Attention and Trading

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Abstract

This study empirically explores the effects of attention levels on investors' trading behavior and on market price dynamics. Specifically, we analyze the ability of market-wide attention-grabbing events – record-breaking events of the Dow index and front page articles about the stock market – to predict the trading behavior of investors and market returns. The empirical results show that the impact of attention is pervasive across the market. High attention causes individual investors to reduce their stock holdings dramatically when the market level is high and to increase their stock holdings modestly when the market level is low. The aggressive selling by individual investors induces institutional investors to trade and has a negative impact on market prices, reducing market returns by 19 basis points on days following attention-grabbing events.

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The fundamental scarcity in the modern world is scarcity of attention.

Herbert Simon

1 Introduction

Finance models generally assume that investors have infinite cognitive resources and hence can always allocate enough attention to the financial market. However, a large body of psychological literature shows that there are limits to the central cognitive-processing capacity of the human brain.[1] In real life, most investors need to allocate their attention between financial activity and other activities. Since attention is an essential part of decision-making, low attention levels cause investors to be less active in processing information and checking portfolios, and extremely low levels of attention may even lead investors into a hibernation state in the financial market. Thus, financial market events that attract investors' attention should produce abnormal trading behavior and are likely to influence the market price level.

This paper analyzes empirically the following two questions: Do attention levels affect the trading behavior of individual and institutional investors? Do attention levels influence the level of the market prices? Specifically, we analyze the ability of record-breaking events of the Dow index or front page articles about the stock market, that is, market-wide attention-grabbing events, to predict trading patterns and market returns. We find that high attention generates abnormal trading among individual investors, leading to significant changes in short-run market prices and trading volume.

Previous theoretical research shows that attention plays a significant role in investors' learning behavior, investors' trading behavior, and the equity premium.[2] Notwithstanding, few empirical studies directly explore the impact of attention due

[1] See Pashler and Johnston (1998) for a review.

[2] See, for example, Hirshleifer and Teoh (2003), Hirshleifer, Lim, and Teoh (2004), Peng and Xiong (2006), Abel, Eberly, and Panageas (2007), Huang and Liu (2007), and Gabaix and Laibson (2002).

to the difficulties in measuring it.[3] Barber and Odean (2006) argue that to get a direct measure of attention, researchers need "to go back in time and, each day, question the hundreds of thousands of investors." This paper chooses an alternative to seeking such an impossible measure. In particular, we use market-wide attention-grabbing events as a proxy for high attention.

Another obstacle to examine the impact of attention is that attention-grabbing events normally coincide with the release of economically meaningful information. For example, exceptional market returns catch investor attention across the market. However, since abnormal returns may be caused by changes in fundamental economic variables, it is unclear whether the empirical patterns following such events are caused by high attention or the economic information unless we control for the latter. Thus, a good candidate event for our test should attract investors' attention but not contain much economic content. Furthermore, the remaining economic information should be controllable in the tests. We propose that Dow record events and news events fit these criteria.

The Dow Jones Industrial Average Index is the oldest and most visible market indicator in the United States. News of the Dow reaching a record level attracts heavy media coverage and investor attention. However, it is unlikely that such events, which represent the nominal price levels of a portfolio of 30 stocks reaching high levels, contain much economically meaningful information. Even if Dow record events contain some economic information, this information should be captured by the market re-

[3]Some empirical papers find results consistent with limits to attention. Most of such studies show that certain types of public information predicts returns on certain types of portfolios. This implies that stock prices do not fully incorporate public information. Limited attention is a potentially reliable and natural explanation. See, for example, Huberman and Regev (2001), Hirshleifer et al (2004), Hou and Moskowitz (2005), Cohen and Frazzini (2006), DellaVigna and Pollet (2007), and Hong, Torous, and Valkanov (2007). Additionally, DellaVigna and Pollet (2006) document stronger earning drift effect on Friday than that on other weekdays, which is consistent with the hypothesis that investor attention is distracted on Friday by coming weekend. Hou, Peng and Xiong (2006) find that the momentum profits are influenced by the trading volume and the sign of the market return, which they select as proxies for attention. Their empirical results are consistent with the hypothesis that attention should influence underreaction and overreaction of investors. Corwin and Coughenour (2008) document that the number of trades on a stock influences its transaction cost. Such results are consistent with the hypothesis that the specialists face attention constraints and allocate their cognitive resources to active stocks.

turns and levels of broader market indices, which we control in the test.

We control for economical information effects by including the record events on three additional market indices: the Nasdaq Composite Index, the NYSE Composite Index, and the Standard & Poor's 500 Index. As we will discuss later, among the four indices, the broader market indicators, the NYSE and the S&P, have lower visibility, since even the Nasdaq appears nearly 20 times often as the NYSE and the S&P in the titles of the front-page articles on the New York Times and the Los Angles Times from 1983 to 2005. From the alternative hypothesis that posits record events are related to economic fundamentals, we expect record events of the broader market indices, the NYSE and the S&P, to show strong empirical patterns. However, significant empirical patterns emerge only for the highly visible indices (the Dow and the Nasdaq), while no patterns emerge for the economically meaningful indices (the NYSE and the S&P). These results strongly suggest that attention rather than economic information drives our empirical findings.

We confirm and generalize our findings using an alternative measure of attention-grabbing events, namely, prominent media coverage of the stock market. To our knowledge, this paper is the first study to comprehensively collect market news and analyze the impact of such news. We build a hand-collected database of domestic stock market news for the New York Times and the Los Angeles Times from January 1983 to December 2005. A "news event" occurs when both the New York Times and the Los Angeles Times cover the change in the price level of the domestic stock market with front-page articles. News should be the primary mechanism for grabbing the attention of unsophisticated investors, and front-page coverage across multiple national newspapers should boost the level of attention given to financial activity. Moreover, we control for the economic content of such events by including the market return as a control variable.

The news events provide a distinct contribution to our investigation of attention effects. In addition to Dow record events, the market news covers many types of events such as market runs, drops, and other indices hitting new highs. Furthermore,

while Dow record events can only happen when the market price level is high, news events span the periods associated with high price levels (good times) and low price levels (bad times).

Using Dow record events and front-page news events, we examine the ability of market-wide attention-grabbing events to predict trading patterns and market returns. The empirical results indicate that the impact of attention is pervasive across the entire market. To be specific, we have reached the following conclusions:

First, we find that attention has a strong impact on the trading behavior of individual investors. High attention causes individual investors to reduce dramatically their stock positions in good times and to increase modestly their stock positions in bad times. We analyze the trading behavior of individual investors using three independent data sources: individual-investor aggregate order flow from ISSM and TAQ, aggregate daily mutual fund flow from Mutual Fund Trim Tabs, and detailed individual trading records from a large brokerage firm. These three sources provide insights from different perspectives, but yield similar conclusions. For example, our empirical results show that following Dow record events, individual investors sell more stocks, they redeem more shares of mutual funds, and they sell winner stocks more heavily.

Second, high attention also influences the aggregate market price level. In a 75-year sample, Dow record events predict the next-day return of the value-weighted NYSE-AMEX index to be 19 basis points lower. Furthermore, when the Dow reaches 17 "milestones" (hundred marks when the Dow is below 1000 and thousand marks when the Dow is over 1000) for the first time, the next-day market returns experience an additional 28 basis points drop. News events in good times show a comparable negative predictive ability to Dow record events, while news events in bad times have insignificant predictive ability. The results imply that aggressive selling places considerable pressure on market prices and lowers next-day returns.

Third, attention raises the trading intensity of institutional investors in good times. This result suggests that attention indirectly influences the trading behavior of

institutional investors through individual-investor trading behavior and price changes.

The empirical results above are consistent with the following intuition. We document that the direction of abnormal trading by individual investors depends on the market price level, which is an aggregate measure of investors' portfolio characteristics. Attention, however, is not the only mechanism that determines trading decisions. Subsequent to two similar events, an investor could make different trading decisions if her portfolio conditions are different; for example, the decisions she makes when she observes a capital gain are likely different from those she makes when she observe a loss. Fortunately, Dow record events create a similar scenario for most investors. Following Dow record events, price levels are high and investors with different portfolios are likely to experience positive returns and capital gains on their stock investments. Turning to news events, we construct a variable to identify when the market price level is high (good times) to create similar portfolio conditions for the majority of investors in each regime. We find that, indeed, news events predict different trading directions in good and bad times.

The empirical results above also show that attention has a stronger impact on individual investors than on institutional investors. Individual investors are more occupied with other activities and have weaker analyzing capacity than institutional investors. Attention-grabbing events should significantly raise the level of attention individual investors give to financial activities and hence have a stronger direct impact on their trading behavior.

As a final step, we explore how investor preferences, together with high attention levels, drive individual investors' selling behavior as documented above. After attention-grabbing events make individual investors more active, they may sell their stocks in good times as a rational response or due to behavioral bias. That is, while rational investors need to rebalance their portfolios in order to maintain the relative weights between stocks and other investments, individual investors may sell stock shares because they are subject to the disposition effect, whereby investors "sell

winners too early and ride losers too long." (Shefrin and Statman (1985))[4] Using individual trading records from a brokerage firm, we are able to distinguish between these mechanisms. We find strong evidence that the disposition effect together with high attention drives individual-investor abnormal selling behavior; we also find some support for the rebalancing hypothesis. This result also suggests that investors with limited attention are also more susceptible to other behavioral biases.

Our paper is closely related to Barber and Odean (2006), which proposes that stock-specific attention-grabbing events should have strong effects on the stock selection of individual investors when buying, but not when selling. These authors use abnormal returns, abnormal trading volume, and stock-specific news as proxies for attention to test their hypothesis, and they find consistent results.[5] Our paper is different from theirs in the following respects. First, we select different proxies for attention. Dow and market news events make it easier to control for the impact of economic information. Second, Barber and Odean (2006) analyze stock-specific events and explore cross-sectional trading patterns, while we examine market-wide attention-grabbing events and investigate aggregate trading patterns. Finally, while Barber and Odean (2006) focus on the impact on individual investors, our study documents that attention also influences the aggregate market price level. Our results indicate that attention effects are not restricted to individual investors but are quite pervasive across the stock market.

