Profiting from Predictability:
Smart Traders, Daily Price Limits, and Investor Attention

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Abstract

This paper studies the trading behavior of smart traders (statistical arbitrageurs) when other market participants act predictably. We examine a group of traders who profit by accumulating shares during days stocks hit their upper price limits. The traders then sell out quickly the next day for an average overnight return of 0.80% after transaction costs. We stress this is not simply a momentum trading strategy; neither daily nor overnight momentum are large factors in this market. The magnitude of observed profits cannot be explained by a liquidity premium nor does it appear to be compensation for increased risk. Our findings are consistent with recent behavioral theories regarding attention-grabbing stocks. We find attention-based buying by unsophisticated individual investors fuels the smart trader profits. There is a transitory impact on prices with reversion to pre-event levels within ten trading days. This paper uses a unique dataset provided by the Market Surveillance Department of the Shanghai Stock Exchange.

Keywords: Smart traders, price limits, behavioral finance
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1. Introduction

Do smart traders (statistical arbitrageurs) enter the market when other participants act predictably? If so, what trading strategies do the smart traders employ? What are the mechanisms by which they profit? How, if at all, are prices affected?

This paper addresses the questions above by studying the behavior of a group of sophisticated traders. The traders buy stocks on days when they hit their daily price limits and sell out quickly the next day for an average overnight profit of 0.80% after transaction costs. Our paper has a number of surprising results. First, the profitable trading strategy is not a simple momentum trading strategy—momentum is not a factor in the market we study. Second, we are unable to explain our results with a liquidity premium. Nor are we entirely able to explain our results as compensation for taking risky positions. Third, our results complement recent work by Barber and Odean (2003), who study which stocks individual investors choose to buy. They hypothesize that individual (unsophisticated) investors have a positive order imbalance following an attention-grabbing event. We believe our results provide a unique out-of-sample test of their theory. We provide an even stronger test of attention-based buying than tests used in existing papers. Finally, we show that attention-based buying has a transitory impact on stock prices. Prices revert to existing levels within ten trading days.

Barber and Odean (2003) hypothesize that individual investors are likely to be net buyers of attention-grabbing stocks. The authors speculate that "attention-based buying is a result of the difficulty that individual investors have searching the thousands of stocks they can potentially buy."[1] Consistent with the attention story, Gervais et al. (2001) find that stocks experiencing unusually high trading volume over a day or a week tend to appreciate over the course of the following month. They argue that shocks in the trading activity of a stock affect its visibility. A recent paper by Graham and Kumar (2004) also find evidence consistent with attention-based trading—older and low-income investors purchase stocks following dividend announcements. Our paper provides an alternative and powerful test of the Barber and Odean (2003) behavioral theory. Rather than looking at the trading behavior of individual investors, we start by outlining the response of smart traders when attention-based buying is present in the market. We focus on a profitable, though risky, strategy that is executed in the presence of daily price limits. We identify a set of traders who profit on days that stocks hit their daily limits.

We are able to carry out our study by examining trading behavior in the People's Republic of China (PRC). There are approximately 1,500 stocks listed on two exchanges in the PRC. Thus, deciding which stock to

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[1] See also Hirshleifer and Teoh (2003) on investors with limited attention and processing power.

invest in is difficult for many individual investors. These difficulties, or search costs, are similar to those mentioned in Barber and Odean (2003). When faced with a large number of listed stocks, individuals are thought to move some candidate stocks into a "consideration set." It is from the consideration set that the eventual purchase is chosen.[2] It is hypothesized that certain stocks catch an investor's attention and it is these stocks that are put into his or her "consideration set." Not all individuals will purchase all stocks in their consideration sets. But some individuals will purchase at least one of the stocks. If we can identify which stocks catch investors' attention, then we can identify which stocks are likely to have net buy order imbalances.

This paper exploits the fact that stock markets in the PRC are subject to daily price limits. Prices are not allowed to rise above the limit, though trading may continue as long as prices do not exceed the limit. Stocks that hit their daily price limit are reported in the news and are excellent candidates to be attention grabbers. These stocks are highlighted on electronic bulletin boards at brokerage branch offices, where most retail investors place their trade orders—see Feng and Seasholes (2003). After the 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 these programs at the end of the trading day in order to get information before the next trading day. In aggregate, attention-based theories predict that individuals will place net buy orders at the next possible opportunity. If there are daily price limits, orders are placed for the following trading day.[3]

If individuals are prone to attention-based buying, what is the rational response? Sophisticated traders will attempt to accumulate shares the day a stock hits its daily price limit. Sophisticated investors will then sell the following day to balance the increase in aggregate demand caused by attention-based buying by individual investors. In short, the theory predicts individuals who had not previously considered a stock now start to do so. These new investors, as well as short sale restrictions, cause the shift in the aggregate demand curve for the stock.

Clearly, studying price limit events poses problems for the econometrician. If a stock price is limited from moving up today, there may be an order imbalance at the end of the trading day. Tomorrow's trading price may rise in order to equilibrate supply and demand. We spend considerable time addressing these concerns. We also test numerous hypotheses that could explain the source the smart traders' profits. While such

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2 Since short selling is not allowed, initiating a new position entails buying a stock one doesn't already own. Short selling restrictions also reduce search costs when selling. Investors can only sell stocks they already own. If an individual holds two or three stocks, the search problem is greatly mitigated.

3 Again, since there is no short selling in this market, we can unambiguously identify net buy order imbalances and not have to worry about net sell order imbalances. Barber and Odean (2003) argue that individuals short stocks so infrequently in the USA that a similar identification (effectively) holds in their sample as well.

issues complicate the analysis, we never have to worry about whether the trading strategy studied in this paper can be implemented. Our paper is based on actual trades by a group of investors that account for over 10% of a stock's trading volume on the days they are active.

This paper touches on a number of areas in financial economics. We provide an in-depth examination into the behavior of smart traders. We also provide evidence as to who is taking the other side of a behavioral trading model. Finally, our paper is linked to research on daily price limits in financial markets. We finish the introduction by reviewing some of the relevant literature. Section 2 describes the data used in this study and provides some overview statistics. Section 3 details the process by which the smart traders profit. Section 4 tests the specific predictions of the Barber and Odean (2003) behavioral model. We show that the trading strategy employed by the smart traders is consistent with a strategy that takes advantage of attention-based buying. Section 5 provides a number of alternative tests that might explain our results. We find that explanations such as simple momentum-based trading strategies, compensation for providing liquidity, and compensation for risk taking cannot explain the magnitude of the observed profits. Section 6 concludes.

1.1 The role of smart traders

Smart traders, or rational arbitrageurs, play a key role in many models of trading. For example, De Long et al. (1990) present a model in which some investors submit buy orders on days following price increases. Smart traders realize that unsophisticated investors blindly submit positive feedback orders. The smart traders take advantage of the situation. Prices move up slowly for a couple trading periods before reverting back to fundamentals. In a similar paper, Mei, Wu and Zhou (2004) model how smart traders take advantage of momentum trading. There are two key differences between these papers and our paper. First, our results do not depend on stock price momentum, nor do the results depend on momentum-based trading. In fact, we are careful to verify that momentum is <u>not</u> driving our results. Second, our paper is empirical and uses the actual trades of market participants.

It is possible that smart traders profit by manipulating prices. In a dynamic model of asset markets, Jarrow (1992) investigates market manipulation trading strategies by large traders in a securities market. Market manipulation trading strategies are shown to exist if there is "price momentum." Allen and Gale (1992) show that a profitable price manipulation is possible, even when there is no price momentum and no possibility of a corner. The key to their argument is information asymmetry. Market participants are uncertain whether a large trader is buying undervalued shares if a large trader intends to manipulate the price. It is this uncertainty that allows manipulation to be profitable. Mahoney (1999) finds little evidence of manipulation of stock pools allegedly formed to manipulate stocks. More recently, Khwaja and

Mian (2003) analyze a data set containing daily firm-level trades of every broker trading on the stock exchange in Pakistan and find evidence that brokers manipulate prices to profit from positive feedback traders. Aggarwal and Wu (2003) provide evidence of manipulation. The authors study security and exchange commission actions in cases of stock manipulation and find that stocks in poorly regulated markets are more likely to be manipulated. Their study suggests that manipulation may be more prevalent in emerging markets than in the United States. We conduct a couple of tests of manipulation and find little evidence that the smart traders have a direct effect on prices.

