events. The two most active accounts each trade about 50% more than the third ranked account. The third and fourth ranked accounts, in turn, each trade about 65% more than the fifth ranked account. This natural breakpoint leads us to consider the top four accounts as prime candidates (we could have chosen just the top two accounts using similar logic.) The top four accounts are individual accounts (meaning they are not associated with a corporation nor are they associated with a broker.)[13]

Our second screening method consists of contacting the Market Surveillance Department of the Shanghai Stock Exchange which monitors all trading activity. The monitoring includes looking for short-term buying and selling as well as abnormally large volumes around price limit events. In fact, the exchange tracks the largest three buyers and sellers every day. The branch locations (not account numbers) of the buyers and sellers are made public at the end of the trading day. The impetus behind contacting the Market Surveillance Department was piqued by an article in a local (Shanghai) business publication that discusses trading around price limit events.[14] It turns out that the Market Surveillance Department had been tracking a group of ten accounts, all from a single city in the PRC. The city is Ningbo and all trading originates from four brokerage connections in that city. The Market Surveillance department believes the ten accounts may act in concert. Some of ten accounts are very active during some events. Other accounts are active during other events. It also turns out that the top five individual accounts identified by the first screening method (ranked volume) are a subset of the ten accounts provided by the Market Surveillance Department. Since the two methodologies produce similar results, we use the list of ten accounts from the Market Surveillance Department for the rest of the paper.[15]

Readers should not think that the smart trader accounts are picked randomly. Quite the opposite is true. We specifically find accounts with consistently high volume on price limit days. We hypothesize that such accounts <u>may</u> be trying to profit from attention-based buying. It is important to emphasize that we

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[13] One difference between studying an emerging market like China and studying an developed market like the United States or Finland is the level of development of the financial sector. Hedge funds in the United States typically execute the most sophisticated trading strategies. In China, sophisticated individuals open accounts, work from VIP rooms within a brokerage office, and carry out their strategies. Finland lies somewhere in between as foreigners appear to be the most sophisticated investors.

[14] The newspaper article is from a Chinese periodical called *21st Century Economic Report* dated 15-May-2003. It highlights the trading activity of smart traders and calls them a "limit order swat team." The article can be found at the following web address: http://stock.163.com/editor/030315/030315_131381.html

[15] Using only the top four accounts from the first screening method gives very similar results since these four accounts make up 82% of all trades from ten accounts from the second screening method. The differences are again reduced since we treat all accounts being controlled by one group of traders and group data into one large account. The treatment is conservative since it reduces the number of observations by a factor of ten. The newspaper article supports this treatment.

do not choose accounts based on profits. The Market Surveillance department also chooses accounts based on volume, not profits. We now turn to testing whether these smart traders do, in fact, profit.

5.2 Smart trader profits

We treat all ten accounts as one trading entity by forming a portfolio of their trades. We refer to this group as the smart traders. The group accumulates shares on date t and sells on date *t+1* during 357 of the upper price limit events.[16] For the most part, the group eschews market wide events (Type I.) While the group would like to buy during the focused informational events (Type II), volume after the price hits the limit is likely to be low and accumulating many shares is likely to be difficult. When active, the smart traders constitute a sizeable fraction of a stock's turnover. They account for 12.91% of turnover when buying on an upper price limit day and 8.60% when selling the following day.

We calculate the one day, gross profit during upper price limit events when they are active. We do this by using the volume-weighted average price *(VWAP)* of the shares bought and of shares sold:

$$\text{Gross Return}_{k,t+1}^{\textit{smart traders}} = \frac{VWAP_{k,t+1}^{sell}}{VWAP_{k,t}^{buy}} - 1 \qquad (2)$$

Table 4, shows the average gross one day return is 1.21% before transaction costs. Most financial studies of risky trading strategies are forced to simulate returns—see Mitchell and Pulvino (2001) or Baker and Savasoglu (2002). We are not subject to the same constraints. The profits we report are from an actual trading strategy that has already been implemented. The price impact of any trade is already accounted for. Accounting for all transaction costs (both direct and indirect) is one of the main strengths of our methodology.

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. Table 4 shows the net return is 0.76% over one day. An average position size of RMB 3.70 mm

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[16] For 264 of the 357 events, the number of shares sold on date *t+1* exactly matches the number bought on date *t*.

[17] Very large traders, such as in our sample, typically negotiate an 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 very 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%.

translates to USD 450,000. The distribution of net profits is shown in Figure 4. Clearly, this is a risky strategy and returns are by no means guaranteed. That said, a net one day return of 0.76% represents a very high annualized return.

5.3 Profit decomposition and the cost of a behavioral bias

A portion of smart trader profits comes from providing liquidity to the market on event days when investors want to sell. A second portion of their profits come from selling to individuals who exhibit attention-based buying.

We are particularly interested in this second portion of profits since we can use it to estimate the cost to individual investors of attention-based buying. The smart traders' gross profits equal the individual investors' gross losses. Again, these gross profits correctly account for all indirect transaction costs such as price impacts since we are using actual transaction data. The total cost of trading for an individual is equal to direct transaction costs (brokerage fees and taxes) plus the cost of attention-based buying.

We initially use Figure 2 to motivate our profit decomposition. For each of the 357 events, we assign λ% to liquidity provision and (1-λ)% to attention-based buying. We then average these measures across the 357 events to get our final estimates. To be conservative, we set λ=100% whenever price changes are permanent or rise for the ten days following an event. We also set λ=100% for all noisy events (Type IV) when prices close below their limit (on date *t*.) Only in cases when there is mean-reversion from date *t+1* to date *t+10* do we assign part of the profits attention-based buying.[18]

Our findings are quite stunning: 58% of smart trader profits can be attributed to liquidity provision and 42% to attention-based trading.[19] The profit decomposition allows us to place an economic cost on behavioral biases (in this case, attention-based trading). Individual investors "pay" approximately 51bp which is calculated by multiplying the smart trader's gross profits of 1.21% by 42%. This value is greater than the one-way transaction cost and approaches the round-trip cost of trading for individual investors

[18] Earlier versions of this paper included a stock price graph for the 357 events when smart traders are active. By and large, the graph resembles that of Type III events shown in Figure 3, Panel C. Smart traders seem even better at identifying attention-grabbing events than simply examining Type III events. In the 357 events, price completely mean-revert after nine days. Graph available upon request from the authors.

[19] It should be clear that during focused informational events (Type II) the vast majority of, if not all, profits come from liquidity provision. During quasi-informational events (Type III) the majority of profits come from attention-based trading. In other words, mean reversion between date *t+1* and *t+10* is strongest during Type III events.

(shown at the end of Footnote 17.) In other words, this behavioral bias almost doubles individual investors' already high trading costs.