The rest of the paper is organized as follows. Section 2 introduces Dow record events and news events. Section 3 presents results on the impact of attention on individual-investor trading patterns. Section 4 provides results on the impact of attention on market returns, and Section 5 discusses the reactions of institutional investors to high attention. Section 6 presents the conclusions.

[4]The disposition effect is one of the most robust behavioral biases of individual investors. In addition to Shefrin and Statman (1985), voluminous research shows that individual investors are subject to disposition effects. See, for example, Odean (1998), Grinblatt and Keloharju (2001), and Seru, Shumway, and Stoffman (2007).

[5]In addition to Barber and Odean (2006), Seasholes and Wu (2007) also test Barber and Odean's hypothesis with the data from the Shanghai Stock Exchange, and find consistent results.

2 Attention-Grabbing Events

2.1 Dow Record Events

The first type of event we analyze is a Dow record event, which occurs when the closing price of the Dow Jones Industrial Average hits a record high.[6] The Dow Jones Industrial Average Index is the oldest continuing US market index. It was first published on May 26, 1896, representing the average of 12 stocks from various important American industries. The number of stocks increased to 30 in 1928 and has remained the same since. Although the Dow is the most widely used index, it is criticized for being price-weighted rather than value-weighted, which gives relatively higher-priced stocks more influence over the index than their lower-priced counterparts. Figure 1 plots the Dow Jones Industrial Average Index from 1928 to 2005. Due to inflation and the high equity market return, the index shows a strong positive trend.

Dow record events attract heavy media coverage and investor attention due to the Dow's widespread use. As the most visible market index, major news media lists the Dow as the first market index measuring equity market performance. A Dow record often appears in news and attracts great attention. Despite its high visibility, however, the record events should not contain much economic information because the Dow is the nominal price level of 30 stocks with a strong positive trend. Even if Dow record events include certain economic information, the economic content should be captured by the market return and levels of broader market indices, which we control in the analysis.

2.2 News Events

The second type of attention-grabbing event is a news event, which occurs when front-page stories about domestic stock market movements appear in both the New York Times and the Los Angeles Times. Media coverage is one of the main sources of information for investors, with unsophisticated investors relying especially heavily

[6]Due to the strong positive trend of the Dow, the index never hits a record low level.

on the public media since they do not have access to as many information channels as professional investors. In turn, media coverage is the primary mechanism to draw the attention of individual investors.

Several existing studies investigate the relation between security-specific news and different aspects of financial markets.[7] However, only a few studies explore the impact of market news.[8] Market news is potentially more interesting than security-specific news for the purpose of analyzing attention. Peng and Xiong (2006) construct a formal model with attention-constrained investors and conclude that such investors tend to process more market-wide information than firm-specific information. Accordingly, market news may cause more variation in attention levels, leading to significant impacts on trading patterns and market price levels.

The main challenge of such research is the labor required to collect aggregate market news. When collecting news on individual stocks or mutual funds, researchers use search engines with the name or ticker of individual securities as key words – a process that does not require much manual labor. In contrast, extensive labor is needed for collecting market news. First, there are no good key words for search engines. To refer to the general stock market, one could use a large number of common words, including "shares", "stock", "market", "price", "Wall Street", "street", "blue-chips","Dow", "Nasdaq", and so on. However, if we build a long keyword list including many commonly used words, while we would obtain numerous pieces of news, many are not related to the stock market. Furthermore, even with a fairly long keyword list, we miss many pieces of stock market news that do not contain those keywords, such as "A Happy Birthday for the Bull".

[7]See, for example, Barber and Odean (2006), Fang and Peress (2007), and Kaniel, Starks, and Vasudevan (2007).

[8]Culter, Poterba, and Summers (1989) is one of the first empirical studies that explore the impact of news. They check whether the 49 major political and financial events (for example, international conflicts, elections, and changes in financial policies) cause large movements of market price levels, and whether the 50 largest movements follow news containing much fundamental information. They conclude that economic news can only explain small portion of the variance of stock market prices. Tetlock (2007) quantitatively measures content of a popular *Wall Street Journal's* column. He finds that high media pessimism in the *Wall Street Journal's* column puts downward pressure on market prices followed by a reversion.

The articles recorded in our database need to satisfy the following conditions. First, the article must appear either on the first page of the entire paper or on the first page of the business section. Such an article is more likely to grab investors' attention directly as they read the newspaper. Additionally, a front-page story is also likely to report an event that draws common interest across the public media. Second, the title of the article must contain information about the change in the domestic stock market price level. With stock market information in the title, the story is more likely to grab investors' attention to financial market. Moreover, this criterion makes sure that the main focus of the news article is the stock market rather than economic variables. We try to avoid non-financial news with the stock market as a minor point, such as a story about GDP growth that mentions the stock market return in the last paragraph.

Stock market news is hand-collected by seven research assistants from the microfilms of the New York Times and the Los Angeles Times for the period from January 1, 1983 to December 31, 2005. Every RA was first trained by the author with the same six-month sample. In order to reduce human error in the data-collection process, after an RA had finished collecting a two-year sample, another RA checked a random two-month subset of two-tear sample. If there was more than one difference in the two-month checking period, the entire two-year sample was recollected.

The New York Times and the Los Angeles Times are selected as the sources for the news data. According to circulation, only the New York Times, the Los Angeles Times, and the Wall Street Journal have constantly been listed in the top five from 1983 to 2005. We exclude the Wall Street Journal because a larger fraction of its subscribers are financial professionals who are less likely to be influenced by limited attention.

2.3 Association Between the Two Types of Events

Dow events and news events both contribute to our analysis. Dow events set up an elegant stage, while news events furnish a more general setting to investigate attention

effect. The market news covers Dow record events and other events, including market runs, falls, and other indices hitting new highs. In addition, while Dow events occur only when price levels are high, news events do not face such a constraint.

For the sample period from January 1, 1983 to December 31, 2005, there are 473 Dow record events and 804 news events in total. The frequency of Dow record events is 8.2%, which is lower than that of news events, which is 13.9%. The frequency of news events is 30.9% when the Dow reaches a record, more than twice the frequency of typical days, suggesting heavy media coverage for Dow record events.

Furthermore, we confirm the high visibility of the Dow and find that the Nasdaq also receive much higher media coverage than the NYSE and the S&P. In our news data, 59.5% of the articles mention at least one specific index in the title. Among these articles, 92.7% refer to the Dow, 9.4% refer the to the Nasdaq, and 0.5% refer to the S&P. Across our 23-year sample, only one news item has NYSE in its title. Thus, economically meaningful indices (the NYSE and the SP) are less visible, which creates an excellent opportunity to distinguish attention effects from economic information effects in horse racing tests.

3 Individual-Investor Trading Patterns Following Attention-Grabbing Events

In this section, we examine the predictive ability of Dow record events and news events for individual-investor aggregate order flow, daily aggregate mutual fund flow, and the selling decisions of households from a brokerage firm. These data sources provide insight on individual-investor trading behavior from distinct perspectives. Aggregate order flow summarizes individual-investor aggregate trading behavior in the stock market. Mutual fund flow indicates how individuals trade their mutual fund shares, which is interesting for our analysis because attention-constrained investors are likely to choose mutual funds as investment vehicles. The third data source, the detailed trading records from a brokerage firm, not only provides an opportunity to check

trading behavior at the household level, but also enables us to check how the preferences of individual investors combined with attention jointly determine their trading decisions. Using these three independent sources, we reach the same conclusion that high attention strongly impacts individual-investor trading behavior.

3.1 Aggregate NYSE-AMEX Order Flow

3.1.1 Data

Following Barber, Odean, and Zhu (2006) and Hvidkjaer (2006), we use small-size order flow as our proxy for individual-investor order flow. Aggregate flow is constructed from the tick-by-tick transaction data compiled by the Institute for the Study of Securities Market (ISSM) for the period from 1983 to 1992 and the New York Stock Exchange (NYSE) for the period after 1993. The latter database is commonly referred to as the Trade and Quote database (TAQ). This combined database contains the quote and trade information for all the stocks on the NYSE and the AMEX from 1983.

We identify every trade as buyer- or seller-initiated using the procedures outlined in Lee and Ready (1991). The Lee and Ready algorithm is a combination of a quote rule and a ticker rule. The quote rule identifies a trade as buyer-initiated if the trade price is above the midpoint of the recent bid-ask quote[9] and seller-initiated if the trade price is below the midpoint. The ticker rule is adopted if the trade price is on the midpoint. A trade is identified as buyer-initiated if the trade price is above the last executed trading price and seller-initiated if the trade price is below the last trade price. A small fraction of trades cannot be identified for the case in which the trade price is on the midpoint of the recent bid-ask price and is equal to the last trade price.

Trade size is used to distinguish individual and institutional investors, as outlined

[9]Lee and Ready (1991) point out that the execution of trades is commonly delayed for seconds after an order is submitted. Following their procedure, we use bid and ask quote prices 5 seconds before the trade price.

by Lee and Radhakrishna (2000). All trades are partitioned into three bins based on trade size. Small trades are defined as trades less than $10,000, which are used to proxy for individual investor trades. Large trades are defined as trades more than $50,000, which are used to proxy for institutional investor trades. The trades in between are classified as medium trades. To adjust for inflation, trade size bins are based on 1991 dollars and adjusted with the consumer price index.

To obtain the daily aggregate order flow of individual and institutional investors, we estimate the sum of the signed trading dollars for all of the common stocks on NYSE and AMEX[10] within every trade size bin. We then calculate the daily buyer- and seller-initiated turnover of the three trade size bins by normalizing the buyer- and seller-initiated dollar volume by the lagged market value of the NYSE and AMEX. The aggregate order flow of each trade size is estimated as the difference between buyer- and seller-initiated dollar turnover within the corresponding size bin.

Figure 2 illustrates the seller- and buyer-initiated turnover of small- and large-size trades from 1983 to 2001. The top and bottom figures on the left are the seller- and buyer-initiated turnover of small trades, respectively, and the top and bottom figures on the right are the seller- and buyer-initiated turnovers of large trades. Both the buyer- and seller-initiated turnover of small trades increase dramatically from the beginning of 2000, while the turnover of the large trades remain stable over the entire period. Both Barber, Odean, and Zhu (2006) and Hvidkjaer (2006) point out that in recent years, institutional investors commonly break large orders down into smaller ones in order to reduce transaction costs. Since this change causes a fundamental shift in the distribution of trade size and undermines the accuracy of identifying trades initiated by individual and institutional investors, our analysis runs through the end of 1999.