1.2 Attention-based trading

As mentioned above, financial economists have recently been trying to understand what makes investors buy certain stocks. Barber and Odean (2003) suggest that investors face a large and confusing search problem. Certain stocks grab investors' attention and are thus considered—see Merton (1987). Because short selling is rare in the United States (although not prohibited as it is in the PRC), the authors consider net order imbalances. Individuals tend to buy stocks with high abnormal trading volume, extreme price moves, and recent news articles. Linnainmaa (2003) finds evidence that day traders purchase "stocks that grab their attention" while Massa and Simonov (undated) find that "investor stock choice is mostly driven by the availability of information."

There are a number of other studies that disagree about the relationshipe between stock price increases and the net buy order imbalance from individual investors. Grinblatt and Keloharju (2001) conduct an extremely thorough examination of what makes investors trade. Investors appear very reluctant to realize losses, but are happy to realize gains. Thus, sell orders outpace buy orders as a stock's price rises. A propensity to sell for a gain appears to overwhelm attention-based buying, except that Grinblatt and Keloharju (2001) do find "one anomaly." Households in the study buy more stock than they sell if returns are positive over the past two days. Choe, Kho, and Stulz (1999), on the other hand, find little evidence that individuals increase buying as prices rise. Finally, Chan (2001) studies stock reactions to news. Unlike our study and those mentioned above, he looks at prices following news releases and not actual order imbalances. The author finds "evidence of post-news drift" in stock prices after public news in released. Our paper complements the above studies by examining which traders are on the other side when net buy orders (of individual investors) suddenly surge.

1.3 Daily price limits

One can also view our paper as an in-depth investigation into the consequences of imposing daily price limits. Price limits are intended to stabilize prices and reduce market volatility. Since emerging capital markets often exhibit high volatility, it is not surprising that regulators adopt these limits in equity markets such as Taiwan, Malaysia, Thailand, the Philippines, Japan, South Korea, Austria, Finland, and Portugal. Lee and Kim (1995) study the Korean market and find evidence that limits help stabilize prices. Ma, Rao, and Sears (1989) come to similar conclusions when examining U.S. Treasury futures data. Looking at high frequency (five minute) intervals, Li et al. (2001) show that when a Shanghai-listed stock is close to its upper price limit, the price is more likely to drop than to rise. When the price is close to the lower price limit, the price is more likely to rise than to drop. Wu et al (2002) find that appropriate price limits not only reduce abnormal fluctuations on the Shanghai Stock Exchange, but the limits increase overall liquidity. However, Shi (2002) finds that price limits do not reduce volatility; nor do they reduce speculation. In fact, limits negatively affect the price discovery process and normal trading activities of investors. In a recent paper, Nath (2004) provides fresh evidence supporting, though only partially, the criticisms against the efficacy of price limits. Our paper does not comment directly on the "pro price limit" vs. "anti price limit" debate. However, our results show that the existence of price limits provides a forum for smart traders to profit.

2. Data

2.1 Stock exchanges 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 makes use of data provided by the Market Surveillance Department of the Shanghai Stock Exchange and only considers stocks listed on that exchange. 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.

The Shanghai Stock Exchange has a ±10% daily price limit on 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 the accounting profit is 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," trading can only take place at prices that do not exceed the limit for the day. As mentioned in the introduction, due to short sale prohibitions we consider only the upper price limits in this study. On a few days, such as immediately after an IPO or if the stock is emerging from trading suspension, the price limits are lifted in order to allow markets to clear.

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 8.27 = 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.

2.2 Brokerage accounts 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 (2003). 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.

2.3 Stock price data

We collect daily price data for all stocks traded on the Shanghai Stock Exchange from January 2, 2001 to July 25, 2003. Data include date, stock ticker code, 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 stocks in the sample. We also collect corresponding information for the major market composite index.

For each trading day, we look for stocks that reach their daily price limit at any time during the trading day and define this as a "price limit event." We define the day to be a "price limit day" and we refer to the next trading day as the "following day." There are a total of 3,688 price limit events. Of these, 2,442 events are "upper price limit events" and 1,246 are "lower price limit events." Due to short sales constraints, we consider only upper price limit events. There is at least one price limit event (at least one stock hits its price limit) on 416 of the 610 trading days in our sample period. There are 657 different stocks with upper price limit events or an average of 3.72 upper price limit events per stock. Of the 2,442 upper price limit events, 1,842 involve "Normal" stocks and 600 involve "ST" stocks. Table 1, Panel A gives an overview of the events used in this study.

2.4 Trading data

For each of the 2,442 upper price limit events, we collect all intraday trading data on both the price limit day and the following day. The high-frequency data provided by the exchange, for the most part, are limited to two types of days (price limit days and the following days). The trading data include: date, stock ticker code, price, size of trade, time stamp, trading account number of buyer, and trading account number of seller. The Market Surveillance Department at the Shanghai Stock Exchange helped to identify ten accounts that engage in trading around price limit events. Appendix 1 outlines the screening procedure they use. It turns out that all ten accounts are from the city of Ningbo. The city has a population of 5.5 million and is about 200 miles south of Shanghai. We sometimes refer to this cabal of smart traders as the "Ningbo traders."

Since we know the account numbers for each of the ten accounts, we can track trading activity closely. The smart traders do not trade all the stocks that reach their price limits. Rather, they buy shares during 389 of the 2,442 upper price limit events. These 389 events include 199 events with "Normal" stocks and 190 events with "ST" stocks. During 373 events, the smart traders sell positions on the following day (they accumulate shares on or before the price limit day). For 357 events, smart traders both buy on the price limit day and they sell the following day. We label the traders "active" for these 357 events and use them as the basis for many of our tests. Table 1, Panel B provides the overview statistics related to trading around upper price limit events.

We do not have order flow data for the entire market (we only have transactions on the price limit days and following days). Therefore we cannot reconstruct the order book throughout the day. We are also not able to reconstruct the bid-ask spread throughout the day.

2.5 Overview statistics

Figure 1 plots the time series of upper price limit events during our sample period. Panel A shows the total number of upper price limit events ("Normal" stocks and "ST" stocks). Panel B shows the 357 events where the smart traders are active. There is a 0.2984 correlation between of the total number of trades in Panel A and Panel B. Over the sample period, 24.57% of all upper price limit events involved "ST" stocks. The smart traders chose "ST" stocks during 47.62% of the 357 price limit events where they were active.

Table 2 shows the frequency with which the smart traders participate in the market. Panel A shows that they are active around price limit events on 358 of the 610 days in the sample. Panel B provides evidence that the smart traders do not concentrate on any one stock. Instead the participate (trade) in 29.07% of all listed stocks. The most important panel is Panel C. It shows that the smart trades can represent a sizable fraction of market volume. On price limit days when they are active, they account for 12.91% of all trading in the stock that has hit its limit. We focus more on their fraction of market volume when we look at liquidity issues in Section 5.

2.6 Unit of analysis

It is probable that the ten smart trader accounts are owned by related persons (or business partners), since all ten accounts were opened from the same brokerage firm in the same city. Trades from the ten accounts originate from two branch offices in the city. Therefore, our analysis treats the ten smart trader accounts as being controlled by one investor. Thus, for each of the 357 upper price limit events where the smart traders are active, we track trades from one conglomerated account. Our approach is conservative since it cuts the potential sample size from ten independent accounts to one consolidated account.