5.4 Alternative method for calculating profit decomposition

We also use transaction-level data to provide an alternative decomposition of the smart trader profits. When smart traders are buying, we note if they initiate trades or whether trades are initiated against the smart traders' standing limit orders. This identification is made possible since we have both the time a transaction is placed and when it is ultimately executed. Not surprisingly, on days when smart traders are buying, they are providing liquidity to investors who want to sell out. Liquidity provision on upper price limit days (date *t*) accounts for 88.45% of the smart traders' transactions. In other words, the smart traders initiate only 11.55% of their buy trades.

This situation reverses itself on the day following an event (date *t+1*.) When the smart traders are selling, they initiated 56.37% of their sell trades. They provide liquidity 43.63% of the time on these days. Averaging across the days the smart traders are buying and the days they are selling, we calculate that smart traders provide liquidity 66.04% of the time and take advantage of attention-based buying 33.96% of the time. These numbers are close to the 58% and 42% presented in Section 5.3.

5.5 Confirmation of smart trader strategies

A reasonable reader will ask if the smart trader profits can actually be attributed to attention-based buying. We firmly believe so and can find no evidence to the contrary. All tests indicate that the smart traders follow exactly the strategy outlined at the beginning of this section. Over 95% of their executed orders are placed *after* a stock initially hits its upper price limit. On the event day, smart traders have positive net buy imbalances while individual investors have negative imbalances. On the following day, smart traders have negative imbalances while individual investors have positive imbalances. These imbalance numbers are not an artifact of an adding-up constraint because two other classes of traders are also present in the market (corporations and brokers.) We carry out four specific tests that support our interpretation of smart trader profits.[20]

[20] Earlier versions of this paper provided the net imbalances for the smart traders, individuals, corporations, and brokers. These results and a graph of execution time relative to the time a stock first hits its upper price limit are available upon request.

5.5.1 Probit analysis of smart trader participation

As mentioned in Section 5.1, the smart traders are identified through their trading activities (volume), and they participate in 357 out of 2,442 upper price limit events. We first conduct a probit analysis of smart trader participation using all 2,442 upper price limit events. Table 5, Regression 1 shows that Type II and Type III events are the most likely for smart traders to participate in. They seem to avoid market-wide events (Type I). This result is consistent with the story that they trade to take advantage of attention-based behavior by individual investors. Further refinement of the estimation shows that high turnover and individual investor buy-sell imbalance on the following day are important determinants of smart trader participation. Regression 4 shows that individual investor imbalance is the most significant of all factors in predicting smart trader participation. It is rather stunning to see that the smart traders actually identify events that catch individual investors' attention. Smart trader participation on date t predicts individual buy imbalances on date $t+1$. Again, these results are not the artifact of an adding-up constraint since there are two other investor types in our data (corporations and brokers.)

5.5.2 Regression analysis of smart trader profits

We investigate the source of smart trader profits in a regression framework. We run this regression using the levels of profits in RMB and the gross level of individual investors imbalances also in RMB. Table 6, Regression 1 shows that net smart trader profits (in RMB million) are related to individual buy gross imbalances on date $t+1$. For a one standard deviation increase in individual gross buy-sell imbalance (RMB 59 million), smart trader profit is expected to increase by RMB 720,000. In Regression 2, further refinement shows individual imbalance on date $t+1$ continues to be an important determinant of smart trader profits for quasi informational events (Type III). This result is encouraging since about 80% of the smart traders' investments involve Type III events. During these Type III events, it is relatively easy for the smart traders to establish a large position on the price limit day compared with Type II events. The standard deviation of individual imbalance for Type II and Type III events are RMB 10 million and RMB 67 million, respectively. Therefore the positive relation between individual buy-sell imbalance and smart trader profit is not only statistically significant, it is also economically important. Regression 3 shows the imbalance is still significant even after controlling for returns on the event date t and the following date $t+1$. More interestingly, Regression 4 shows that profits are lower when turnover is lower on the event date. In other words, the smart traders have a more difficult time building up their positions. The following day (date $t+1$) the higher turnover leads to greater profits—a sign the smart traders can sell off their position.

5.5.3 Analysis of non-event trading days

Our paper shows that smart traders take advantage of attention-based behavior by individual investors following a well defined attention-grabbing event. It is likely the smart traders also operate during other attention-grabbing events. One of the strengths of our study is that upper price limit events are easy for the econometrician to identify, date, and use in a study. Other events, such as company specific news, are more difficult to deal with. We do not know of a searchable and suitable business news database in Chinese that is linked to traded stocks. Therefore, we simply look for a similar pattern of trading by the smart traders.

We are not surprised to find that the smart traders are active on days other than around upper price limits. We use the auxiliary dataset to analyze all smart trader activity and provide an overview of their trading activity in Table 7. Recall that the auxiliary data contain all transactions by the smart traders (and other investors from the city of Ningbo.) We find the smart traders consistently engage in overnight trading. They accumulate shares one day and sell out quickly the next day. They are active during 1,626 stock days of which 357 are associated with upper price limits. Interestingly, about 40% of all their investments are targeted to upper price limit events.

Readers should not think that smart trader activity on other days is evidence against our story. Instead, readers should think how hard it may be to identify certain types of attention-grabbing events. We believe that examining the smart trader activity on the 1,269 non-price limit days enforces our assertion about attention-based trading. These other trading days are characterized by similarly high turnover, positive individual buy-sell imbalance, and extreme returns. The smart trader's overnight returns are also similar. Smart trader activity on non-price limit event days is consistent with attention-based trading.

Some of our most convincing results come from looking at the individual investor imbalances on date *t+1* and shown in Table 7. Smart traders take positions on date *t* which are able to predict the large individual imbalances the following day. This finding is true for both columns in Table 7. Again, the finding is not an artifact of an adding up constraint as two other types of investors (corporations and brokers) are also active in the market.

5.5.4 Sharpe ratios

As Figure 4 shows, the smart traders' strategy is risky. To take advantage of attention-based buying associated with price limit events, smart traders could buy on the limit day and sell in any of the following days. They prefer to sell immediately next day (date *t+1*.) We compute empirical Sharpe ratios for hypothetical strategies of buying on the limit day and selling on any of the next ten days. We find the Sharpe ratio to be the highest when selling the very next day for all five event types. The Sharpe ratio declines monotonically as the selling day moves from date *t+1* to date *t+10*. In this very limited sense we view the smart traders' strategy as "optimal."[21]

The four analyses in Section 5.5 give additional insights into the source of smart trader profits and confirm our interpretation. The next part of this paper, Section 6, is devoted to checking alternative explanations of the smart trader's profits.

6. Alternative Explanations

Section 5 shows a direct link between smart trader profits (the cost to individual investors) and attention-based buying. In this section we test alternative theories that might explain the profits and trading patterns we observe. We start with the most obvious explanation—momentum trading in the style of De Long et. al. (1990a).