[10]TAQ and ISSM also include the quote and trade information on Nasdaq. However, Nasdaq data is only available from 1987 and has much missing data for six months. Furthermore, the market structure of Nasdaq is different from NYSE and AMEX which may require a different procedure to identify trading directions.

3.1.2 Aggregate NYSE-AMEX Order Flow Following the Dow Record Events

We analyze the impact of attention on order flow in the following predictive regression:

$$ord_{t+1} = a + b\ DOW_t + c\ ord_t + d_1\ ret_t + d_2\ ret_{t-250,t} + \epsilon_{t+1}.$$

The dependent variable, ord_{t+1}, is the order flow of small, medium, or large-size trades on day $t+1$. The variable, DOW_t, is the dummy variable for Dow record events. If high attention influences the trading behavior, we expect to observe significant predictive ability of DOW_t. Lagged order flow, ord_t, is included as a control variable. Chordin and Subrahmanyam (2004) show that order flow is first-order correlated. To control for market return information, we also include the return of the previous day, ret_t, and the cumulative return over the previous 250 trading days, $ret_{t-250,t}$, on the value-weighted NYSE-AMEX in the regression.[11] All series except DOW_t are normalized to have unit variance.

Panel A reports the coefficients and the t-statistics of the above regression. The evidence shows that Dow record events strongly influence individual order flow. The coefficient on DOW_t is significantly negative for small-size order flow, implying that individual investors sell more shares following Dow events. The magnitude is also economically significant. The net selling of individual investors is 17.1% standard deviations higher following Dow record events.

Next, we compare the impact of the record events of the following four market indicators: the Dow Industrial Average Index, the Nasdaq Composite Index, the NYSE Composite Index, and the Standard & Poor's 500 Index. These four indices are the most commonly used market indicators of the last several decades.[12] The

[11] The empirical results remain essentially the same with more lagged returns (such as, the returns over the previous 5 trading days, the previous 22 trading days, the previous 66 trading days, and the previous 125 trading days) as control variables.

[12] The Nasdaq Composite Index was introduced on February 8, 1971, the same day that the Nasdaq market was created, with an initial value of 100. The NYSE Composite Index was created in 1966, with a base value of 50 points, in order to reflect the value of all stocks trading at the exchange. The S&P 500 Index was introduced on March 4, 1957, and contains the stocks of 500 large-cap

NYSE and the S&P are value-weighted broad-market indicators that contain more economic information than the other two indices. However, as our news data show, both indices have low visibility, especially the NYSE. The Nasdaq has higher visibility than the NYSE and the S&P; it should contain the least economic information for our analysis, since the stock universe used to build our aggregate order flow measures does not include any stock listed on it. If visibility rather than economic content is the mechanism driving the results, the highly visible indices rather than the economically meaningful market indicators should show significant predictive ability.

Panel B reports the coefficients and the t-statistics of the horse racing test where we include the record events of the four indices and their interactions as predictive variables. The Dow shows the strongest predictive ability for small-size order flow with a similar magnitude as that in Panel A. The coefficient on the Nasdaq record events is also significantly negative, while the NYSE and the S&P do not exhibit any significant patterns. The empirical results indicate that high attention, not economic information, drives the abnormal net selling behavior of individual investors. The Dow and the Nasdaq also show negative predictive abilities for the order flow of medium-size trades but no abilities for large trades.

Dow record events do not seem to have a strong influence on the trading directions of institutional investors. Despite some patterns in Panel A, the significant predictive capacity disappears in the joint test.

Our empirical results also provide new insight on the trading behavior of individual and institutional investors in general. The slopes of the lagged order flow, c, show that the aggregate order flow of individual investors is more persistent than that of institutional investors. Furthermore, the coefficients on market returns, d_1 and d_2, indicate that individual investors behave as a contrarian trader in the short run and a momentum trader in the long run.

The trading decisions of individual investors should be influenced by the characteristics of their portfolios. Attention level determines investor activeness, while their

corporations.

trading decisions could differ with different portfolios. That is, the same investor with concentrated attention could sell, buy, or even do nothing depending on her portfolio properties. We can obtain significant predictive ability of high attention for aggregate trading behavior only if the majority of investors face similar portfolio allocation problems and simultaneously make the same trading decision. Fortunately, Dow record events provide such a setting with various investors facing a similar scenario: investors hold portfolios with recent positive returns and capital gains. In the third part of this section, the individual trading records data enable us to analyze the question: how do attention and the preferences of individual investors together drive abnormal selling behavior?

3.1.3 Aggregate NYSE-AMEX Order Flow Following News Events

News events provide a more general stage for our analysis. Unlike Dow record events, which only happen in good times, news events are distributed more uniformly over time. However, as usual, generality also brings challenges. Following news events, the majority of investors could face quite different portfolio allocation problems at distinct points in time. We introduce the variable D_t^G to identify those periods in which the majority of investors face a similar scenario as the record events, that is, those periods for which price levels are high. In particular, D_t^G equals one if the closing value-weighted NYSE-AMEX index level of day t falls into the top 10% quantile within the last two years.[13] We refer to such periods as "good times". For the sample from 1983 to 1999, 58.9% of the trading days and 51.0% of news events occur in good times.

The good times dummy variable is completely determined by the market price level. Thus, the question of what it represents is exactly the same as the question of why the market price level is high. The complete market camp believes that in good times, the economy is better, risk is lower, and hence prices are higher. The behavioral camp argues that the market can become overpriced by optimistic

[13]The empirical results are robust across different quantiles and lengths of time.

sentiment in addition to economic fundamentals. Fortunately for our analysis, we do not need to distinguish between the two explanations since D_t^G is constructed to identify scenarios in which various individual investors face similar portfolio allocation problems.

We analyze the predictive ability of news events in the following regression:

$$ord_{t+1} = a + \beta_1\ News_t + \beta_2 D_t^G + \beta_{12} News_t D_t^G + c\ ord_t + d_1\ ret_t + d_2\ ret_{t-250,t} + \epsilon_{t+1}.$$

$News_t$ is the dummy variable for the front-page news coverage, and D_t^G is the dummy variable for high price periods. The coefficient on $News_t$, β_1, gives the predictive ability of news in bad times, and β_{12} is the difference between the predictive abilities of news in the good times and bad times.[14]

Panel B of Table 2 presents the results of the above regression. The impact of news events on small-size net order flow is positive in bad times and negative in good times. β_1 is 0.183 with a t-statistic of 2.17. In bad times, individual investors buy more stocks following news events. β_{12} is -0.399 with a t-statistic of -3.81. The coefficient on news in good times, $\beta_1 + \beta_{12}$, is -0.216 with a t-statistic of -3.88. Individual-investor net selling is 21.6% standard deviations higher following news in good times. For the medium-size trades, while the positive predictive capacity of news disappears in bad times, the negative predictive ability in good times remains strong and significant: $\beta_1 + \beta_{12}$ is -0.170 with a t-statistic of -2.71. Similar to Dow record events, news events show no ability to predict large-size order flow.

[14]In this paper, market news is treated as a pure attention-grabbing event, that is, the front-page news coverage activates inattentive investors but does not play a role after they are activated. An alternative mechanism is that an news event not only activates investors but also could guide investors to make their final trading decisions. The alternative could happen if the news contains strong predictions about the future returns. However, we find that most of market news articles mainly repeat public information (for example, the closing level of Dow and the trading volume of the previous trading day) but do not provide a clear prediction about future returns. We asked two RAs to read the news articles in our dataset on the New York Times in a two-year period. Over 96% of the articles do not provide any predictions about the future returns in the first three paragraphs, which suggests most of the market news articles are neutral to predict the future returns. Even among the remaining articles that include the predictions, most of them offer both positive and negative predictions comprehensively, rather than asserting a strong opinion on the future market performance.

The results above show that news influences the trading behavior of individual investors in both good times and bad times. Such impacts are particularly strong in good times. Moreover, the news results are consistent with the findings from Dow record events, since both Dow record events and news events in good times predict negative order flow of individual investors.

Panel C presents the regressions of order flow on news events and Dow record events together. Dow record events necessarily occur in good times. We only need to add DOW_t to the regression since DOW_t and $DOW_t \times D_t^G$ are the same.[15] The coefficients on news events and on Dow events are both statistically and economically significant in predicting individual order flow.

3.2 Aggregate Mutual Fund Flow

In the last subsection, we document the strong impact of attention on trading behavior in the equity market. If this impact is pervasive in financial markets, attention-grabbing events should also predict aggregate mutual fund flow. In fact, the mutual fund analysis is particularly interesting for our analysis. First, conventional wisdom holds that unsophisticated investors are more likely to choose mutual funds as investment vehicles. Consistent with this view, Peng and Xiong (2006) build a formal equilibrium model and conclude that attention-constrained investors process more market- and section-wide information than security-level information. Such attention allocation across information would make mutual funds more attractive to attention-constrained investors.

Second, we do not need to estimate trader identities with mutual fund flow data. Since individual investors hold about 90 percent of total mutual fund assets,[16] the risk of mismeasuring is low for mutual fund flow data.

Using the mutual fund flow data, we obtain empirical results consistent with the

[15]Strictly speaking, DOW_t and $DOW_t \times D_t^G$ need not be the same, since D_t^G is based on the value-weighted NYSE-AMEX index instead of the Dow. However, in our sample period from 1983 to 1999, these two variables are exactly the same.

[16]See the 2006 Investment Company Fact Book by Investment Company Institute.

findings in the last subsection: high attention causes individual investors to redeem mutual fund shares in good times and to buy shares in bad times.

3.2.1 Data

The daily mutual fund flow data come from Mutual Fund Trim Tabs, published by Trim Tabs Financial Services of Santa Rosa, California. The data include the daily aggregate net flow (inflow minus outflow) from February 1998 to December 2005 for their sample of equity mutual funds. Edelen and Warner (2001) analyze a shorter sample period from the same source and document that the Trim Tabs data contains 16.5% (20%) of all US equity mutual funds by number of funds (by net assets).