3. Profitable Trading Strategies by Smart Traders

3.1 The profit and loss of the smart traders

We consider the 357 upper price limit events where the smart traders are active. For some events, the number of shares bought on the price limit day is not equal to the number of shares sold the following day. To address the mismatch, we estimate profit using two methods. For each account, we compute the cumulative number of shares bought (N_B) on the price limit day, the cumulative value of shares bought (V_B) on the price limit day, the cumulative number of shares sold (N_S) on the following day, and the cumulative value of shares sold (V_S) on the following day. There is a 0.2000% transaction tax for each trade, and the exchange charges a 0.0150% service fee. In addition, brokerage houses charge commissions. High-volume traders receive deep, deep discounts. Very large traders, such as the ones in our sample, negotiate an annual flat fee that gives them access to the brokerage office's line to the exchange. These large traders must still pay the transaction tax and exchange service fee on all trades. For the purposes of this paper, we assume that the smart traders pay 0.4500% in round-trip transaction costs and we subtract this amount from all gross profit calculations to determine net profit.

We calculated gross profits using two different methods. Method 1 effectively ignores mismatched shares and focuses on transaction prices. Method 2 estimates the transaction prices of the mismatched shares. For example, in method 2, 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 the smart traders sell at the opening price without applying their trading skills. If the cumulative shares purchased is lower than the cumulative sale, we use the limit price to compute the cost of those extra shares sold. Our assumption is again conservative since the smart traders are able to take up their positions at an average price several pennies below the limit price.

Method 1

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

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

Method 2

$$\text{Gross Profit \#2} = V_S + \left(N_B - N_S\right) \cdot p_{\text{open}} - V_B \qquad \text{if} \qquad N_B > N_S \tag{1c}$$

$$\text{Gross Profit \#2} = V_S + \left(N_B - N_S\right) \cdot p_{\text{limit}} - V_B \qquad \text{if} \qquad N_B < N_S \tag{1d}$$

Table 3 reports the profits and losses earned by the smart traders. In Panel A we report profits for trading in "Normal" stocks (those with the ±10% limit). There are 187 events where the smart traders are active. The average profit is RMB 101,128 under method 1, and RMB 101,701 under method 2. The first method is likely to underestimate profit since any unmatched buy and sell orders after the event are ignored. Under certain market conditions, any delayed profit-taking is ignored. For example, if an upper price limit event is followed by another upper price limit event, the smart traders might not be able to sell. This profit is not considered with method 1, yet the true profit is very large since the second-day price increase is very significant. In addition, for positions taken up earlier at a lower cost the profit is also ignored.

The table also reports the profit for "ST" stocks (those with the ±5% limit.). There are 170 observations for "ST" stocks and the mean profit is RMB 23,622 and RMB 25,983 under method 1 and method 2 respectively. On average, the normal stocks generate four to five times as much profit as the "ST" stocks per price limit event for the smart traders.

The smart traders earn an overnight return of 0.80% after transaction costs. Given 240 trading days in a year (or the smart traders participation in approximately 150 events per year), this represents an astronomically high annual return. Of course, this return is not without risk. Figure 2 shows the distribution of profits for the 357 events. For some events, the smart traders do lose money.

While the amount of money at stake may seem small by developed market standards, one must remember that the PRC is a developing economy. The average monthly household income is around RMB 800 (less than USD 100) for the country as a whole. In the more wealthy provinces, the average monthly household income is almost double, at RMB 1,500 (less than USD 200). See Appendix 1 of Feng and Seasholes (2004) for a more complete description. The average amount bought during each of the 357 events is over RMB 3,800,000 or approximately USD 450,000. The total profit is approximately USD 1,000,000 per year—a handsome sum in the PRC.

In Section 5 we perform a number of robustness checks. We also consider cases when the number of shares bought on the upper price limit day exactly matches the number of shares sold the following day. In such cases there is no need to estimate profit using equations (1a) to (1d). We also calculate profits when it takes more than one day to unwind a position. Qualitatively our results don't change.

3.2 Characteristics of price limit events when smart traders are active

While it is clear that the smart traders earn high overnight returns, it is not as clear which events they choose to participate in. To understand what factors may influence their decision to participate, we estimate a probit regression for all 2,442 upper price limit events "i".

$$D_{participate,i} = \alpha + \beta X_i + \varepsilon_i \tag{2}$$

Here, the dependent variable (D) takes a value of one for the 357 events where the smart traders are active and zero otherwise. The right-hand side variables (X) are restricted to include only public information available that trading day. The results of the probit regression are shown in Table 4. Rather than report actual coefficients, we choose to report the change in probability associated with a small change in the independent variable. For right-hand side dummy variables the associated changes represents a discrete jump from zero to one.

The first dummy variable indicates the stock's status ("Normal" stock=0; "ST" stock=1) and is not significant. The next three dummy variable control for multiple events on the same day. From Figure 1 we see that many stocks hit the price limit during the same time interval. We therefore include three dummy variables that take a value of one if: i) between ten and fifty stocks hit on the same day; ii) fifty-one and 100 stocks hit on the same day; and iii) 100 or more stocks hit on the same day. All three variables are negative and statistically significant at all conventional levels. The results indicate that the smart traders are not active on days when the entire market shoots upward. Instead, they concentrate on individual stocks-days. Note, we use robust standard errors to control for simultaneous events.

We include a dummy variable if a stock opens at it's upper price limit. We then include a continuous variable that indicates the time during the day that a stock first hits the upper price limit. This variable is recorded as a fraction of the way through a day, where 0.5417 indicates 1:00pm since 0.5417 is 13/24$^{\text{ths}}$ of the way through the day. Smart traders are less likely to take a position in a stock that opens at its limit. They are also less like to take a position as the day goes on.

The next variables measure a stock's trading activity or turnover. In regression #1, we simply include turnover a day *before* the price limit day. Yesterday's turnover is positive and significant indicating that the smart traders focus on recently active stocks (or stocks for which there is disagreement amoung market participants as to the value of the stock):

$$turnover_{k,t-1} = \frac{\text{shares traded}_{\text{k,t-1}}}{\text{free float}_{\text{k,t-1}}} \tag{3a}$$

In regression #2 we include a measure of average turnover. We also include a variable called "Relative turnover," which is a measure of a stock's turnover compared to it's average turnover over the entire sample period. The measures are calculated as follows:

$$\overline{turnover_k} = \frac{1}{T}\sum_{t=1}^{T} turnover_{k,t} \tag{3b}$$

$$\text{relative turnover}_{\text{k,t-1}} = \ln\left(turnover_{k,t-1}\right) - \ln\left(\overline{turnover_k}\right) \tag{3c}$$

The second specification in Table 4 shows each stock's average daily turnover (sample average) as well as the log difference between the previous day's turnover and the average (we call this a relative turnover measure.) The average turnover is significant at all conventional levels while yesterday's deviation is only significant at the 10% level. The results indicates that the smart traders focus on high volume stocks and not stocks that have suddenly become very active.

Finally, we include the natural log of the firm's market capitalization calculated as the closing price on the previous day multiplied the free float. This variable is not significant indicating that the smart traders take positions in both large and small stocks.

3.3 Timing of orders around upper price limit events

We end this descriptive section by asking whether the smart traders anticipate, or react to, upper price limit events. To answer this question, we get the exact time (hour, minute, second) when a stock first hits its upper price limit. We then measure the difference in time (in seconds) between when orders are placed and when the first hitting time. A positive measure indicates that orders come after the event while a negative measure indicates that orders precede (anticipate) the event. Note that, as mentioned in Section 2, our data only contain transactions (and the associated order times) and not orders that are withdrawn before execution.

Figure 3 shows a histogram of our results. Over 84.11% of all smart trader orders are submitted during the two-hour window surrounding the event. Over 61.91% of orders are submitted during the five minutes that immediately follow the event. In total, only 4.42% of orders precede the event, indicating the smart traders do not try to predict when, or if, a stock may hit its upper price limit. This results suggests the trading strategy studied in this paper does not require inside information or special forecasting tools.

4. Attention-based trading

What drives the smart traders profitability? We propose that smart traders take advantage of a behavioral bias that is present in unsophisticated investors. The smart traders accumulate positions in stocks on special days. These stocks receive increased coverage in the news media overnight due to the circumstances of the day. Individual investors move some of these stocks into their "consideration sets" of stocks to buy. The day following the attention-grabbing event, increased consideration manifests itself as a net buy order imbalance from individual investors. The smart traders can help the market equilibrate this spike in demand by selling out at a profit.