6.1 Momentum

It is possible that the smart traders take advantage of price momentum on the Shanghai Stock Exchange. We test for evidence of momentum by estimating various forms of the regression shown in equation (3) below. Results are reported in Appendix B. We use all 743 stocks in our sample, and note that standard errors allow for contemporaneous clustering on a daily frequency. The variable "$I_{k,t}^{lower}$" is an indicator function that equals one if stock "k" reaches its lower price limit on date t and zero otherwise, and "$I_{k,t}^{upper}$" is an indicator function that equals one if stock "k" reaches its upper price limit on date t and zero otherwise. Also, $D_{k,t}$ is a dummy variable that equals one if the smart traders are actively trading stock "k" on date t and zero otherwise.

$$r_{k,t+1} = \alpha + \phi r_{k,t} + \gamma_l I_{k,t}^{lower} + \gamma_u I_{k,t}^{upper} + \lambda D_{k,t} + \varepsilon_{k,t+1} \quad (3)$$

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[21] To conserve space we do not include the table of Sharpe Ratios. The results are available upon request from the authors.

In total, Appendix B reports the results of six different regressions. Three of the regressions (A1, A2, and A3) use close-to-close returns on the left-hand side. Three of the regressions (B1, B2, and B3) use over night, or close-to-open, returns on the left-hand side.

Momentum only: In Regression A1 we test for daily momentum only. We see the coefficient on past returns (ϕ) is not significantly positive, indicating that daily momentum is not present. We also estimate the regression model shown in equation (3) after sorting stocks by: i) average total market capitalization; ii) average total market capitalization of the tradable shares only; iii) average trading volume; and iv) average turnover ratio. All the averages are taken over the entire sample period. In each of the four cases we sort stocks into high, medium, and low groups. By and large, results are similar to those presented in Regression A1 and are not reported. As a final check, we estimate equation (3) using overnight returns on the left-hand side—see regression B1. We calculate the overnight return from the close on date "t" to the opening price on date "t+1". This new specification indicates the presence of a little overnight momentum. While there is some statistical significance for the ϕ-coefficient, the economic significance is almost nil. If returns are 10% on a given day, the overnight expected return is only nine basis points. This small change cannot explain the profitability shown in Table 4.

Momentum and daily price limits: A change in the value of a firm may be larger than the daily price limit. Due to the price limit, a steady-state trading price cannot be reached in a single trading day. Hence price discovery is delayed. Kim and Rhee (1997) study delayed price discovery in Japan. Fama (1989) points out that investors may speed up their trades when a stock is close to its limit. Li et al. (2001) do not find such an effect in the Shanghai market. Based on the delayed price discovery hypothesis, there should be price momentum after a price limit has been reached. In Appendix B, Regression A2 we see little evidence of daily momentum for the stocks in our sample. The estimate of ϕ is 0.0013 and statistically insignificant. Our result is consistent with earlier work on momentum in the Chinese stock market by Wu (2002). We see the estimate for γ_{upper} is 0.0113 for the pooled regression for all stocks, though the statistical significance is marginal. The coefficient value indicates the second-day return after an upper price limit event is 1.13% on average for all stocks. In the overnight specification, the estimate of γ_{upper} is 0.0126 but not statistically significant. In Appendix 2, regressions A3 and B3, we control for smart trader activity. The coefficient λ is slightly positive and statistically insignificant in both the close-to-close (A3) and overnight (B3) regressions. We conclude that the smart traders are not simply trading on daily price momentum.

6.2 Risk taking

It is possible that stocks that hit their upper price limits are simply more volatile than other stocks. For undiversified arbitrageurs (smart traders), this volatility might be a source of risk. We test for volatility while addressing the fact that volatility and returns are correlated by sorting stock into different groups based on a measure we call "high return" for stock *k* on date *t*:

$$high\ return_{k,t} = \frac{\text{daily high}_{\text{k,,t}}}{\text{close}_{\text{k,t-1}}} - 1 \tag{4}$$

Appendix C reports the intra day volatility of various stocks on the five days following the price limit day using the Parkinson (1980) measure:

$$\sigma_{k,t} = \ln\left(\frac{high_{k,t}}{low_{k,t}}\right) / 4\ln(2) \tag{5}$$

We see that on the day immediately following an upper price limit event, stocks the smart traders buy are approximately 1.09 times as volatile as other upper price limit stocks, and 1.30 times as volatile as stocks in the high return group (called "C10".) Note that 1.09=0.0215/0.0198 and 1.30=0.0215/0.0165. The differences are much smaller when looking at "ST" stocks. We conclude that risk may explain some of the smart trader profits and we don't want to rule out a risk explanation. However, it seems implausible that it can explain an overnight return of 0.76% after transaction costs.

6.3 Blind selling puzzle

Figure 3, Panel B in conjunction with Table 1, Panel B presents a bit of a puzzle. During the focused informational events (Type II), prices on the event day are almost surely censored. In fact, we see prices rise 6% the following day and end at this same +6% level after ten days. Yet turnover numbers of 254% and 39% above normal indicate many investors are selling. Since 82% of these types of events go up the next day (and the average one day return is 6%) is makes little sense that anyone would sell. We refer to this phenomenon as the "blind selling puzzle" and hold-off studying the phenomenon in depth. We are, however, careful to make sure that this phenomenon does not affect our conclusions qualitatively. First, only 3.28% of all events are of this type. Second, blind selling does not affect our estimate of the cost of attention-based buying because we attribute most, if not all, of smart trader profits to liquidity provision during Type II events.

6.4 Alternative methods for calculating profits

In the above analysis smart trader profit is computed using volume-weighted average price. As a robustness check we use two alternative methods for calculating profit. Smart traders are active during 357 upper price limit events. For 264 events, the smart traders sell the exact same number of shares on date *t+1* as they buy on date *t*. For these events all our profit measures are the same (since we have all trades on date *t* and date *t+1*). For the other 93 events we estimate profits based on the mis-matched number of shares using two methods. Method 1 effectively ignores the mis-matched shares; Method 2 estimates the transaction prices of the mis-matched shares:

Method 1

$$\text{Gross Profit \#1} = V_S - V_B \frac{N_S}{N_B} \qquad \text{if} \quad N_B > N_S \tag{6}$$

$$\text{Gross Profit \#1} = V_S \frac{N_B}{N_S} - V_B \qquad \text{if} \quad N_B < N_S \tag{7}$$

Method 2

$$\text{Gross Profit \#2} = V_S + (N_B - N_S) \cdot p_{\text{open}} - V_B \qquad \text{if} \quad N_B > N_S \tag{8}$$

$$\text{Gross Profit \#2} = V_S + (N_B - N_S) \cdot p_{\text{limit}} - V_B \qquad \text{if} \quad N_B < N_S \tag{9}$$

Here, N_B (N_S) is the cumulative number of shares bought (sold) on date *t* (*t+1*) and V_B (V_S) is the cumulative value of shares bought (sold) on date *t* (*t+1*). P_{open} and P_{limit} are the open and limit price on date *t* and date *t+1*. Average gross profits are 1.25% using Method 1 and 1.29% using Method 2. The 1.21% based on VWAP reported in Table 4 is therefore the most conservative estimate (though all measures are very close.)