The mutual fund flow of Trim Tabs is calculated from net asset value (NAV) which is publicly available, and total asset value, which is privately received by Trim Tabs in the morning of the next day. Despite the obvious accuracy of NAV, total asset information is delayed one day for some funds. The first issue of Mutual Fund Trim Tabs notes that there should be a "lag on updating total assets" for a significant portion of funds. Edelen and Warner (2001) also highlight this problem and analyze its influence on their conclusions. Consequently, the daily aggregate mutual fund data comprise two-day average series. The aggregate flow reported at day $t + 3$ includes the flows of some funds in day $t + 2$ and the flows of the other funds in day $t + 1$. This property does not pose a problem for our analysis since we investigate attention with predictive regressions, in which the attention-grabbing event at day t is used to predict the average flow of days $t + 1$ and $t + 2$.

3.2.2 Results

Table 3 presents the regressions of aggregate fund flow on attention-grabbing events, lags of the market returns, and lags of fund flow. With a subsample from the same data source, Edelen and Warner (2001) document the fund flow's complicated autocorrelation structure of the fund flow: a negative autocorrelation with close lags and a positive autocorrelation with far lags. We include eight lags of fund flow in

our analysis and find a similar autocorrelation structure with a longer sample period. The empirical patterns below are unaffected by the choice of lag number.

Following Dow record events, individual investors redeem more fund shares. The coefficient on Dow events is -0.344 with a t-statistic of -2.70 in Column 1. Net outflow is 34.4% standard deviations higher following Dow events. Based on the total assets in equity mutual funds in 1999,[17] this magnitude implies that net outflow is $1.4 billion higher on days following a Dow record.

Column 2 presents the regression of fund flow on the record events of the four indices. The evidence suggests that exceptional redemption patterns are caused by attention rather than by economic information. The coefficients on both the Dow and the Nasdaq are significantly negative and neither of the coefficients on the NYSE or the S&P is significantly different from zero.

Columns 3, 4, and 5 report the results of news events. The news shows significant predictive ability in good and bad times. In Column 4, the coefficient on news is 0.220 with a t-statistic of 2.11, and the coefficient on the interaction of news and D_t^G is -0.524 with a t-statistic of -2.68. The sum of the two coefficients is -0.304, which is significant. Thus, net outflow is 30.4% higher following news in good times. In addition to the variables in Column 4, Column 5 adds the Dow dummy as an additional regressor. The magnitude and significance remain necessarily the same for most of the estimates, which illustrates that both news and Dow events have a strong influence on fund flow.

In sum, this subsection explores the effect of attention on mutual fund flow. The empirical results consistent with those of the last subsection: individual investors decrease their stock holdings following attention-grabbing events in good times, and modestly increase their holdings following the events in bad times. Hence, high attention not only influences individual investors who actively trade individual stocks, but also the households who invest in mutual funds.

[17] According to the 2000 Mutual Fund Fact Book by Investment Company Institute, the total assets managed by equity mutual funds amounts to $4.04 trillion at the end of 1999.

3.3 Individual-Investor Transactions

The most salient impact of high attention on individual trading, which is documented in the last two subsections, is to cause individuals to reduce their stock holdings aggressively in good times. In this subsection, we study individuals' selling decisions through logistic regressions. The data include the detailed trading and position records of all households in a large discount brokerage firm. Different from the previous two aggregate data sources, this data source provides us an opportunity to check trading behavior at the household level. The results show that the probability of selling stock by households is significantly higher after attention-grabbing events.

Furthermore, the detailed portfolio information of the third source enables us to investigate how the preferences of individual investors together with attention cause the abnormal selling among individual investors. Such patterns could be driven by the rebalancing need or the disposition effect. On the one hand, individuals may rebalance their portfolios in order to maintain the relative weights of stocks and other investments such as bonds. After an attention-grabbing event in good times, individual investors become more active and, realizing that the recent positive equity return leads to too high weights on stock, they sell certain shares of their stocks to adjust the relative weights back to desired levels. On the other hand, individual investors with concentrated attention may sell stocks because they are subject to the disposition effect, whereby investors "sell winners too early and ride losers too long." (Shefrin and Statman (1985)) The disposition effect is one of the most robust behavioral biases of individual investors. According to this hypothesis, after the attention levels of investors are raised, they notice many winner stocks in their portfolios and decide to sell those winners due to their behavioral bias. The empirical findings provide strong support for the disposition effect and some evidence for the rebalancing hypothesis.

3.3.1 Data

The data record the trading and position information of 78,000 households from January 1991 to December 1996. The brokerage firm labels households as general (60,000 households), affluent (12,000 households), or active household (6,000 households), with those that make more than 48 trades in any year classified as active, those with $100,000 in equity at any point as affluent, and all others as general.[18] Active households are excluded from our analysis, since the target group of our analysis comprises the investors with attention constraints.[19]

Most individual investors sell only the stocks that they own. That is, they do not sell short. This feature makes it possible to investigate selling decisions with logistic regressions, because we can focus on the stocks in investors' portfolios. Since an individual investor normally invests only in a few common stocks,[20] the potential candidate for selling in our analysis is among the several stocks in the investor's portfolio instead of the several thousand stocks in the market.

We compile stock-level holdings data for all the sample investors. Each observation represents a stock in one investor's portfolio on a given day. A stock is added to the panel data after the household buys this stock and is deleted after the stock is completely sold out. In the rest of this paragraph, we provide an example to illustrate how the panel data are constructed. Assume there are two investors A and B and the entire sample length is 10 days. Investor A buys one share of IBM on the second day and sells the share on the fifth day. He also buys two shares of Microsoft on the third day, sells one share on the sixth day, and sells the other share on the ninth day. Investor B buys one share of IBM on the fifth day and holds it until the end of the period. B shorts a share of Microsoft on the fourth day and buys one share on the ninth day. For investor A, IBM is included in the sample from the third day to the fifth day, and Microsoft from the fourth day to the ninth day. For investor B, IBM

[18] If a household qualifies as both active and affluent, it is labeled an active household.

[19] The empirical patterns are weaker but significant if we include active traders in the sample.

[20] Barber and Odean (2006) document that the mean household holds 4.3 stocks and the median household hold 2.6 stocks in these data.

is included from the fifth day to the tenth day, with Microsoft not included. In total, our sample consists of $15(3 + 6 + 6)$ observations. Finally, we construct $Sell_{i,j,t+1}$, which equals to one if investor i sells the stock j partly or completely on day $t + 1$, and zero otherwise.

Without the feature that most individual investors do not sell short, we would have much more data, since the potential candidates for selling are all the stocks in the market. Such huge data would bring tremendous estimating burden, making any estimation impossible.[21] In fact, to test individual buying behavior with a similar methodology, impossibly huge data are required, because the candidates of purchase are all the stocks in the market.

3.3.2 Results

Table 4 reports the coefficients and the t-statistics of the logistic regressions for the record events of the four indices. The dependent variable is $Sell_{i,j,t+1}$, which equals to one if investor j sells stock i partly or completely on day $t + 1$. In addition to the variables listed in the table, we also include the lagged returns on the value-weighted market index and lagged returns of the stock as control variables. To address the concern about correlated residuals, two types of t-statistics are present in the table. The first type is estimated from the standard procedure of the logistic regression. The second is the clustered standard deviation, which allows the residuals on the same day to be correlated.

Regression 1 tests the predictive ability of the four record events for households' selling decisions. The Dow and the Nasdaq events predict higher possibility of selling a stock, while the NYSE and the S&P exhibit no significant patterns. The coefficient on the Dow is 0.139, which implies that the odds ratio is 14.9% higher following Dow record events. Since the probability of a sale is relatively low, the magnitude of the change in odds ratio should be close to the magnitude of the probability change in

[21] Even the dataset that only includes the stocks in investors' portfolios contains 75,820,033 observations.

selling. Hence, following Dow record events, the probability of selling is around 14.9% higher. High attention significantly raises the possibility of selling.

Next, we test whether disposition effects or rebalancing needs drive abnormal selling behavior of individual investors following attention-grabbing events. The disposition effect hypothesis suggests that investors are more likely to sell winner stocks than losers. The rebalancing hypothesis implies that investors sell stocks with positive cumulative returns from the last time they adjusted their portfolios. It is straightforward to test the rebalancing hypothesis. We define $D^{Pos}_{i,j,t+1}$ to be one if the cumulative return of stock i from the last time investor j trade is positive.

To test for the disposition effect, we need to specify the reference point from which gains and losses are determined. Some possible choices are the average purchase price, the highest purchase price, the lowest purchase price, and the last purchase price. Following Odean (1998), we select the average purchase price as the proxy for the reference point. The empirical patterns are unaffected by this choice. For the observations when a sale takes place, we compare the selling price with the average purchase price to determine whether the stock is a winner for the investor. For the rest of the observations, we compare the closing price on the day with the average purchase price. Finally, we construct the variable $D^{Win}_{i,j,t+1}$, which equals one if the selling price or the closing price of stock i is higher than the average purchase price by investor j on day $t+1$.

We test the disposition effect in Regression 2, where we also include $D^{Win}_{i,j,t+1}$ and the interactions between the four record events and $D^{Win}_{i,j,t+1}$. If the disposition effect is one of the mechanisms that drive abnormal selling, we expect to observe a significantly positive coefficient on the interaction term between Dow record events and $D^{Win}_{i,j,t+1}$, which would imply that attention effects are stronger for winner stocks. The results support the view that disposition effects together with high attention lead to the abnormal selling behavior. The coefficient on the interaction between Dow events and the winner dummy is 0.114, which is significant with both standard deviation estimating procedures. In contrast, no significant empirical patterns emerge for the

NYSE and the S&P. Additionally, the coefficient on the Dow itself is not significant in accordance with the t-statistic from the clustered standard deviations. This result demonstrates that high attention increases the probability of selling winner stocks significantly and that the impact on losers is relatively weak. Moreover, the coefficient on $D^{Win}_{i,j,t+1}$ is 0.460 with a t-statistic of over 30, which provides strong support for disposition effects in general.