Of course a reasonable reader is skeptical that the behavioral bias is driving the smart trader profits. There are some days when "Normal" stocks receive news that should increase their price by 15%. In these cases, we expect the price to rise 10% today, hit the limit, and then rise 5% the following day. In fact, we show that the smart traders tend to avoid these 15% events for a very obvious reason.[4] When unambigously good news is released about a company, the price shoots up to the limit and the volume is low. In other words, very few investors are willing to sell at times when there in unambiguously good news about a stock and the price is limited in its abilitiy to adjust. Low volume makes executing a profitable trading strategy difficult. Instead, we show in Section 4.4 that the smart traders choose to trade on stocks that hit the upper price limit and have unusually high volume. These stocks then catch the attention of individual investors and have a net buy demand the following day. This section is, therefore, entirely devoted to tests that show that attention based buying by unsophisticated investors is fueling smart trader profits (and not another trading strategy that relies on buying stocks that should have risen 15% but are limited to going up only 10%.)

4.1 Buy-sell imbalances of individual investors

A clear and testable hypothesis of the Barber and Odean (2003) theory of attention-based buying is that individual (unsophisticated) investors should have net buy imbalances on the day after the attention-grabbing event. We test this hypothesis directly using a special feature of our data. For every trade in our data, we are able to identify the "type" of each account as defined by Chinese security law. For example, "A-type" accounts are individual accounts held by retail investors, "B-type" accounts are for corporations, and "D-type" accounts are broker accounts[5]. We compute a measure of buy-sell imbalance for each type of account:

$$imbalance_{i,t} = \frac{buy_{i,t} - sell_{i,t}}{buy_{i,t} + sell_{i,t}} \tag{4}$$

Here $buy_{i,t}$ ($sell_{i,t}$) is the total buy (sell) volume (in shares) on day "t" for investors of type "i". This imbalance measure is bounded below by negative one (when there are only sells from a certain type of investor) and bounded above by positive one (when there are only buys.)

[4] Table 4 shows that the smart traders avoid stocks that open at the price limit. Table 6 (discussed below in Section 4.4) shows that smart traders profit most when turnover is high.

[5] There are also "C-type" accounts are for trading B-shares. B-shares which are denominated in US dollars in the Shanghai market. We exclude B-shares from our analysis.

Table 5 reports summary statistics of the imbalances on the price limit day and the following day. Panel A shows the results for upper price limit days when the smart traders are active. On price limit days, the smart traders are mainly engaged in buying activities. The mean imbalance measure is 0.871, which is statistically different from zero. Notice the 25^{th}, 50^{th}, and 75^{th} percentiles are all equal to one. In contrast, retail investors are significant net sellers on price limit days, as can be seen from the –0.052 measure. The selling behavior can come from two sources. First, there is an adding-up constraint in the market. If the smart traders are buying heavily, then somebody is selling. Second, consistent with the findings of Odean (1998) and Grinblatt and Keloharju (2001), individual investors are more likely to sell winners than losers.

The direct test of the Barber and Odean (2003) theory can be seen in Table 5, Panel B. Retail investors are net buyers on the day following an upper price limit event. We also see that smart traders sell out on this day. Again, notice that the 25^{th}, 50^{th}, and 75^{th} percentiles are all equal to negative one.

4.2 An even stronger test of attention-based buying

We now provide an even stronger test of attention-based buying than currently exists in the literature. If price limit events truly catch the attention of individual investors, then we should see more first-time buyers of a stock the day following an attention-grabbing event than on other days. In other words, we test whether price limit events cause investors to consider stocks they had not considered previously.

To do this we collect all trades between January 2001 and July 2003 from all "A-type" accounts based in the city Ningbo. For each trade we note whether this is the first time the account has bought a particular stock. We then compare the distribution of first-time buys on stock-day combinations following price limit events to all other stock-day combinations. Our results are quite stunning. For a typical stock-day, 47.94% of all buys are first-time buys. Following a price limit event, this number jumps to 65.76%, indicating a large surge in new buyers. The percentage of first-time buyers is even larger, 72.65%, on stock-days following events where the smart traders are active.

Note that since we do not have each account's trading history before 2001, we are forced to assume that the first trade we view is the first trade. Clearly this raises our measure of the percentage of first-time buyers. One way to check our results is to only consider upper price limit events (and all other stock-days) in 2003. In this way, we use the 2001 and 2002 trading history 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 buyers. Days following price limit events have 63.50% first time buyers (68.15% when the smart traders are active.) These tests are the second piece of evidence that smart trader profits are driven by attention-based buying.

4.3 Stock price reactions when attention-based buying is present

Another testable hypothesis from Barber and Odean (2003) is that stock prices fall after the unsophisticated investors buy (see Proposition 1 in their paper.) We test this directly by looking at the cumulative returns for a stock after it has hit its daily price limit. Figure 4 shows cumulative returns and excess cumulative returns. When the smart traders are active, we see the stock closes the following day about 1.00% to 1.20% higher than it did on the event day. Prices then revert back to original levels in the next seven to ten days. Figure 4 is the third piece of evidence that is consistent with the Barber and Odean (2003) theory of attention-based buying. Our results also assuage fears that the so-called 15% events drive the smart trader profits. If news on "Normal" stocks (when the smart traders are active) is causing prices to hit the upper limit, we would expect price rises to be permanent and not transitory.

4.4 Smart Trader Profits and Measures of Attention

To further understand how the smart traders profit from attention-based buying, we regress their profits (and losses) on measures of attention. The results are shown in Table 6. "Close at limit price" is dummy variable which equals one if the stock price reached its daily limit and closed at the limit price (and zero otherwise.) The "close at limit price" dummy is significant for both measures of profit and for both the "Normal" stocks and "ST" stocks. This result is consistent with the attention theory since when a stock closes at its daily limit price, it receives special attention from investors due to special reporting in brokerage branches and the financial press. This result, however, may also be consistent with the story where the real change in the value of the stock is more than the limit, say a 15% change. Yet under this scenario, it should be difficult to build up a position on the price limit day, since other investors would be reluctant to sell at the limit price.

We use also include our measures of relative turnover from equation (3c). The relative turnover on the following day is also significant in explaining profit by the smart traders. Doubling the turnover is associated with an additional average profit of about RMB 7,000 to RMB 19,000.

We use trade imbalances for three groups of investors on the day following a price limit event. We compute separate imbalance measures for retail investors, corporations, and brokers. On average, imbalance coefficient is larger for retail investors than it is for the other two groups of investors. The more the retail investors buy over sell, the more profitable the smarter traders are. The retail investor imbalance measure is particularly significant for the "ST" stocks (shown in Table 6 Panel B). These results provide the fourth piece of evidence that the smart traders profit from the buying behavior of individual investors.

5. Alternative Explanations

Section 4 presents evidence that attention-based buying by unsophisticated (individual) investors drives the smart trader profits. In this section we test alternative theories that might explain our results. We start with the most obvious one—momentum trading in the style of De Long et. al. (1990).

5.1 Momentum

It is possible that the smart traders simply execute trades in a manner that takes 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 (5) below. Results are reported in Appendix 2. We test all 743 stocks in our sample, and note that standard errors allow for clustering at the daily level.[6] $I_{t,lower}$ is an indicator function that equals one if the lower price limit is reached on day "t" and zero otherwise, and $I_{t,upper}$ is an indicator function that equals one if the upper price limit is reached on day "t" and zero otherwise. Also, D_t is a dummy variable that equals one if the smart traders are active and zero otherwise.

$$r_{t+1} = \alpha + \phi r_t + \gamma_l I_{t,lower} + \gamma_u I_{t,upper} + \lambda D_t + \varepsilon_{t+1} \tag{5}$$

In total, Appendix 2 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 Appendix 2, 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 (5) 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 (5) using overnight returns on the left-hand side—see regression B1. We calculate the overnight return from the close on day "t" to the opening price on day "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

[6] We have 608 clusters which equals the 610 days in our sample minus two days need to calculate returns today and returns tomorrow.