6.5 Private information

Some readers may worry that the smart traders profit by trading on private information. We find no support for this hypothesis. First of all, they place 95% of their orders after a stock first hits its upper price limit. Second, of the 357 upper price limit events where they are active, they trade 191 different stocks. Finally, we have discussed their trading activities with market surveillance professionals at the Shenzhen Stock Exchange and find that the same group of smart traders from Ningbo employs similar trading strategies in trading stocks listed on the other exchange in the PRC. Since the smart traders carry out overnight trading with a large number of stocks, from different industries, and listed on different markets, it is highly unlikely that their trades are based on private information. We conclude that the smart traders are able to generate significant profit without specific information about company fundamentals.

7. Conclusion

This paper studies the set of links between attention-grabbing events, predictable behavior by individual investors, transitory price movements, and the rational response to the presence of a behavioral bias. We show that attention-grabbing events lead active individual investors who have not previously owned a stock to consider and ultimately purchase the stock. We argue and present evidence that attention-grabbing events do not necessarily 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 also links the predictable behavior to transitory price movements. Stock prices temporarily rise 1.29% following attention-grabbing events before mean-reverting to pre-event levels over the next ten days. More importantly, we hypothesize that behavioral biases do not exist in a vacuum—especially when the 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 0.76% net of transaction costs. We find a direct positive relationship between smart trader profits and the buy-sell imbalances of individual investors. We decompose smart trader profits into a liquidity provision component (58%) and component based on taking advantage of attention-based buying (42%). Our methodology provides a new measure of the substantial economic costs associated with behavioral biases.

Finally, our paper points to a number of future research projects. Foremost, we are interested in testing the rational response to other well-documented biases that affect individual investors. A study of profits and disposition effect follows naturally from this paper. That is, do liquidity providers earn higher returns when buying stocks that have recently risen than they earn at other times? Individuals are, of course, eager to sell such stocks. The disposition effect might help explain the "blind selling puzzle" mentioned in Section 6.3. Our paper also points to a fundamental difference in the behavior of active individual investors and those entering the market for the first time. This second group of investors seems to be particularly influenced by market-wide events.

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Figure 1
Upper Price Limit Events

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.

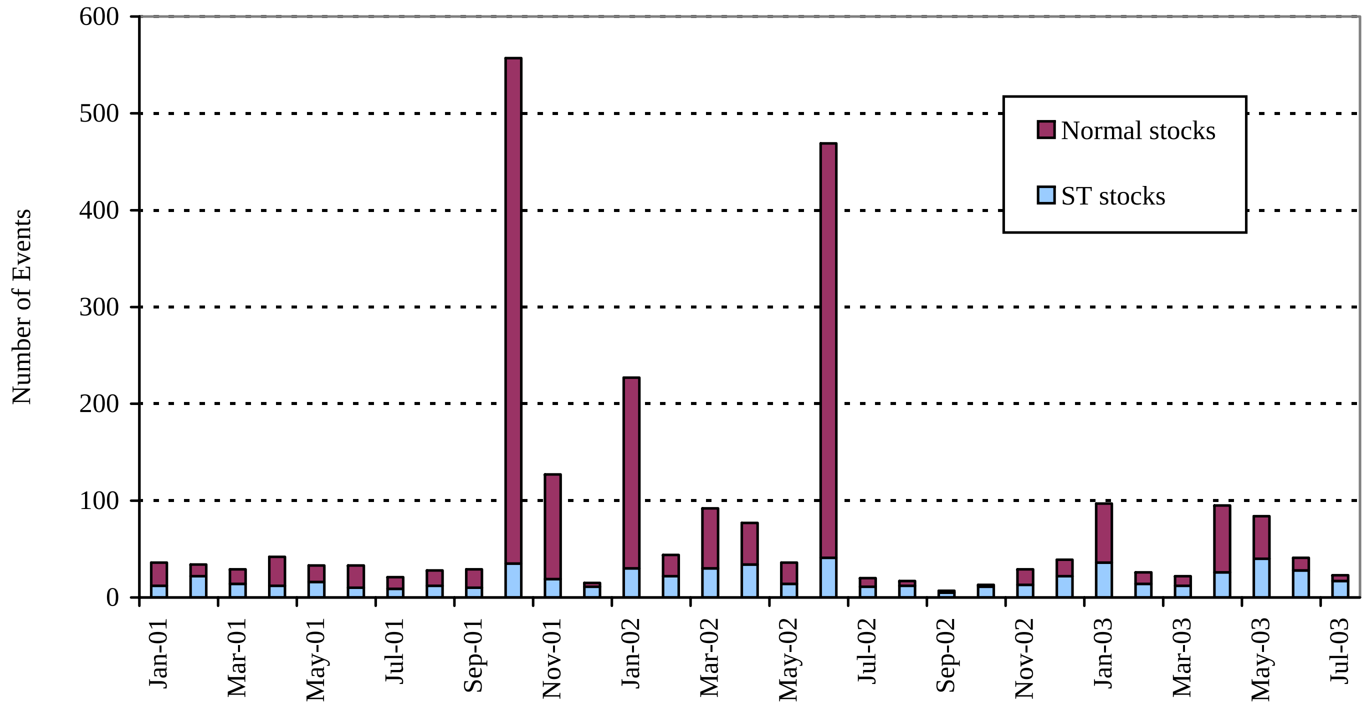


Figure 2
Two Price Reactions

The graph shows two price reactions. We only consider "Normal" stocks, i.e., those with a ±10% daily price limits. This graph shows a hypothetical news release that indicates a company's value is increasing by 12%. Traditional asset pricing theory predicts the price should jump by 10% on the event date *t*. Without attention-based trading, the price should rise another (open up) 2% the following date *t+1* and stay at that level. In a market with limited risk bearing capabilities and attention-based buying, the price actually rises more than 2% on day *t+1* (the graph shows a 3.29% rise). The price will then reverts back to a 12% total return over the next ten trading days. We consider a trading strategy that accumulates shares on the limit day and sells the position on date *t+1*. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