Regression 3 jointly tests the disposition effect and the rebalancing hypothesis. In addition to all of the variables in Regression 2, we also include $D^{POS}_{i,j,t+1}$ and the interaction terms. The coefficient on $DOW_t D^{POS}_{i,j,t+1}$ is 0.028, which is not significantly different from zero, and the coefficient on $DOW_t D^{Win}_{i,j,t+1}$ is 0.105, which is significantly positive. Hence, the influence of attention is not significantly different for the stocks with positive returns and those with negative returns, while the attention impact is stronger for winner stocks than losers. We find some empirical support for the rebalancing hypothesis. The coefficient on $NAS_t D^{POS}_{i,j,t+1}$ is significantly positive with a magnitude of 0.073, which shows that the impact of Nasdaq record events is stronger for the stocks with positive returns. Moreover, the coefficients on both $D^{Win}_{i,j,t+1}$ and $D^{POS}_{i,j,t+1}$ are significantly positive, which suggests that, in general, individual investors follow both investing rationales.

In Regression 4, we report the ability of the record events to predict complete sales. Different from the above regressions, the dependent variable is $Comsell_{i,j,t+1}$, which equals one when investor j sells stock i completely on day $t+1$. According to the rebalancing hypothesis, an investor should sell stocks partly to maintain the relative weights across her stock investments. Thus, a complete sale is less likely to be caused by the rebalancing need. The strong predictability of complete sales would imply that the disposition effect, at least partly, drives the abnormal selling patterns. From the empirical results, the Dow and the Nasdaq predict a higher probability of complete selling, while the other two indices show no patterns.

Table 5 reports the coefficients and t-statistics for news events. The first line presents the regression of $Sell_{i,j,t+1}$ on $News_t$. The coefficient on $News_t$ is 0.206,

which is both statistically and economically significant. Thus, news events, like Dow record events, raise the probability of selling.

Regressions 2, 3, and 4 analyze the rebalancing hypothesis and the disposition effect. We find strong support for the disposition effect but little evidence for the rebalancing hypothesis. In Regression 3 that jointly tests the two hypotheses, the coefficient on $News_t$ is 0.123, and the coefficient on the interaction of $News_t$ and $D_{i,j,t+1}^{Win}$ is 0.121, which is significant. The impact of attention on winner stocks is twice that on losers. The coefficient on the interaction of $News_t$ and $D_{i,j,t+1}^{Pos}$ is 0.015 and not significantly different from zero. Regression 4 shows that news events predict higher possibilities of complete sales. This finding provides additional evidence that the disposition effect and attention jointly drive the abnormal selling behavior.

In this subsection, we do not include D_t^G when we test for the effects of news events. The purpose of constructing D_t^G is to summarize investor portfolio conditions. With the detailed trading records, we obtain two individual-level measures, $D_{i,j,t+1}^{Win}$ and $D_{i,j,t+1}^{Pos}$, which measure the individual portfolio properties better than the aggregate-level measure, D_t^G.

The positive coefficients on the interaction between attention-grabbing events and winner dummies not only imply that attention effects are stronger for winner stocks; the results also indicate that the disposition effect is stronger with high attention. This result suggests that investors with limited attention are more susceptible to the disposition effect, since following attention-grabbing events, these investors are more active and we observe stronger disposition effects.

To summarize this subsection, we find results consistent with the previous subsections: high attention directly impacts the selling behavior of individual investors. We also explore how preferences of individual investors jointly with high attention cause the abnormal selling. The empirical evidence casts strong support for the disposition effect while providing some evidence for the rebalancing hypothesis.

4 Market Returns Following Attention-Grabbing Events

The previous section demonstrates that high attention strongly influences individual-investor trading behavior. In this section, we will explore whether attention also impacts the aggregate price level. We find that Dow events predict a lower next-day return on the value-weighted NYSE-AMEX index. The news events show a similar negative predictive ability in good times, while news displays no significant predictive capacity in bad times. Thus, attention moves the aggregate price level in good times when individual investors aggressively sell stock and fund shares following attention-grabbing events. Such results suggest that the depressed price level is caused by the abnormal selling behavior of individual investors.

Table 6 presents the ability of attention-grabbing events to predict daily returns on the value-weighted NYSE-AMEX index. In the regression, we also include the lag of the returns, the lag of market trading volume, and the interaction between the two as control variables. Gervais, Kaniel, and Mingelgrin (2001) show that higher volumes predict higher returns. Campbell, Grossman, and Wang (1993) demonstrate that trading volume also influences the first autocorrelation of returns. Hence, the interaction term could also contain predictive information for next-day returns. The empirical results are essentially the same in the regression with the lagged return as the only control variable.[22]

Regression 1 presents the results of regressing market returns on the record events of the four indices and control variables. The sample period begins in 1974, three years after the Nasdaq, the youngest index among the four was introduced. The Dow events predict next-day return at 28.4 basis points lower with a t-statistic of -5.07. Another visible index, the Nasdaq, predicts next-day return at 7.5 basis points lower,

[22]The coefficients and the significance levels of the Dow dummy and the news dummy are very stable with different sets of control variables. For example, if we add volatility as an additional control variable in the predictive regression, the coefficients and the t statistics of the Dow and news dummy variables remain essentially the same.

which is significant using a one-sided t-test. The coefficients of the NYSE and the S&P are insignificantly different from zero.

Regression 2 reports the results with the record events of the Dow and the S&P for a long sample from 1931 to 2005. Except for the Dow Jones Industrial Average Index, the only index with a long history in the US is the Standard & Poor's Composite Index, which was introduced in January 1928 and included 90 stocks until 1957.[23] On March 4, 1957, the index was extended to contain a total of 500 stocks. The coefficient on the Dow is -0.193 with a t-statistic of -4.73, while the coefficient on the S&P is 0.013 with a t-statistic of 0.45. The empirical results imply that the next-day return is 19.3 basis points lower following Dow record events. Regressions 3 and 4 report the results of the Dow and the S&P record events for subsample analysis, which are consistent with the findings for the entire sample.

The record events of the visible indices show strong negative predictive ability for next-day market returns, while the predictive ability disappears for the economically meaningful indices. These results indicate that high attention causes lower market price levels following Dow record events.

The long sample period enables us to analyze another type of attention-grabbing events, namely, "milestone events", which rarely happen but are interesting for analyzing attention. We define a milestone event as an instance of the closing level of the Dow breaking hundred marks (when the Dow is below 1,000) or thousand marks (when the Dow is above 1,000) for the first time. Such events are highly visible but should contain no more economic information than standard Dow record events, since the impact of hundred or thousand marks should be purely psychological. Compared to Dow record events and news events, milestone events rarely happen. Even with a 75-year sample from 1931 to 2005, there are only 17 milestone events. Regression 5 presents results with $Milestone_t$ as an additional regressor. The slope of $Milestone_t$,

[23]The Nasdaq Composite Index was created on February 8, 1971 with initial value 100, and the NYSE Composite Index was introduced on January 1, 1966 with initial value 50. The data of the S&P composite index in the period from 1928 to 1957 is downloaded from William Schwert's website. See Schwert (1990) for a description of the data.

which demonstrates the additional impact of milestone events on the market return, is -0.277 with a t-statistic of -2.67. The slopes of Dow_t and SP_t remain essentially the same as in Regression 3.[24] These results suggest that milestone events, which grab more investor attention, have larger impacts on price levels than standard Dow record days. The market returns are 46.4 basis points lower after milestone events. We also explore the impact of milestone events on individual-investor trading patterns and, in most cases, obtain consistent but insignificant results due to few milestone events in the sample periods.

Finally, Regression 6 reports the results of the regressions of next-day returns on news and the good times dummy. The coefficient on $News_t$ is 0.088, which is not significantly different from zero. The coefficient on $News_t \times D_t^G$ is -0.238 with a t-statistic of -2.17. The sum of these coefficients is -0.150, with a t-statistic of -2.70, which indicates that the returns are 15.0 basis points lower following news events in good times.

News events in good times, like Dow record events, show a strong negative predictive ability for next-day market returns. The results suggest that while modest buying behavior cannot move the price level significantly in bad times, aggressive selling by individual investors in good times depresses the market price. The empirical evidence from the last section shows that after attention-grabbing events in good times, individual investors sell more stocks, which could directly lower price levels, and redeem more shares of mutual funds, which could depress price levels through the trading activities of mutual fund managers.

The negative impact on market returns persists for more than one day. For example, Dow record events predict that the cumulative market returns of the following three days are 44.3 basis points lower for the sample from 1974 to 2005. Furthermore, the record events also seem to foresee a price reversal after the price slide of the first several days. However, we do not obtain significant results in this case, due to more

[24]We can define similar milestone events for the S&P Composite Index. In the regression including these events, the coefficient on the S&P milestone events is not significantly different from zero and all the other coefficients remain necessarily the same.

noise as we extend the length of the cumulative returns.

5 Potential Roles of Institutional Investors

Section 3.1 analyzes aggregate order flow of individual and institutional investors following two types of attention-grabbing events. In contrast to the strong influence on individual-investor order flow, high attention does not show significant predictive ability for aggregate institutional-investor order flow. Two possibilities could lead to such an outcome. First, high attention does not affect institutional investors. Second, attention affects the two groups of institutional investors in opposite ways, which cancels out the effects on aggregate flow. We propose a hypothesis consistent with the second possibility. Given our data constraints, we cannot execute a rigorous test for this hypothesis. Instead, we carry out a suggestive test by examining the predictive ability of the attention-grabbing events for small, medium, and large-size trading volumes. High attention raises the trading volume of institutional investors in good times, which is consistent with the second hypothesis.

Based on intuition, the behavior of institutional investors should be less affected by attention-grabbing events since the majority of them always pay a relatively high level of attention to investment activity. However, high attention can indirectly influence institutional investors since institutional investors may react to individual-investor aggregate trading behavior or to price changes. We have shown that individual investors redeem their fund shares following attention-grabbing events in good times. Although mutual fund managers may be unaffected directly by the events, the high outflow could force them to follow individual investors and sell stocks, moving the price levels even lower. Other funds (for example, pension funds), which do not need to follow individuals, should observe such price movement and may decide to counter individual investors. Thus, following Dow events, mutual funds and pension funds may trade against each other, in which case the direction of the aggregate order flow of institutional investors would depend on the relative magnitude of the two sides. To

rigorously test the above hypothesis, we would need the order flows of mutual funds and pension funds. Unfortunately, we cannot find such data at this time.

This hypothesis also has implications for the trading volume of institutional investors. Despite different trading directions, both groups of institutional investors should increase their trading intensity following attention-grabbing events, leading to higher aggregate trading volume of institutional investors. In contrast, if attention does not influence institutional investors at all, attention should not impact trading volume either.