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 2.

Momentum and daily price limits: When there is a large change in the fundamental value of a firm, the resulting change in the equilibrium price may be larger than the daily price limit. Due to the price limit, the equilibrium price cannot be reached in a single trading day. Hence price discovery is delayed. Kim and Rhee (1997) study delayed price discovery in Japan, while Choi and Lee (2001) find the effect in Korea. Fama (1989) points out that investors may speed up their trades when a stock is close to its limit. Empirical evidence of such behavior is shown in Cho and Russell (2001) and Choi and Lee (2001) using data from the Taiwan and Korean markets, respectively. However, 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 2, 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.

5.2 Turnover and liquidity

It is possible that our results are being driven by compensation for providing liquidity. On upper price limit days, some investors might want to sell out. The smart traders enter the market, agree to buy shares, and are compensated for providing liquidity. Compensation would be in the form of higher future returns.

To test the liquidity provision hypothesis, we calculate relative turnover on upper price limit days and days immediately following the event. We use the same relative turnover measure as in equation (3c). In order to better understand our results we divide our sample into three main groups: "Group A" is upper price limit events with smart trader activity; "Group B" is upper price limit events without smart trader activity; "Group C" is all other stock days (non-price-limit days). Because turnover and stock returns are known to be correlated, we further divide "Group C" based on day zero returns. We calculate returns in the same manner as upper price limits are calculated and call this measure *high return (t)*:

$$high\ return_t = \frac{\text{daily high}_t}{\text{close}_{t\text{-}1}} - 1 \tag{6}$$

Group C10 is all non-price-limit stock days with high returns between 9.00% and 10.00%; group C9 is all non-price-limit stock days with high returns between 8.00% and 9.00%, and so on.

Appendix 3 shows our results. In Panel A, for "Normal" stocks, we see that Group A has a relative turnover measure of 1.7769 on upper price limit days (t+0). Group B's comparable measure is 1.1107, while group C10 has a 1.0771 measure. Economically, a measure of 1.7769 indicates that turnover on these days is 5.91 times as high as the stock's average daily turnover. The stocks the smart traders trade continue to have higher than average turnover for the following five days. There is little evidence that these stocks are illiquid. Similar results are found in Panel B for the "ST" stocks.

We do another test to see if the smart traders are providing liquidity. We measure the time between when they place an order and when the order is actually executed. Orders that are executed instantly are called "marketable limit orders" and can be thought of as demanding liquidity. Orders that are executed long after submission can be thought of as supplying liquidity to the market. Only 9.18% of buys on price limit days are executed immediately, 11.53% are executed in the first minute after submission, and 8.11% are executed in the second minute. These results (not reported in a table) are indicative of smart traders providing liquidity. However, when it comes to selling, we see a completely different pattern: 44.35% of sell orders are executed immediately, another 39.94% are executed in the first minute, and 3.86% are executed two minutes after submission. On the sell side, the smart traders demand liquidity and presumably are not compensated for it, but pay for it.

The results of the study of execution times give no compelling evidence that smart trader profits are compensation for providing liquidity. First, the stocks are extremely liquid on the upper price limit and following days. Second, smart traders provide liquidity when buying, but demand liquidity (heavily) when selling.

5.3 Risk taking

It is possible that the smart trader profits are compensation for increased risk taking. On upper price limit days, prices become censored. It is possible that some investors do not like to hold such stocks and are willing to sell out (cheaply) to the smart traders. Buying on the price limit day and selling in the future would be profitable in such cases. Also, it is possible that stocks that hit their upper price limits are simply more volatile and risky than other stocks.

In Appendix 4 we report the intra day volatility of various stocks on the five days following the price limit day. We use the Parkinson (1980) measure and again sort stocks based on high return at date zero:

$$\sigma_{k,t} = \ln\left(\frac{high_{k,t}}{low_{k,t}}\right) / 4\ln(2) \qquad (7)$$

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 group G10.[7] 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 explanations. However, it seems implausible that it can explain overnight returns of 0.80% after transaction costs.

5.4 Execution prices

We study the prices at which the smart traders are able to execute. What prices do they pay for their shares as compared to the limit prices or closing prices on the price limit days? What prices do they get for the shares they sell? To answer these questions, we compute the difference between: a) the smart traders' value-weighted average buying price ($VWAP^B$) and closing price on the price limiet day, b) $VWAP^B$ and the limit price on the price limit day; c) the value-weighted average selling price ($VWAP^S$) on the following day and the closing price on the following day, and d) $VWAP^S$ on the following day and the open price on the following day. The smart traders pay 0.285% more than the closing prices on the price limit days, but 0.272% less than the limit prices. When they sell shares they receive an average of 0.229% more than the closing prices and 0.0091% more than the opening prices.

5.5 Identification of smart traders

Identifying smart traders is problematic for a number of reasons. The mere fact that the Market Surveillance Department of the Shanghai Stock Exchange identified the ten accounts used in this paper could be evidence that these traders are not that skilled. One might argue that if they were truly skilled, they

[7] 1.09 = 0.0215 / 0.0198; 1.30 = 0.0215 / 1.0165.

would have not been identified. Even if we believe that *smarter* traders exist, the results in this paper can serve as a lower bound of the profitability of these traders.

Some readers may be skeptical of using accounts provided by the market surveillance department. From the econometricians point of view, these accounts were chosen before running any test in this paper and, thus, can be considered out of sample. Also, our sample consists of the only group of accounts that was being tracked by the market surveillance department. In order to check our results, we adopt our own screening procedure. For all the price limit events, we look for accounts whose buying volume is consistently in the top five on the price limit day and whose sale volume is also consistently in the top five percent on the following trading day. We identify five accounts. Four of these accounts are among the ten accounts identified by the market surveillance department of the Shanghai Stock Exchange and they represent 89% of the trading by the top five accounts. Our results do not change qualitatively if we use this sample of accounts.

5.6 Sample size

Some readers may be unsatisfied with our definition of the 357 events when smart traders are active. We chose this definition so as to present comparable tables with consistent sample sizes. Part of our motivation comes from data availability. We only have all market trades on upper price limit days and the following day. This said, we could just as easily have chosen our definition of active smart traders to be the 389 events when smart traders are buying, the 373 events when they are selling, or the 405 events when they are either buying or selling. But with these definitions, there are no qualitative changes in our results.

6. Conclusion

This paper studies the trading behavior of smart traders (statistical arbitrageurs) when other market participants act predictably. We show that a group of traders profits by accumulating shares during days that stocks hit their upper price limits. The traders then sell out quickly the next day for an average overnight return of 0.80% after transaction costs. We stress this is not simply a momentum trading strategy. Neither daily nor overnight momentum is a major factor in this market. We do not find evidence that the smart traders are being compensated for providing liquidity to the market, nor do we believe they are being compensated for taking particularly risky positions.

Our findings are consistent with recent behavioral theories regarding attention-grabbing stocks. We show that unsophisticated (individual) investors have net buy order imbalances directly following an attention-grabbing event. More importantly, we show that the number of first-time buyers in a given stock rises dramatically after a price limit event. In total we provide four separate tests that support the attention-based theory of buying.

We also rule out the possibility that the smart traders profit from trading in stocks with censored information (i.e., those that hit their price limits). If a stock that has a 10% price limit receives news that should raise the price 15% we would expect today's price to jump up by 10% with low volume. The following day's price should then open 5% higher and the overall change of 15% should be permanent. When smart traders are active, we do not see these phenomena. Smart traders are active on high volume days. Price changes around events when the smart traders are active are temporary and not permanent. Put another way, we find that attention-based buying has minimal long-term impact on stock returns as prices revert within ten trading days. This paper makes use of a unique dataset provided by the Market Surveillance Department of the Shanghai Stock Exchange. The data, not previously available, allows us to explore trading behavior in ways that have not previously been possible.