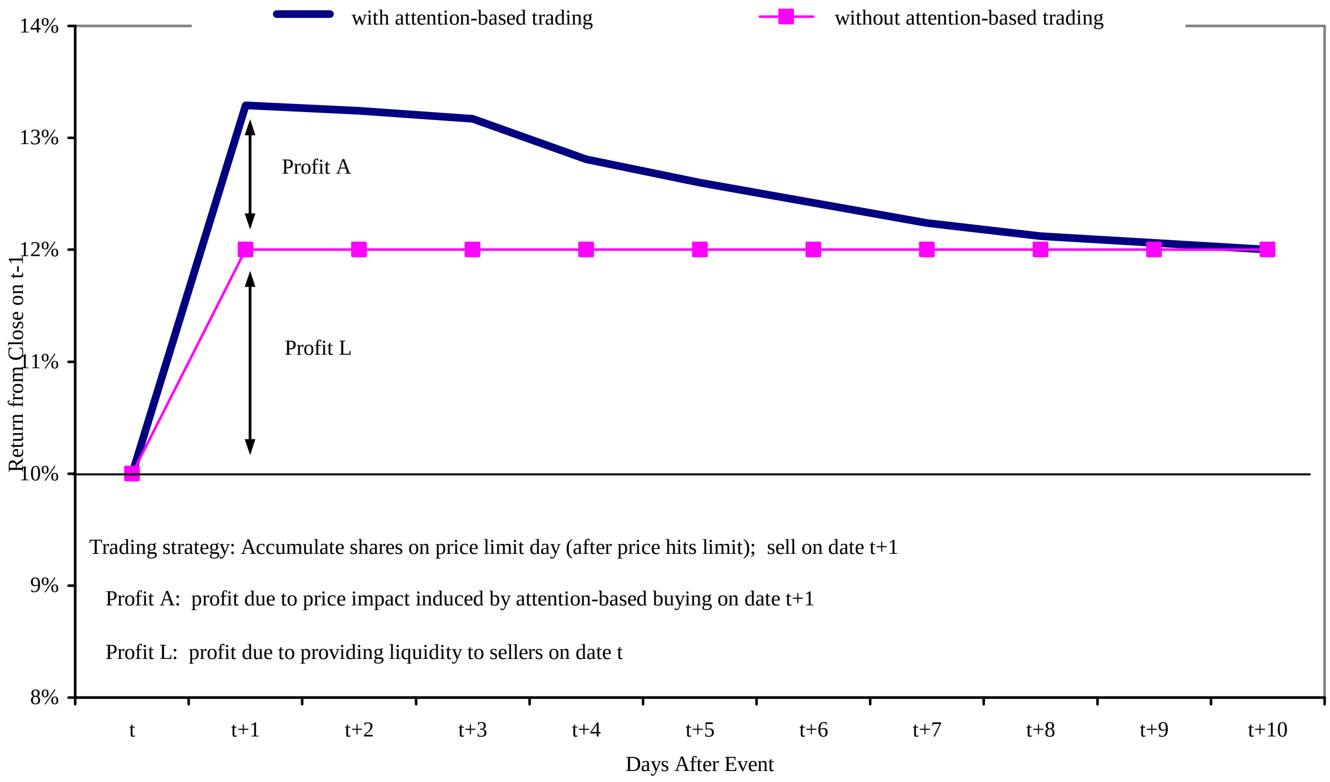
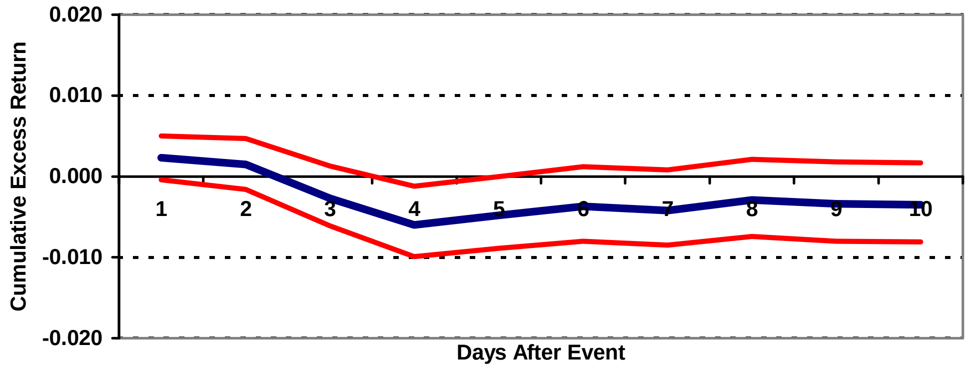


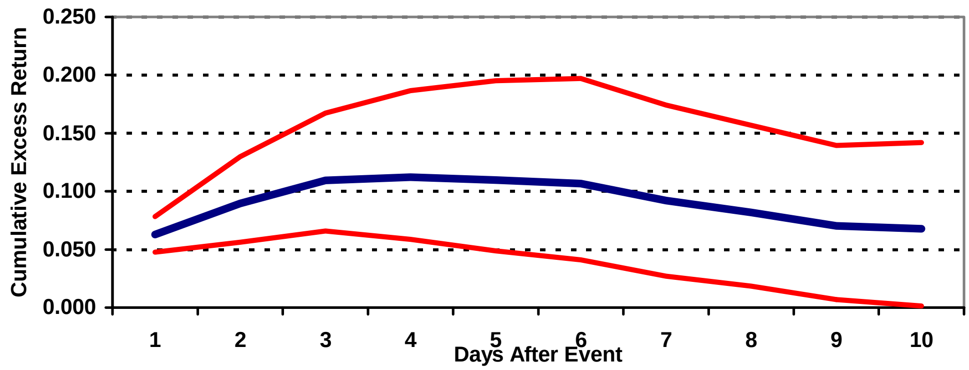
Figure 3
Excess Returns ($r_{k,t} - r_{m,t}$) Following Upper Price Limit Events

Panels show average price reactions (cumulative excess returns $r_{k,t} - r_{m,t}$) following upper price limit events. We also plot confidence intervals (±2 s.e. of the mean.) An upper price limit event is defined as a day a stock hits its upper price limit. Graphs are for "Normal" stocks only—i.e., those with a ±10% daily price limit. Panel A shows market wide events where at least 200 stocks hit their upper price limit on the same day. Panel B shows focused informational events where stock prices jump up to, and close at, their price limits. Panel C shows quasi-informational events where the stock price rises slowly to hit, and then close at, the limit. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

Panel A: Market-Wide Events (Type I)



Panel B: Focused Informational Events (Type II)



Panel C: Quasi-Informational Events (Type III)