Table 7 presents the regressions of small, medium, and large-size trading volumes on attention-grabbing events and a set of control variables.[25] In Panel A, only Dow events and the control variables are included. Following the Dow hitting a record, the trading volumes of small, medium, and large size are all higher, which implies that both individual and institutional investors trade more intensely. Panel B presents the regressions with the four indices. Only highly visible indices predict a higher volume, which demonstrates that high attention raises the trading intensity of all investors.

In Panel C, we report the results for news events. We expect stronger effects in good times for two reasons. First, we have documented that individuals sell more aggressively in such periods, which should lead to stronger selling of mutual funds. Second, we also document that news only has a price impact in good times. Since other institutional investors, such as pension funds, are induced to trade by price changes, they should also trade more in such times. The empirical results are consistent with these expectations. The coefficient on the interaction of news and good times, β_{12}, is significantly positive, while the coefficient of news, β_1, is not significantly different from zero. High attention raises the trading volume of institutional investors in good times but has little impact on institutions in bad times.

[25]The set includes the lagged trading volume of the corresponding trade size and the absolute values of the lagged market returns.

6 Conclusion

This paper analyzes the impact of attention on the stock market. The evidence demonstrates that the impact is pervasive across the market. High attention causes individual investors to dramatically reduce stock positions in good times and modestly increase stock positions in bad times. The impact of attention is not restricted to individual investors. The abnormal selling behavior of individual investors lowers the market price level and induces institutional investors to trade. Moreover, high attention also brings in stronger disposition effects.

These findings have implications for other research topics in finance. First, we provide some consistent empirical results for the literature on infrequent trading, which claims that investors should trade infrequently with the cost of monitoring portfolios. Our results also indicate that attention is one source of the cost of monitoring portfolios.

Our paper also sheds light on the time-varying degree of market efficiency. The empirical results suggest that attention-constrained investors are more subject to the disposition effect. Since high attention activates many behavioral traders, attention should be a state variable that influences the efficiency of the entire market.

Finally, our research also has implications for the microstructure literature. Attention-constrained investors allocate fewer cognitive sources to investment activities and process fewer pieces of information. High attention increases the number of active uninformed investors and the magnitude of uninformed trading in the market. Our results suggest that microstructure models should integrate attention and assign it a significant role.

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Figure 1: The Dow Jones Industrial Average Index from 1928 to 2005.

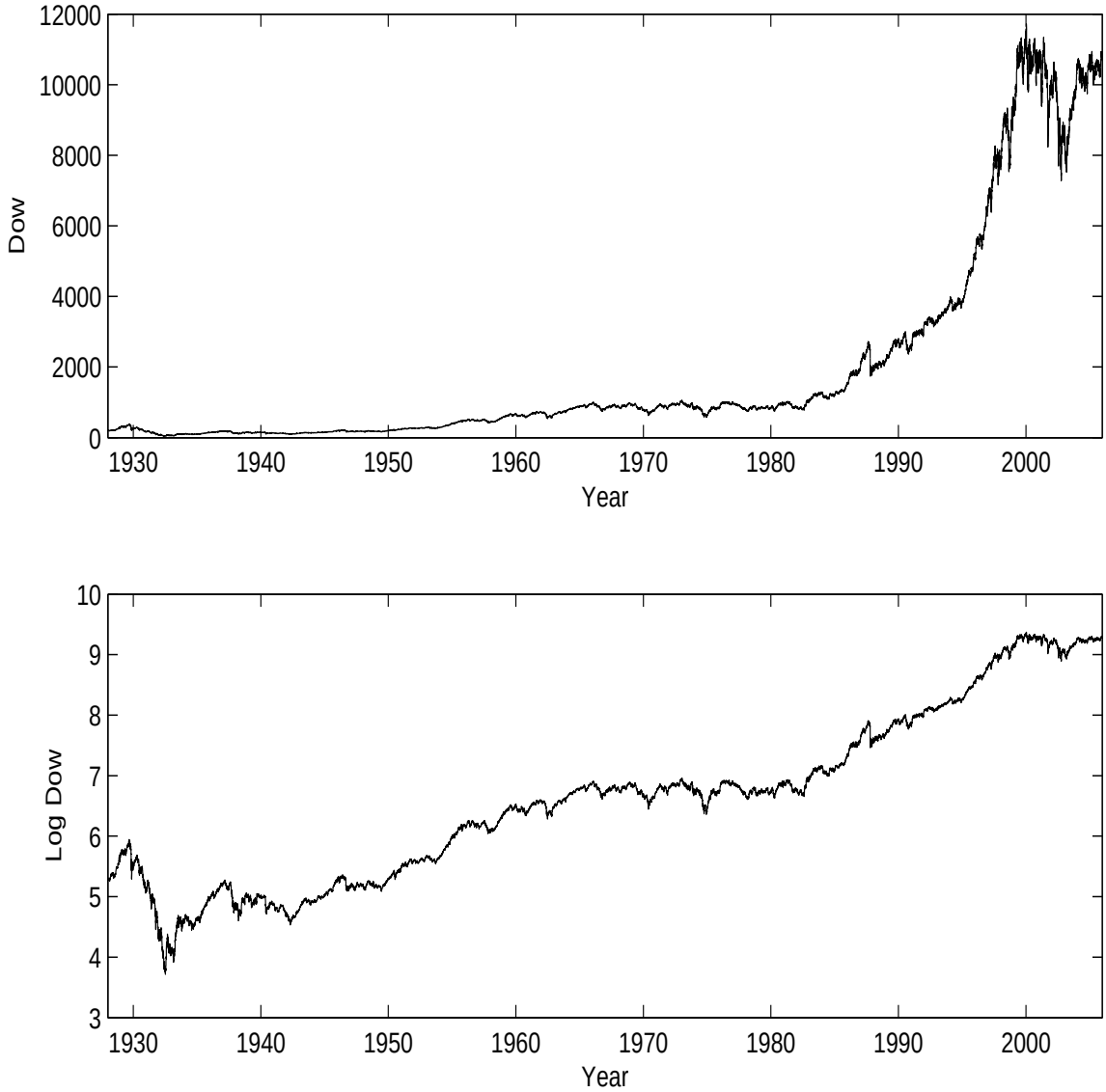
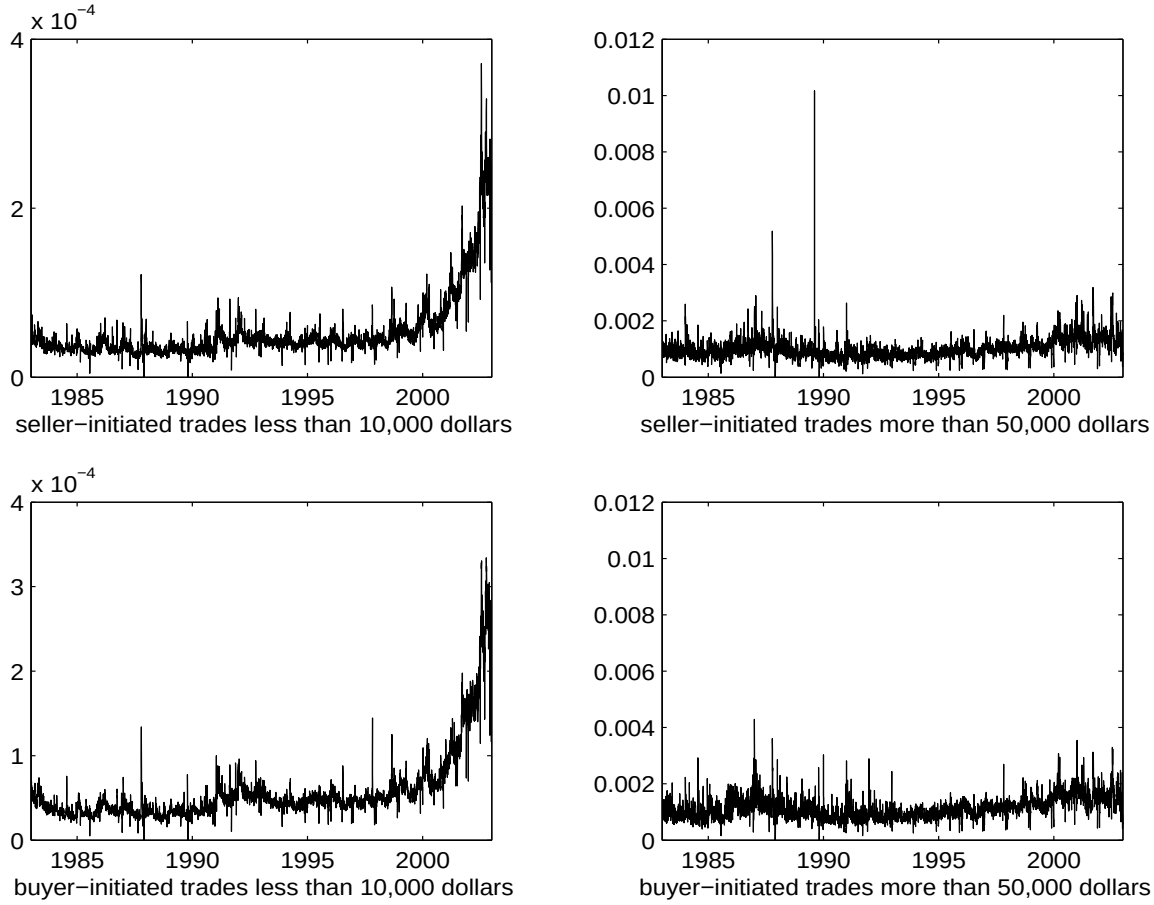


Figure 2: Buyer- and Seller-initiated Turnover for Small or Large Trades.



The top and bottom figures on the left are the seller- and buyer-initiated turnover (dollar volume normalized by the lag of market value) of small trades. The top and bottom figures on the right are the seller- and buyer-initiated turnover of large trades. While the turnover of large trades remains stable in the entire sample period, that of small trades show positive trend from 2000. We end our order flow analysis at the end of 1999 for the reasons discussed on Page 13.