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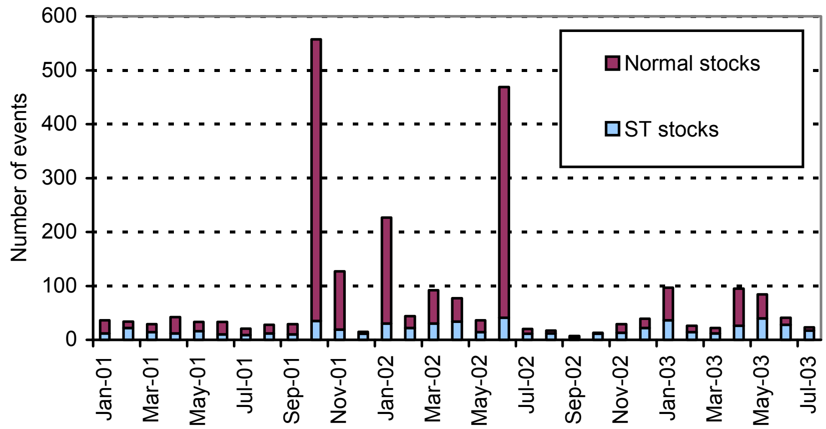
Figure 1: Upper Price Limit Events

This figure graphs the number of upper price limit events. Panel A shows the distribution of all 2,442 upper price limit events during our sample period. Panel B shows the distribution of the 357 price limit events where smart traders are active. Smart traders are said to be active when they buy on a price limit day and sell the following day. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

Panel A: All Upper Price Limit Events



Panel B: Upper Price Limit Events with Smart Traders Active

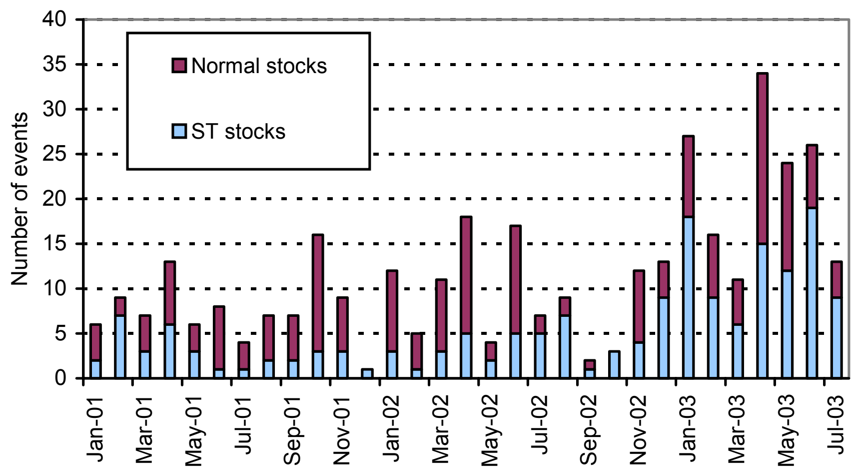


Figure 2: Distribution of Smart Trader Net Profits

This figure graphs smart trader net profits and losses based on trading around price limit events. The graph shows the total profit for all 357 events where smart traders are active. Smart traders are said to be active when they buy on a price limit day and sell the following day. Profits include round-trip transaction taxes, exchange services fees, and brokerage fees. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

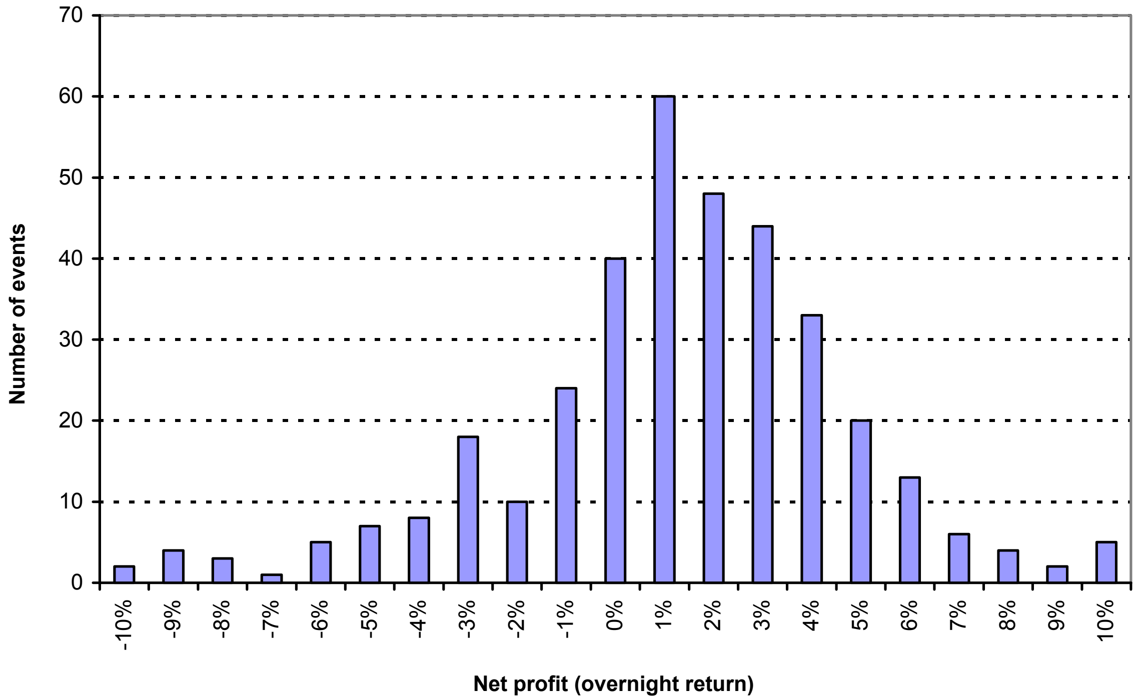


Figure 3: Order Placement Relative to Upper Price Limit Events

This figure graphs the distribution of order submission times. Times are measured in minutes relative to the time that a stock first hits its upper price limit. Over 84.11% of all orders occur in the two hours that surround the upper price limit event. The sample period is from January 2001 to July 2003.

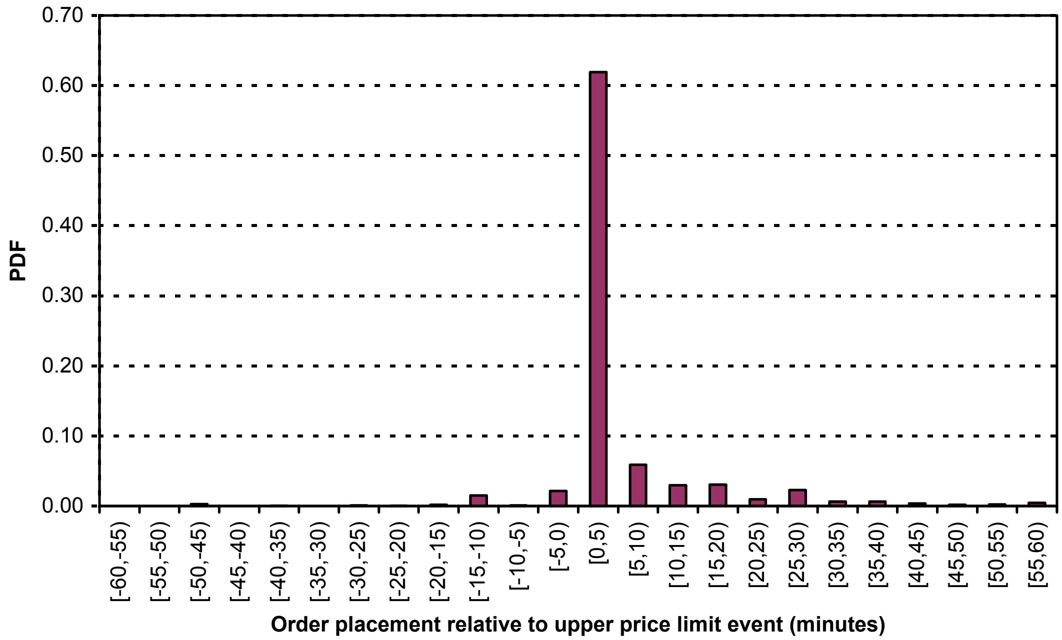


Figure 4: Performance of Stocks after Reaching Price Limits

This figure graphs the average cumulative return and cumulative excess return. Our sample includes the 357 events where stocks reach their upper price limit and the smart traders are active. We compute the mean returns from one day after the price limit event to ten days after the event. We then cumulate returns to get the plotted figure. The cumulative excess return is computed by subtracting the composite index return from the mean stock return. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