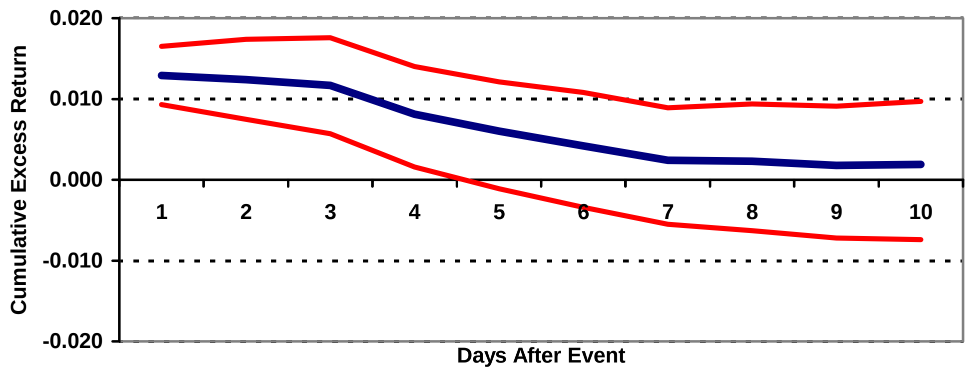


Figure 4
Distribution of Smart Trader Net Profits

Table reports distribution of smart trader net profits. Net profits equal gross one day returns minus 0.45% for transaction costs. Gross one day returns are computed using the volume-weighted average sell price ($VWAP^{sell}$) on the second day and volume-weighted average buy price ($VWAP^{buy}$) on the limit day. Smart traders are active during 357 upper price limit events. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

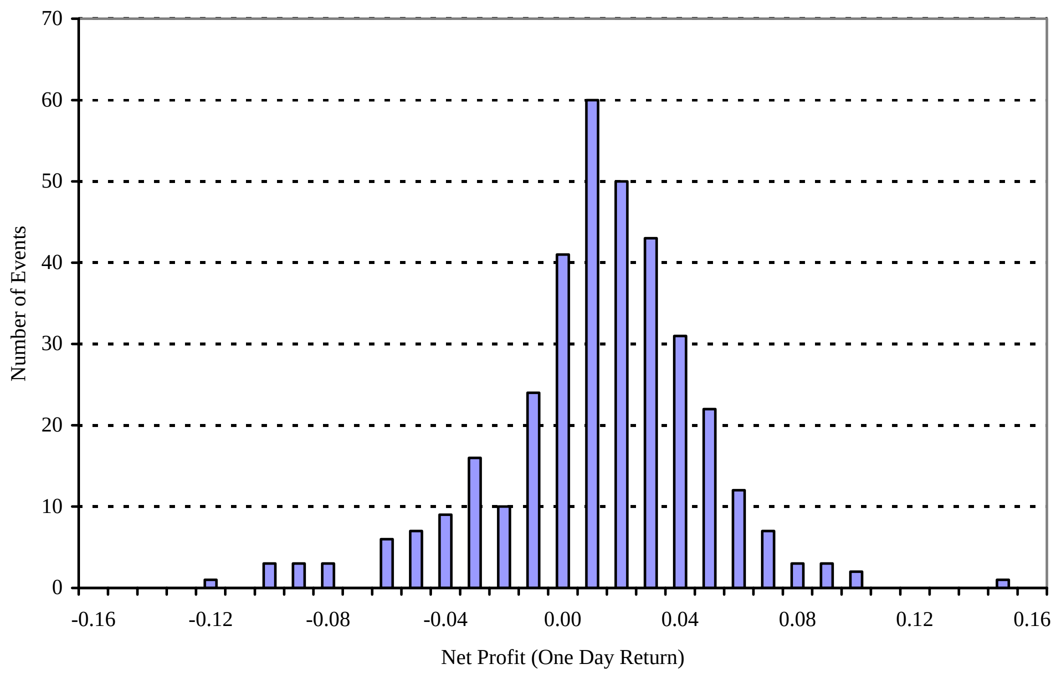


Table 1
Overview of Events

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 to ST over time. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

Panel A: Number of Upper Price Limit Events

	Normal Stocks	**ST Stocks**	**Total Events**
Upper price limit events	1,842	600	2,442
Number of unique stock tickers	635	76	657*

* *Number of unique stock tickers is not additive since stocks may change classification over time.*

Panel B: Overview Statistics For Event Dates (t=0)

	Normal stocks			***ST stocks***			
	# of Events	**Rel. Turn.**	**Ret.**	**# of Events**	**Rel. Turn.**	**Ret.**	**Total Events**
I. Market-wide events • at least 200 events in given day • only two days during sample period	815	2.95	9.90%	22	1.05	4.99%	837
II. Focused informational events • at most 50 events in a given day • price jumps at least 4% to hit limit • price closes within RMB 0.05 of limit	35	2.54	10.02%	45	0.39	5.03%	80
III. Quasi-informational events • at most 50 events in a given day • price slowly reaches limit during day • price closes within RMB 0.05 of limit	361	5.54	10.01%	315	1.64	4.99%	676
IV. Noisy events • at most 50 events in a given day • price hits limit at some point during day • price closes at least 1% below limit	284	6.22	6.06%	150	2.42	2.00%	434
V. Other events • price hits limit at some point during day • event doesn't fall into above categories	347	2.20	7.73%	68	1.43	3.96%	415
All events	1,842	3.81	8.92%	600	1.70	4.13%	2,442

Table 2
Buy-Sell Imbalances of Individual Investors

This table reports summary statistics of buy-sell imbalances of individual investors on the day following an upper price limit event (occurring on date *t*). The imbalance measure is defined as shares bought of stock "*k*" on date *t+1* minus shares sold divided by the sum of shares bought and sold. "N" shows the number of events with imbalance information / the total number of events. We report robust standard errors that take into account clustering of simultaneous events. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

$$\text{Imbalance}_{k,t+1}^{indiv} = \frac{buys_{k,t+1}^{indiv} - sells_{k,t+1}^{indiv}}{buys_{k,t+1}^{indiv} + sells_{k,t+1}^{indiv}}$$

	Mean Imbalance	**Std. Err. of Mean**	**N**	**25th P-tile**	**50th P-tile**	**75th P-tile**
I. Market-wide events	-0.0155	0.0222	821/837	-0.0451	-0.0016	0.0190
II. Focused informational events	0.0260	0.0106	79/80	-0.0024	0.0057	0.0419
III. Quasi-informational events	0.0189	0.0026	664/676	-0.0013	0.0059	0.0296
IV. Noisy events	0.0088	0.0042	425/434	-0.0086	0.0000	0.0197
V. Other	-0.0025	0.0030	413/415	-0.0122	0.0000	0.0092
All events	0.0019	0.0068	2,402/2,442	-0.0124	0.0006	0.0217

Table 3
First-Time Buys for Individual Accounts

This table estimates the fraction of first-time buys following attention-grabbing events. We examine all trades that originate from brokerage offices in the city of Ningbo. For each account-stock-day combination, we code first-time buys, second-time buys, third-time buys, etc. In Panel A, we calculate the fraction of account-stock-days that exhibit first-time buying (our baseline.) In Panel B, we calculate the fraction of account-stock-days 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.