Table 1:
Aggregate Daily Order Flow Following Dow Record Events
(1983-1999)

Panel A: $ord_{t+1} = a + b\ DOW_t + c\ ord_t + d_1\ ret_t + d_2\ ret_{t-250,t}$

	a	b	c	d_1	d_2	R^2
small	-0.036	-0.171	0.559	-0.216	0.057	0.232
	(-1.21)	(-4.30)	(17.25)	(-8.30)	(3.18)	
medium	0.016	-0.103	0.326	-0.065	0.008	0.076
	(0.50)	(-2.31)	(11.37)	(-2.31)	(0.38)	
large	0.049	0.147	0.116	0.159	-0.046	0.064
	(1.55)	(2.42)	(1.96)	(5.43)	(-1.94)	

Panel B: $ord_{t+1} = a + b_1 DOW_t + b_2 NAS_t + b_3 NY_t + b_4 SP_t + b_{12} DOW_t NAS_t + b_{13} DOW_t NY_t$
$+ b_{14} DOW_t DP_t + b_{23} NAS_t NY_t + b_{24} NAS_t SP_t + b_{34} NY_t SP_t + c\ ord_t + d\ ret_t + d_2\ ret_{t-250,t}$

	b_1	b_2	b_3	b_4	b_{12}	b_{13}	b_{14}	b_{23}	b_{24}	b_{34}
small	-0.210	-0.168	0.109	0.118	-0.007	-0.047	0.052	0.114	-0.079	-0.110
	(-3.30)	(-2.52)	(0.95)	(1.47)	(-0.07)	(-0.34)	(0.41)	(0.64)	(-0.57)	(-0.80)
medium	-0.194	-0.109	0.186	0.174	-0.071	-0.016	0.141	0.049	0.016	-0.300
	(-2.56)	(-1.77)	(1.22)	(1.55)	(-0.46)	(-0.10)	(0.96)	(0.25)	(0.09)	(-1.93)
large	0.066	-0.175	0.051	0.155	-0.016	0.020	0.011	0.245	-0.018	-0.130
	(0.86)	(-1.04)	(0.48)	(1.53)	(-0.11)	(0.17)	(0.09)	(1.52)	(-0.12)	(-0.98)

The dependent variables are the order flow of small, middle, and large trades. Trades less than $10,000 dollars are defined as small trades, trades more than $50,000 are defined as large trades, and those in between are classified as middle trades. For a specific size, the order flow is defined as the buyer-initiated dollar turnover minus the seller-initiated turnover of NYSE-AMEX. Finally, the order flow is detrended by the average of the flows over the last 250 days. DOW_t is the dummy variable for Dow record events, which is 1 if the close level of the Dow Jones Industrial Index hits a record high on day t. NAS_t, NY_t, and SP_t are the dummies for the record events of the Nasdaq Composite Index, the NYSE Composite Index, and S&P 500 Index, respectively. ret is the return of the value-weighted NYSE-AMEX index. All of the variables except the dummy variables are normalized to have unit variance. The numbers in parentheses are the t-statistics estimated by the Newey-West method.

Table 2:
Aggregate Daily Order Flow Following News
(1983-1999)

Panel A: $ord_{t+1} = a + \beta_1\ News_t + c\ ord_t + d_1\ ret_t + d_2\ ret_{t-250,t}$

	a	β_1	c	d_1	d_2	R^2
small	-0.035	-0.025	0.560	-0.226	0.046	0.230
	(-1.14)	(-0.50)	(17.44)	(-8.95)	(2.59)	
medium	0.023	-0.062	0.323	-0.068	0.001	0.076
	(0.69)	(-1.12)	(11.38)	(-2.39)	(0.04)	
large	0.056	-0.024	0.124	0.164	-0.037	0.063
	(1.87)	(-0.44)	(2.02)	(5.20)	(-1.69)	

Panel B: $ord_{t+1} = a + \beta_1\ News_t + \beta_2 D_t^G + \beta_{12} News_t D_t^G + c\ ord_t + d_1\ ret_t + d_2\ ret_{t-250,t}$

	a	β_1	β_2	β_{12}	c	d_1	d_2	R^2
small	-0.062	0.183	-0.001	-0.399	0.557	-0.217	0.067	0.235
	(-1.85)	(2.17)	(-0.03)	(-3.81)	(16.96)	(-8.85)	(2.76)	
medium	-0.002	0.059	0.046	-0.229	0.324	-0.066	-0.001	0.077
	(-0.07)	(0.68)	(0.99)	(-2.12)	(11.55)	(-2.38)	(-0.04)	
large	0.047	0.002	0.026	-0.048	0.124	0.164	-0.042	0.063
	(1.47)	(0.03)	(0.68)	(-0.50)	(2.01)	(5.29)	(-1.58)	

Panel C: $ord_{t+1} = a + \beta_1\ News_t + \beta_2 D_t^G + \beta_{12} News_t D_t^G + \beta_3 DOW_t + c\ ord_t + d_1\ ret_t + d_2\ ret_{t-250,t}$

	a	β_1	β_2	β_{12}	β_3	c	d_1	d_2	R^2
small	-0.063	0.185	0.015	-0.370	-0.132	0.557	-0.210	0.069	0.237
	(-1.89)	(2.19)	(0.34)	(-3.43)	(-3.05)	(16.86)	(-8.27)	(2.86)	
medium	-0.003	0.060	0.056	-0.210	-0.087	0.327	-0.064	0.000	0.078
	(-0.07)	(0.69)	(1.19)	(-1.91)	(-1.81)	(11.51)	(-2.32)	(0.01)	
large	0.048	0.001	0.007	-0.081	0.160	0.118	0.159	-0.045	0.065
	(1.49)	(0.01)	(0.17)	(-0.87)	(2.70)	(1.95)	(5.44)	(-1.68)	

The dependent variables are the order flow of small, middle, and large trades. Trades less than \$10,000 dollars are defined as small trades, trades more than \$50,000 are defined as large trades, and those in between are classified as middle trades. For a specific size, the order flow is defined as the buyer-initiated dollar turnover minus the seller-initiated turnover of NYSE-AMEX. Finally, the order flow is detrended by the average of the flows over the last 250 days. $News_t$ is the news dummy, which is 1 if both the NY Times and the LA Times cover the stock market with front-page articles. D_t^G is the good times dummy, which is 1 if the closing NYSE-AMEX index level on day t falls into the top 10% quantile among the last 500 days. DOW_t is the dummy variable for the Dow record events. *ret* is the return of the value-weighted NYSE-AMEX index. All the variables except the dummies are normalized to have unit variance. The numbers in parentheses are the t-statistics estimated by the Newey-West method.

Table 3:
Aggregate Daily Mutual Fund Flow Following Attention-Grabbing Events
(1998-2005)

Regression	(1)	(2)	(3)	(4)	(5)
DOW_t	-0.344	-0.553			-0.300
	(-2.70)	(-3.21)			(-2.28)
$News_t$			0.077	0.220	0.226
			(0.83)	(2.11)	(2.20)
D_t^G				-0.023	-0.006
				(-0.44)	(-0.11)
$News_t \times D_t^G$				-0.524	-0.479
				(-2.68)	(-2.44)
NAS_t		-0.351			
		(-2.62)			
NY_t		-0.114			
		(-1.05)			
SP_t		0.098			
		(0.44)			
$Flow_t$	-0.171	-0.153	-0.176	-0.176	-0.172
	(-4.47)	(-4.06)	(-4.69)	(-4.66)	(-4.48)
$Flow_{t-1}$	-0.092	-0.078	-0.097	-0.091	-0.087
	(-2.78)	(-2.35)	(-2.97)	(-2.80)	(-2.65)
ret_t	-0.077	-0.080	-0.080	-0.074	-0.070
	(-2.34)	(-2.42)	(-2.41)	(-2.25)	(-2.17)
$ret_{t-250,t}$	0.060	0.069	0.057	0.069	0.069
	(2.76)	(2.85)	(2.73)	(2.77)	(2.72)
Constant	-0.007	0.012	-0.024	-0.022	-0.021
	(-0.29)	(0.46)	(-0.92)	(-0.79)	(-0.77)
R^2	0.109	0.121	0.106	0.111	0.114

The dependent variable is $Flow_{t+1}$, the aggregate daily mutual fund flow, which starts on February 19, 1998 and ends on December 31, 2005. DOW_t, NAS_t, NY_t, and SP_t are the dummy variables for the record events of the four indices. $News_t$ is the News dummy, which is 1 if both the NY Times and the LA Times cover the stock market with front-page articles. D_t^G is the good times dummy, which is 1 if the closing NYSE-AMEX index level falls into the top 10% quantile within the last 500 days. $Flow_{t-i}$ is the lagged mutual fund flow and eight lags of the flow are included in the regressions. To be concise, only the coefficients on the first two lags are reported in this table. In regression (2), the interactions of the four dummy variables are also included in the regression, whose coefficients are not reported here. All of the variables except the dummies are normalized to have unit variance. The numbers in parentheses are the t-statistics estimated by the Newey-West method.

Table 4:
Individual-Investor Selling Decisions Following Record Events
(1991-1996)

							$D^{Win}_{i,j,t+1}\times$				$D^{Pos}_{i,j,t+1}\times$			
	DOW_t	NAS_t	NY_t	SP_t	$D^{Win}_{i,j,t+1}$	$D^{Pos}_{i,j,t+1}$	DOW_t	NAS_t	NY_t	SP_t	DOW_t	NAS_t	NY_t	SP_t
(1)	0.139	0.185	0.009	-0.045										
	(13.67)	(21.34)	(0.42)	(-1.77)										
	[3.04]	[5.14]	[0.15]	[-0.70]										
(2)	0.059	0.094	0.047	-0.011	0.460		0.114	0.105	-0.074	-0.076				
	(3.23)	(5.86)	(1.19)	(-0.25)	(83.41)		(5.23)	(5.57)	(-1.59)	(-1.39)				
	[1.24]	[1.65]	[0.67]	[-0.14]	[31.36]		[2.45]	[1.82]	[-0.97]	[-0.85]				
(3)	0.041	0.059	0.068	-0.020	0.350	0.218	0.105	0.068	-0.040	-0.071	0.028	0.073	-0.074	-0.005
	(2.02)	(3.26)	(1.56)	(-0.39)	(55.12)	(34.39)	(4.22)	(3.14)	(-0.74)	(-1.14)	(1.12)	(3.32)	(-1.38)	(-0.07)
	[0.78]	[0.98]	[0.90]	[-0.24]	[25.54]	[21.14]	[2.46]	[1.23]	[-0.52]	[-0.81]	[0.74]	[2.15]	[-1.11]	[-0.08]
(4)	0.152	0.172	0.014	-0.034										
	(13.46)	(17.76)	(0.62)	(-1.22)										
	[3.12]	[4.64]	[0.22]	[-0.51]										