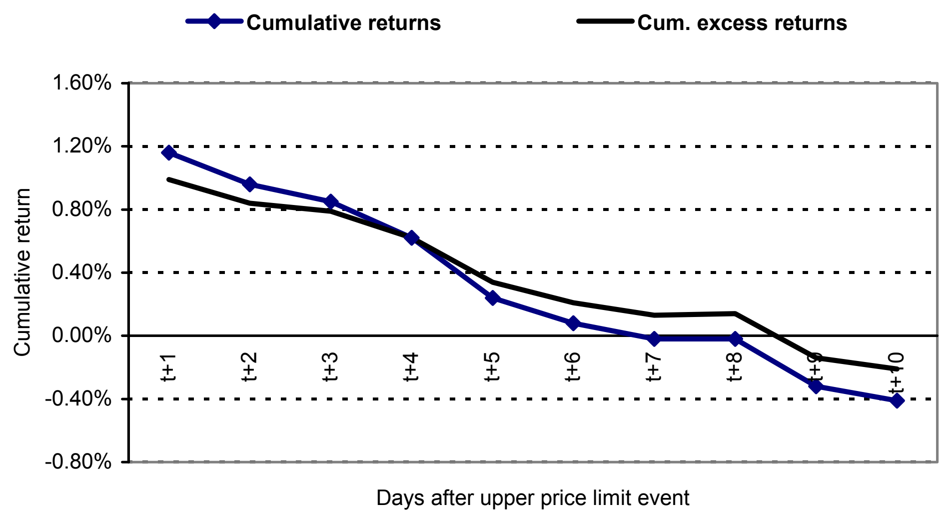


Table 1: Overview of Events and Smart Trader Activity

This table reports summary statistics of price limit events and activity by the smart traders. Price limit events are in units of ticker-days. "Normal" stocks have a ±10% daily price limit, while "ST" stocks have a ±5% limit. A given stock may change classification from normal to ST over time. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

Panel A: Price limit events

A price limit event is defined as a day a stock hits its price limit. Price limit events are in units of ticker-days.

	Normal stocks	**ST stocks**	**Total**
All price limit events	2,434	1,254	3,688
Upper price limit events	1,842	600	2,442
Number of unique stock tickers with upper price limit events	635	76	657*

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

Panel B: Overview of smart trader activity

We treat all ten smart-trader accounts as one (grouped) account. Row (a) matches the second row from Panel A (above). Certain rows add as follows: b+e=f; c+d=f; d+e+g=f.

		Normal stocks	**ST stocks**	**Total**
(a)	Upper price limit events	1,842	600	2,442
(b)	Upper price limit events/smart traders: • buying on price limit day	199	190	389
(c)	Upper price limit events/smart traders: • selling on day following price limit day	195	178	373
(d)	Upper price limit events/smart traders: • buying on price limit day **and** • **not** selling on day following price limit day	12	20	32
(e)	Upper price limit events/smart traders: • **not** buying on price limit day **and** • selling on day following price limit day	8	8	16
(f)	Upper price limit events/smart traders: • buying on price limit day **or** • selling on day following price limit day	207	198	405
(g)	**Upper price limit events/smart traders: • buying on price limit day and • selling on day following price limit day**	**187**	**170**	**357**

Table 2: Overview of Smart Trader Participation

This table reports summary statistics for smart trader trading. For the purposes of this table, we group all ten smart-trader accounts into one (grouped) account. Smart traders are said to be active when they buy on a price limit day and sell the following day. "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, which includes 610 total trading days.

Panel A: Unique dates with smart traders active

	Normal stocks	ST stocks	Total
Unique upper price limit dates or following dates with smart traders active	225	223	358*
Total days in sample	610	610	610
Participation %	36.89%	36.56%	58.69%

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

Panel B: Unique stock tickers with stock traders active

	Normal stocks	ST stocks	Total
Unique tickers with smart traders active	141	61	191*
Unique tickers with an upper price limit event	635	76	657*
Participation %	22.20%	80.26%	29.07%

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

Panel C: Smart traders' fraction of a stocks' turnover when active

We measure the average fraction of a stock's turnover that can be attributed to the smart traders on upper price limit event days and the following day. These measures apply only to upper price limit days and following days when smart traders are active.

	Normal stocks	ST stocks	Average
Upper price limit day	9.76%	16.37%	12.91%
Following day	6.55%	10.85%	8.60%
N	187	170	—

Table 3: Smart Traders Profitability

This table reports summary statistics of profitability for the smart traders. We treat all ten accounts as one large account. We report profits when the smart traders are actively trading around a price limit event. "Normal" stocks have a ±10% daily price limit while "ST" stocks have a ±5% limit. Smart traders are said to be active when they buy on a price limit day and sell the following day. Net profit takes into account the 0.45% round-trip transaction cost explained in Section 3.1. The table presents two measures of profitability to account for the fact that the number of shares sold (at times) does not exactly match the number of shares bought. In addition to average profit, the table shows the 25^{th}, 50^{th}, and 75^{th} percentiles of profitability. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003. Amounts are in RMB.

Panel A: "Normal" stocks

	mean	std. err. of mean	N	25^{th} p-tile	50^{th} p-tile	75^{th} p-tile
Gross profit #1 (RMB)	101,128	21,414	187	-4,691	22,504	112,375
Net profit #1 (return %)	1.16%	0.28%	187	-0.82%	0.92%	3.30%
Gross profit #2 (RMB)	101,701	22,930	187	-2,869	29,040	124,103
Net profit #2 (return %)	1.24%	0.27%	187	-0.65%	0.94%	3.30%

Panel B: "ST" stocks

	mean	std. err. of mean	N	25^{th} p-tile	50^{th} p-tile	75^{th} p-tile
Gross profit #1 (RMB)	23,622	5,415	170	-1,385	9,421	39,223
Net profit #1 (return %)	0.39%	0.24%	170	-0.60%	1.17%	2.67%
Gross profit #2 (RMB)	25,983	6,732	170	-1,385	12,448	45,666
Net profit #2 (return %)	0.40%	0.24%	170	-0.62%	1.03%	2.49%

Table 4: Probit Analysis of Smart Trader Participation

This table reports results of a probit regression of smart trader activity on explanatory variables. Smart traders are said to be active when they buy on a price limit day and sell the following day. The dependent variable takes a value of one if smart traders are active and zero otherwise. We report the change in the probability of smart traders being active for a small change in the continuous variable (for dummy variables the reported change is for a discrete jump.) We treat all ten accounts as one large account. "Normal" stocks have a ±10% daily price lime while "ST" stocks have a ±5% limit. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003. Amounts are in RMB.

$$\textbf{dependent variable} = \begin{cases} 1 & \text{smart traders active} \\ 0 & \text{otherwise} \end{cases}$$

independent variables	**reg #1**	***(z-stat)***	**reg #2**	***(z-stat)***
Dummy (Normal stock=0; ST stock=1)	0.0167	*(1.35)*	0.0121	*(0.99)*
Dummy if [10,50) events on same day	-0.0420	*(-3.64)*	-0.0419	*(-3.60)*
Dummy if [50,100) events on same day	-0.0851	*(-6.56)*	-0.0846	*(-6.62)*
Dummy if ≥100 events on same day	-0.1987	*(-10.72)*	-0.1984	*(-10.62)*
Dummy if opens at upper limit	-0.0676	*(-4.09)*	-0.0669	*(-3.95)*
Time in day stock hit limit	-0.6926	*(-10.11)*	-0.6938	*(-10.13)*
Turnover (t-1)	0.4816	*(3.58)*	—	—
Average turnover for stock	—	—	1.8470	*(2.95)*
Relative turnover (t-1)	—	—	0.0085	*(1.65)*
ln market value (t-1)	0.0047	*(0.58)*	0.0070	*(0.88)*