Panel A: First-Time Buys Considering All Account-Stock-Days (baseline)

	Fraction of Acct-Stk-Days with First-Time Buys	Difference from Baseline	Total Number of Acct-Stock-Day Combinations
All acct-stock-day combinations	47.94%	---	563,488

Panel B: First-time Buys Following Upper Price Limit Events

	Fraction of Acct-Stk-Days with First-Time Buys	Difference from Baseline	Total Number of Acct-Stock-Day Combinations
I. Market-wide events	61.56%	13.62%***	4,035
II. Focused informational events	81.89%	33.95%***	613
III. Quasi-informational events	71.82%	23.88%***	4,958
IV. Noisy events	57.93%	9.99%***	1,980
V. Other	58.08%	10.15%***	971
All upper price limit events	65.76%	17.83%***	12,557

Table 4
The Rational Response of Smart Trader

Table reports summary information regarding smart trader activity around upper price limit events. We define smart traders to be active when they buy on the limit day and sell the following day. Net profit equals the average gross one day return minus 0.45% round-trip transaction costs. "Total Invest" is the total amount of capital employed in trading strategies in RMB mm (RMB 8.28 = USD 1.00). Gross one day returns are computed using volume-weighted average sell price ($VWAP^{sell}$) on the second day and volume-weighted average buy price ($VWAP^{buy}$) on the limit day. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

				Gross One Day Return				
	# Events Active	**Net return**	**Tot. Invest. (RMB mm)**	**Mean**	**Std. Err.**	**25th P-tile**	**50th P-tile**	**75th P-tile**
I. Market-wide events	12	**1.26%**	9	1.71%	1.23%	0.92%	1.98%	4.97%
II. Focused info. events	20	**2.23%**	83	2.68%	0.57%	1.33%	2.40%	4.57%
III. Quasi-info. events	257	**1.61%**	1,050	2.06%	0.17%	0.50%	1.83%	3.48%
IV. Noisy events	55	**-4.16%**	164	-3.71%	0.48%	-5.88%	-3.08%	-1.77%
V. Other	13	**1.32%**	16	1.77%	0.72%	-0.02%	0.94%	3.29%
All events	357	**0.76%**	1,322	1.21%	0.19%	-0.23%	1.39%	3.31%

Table 5
Probit Regression Analysis of Smart Trader Being Active (Limit Events Only)

Results from Probit regressions of smart trader being active for all 2,442 upper limit price events. The smart traders are active during 357 upper price limit events. The dependent variable is the dummy variable that equals one when smarter trader is active and zero otherwise. "D_I "D_{II} , "D_{III} and "D_{IV}" are dummy variables indicating the type of upper limit price event. Individual imbalances (in RMB million) are defined as the difference in retail buys and sells of stock "k" on date "t+1". Turnover is the volume traded in stock "k" divided by shares outstanding on date t. The absolute value of return for stock "k" on date "t" (in percent) is the close-to-close return. "ST" is a dummy variable that equals one when the stock in ST status. The coefficients reported are the change in probability over the change in the explanatory variable (dF/dx.) Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

Dependent Variable: Smart Traders Active ("0" or "1")

dF/dx	**Reg 1**	**Reg 2**	**Reg 3**	**Reg 4**
D_I	**-0.0472**	**-0.0495**	**-0.0541**	**-0.0511**
(t-stat)	*(-1.97)*	*(-2.08)*	*(-2.53)*	*(-2.39)*
D_{II}	**0.3314**	**0.2422**	**0.1727**	**0.1192**
	(6.10)	*(4.69)*	*(3.83)*	*(2.86)*
D_{III}	**0.3659**	**0.2770**	**0.2328**	**0.2137**
	(11.90)	*(9.04)*	*(8.40)*	*(7.83)*
D_{IV}	**0.1502**	**0.1079**	**0.0847**	**0.0850**
	(5.01)	*(3.49)*	*(3.00)*	*(3.04)*
$Turnover_{k,t} \times 100$		**0.0061**	**0.0058**	**0.0033**
		(7.68)	*(8.02)*	*(3.64)*
$\| r_{k,t} \| \times 100$		0.0074	0.0085	0.0060
		(1.36)	*(1.66)*	*(1.20)*
ST		**0.1120**	**0.1250**	**0.1218**
		(3.30)	*(3.67)*	*(3.69)*
$Imbal_{k,t+1}$			**0.5473**	**0.5311**
			(8.41)	*(8.21)*
$Turnover_{k,t+1} \times 100$				**0.0040**
				(4.00)
R-squared	*0.233*	*0.268*	*0.307*	*0.315*
No. of obs.	*2,392*	*2,392*	*2,392*	*2,392*

Table 6
Regression Analysis of Smart Trader Profits

Results from regressions of smart trader profits. The dependent variable is the smart trader profits (in RMB million.) Gross individual imbalances (in RMB million) are defined as the difference in retail buys and sells of stock "k" on date "t+1". "D_{II}" is a dummy variable indicating a focused information event (Type II). "D_{III}" is a dummy variable indicating a quasi-informational event (Type III). Turnover (in percent) is the volume traded in stock "k" divided by shares outstanding on date t. The absolute value of return for stock "k" on date "t" (in percent) is the close-to-close return. The smart traders are active during 357 upper price limit events. The t-statistics are computed using robust standard errors which take into account the clustering of price limit events. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

Dependent Variable: Net Profits of Smart Traders (in RMB mm)

	Reg 1	**Reg 2**	**Reg 3**	**Reg 4**
Constant	**0.5204**	**0.5167**	**-1.2358**	**-0.8894**
(t-stat)	***(4.14)***	***(4.12)***	*(-4.01)*	*(-3.28)*
Gross $Imbal_{k,t+1}$	**0.0122**	---	---	---
	(4.79)	--	--	--
$D_{II} \times$ Gr. $Imbal_{k,t+1}$		**0.0232**	0.0159	-0.0103
		(2.20)	*(1.58)*	*(-0.84)*
$D_{III} \times$ Gr. $Imbal_{k,t+1}$		**0.0124**	**0.0105**	**0.0073**
		(4.35)	*(4.13)*	*(3.57)*
$\| r_{k,t} \| \times 100$			**0.1983**	**0.0934**
			(4.98)	*(2.61)*
$\| r_{k,t+1} \| \times 100$			**0.1516**	0.0688
			(2.10)	*(1.01)*
$Turnover_{k,t} \times 100$				**-0.0634**
				(-3.38)
$Turnover_{k,t+1} \times 100$				**0.1357**
				(4.65)
R-squared	*0.098*	*0.114*	*0.200*	*0.296*
No. of obs.	*357*	*357*	*356*	*356*

Table 7
Overview of All Smart Trader Activity

This table reports summary information about smart traders activity. We compare trading around upper price limit events with their trading at other times. Net return is the average gross return minus 0.45% of transaction costs. The gross one-day return is computed using the volume-weighted average sell price ($VWAP^{sell}$) on the second day and volume-weighted average buy price ($VWAP^{buy}$) on the first day. Total invested is the sum of $VWAP^{buy}$ over all events during our sample period. The number is given in millions of RMB but can be converted using (RMB 8.28 = USD 1.00). Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

	Upper Price Limit Events (full sample)	**Other Trading Days (auxiliary)**
Number of events	357	1,269
Net return (one day)	0.76%	0.88%
Gross return (one day)	1.21%	1.33%
Total invested (RMB mm)	1,322	2,059
Relative turnover (t=0)	3.29	3.26
Individual buy-sell imbalance (t+1)	0.0424*	very high**
abs(ret) on event day (t=0)	7.09%	7.84%
Fraction of "ST" stock-days	0.48	0.20

* Retail buy-sell imbalances(on date *t+1*) are higher after events when smart traders are active than during the other events. See Table 2 for comparison.