We report the coefficients and the t-statistics of logistic regressions. The data include the trading records of 72,000 households from a large brokerage firm. In Regression 1, 2, and 3, the dependent variable is $Sell_{i,j,t+1}$, which is 1 if stock i is sold partly or completely by investor j at time $t+1$, and 0 otherwise. In Regression 4, the dependent variable is $Comsell_{i,j,t+1}$, which is 1 if stock i is sold completely by investor j at time $t+1$, and 0 otherwise. DOW_t, NAS_t, NY_t, and SP_t are for the record events of the Dow Jones Industrial Average Index, the Nasdaq Composite Index, the NYSE Composite Index, and the S&P 500 Index, respectively. $D^{Win}_{i,j,t+1}$ is the winner dummy, which is 1 if the selling price of stock i (if the stock is traded) or the closing price (if the stock is not traded) is higher than its average purchase price by investor j. $D^{Pos}_{i,j,t+1}$ is the positive return dummy, which is 1 if the return of stock i from the last time investor j makes a trade is positive. To save space, some estimates are not reported here. In all of the regressions, I include the value-weighted NYSE-AMEX-NASDAQ market returns (ret_t and $ret_{t-250,t}$), the returns of stock i (ret^i_t and $ret^i_{t-250,t}$), and the interactions of the four record dummy variables. The numbers in () are the t-statistics estimated with the standard method, and the numbers in [] are estimated with the standard deviations clustering the residuals on the same day.

Table 5:
Individual-Investor Selling Decisions Following News Events
(1991-1996)

	$News_t$	$D^{Win}_{i,j,t+1}$	$D^{Pos}_{i,j,t+1}$	$News_t D^{Win}_{i,j,t+1}$	$News_t D^{Pos}_{i,j,t+1}$
(1)	0.206				
	(29.39)				
	[5.36]				
(2)	0.126	0.468		0.128	
	(10.30)	(93.71)		(8.59)	
	[2.76]	[35.33]		[3.34]	
(3)	0.123	0.352	0.230	0.121	0.015
	(9.15)	(61.05)	(39.81)	(7.02)	(0.89)
	[2.43]	[27.99]	[25.41]	[3.78]	[0.47]
(4)	0.221				
	(28.63)				
	[5.51]				

We report the coefficients and the t-statistics of logistic regressions. The data include the trading records of 72,000 households from a large brokerage firm. In Regression 1,2, and 3, the dependent variable is $Sell_{i,j,t+1}$, which is 1 if stock i is sold partly or completely by investor j at time $t+1$, and 0 otherwise. In Regression 4, the dependent variable is $Comsell_{i,j,t+1}$, which is 1 if stock i is sold completely by investor j at time $t+1$, and 0 otherwise. $News_t$ is the news dummy, which is 1 if both the NY Times and the LA Times have front-page articles about the domestic stock market. $D^{Win}_{i,j,t+1}$ is the winner dummy, which is 1 if the selling price of stock i (if the stock is traded) or the closing price (if the stock is not traded) is higher than its average purchase price by investor j. $D^{Pos}_{i,j,t+1}$ is the positive return dummy, which is 1 if the return of stock i from the last time investor j makes a trade is positive. To save space, some estimates are not reported here. In all of the regressions, we include the value-weighted NYSE-AMEX-NASDAQ market returns (ret_t and $ret_{t-250,t}$), the returns of stock i (ret^i_t and $ret^i_{t-250,t}$), and the interactions of the four record dummy variables. The numbers in () are the t-statistics estimated with the standard method, and the numbers in [] are estimated with the standard deviations by clustering the residuals on the same day.

Table 6:
Market Returns Following Attention-Grabbing Events

Regression	(1)	(2)	(3)	(4)	(5)	(6)
	1974-2005	1931-2005	1931-1970	1971-2005	1931-2005	1983-2005
DOW_t	-0.284	-0.193	-0.123	-0.225	-0.187	
	(-5.07)	(-4.73)	(-2.40)	(-4.13)	(-4.68)	
$News_t$						0.088
						(0.93)
D_t^G						-0.008
						(-0.34)
$News_t \times D_t^G$						-0.238
						(-2.17)
NAS_t	-0.075					
	(-1.76)					
NY_t	-0.041					
	(-0.54)					
SP_t	0.122	0.013	0.056	-0.014	0.015	
	(1.40)	(0.45)	(1.72)	(-0.32)	(0.49)	
$Milestone_t$					-0.277	
					(-2.67)	
ret_t	0.114	0.118	0.100	0.135	0.118	0.082
	(6.87)	(9.60)	(5.74)	(9.63)	(9.60)	(4.05)
V_t	0.008	0.008	0.009	0.007	0.008	-0.000
	(0.65)	(0.59)	(0.31)	(0.57)	(0.59)	(-0.01)
$ret_t \times V_t$	-0.013	-0.006	-0.004	-0.015	-0.006	-0.010
	(-4.01)	(-0.93)	(-0.35)	(-4.22)	(-0.93)	(-3.06)
Constant	0.061	0.049	0.053	0.045	0.049	0.050
	(5.45)	(6.82)	(4.99)	(4.44)	(6.82)	(2.49)
R^2	0.012	0.013	0.013	0.015	0.014	0.007

The dependent variable is the next-day percent return on the value-weighted NYSE-AMEX index, ret_{t+1}. DOW_t, NY_t, NAS_t, and SP_t are the dummy variables for the record events of the Dow Jones Industrial Average Index, the Nasdaq Composite Index, the NYSE Composite Index, and S&P 500 Index respectively. $Milestone_t$ is the dummy variable for the milestone event, which is 1 if the Dow breaks hundred marks (when the Dow is below 1,000) or thousand marks (when the Dow is above 1,000) for the first time. $News_t$ is 1 if both the NY Times and the LA Times cover the stock market with front-page articles. D_t^G is the good times dummy, which is 1 if the closing NYSE-AMEX index level falls into the top 10% quantile within the last 500 days. V_t is the detrended dollar turnover of NYSE-AMEX. V_t is normalized to have unit variance. The numbers in parentheses are the t-statistics estimated by the Newey-West method.

Table 7:
Trading Volume Following Attention-Grabbing Events
(1983 - 1999)

Panel A: $vol_{t+1} = a + b\ DOW_t + c\ vol_t + d_1\ |ret_t| + d_2\ |ret_{t-250,t}|$

	a	b	c	d_1	d_2	R^2
small	-0.092	0.237	0.654	0.163	-0.009	0.518
	(-2.56)	(5.88)	(25.32)	(6.56)	(-0.53)	
medium	-0.172	0.198	0.578	0.151	0.061	0.422
	(-4.07)	(4.32)	(20.58)	(6.20)	(2.67)	
large	-0.226	0.243	0.385	0.182	0.067	0.226
	(-5.04)	(4.67)	(8.90)	(4.33)	(2.76)	

Panel B: $vol_{t+1} = a + b_1 DOW_t + b_2 NAS_t + b_3 NY_t + b_4 SP_t + b_{12} DOW_t NAS_t + b_{13} DOW_t NY_t + b_{14} DOW_t SP_t + b_{23} NAS_t NY_t + b_{24} NAS_t SP_t + b_{34} NY_t SP_t + c\ vol_t + d\ |ret_t| + d_2\ |ret_{t-250,t}|$

	b_1	b_2	b_3	b_4	b_{12}	b_{13}	b_{14}	b_{23}	b_{24}	b_{34}
small	0.171	0.248	0.074	0.020	0.137	-0.228	-0.004	-0.122	-0.011	0.169
	(2.52)	(5.34)	(0.69)	(0.14)	(1.22)	(-1.55)	(-0.03)	(-0.67)	(-0.06)	(1.16)
medium	0.136	0.197	0.097	-0.076	0.221	-0.244	-0.006	-0.073	-0.080	0.235
	(1.96)	(3.92)	(0.86)	(-0.51)	(1.90)	(-1.68)	(-0.04)	(-0.40)	(-0.41)	(1.55)
large	0.173	0.241	-0.050	0.009	0.002	0.009	-0.058	0.198	-0.381	0.225
	(2.22)	(2.60)	(-0.40)	(0.06)	(0.02)	(0.06)	(-0.38)	(1.05)	(-1.99)	(1.40)

Panel C: $vol_{t+1} = a + \beta_1\ News_t + \beta_2 D_t^G + \beta_{12}\ News_t D_t^G + c\ vol_t + d_1\ |ret_t| + d_2\ |ret_{t-250,t}|$

	a	β_1	β_2	β_{12}	c	d_1	d_2	R^2
small	-0.092	-0.022	0.070	0.202	0.658	0.156	-0.026	0.517
	(-3.04)	(-0.33)	(2.71)	(2.44)	(31.42)	(4.94)	(-1.60)	
medium	-0.177	-0.001	0.087	0.198	0.577	0.144	0.036	0.423
	(-5.20)	(-0.02)	(3.00)	(2.28)	(26.97)	(5.05)	(1.90)	
large	-0.241	-0.057	0.155	0.178	0.385	0.192	0.025	0.227
	(-5.61)	(-0.83)	(4.15)	(1.91)	(9.37)	(4.37)	(1.08)	

The dependent variables are dollar turnover of small, middle, and large trades for NYSE-AMEX. Trades less than $10,000 dollars are defined as small trades, trades more than $50,000 are defined as large trades, and those in between are classified as middle trades. The turnover is detrended by the average of the last 250 days. DOW_t, NAS_t, NY_t, and SP_t are the dummy variables for the record events of the Dow Jones Industrial Average Index, the NYSE Composite Index, the Nasdaq Composite Index, and the S&P 500 Index, respectively. D_t^{News} is 1 if both the NY Times and the LA Times cover the stock market with front-page articles. D_t^G is the good times dummy, which is 1 if the closing NYSE-AMEX index level falls into the top 10% quantile within the last 500 days. *ret* is the return on the value-weighted NYSE-AMEX index. All of the variables except the dummy variables are normalized to have unit variance. The numbers in parentheses are the t-statistics estimated by the Newey-West method.