Table 5: Buy-Sell Imbalances

This table reports summary statistics of buy-sell imbalances for the smart traders, retail investors, corporations, and brokers. We consider the 357 events when the smart traders are active. The imbalance is defined as the difference between the numbers of shares bought and sold by investors of type "i" on day "t" divided by the sum of total shares bought and sold. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

Panel A: Upper price limit day

	mean imbalance	std. err. of mean	N	25^{th} p-tile	50^{th} p-tile	75^{th} p-tile
smart traders	0.871	0.020	357	1.000	1.000	1.000
retail investors	-0.052	0.007	357	-0.089	-0.025	0.003
corporations	-0.064	0.036	357	-0.640	0.000	0.468
brokers	-0.163	0.029	357	-0.636	0.000	0.000

Panel B: Day following an upper price limit day

	mean imbalance	std. err. of mean	N	25^{th} p-tile	50^{th} p-tile	75^{th} p-tile
smart traders	-0.884	0.017	357	-1.000	-1.000	-1.000
retail investors	0.042	0.004	357	0.008	0.028	0.063
corporations	0.022	0.034	357	-0.544	0.000	0.575
brokers	-0.124	0.030	357	-0.439	0.000	0.000

Table 6: Smart Trader Profits and Measures of Attention

This table reports results for the regression of smart trader profit on measures of attention for all the upper price limit events in the sample. Details on calculating our two profit measures (the dependent variable) are given in the text. "Close at limit price" is dummy variable which equals one if the stock price reached its daily limit and close at the limit price and zero otherwise. "Relative volume (t+1)" is a stock-specific measure of turnover on the day following the upper price limit event. Details on how it is calculated are given in the text. Imbalance numbers are defined as buys minus sells over buys plus sells for a specific investor type in a specific stock—for the day following an upper price limit event. We compute separate imbalance measures for retail investors, corporations, and brokers. "Normal" stocks have a ±10% daily price lime while "ST" stocks have a ±5% limit. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

Panel A: "Normal" stocks

	profit measure #1		***profit measure #2***	
	coef.	***(t-stat)***	**coef.**	***(t-sta)t***
constant	-19,805	*(-4.52)*	-22,868	*(-4.90)*
dummy (close at limit)	13,536	*(2.71)*	17,530	*(3.30)*
relative volume (t+1)	19,203	*(7.09)*	19,418	*(6.74)*
retail imbalance	28,525	*(1.01)*	26,263	*(0.87)*
corporate imbalance	1,039	*(0.30)*	-548	*(-0.15)*
broker imbalance	-7,269	*(-1.93)*	-7,483	*(-1.87)*
R-squared	0.0456		0.0452	
obs.	1842		1842	

Panel B: "ST" stocks

	profit measure #1		***profit measure #2***	
	coef.	***t-stat***	***coef.***	***t-stat***
constant	8,361	*(-3.33)*	-11,625	*(-3.78)*
dummy (close at limit)	16,390	*(5.25)*	21,049	*(5.50)*
relative volume (t+1)	6,643	*(3.88)*	7,538	*(3.60)*
retail imbalance	56,403	*(2.15)*	78,852	*(2.46)*
corporate imbalance	5,079	*(2.27)*	6,049	*(2.20)*
broker imbalance	-6,469	*(-1.70)*	-11,970	*(-2.57)*
R-squared	0.1048		0.1171	
obs.	600		600	

Appendix 1: Screening Procedure

The procedure used to identify the ten accounts we refer to as the "smart traders" is an amalgam of different procedures. First, the Market Surveillance Department of the Shanghai Stock Exchange monitors abnormal trading activity. The monitoring includes looking for short-term buying and selling as well as activity 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. Thus, the large volume coming out of two branches in Ningbo were public information. A newspaper article from a Chinese periodical called *21st Century Economic Report* (15-May-2003) highlighted the trading activity of the smart traders (called the "limit order swat team"). The article can be found at the following web address: http://stock.163.com/editor/030315/030315_131381.html

The newspaper article prompted our academic study. When we approached the Market Surveillance Department with questions about the Ningbo traders, it turns out that they were already tracking the group's trading activities. They had been tracking the group for a long time. What's more, this was the only group the surveillance team was tracking related to trading activities on price limit days.

Appendix 2: Momentum and Daily Price Limits

This table reports regression coefficients from different momentum models. In Panel A, we calculate daily momentum where r_{t+1} is either the return using 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". In both cases r_t is the return using 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): $$r_{t+1} = \alpha + \phi r_t + \gamma_l I_{t,lower} + \gamma_u I_{t,upper} + \lambda D_t + \varepsilon_{t+1}$$

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

	A) dep. var = r_{t+1}			B) dep. var = $r_{t+1,\ overnight}$		
	regression A1	regression A2	regression A3	regression B1	regression B2	regression 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 3: Turnover and Liquidity

This table reports relative turnover for the stocks-days in our sample. Data are from the Shanghai Stock Exchange. The sample period is from January 2001 to July 2003.

Panel A: "Normal" stocks

			Relative turnover					
Group	**high return (t)**	**N**	**(t+0)**	**(t+1)**	**(t+2)**	**(t+3)**	**(t+4)**	**(t+5)**
A	0.1003	187	1.7769	1.9393	1.3005	1.0718	0.8373	0.6768
B	0.1002	1,655	1.1107	1.0233	0.4513	0.1923	0.1319	-0.1648
C10	0.0970	7,996	1.0771	0.3665	0.1801	0.0631	-0.0031	-0.1016
C9	0.0849	1,309	0.8214	0.3419	0.1097	0.0103	-0.1036	-0.1900
C8	0.0748	1,782	0.8237	0.3950	0.1066	0.0196	-0.0838	-0.1445
C7	0.0647	2,849	0.6748	0.3047	0.0727	-0.0404	-0.1523	-0.1823
C6	0.0545	4,884	0.5541	0.2121	0.0258	-0.0469	-0.1321	-0.1570
C5	0.0446	9,730	0.3660	0.0894	-0.0441	-0.1071	-0.1344	-0.1632
C4	0.0345	19,624	0.0820	-0.1070	-0.1863	-0.2241	-0.2126	-0.2493
C3	0.0244	42,784	-0.2432	-0.3366	-0.3424	-0.3772	-0.3622	-0.3678
C2	0.0144	92,427	-0.5775	-0.5407	-0.5048	-0.5207	-0.5043	-0.5029
C1	0.0047	160,927	-0.7560	-0.6783	-0.6582	-0.6343	-0.6335	-0.6264

Panel B: "ST" stocks

			Relative turnover					
Group	**high return (t)**	**N**	**(t+0)**	**(t+1)**	**(t+2)**	**(t+3)**	**(t+4)**	**(t+5)**
A	0.0503	170	0.7634	0.9535	0.3930	0.2234	0.1631	0.2280
B	0.0503	430	0.5536	0.4681	0.2830	0.1745	0.1507	0.0173
C5	0.0467	1,226	0.4614	0.2647	0.1191	0.0787	0.0447	0.0191
C4	0.0345	1,120	0.0943	-0.0835	-0.1265	-0.1183	-0.0958	-0.1054
C3	0.0246	2,047	-0.1965	-0.2494	-0.2507	-0.2502	-0.2454	-0.2370
C2	0.0146	3,766	-0.4460	-0.3866	-0.3285	-0.3387	-0.3406	-0.3281
C1	0.0049	5,115	-0.6126	-0.5393	-0.4906	-0.4760	-0.4669	-0.4623

Group	**notes**
A	upper events with smart traders active
B	upper events with 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%)

Appendix 4: Future Volatility

This table reports intraday volatility for the stocks in our sample based on the Parkinson (1980) measure as describe in the text. 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%)