** Retail buy-sell imbalance values cannot be compared across samples. Imbalance measures from the auxiliary dataset are very noisy due to sampling issues. A full table of imbalance measures using the auxiliary dataset (similar to Table 2 in this paper) is available from the authors upon request.

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 is calculated that maximizes the transaction volume. Unexecuted orders are automatically entered into the limit order book for the continuous auction that begins 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). 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, the 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 offices. Each investor applies for a unique stock trading account number. This number allows the exchange—and financial economists—to exactly 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.

Appendix B
Momentum and Daily Price Limits

This table reports regression coefficients from different momentum models. In Panel A, we calculate daily momentum where $r_{k,t+1}$ is the return of stock "k" using either the closing price from day "t" to the closing price from day "t+1" or the overnight return using the opening price on day "t+1". On the right hand side of either specifications we use the previous day's return (r_t). This is the closing price from day "t-1" to the closing price from day "t". We include indicator variables that takes a value of one on days when stocks hit their lower price limit ($I_{t,lower}$) or upper price limit ($I_{t,upper}$). In regression A3 and B3 we include an indicator variable, D_t, that takes a value of one if the smart traders are active—this only happens on upper price limit days. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

close-to-close (A1, A2, A3): $$r_{k,t+1} = \alpha + \phi r_{k,t} + \gamma_l I_{k,t}^{lower} + \gamma_u I_{k,t}^{upper} + \lambda D_{k,t} + \varepsilon_{k,t+1}$$

overnight (B1, B2, B3): $$r_{k,t+1}^{overnight} = \alpha + \phi r_{k,t} + \gamma_l I_{k,t}^{lower} + \gamma_u I_{k,t}^{upper} + \lambda D_{k,t} + \varepsilon_{k,t+1}^{overnight}$$

	A) dep. var = $r_{k,t}$			B) dep. var = $r_{k,t+}^{overnight}$		
	Reg A1	**Reg A2**	**Reg A3**	**Reg B1**	**Reg B2**	**Reg B3**
α	-0.0002	-0.0003	-0.0003	0.0003	0.0003	0.0003
(t-stat)	*(-0.40)*	*(-0.48)*	*(-0.48)*	*(1.09)*	*(1.05)*	*(1.05)*
ϕ	0.0034	0.0013	0.0013	0.0098	0.0070	0.0070
(t-stat)	*(0.70)*	*(0.31)*	*(0.31)*	*(2.05)*	*(1.88)*	*(1.88)*
γ_{lower}		-0.0083	-0.0083		-0.0185	-0.0185
(t-stat)		*(-2.18)*	*(-2.18)*		*(-9.81)*	*(-9.81)*
γ_{upper}		0.0113	0.0112		0.0126	0.0125
(t-stat)		*(2.15)*	*(1.83)*		*(1.49)*	*(1.27)*
λ			0.0007			0.0007
(t-stat)			*(0.11)*			*(0.07)*

Appendix C
Future Volatility

This table reports intraday volatility for the stocks in our sample based on the Parkinson (1980) measure as describe in the text. Stocks are grouped by "high return" on date "t" where high return is calculated as the high price on date *t* divided by the close on date *t+1* minus one. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

Panel A: "Normal" stocks

Group	high return (t)	N	volatility (t+1)	volatility (t+2)	volatility (t+3)	volatility (t+4)	volatility (t+5)
A	0.1003	187	0.0215	0.0197	0.0185	0.0170	0.0154
B	0.1002	1,655	0.0198	0.0160	0.0141	0.0141	0.0123
C10	0.0970	7,996	0.0165	0.0142	0.0139	0.0139	0.0126
C9	0.0849	1,309	0.0157	0.0143	0.0144	0.0139	0.0130
C8	0.0748	1,782	0.0154	0.0141	0.0141	0.0137	0.0130
C7	0.0647	2,849	0.0146	0.0138	0.0133	0.0128	0.0127
C6	0.0545	4,884	0.0137	0.0132	0.0128	0.0125	0.0122
C5	0.0446	9,730	0.0130	0.0128	0.0125	0.0125	0.0123
C4	0.0345	19,624	0.0121	0.0118	0.0117	0.0118	0.0117
C3	0.0244	42,784	0.0108	0.0109	0.0108	0.0110	0.0109
C2	0.0144	92,427	0.0100	0.0101	0.0100	0.0101	0.0101
C1	0.0047	160,927	0.0092	0.0093	0.0094	0.0094	0.0095

Panel B: "ST" stocks

Group	high return (t)	N	volatility (t+1)	volatility (t+2)	volatility (t+3)	volatility (t+4)	volatility (t+5)
A	0.0503	170	0.0157	0.0150	0.0143	0.0137	0.0148
B	0.0503	430	0.0148	0.0145	0.0145	0.0143	0.0135
C5	0.0467	1,226	0.0142	0.0139	0.0139	0.0137	0.0137
C4	0.0345	1,120	0.0125	0.0126	0.0127	0.0126	0.0129
C3	0.0246	2,047	0.0118	0.0116	0.0121	0.0120	0.0121
C2	0.0146	3,766	0.0112	0.0114	0.0113	0.0114	0.0114
C1	0.0049	5,115	0.0107	0.0108	0.0108	0.0109	0.0109

Group	notes
A	upper events & smart traders active
B	upper events & smart traders not active
C10	non-event days with return >+9%
C9	non-event days with return=[+8%,+9%)
C8	non-event days with return=[+7%,+8%)
C7	non-event days with return=[+6%,+7%)
C6	non-event days with return=[+5%,+6%)
C5	non-event days with return=[+4%,+5%)
C4	non-event days with return=[+3%,+4%)
C3	non-event days with return=[+2%,+3%)
C2	non-event days with return=[+1%,+2%)
C1	non-event days with return=[0%,+1%)